

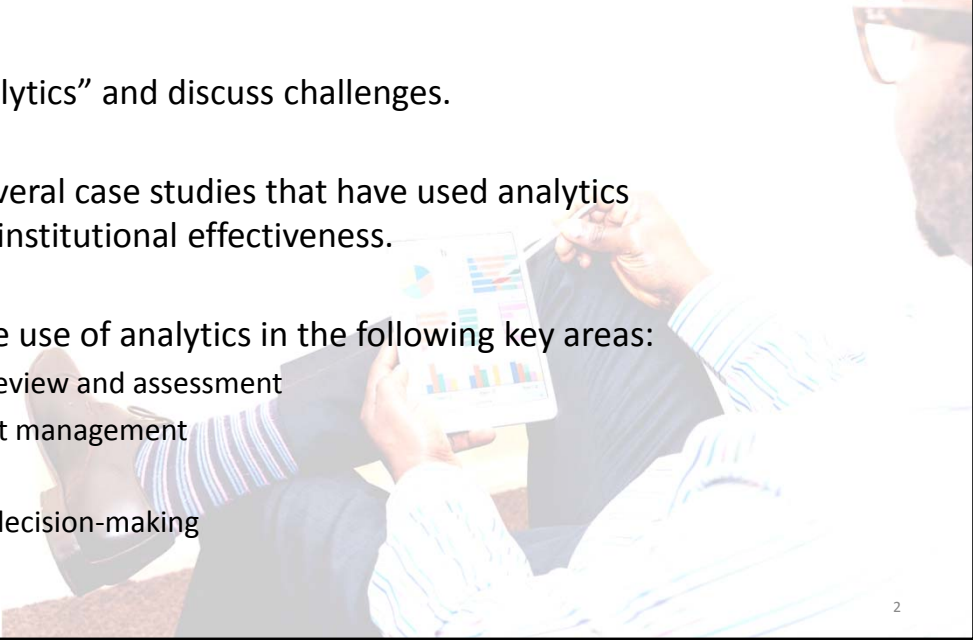


W5: A Primer on Analytics and Visualization in Higher Education

John Stanley, University of Hawai'i – West Oahu
Ken Nelson, Loma Linda University

WSCUC ARC Pre-Conference Workshop, San Diego, CA, April 19, 2017

Session objectives

1. Define “analytics” and discuss challenges.
 2. Examine several case studies that have used analytics to improve institutional effectiveness.
 3. Examine the use of analytics in the following key areas:
 - a) Program review and assessment
 - b) Enrollment management
 - c) Surveys
 - d) ‘What-if’ decision-making
- 

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Two institutions, one mission



3

Activity

Think – Pair – Share Activity

3 minute questionnaire + 5 minute share

1. Area(s) of notable strength?
2. Area(s) for improvement?
3. If IR analytical capacity were **enhanced**, what **campus/program issue could be better addressed or potentially solved?**

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Challenges for Institutional Research

- Compliance vs. Self-Improvement
- Developing a culture of evidence
- From reporting to analysis
- Converting data into 'actionable' information
- Follow highest standards, best practices
- Know your customers, mission
- Leverage technology, stay abreast of tech
- Empower staff, continuous honing of skills
- Effective senior-management support working with IR (and IT)

AIR Newsletter March 2016

"I've seen too many IR offices that operate like a reporting agency and focus IR analysis only on what has happened in the past. Decisions, however, are made about the future – specifically, about the expected outcomes of future events... For the future of IR, professionals should become active in helping to minimize the risks of a decision by providing insightful analysis about possible outcomes."

– Bob Daly, eAIR Newsletter, March 2016

The screenshot shows the eAIR website interface. At the top, it says "50th Anniversary ASSOCIATION FOR INSTITUTIONAL RESEARCH Data and Decisions for Higher Education". Below the navigation bar, the article title "THE FUTURE OF IR" is prominently displayed. The author is identified as Bob Daly, Assistant Vice Chancellor Emeritus at the University of California-Riverside. The article text begins with a quote from Bob Daly: "I've seen too many IR offices that operate like a reporting agency and focus IR analysis only on what has happened in the past. Decisions, however, are made about the future – specifically, about the expected outcomes of future events... For the future of IR, professionals should become active in helping to minimize the risks of a decision by providing insightful analysis about possible outcomes." The article continues to discuss the importance of future-oriented analysis in decision-making.

SOURCE: <https://www.airweb.org/eAIR/specialfeatures/Pages/The-Future-Of-IR.aspx>

What is analytics?

“Analytics is the use of data, statistical analysis, and **explanatory and predictive** models to gain insights and **act** on complex issues.”

-EDUCAUSE Center for Applied Research

EDUCAUSE Center for Applied Research Video: “What is Analytics?”

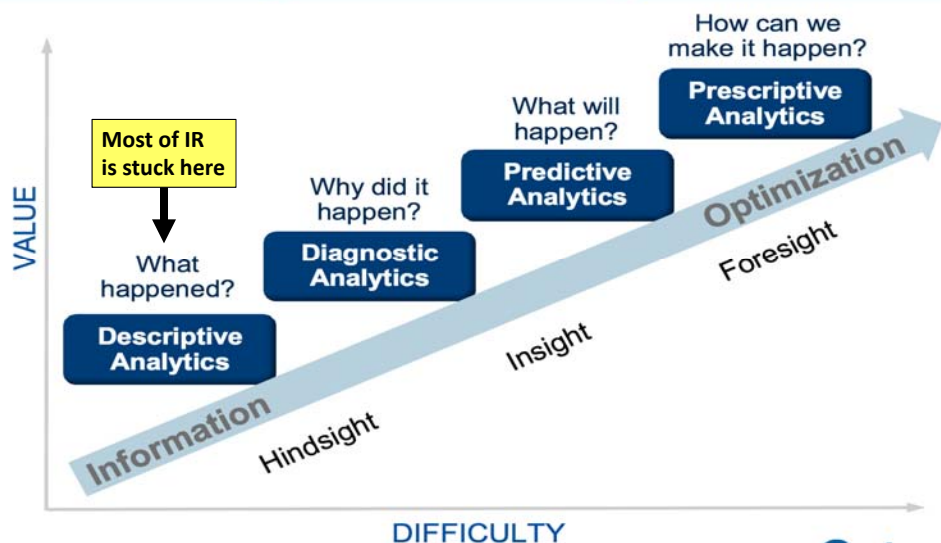
Downloaded from:

<http://www.educause.edu/ero/article/video-what-analytics>

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From hindsight to foresight

Gartner Analytic Ascendancy Model



SOURCE: <http://evollution.com/wp-content/uploads/2016/02/From-Hindsight-to-Foresight.png>

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Gartner

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IR tasks applied to Gartner Ascendancy Model

DESCRIPTIVE

1. Disaggregating student retention rates by gender, ethnicity, Pell, first generation status, etc.
2. Descriptive data in tables, charts, and graphs.
3. A cross-tabulation showing retention rates for students in learning communities versus non-learning community students.

DIAGNOSTIC

1. Using inferential statistics to determine if there are statistically significant differences between groups and identify important drivers of behavior.
2. Interactive dashboards with slice and dice capability, drop downs.
3. A counter-factual analysis that controls for self-selection bias using student matching techniques.

PREDICTIVE

1. Building a prediction model to identify which students are 'at-risk' of dropping out.
2. Interactive dashboards with 'what-if' capability for key decision-makers.
3. Using learning community as a variable in a prediction model for retention or time-to-degree.

PRESCRIPTIVE

1. Delivering dropout risk assessment lists to student support services in order to provide actionable information.
2. Interactive dashboards used to push dropout risk data to academic advisors.
3. A more precise gauge of the impact of learning communities given to LC coordinators.

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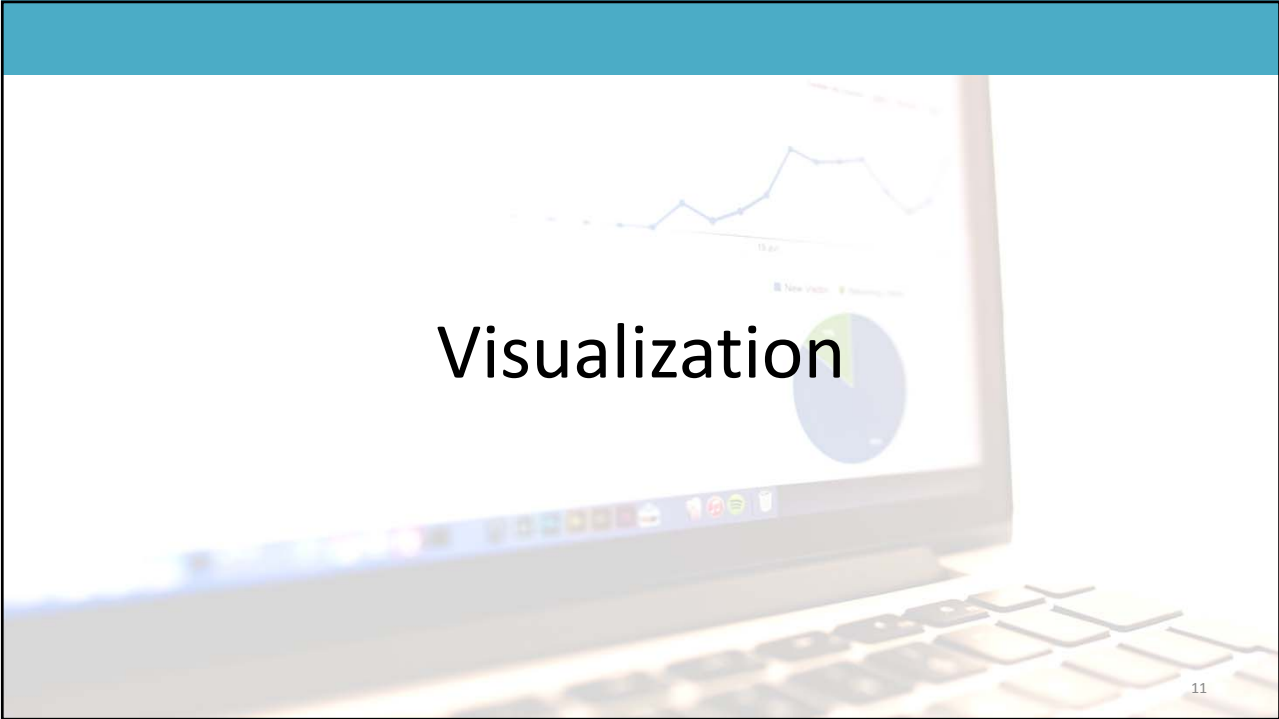
Analytics typology

Covered Today



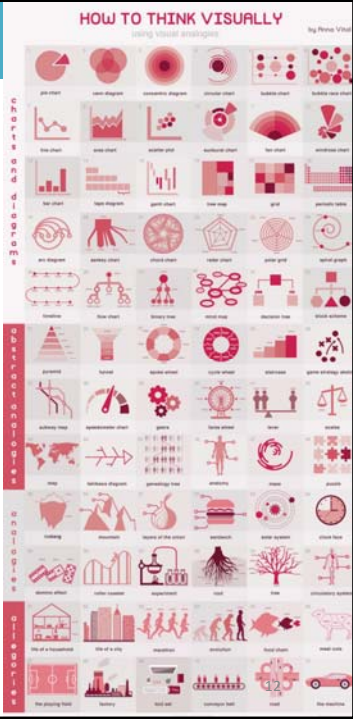
Source: <https://library.educause.edu/~media/files/library/2012/1/eli3026-pdf.pdf>

10



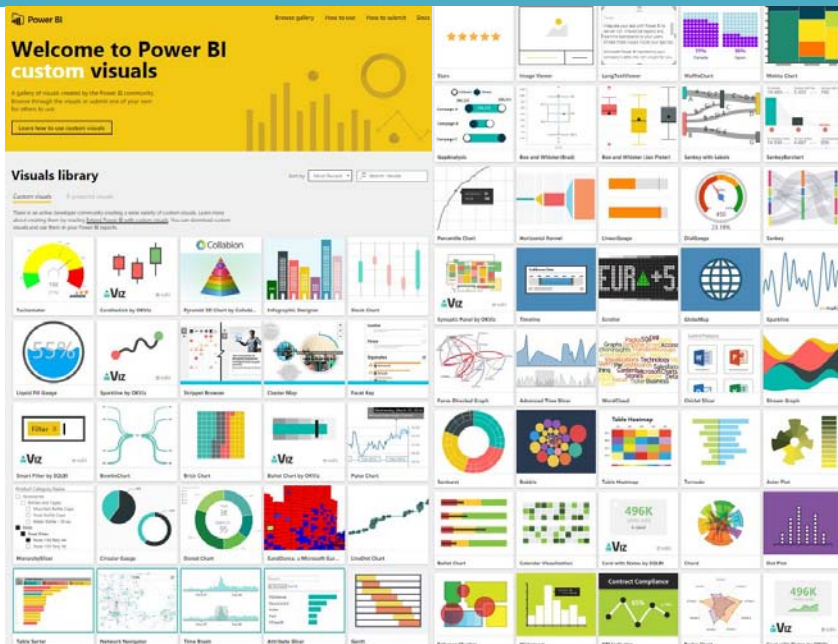
Visualization

- Data visualization is used to communicate data or information by representing it as visual objects (e.g., heatmaps, chords, sankeys).
- The goal is to communicate information clearly and efficiently to help users make:
 - faster insights
 - clearer choices
 - faster decision making



Source: <http://designtaxi.com/news/376549/Infographic-72-Ways-To-Think-Present-Your-Ideas/>

Visualization with Microsoft Power BI (free)



Source: <https://app.powerbi.com/visuals/>

Gartner Magic Quadrant for BI (2017)

Microsoft | Power BI | Products | Solutions | Partners | Learn

Microsoft Power BI Blog

BLOG » ANNOUNCEMENTS » FEATURES

Gartner positions Microsoft as a leader in BI and Analytics Platforms for ten consecutive years

 **Miguel Martinez**
Sr. Product Marketing Manager

February 16, 2017

[Share](#) [Tweet](#) [Like](#)



SOURCE: <http://optimalbi.com/blog/2017/02/17/gartner-magic-quadrant-for-business-intelligence-2017-cloud-is-coming-slowly/>

Visualization with Microsoft Power BI

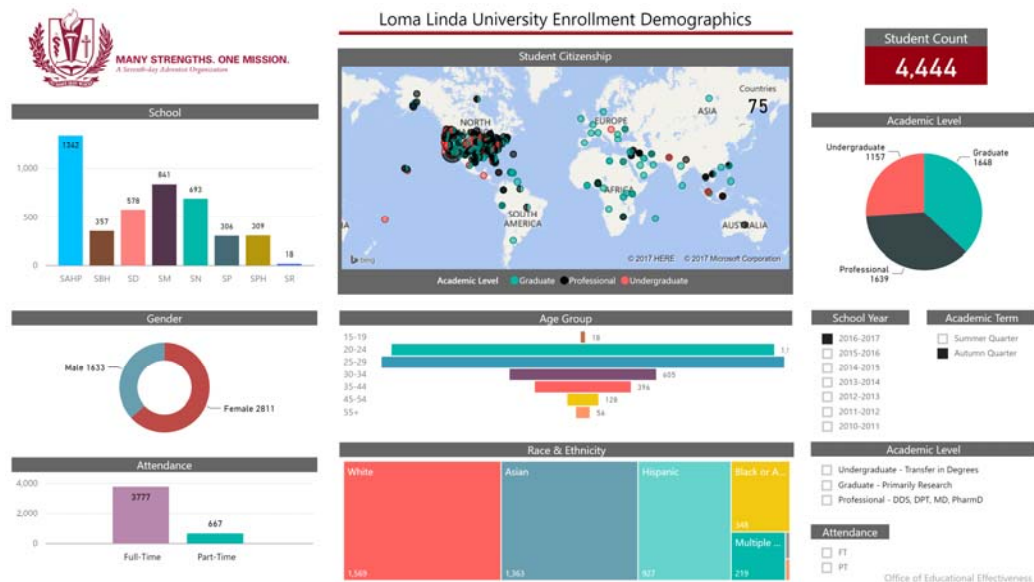
Dashboards
as a
Collection of
Tiles
Providing
Links to
Underlying
Reports



15

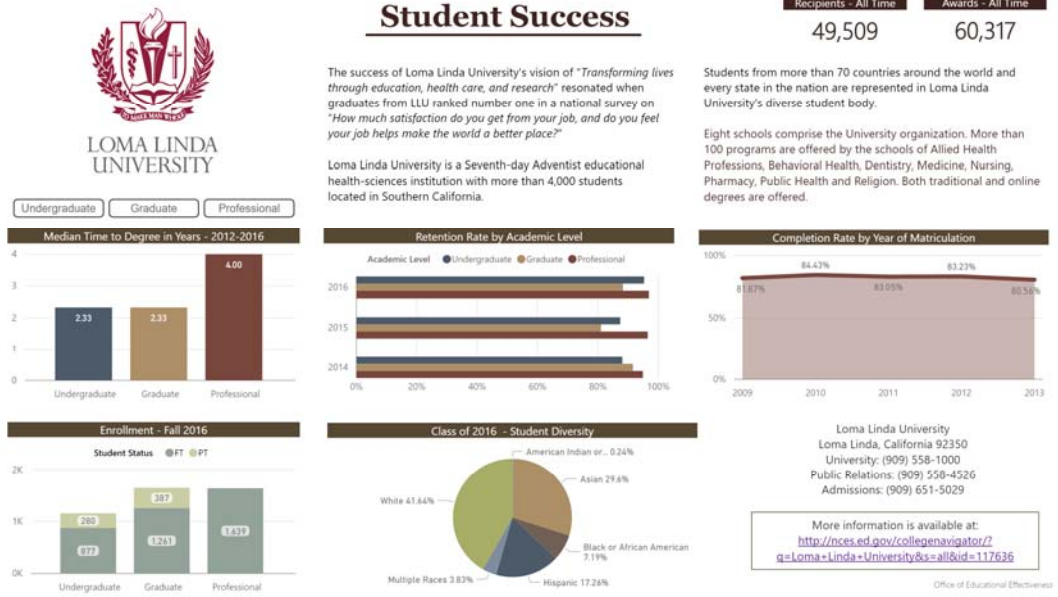
Visualization with Microsoft Power BI

Public
informative
dashboards.
In this
example
Loma Linda
University's
enrollment
demographics
are displayed
on the
University's
website.



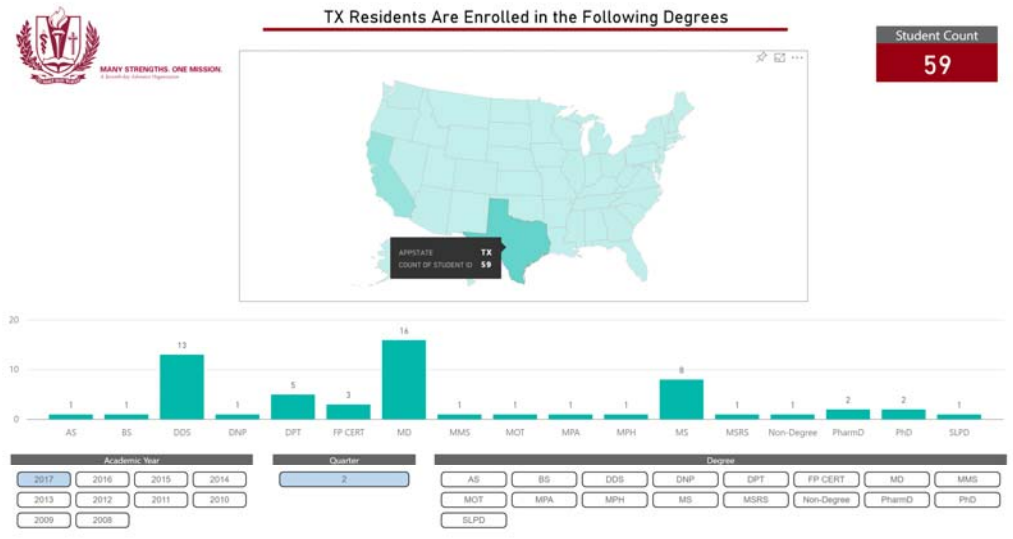
Visualization with Microsoft Power BI

Interactive charts and graphs with explanatory text. This example provides student success information as required by the regional accreditor.



Visualization with Microsoft Power BI

Interactive maps that allow disaggregating data by selecting areas of interest. In this example program enrollment is displayed by state selected.





Predictive Analytics

- Uses historical data to predict or forecast future behaviors, trends, or outcomes
(i.e. enrollment likelihood, retention, course pass/fail, degree completion, gainful employment, etc.)

| | | | | | | | | | |
|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 81% | 30% | 85% | 40% | 50% | 95% | 40% | 65% | 10% | 25% |
|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|

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Benefits of predictive analytics

- Can generate “actionable” data (i.e., data used by academic support services to effectively assist students).
- Powerful and accurate predictive models can be constructed using matriculation data from your Student Information System (SIS).



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Possible uses of predictive analytics

- Admissions recruitment
 - Predict which students are likely to enroll at your institution (Goenner & Pauls, 2006)
- Identifying at-risk students
 - Predict which students are likely to drop out or fall behind (Herzog, 2006 ; Sujitparapitaya, 2006)
- Students’ price responsiveness to tuition increases or financial aid incentives (Des Jardins, 2001; Herzog & Stanley, 2017)
- Other uses?
 - Student Learning
 - Strategic Planning
 - Finance



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A few examples of colleges using predictive analytics...



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University of Texas at Austin

Predictive Modeling | Student Success

studentsuccess.utexas.edu/approach/predictive-modeling

Office of the Executive Vice President & Provost

TEXAS

The University of Texas at Austin
Student Success Initiatives
Office of the Executive Vice President and Provost

APPROACH INITIATIVES UTELL US NEWS TEAM

HOME > Approach > Predictive Modeling

Predictive Modeling

Data Informs Every Decision

With more than 35,000 applicants to The University of Texas at Austin last year, it is critical we make data-informed decisions to ensure the enrollment of a high-quality class that has the resolve to graduate in four years.

David Laude, PhD
"Graduation Champion"

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University of Texas at Austin

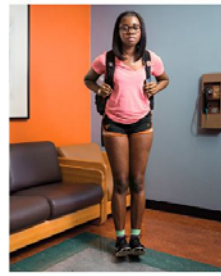
For the Class of 2017:

- 94.6 percent retention, up from 93.6 percent prior year, resulting in the highest one-year retention rate in the university's history for returning freshmen.
- Average GPA of 3.28, up from 3.22 for the previous class.
- Students enrolled in and passed more SSH (average 13.32 hours passed) than any entering class in the past five years. Taking more credit hours each semester will help these students stay on track to graduate in four years.

The New York Times

Who Gets to Graduate?

By PAUL TOUGH MAY 18, 2014



Vanessa Brewer for The New York Times

For as long as she could remember, Vanessa Brewer had her mind set on going to college. The image of herself as college student appealed to her — independent, intelligent, a young woman full of potential — but it was more than that; it was a chance to rewrite the ending to a family story that went off track 18 years earlier, when Vanessa's mother, then a high-achieving high-school senior in a small town in Arkansas, became pregnant with Vanessa.

Vanessa's mom did better than most teenage mothers. She married her high-

Source: https://www.nytimes.com/2014/05/18/magazine/who-gets-to-graduate.html?_r=0²⁵

Other Noteworthy Examples

1. Georgia State University (reduced achievement gaps, featured nationally)
2. University of Nevada, Reno (early pioneer, raised retention 4% pts, featured nationally)

...See syllabus for more references

Learning Analytics



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What is Learning Analytics?

- Defined as “the measurement, collection, analysis, and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs”

– (Long & Siemens, 2011, p. 32).

- Data may be available in your institution’s Learning Management System (LMS).

Learning Analytics via Sakai LMS

The screenshot displays the Sakai LMS interface for the course HIST-459-1 [WOA.65044.FA16]. The top navigation bar includes the course name and a dropdown menu for 'View Site As' set to 'Instructor'. The left-hand navigation menu is circled in red and contains the following items: Unpublished Site, Publish Now, University of Hawai'i, Home, Da Motherload (Course Files), Schedule, Announcements, Assignments, Online Discussions, Links, Gradebook, Quizzes, Polls, Email, Statistics, Site Info, and Help.

The main content area is divided into three sections:

- HIST-459-1 [WOA.65044.FA16]: Worksite Information**
 - HIST 459 WI: Europe since 1945**
 - Instructor: [Redacted]
 - Email: [Redacted] (please do not send messages to no-reply@lauilima.hawaii.edu)
 - Phone: [Redacted]
 - Campus Office: [Redacted]
 - Office Hours: TUE/THU, 9:30-10:30 am and via appointment (online, phone, or face-to-face)
 - Required books:
 - Buchi Emecheta, *Second-Class Citizen*
 - Franklin Foer, *How Soccer Explains the World*
 - Anna Funder, *Stasiland*
 - Schildt and Siegfried, *Between Marx and Coca Cola*
- HIST-459-1 [WOA.65044.FA16]: Recent Announcements**
 - Options
 - Announcements (viewing announcements from the last 10 days)
 - There are currently no announcements at this location.
- HIST-459-1 [WOA.65044.FA16]: Calendar**
 - Options
 - April 2017

| Sun | Mon | Tue | Wed | Thu | Fri | Sat |
|-----|-----|-----|-----|-----|-----|-----|
| 26 | 27 | 28 | 29 | 30 | 31 | 1 |
| 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| 9 | 10 | 11 | 12 | 13 | 14 | 15 |
| 16 | 17 | 18 | 19 | 20 | 21 | 22 |
| 23 | 24 | 25 | 26 | 27 | 28 | 29 |
| 30 | 1 | 2 | 3 | 4 | 5 | 6 |

LA predictors commonly used

- Performance/Activity in Class (LMS)
 - Number and frequency of LMS logins
 - Amount of time spend on course website
 - Number of discussion posts
 - Responses to class polls
 - Grades and formative quiz scores
 - Percentage of points earned in course to date
 - Change between past and current test/quiz scores
- Student In-Class Assignments (LMS)
 - Blogs, discussion forum posts,
 - Essays, written assignments
- Student Learning Outcomes (LMS)
 - Measurements of student achievements in core competencies in class.
- Matriculation Predictors (SIS)
 - Demographics (age, gender & ethnicity), GPA, pre-collegiate HS GPA, standardized tests scores, first-generation, socio-economic & financial need

LA can help answer questions like...

- What is the likelihood that a particular student will pass the class?... or master a certain learning outcome?
- Are there dispositional characteristics that predict or explain performance in certain classes (i.e. Do males outperform females in STEM classes or vice versa)
- Can LMS data be used with SIS data to predict student persistence and degree completion?

LA at Purdue University

Signals Home About Help

Intervention Successfully Ran!
View your results below, or click on the Intervention title for more details. Next, take action by composing emails for your students or releasing stoplights to Blackboard. These options will always be available for the current intervention by clicking on the buttons at the top of the dashboard.

Biology 300 001 Spring 2009 Add Intervention Blackboard Stoplights Compose Emails

Section Dashboard

Show/Hide Filter

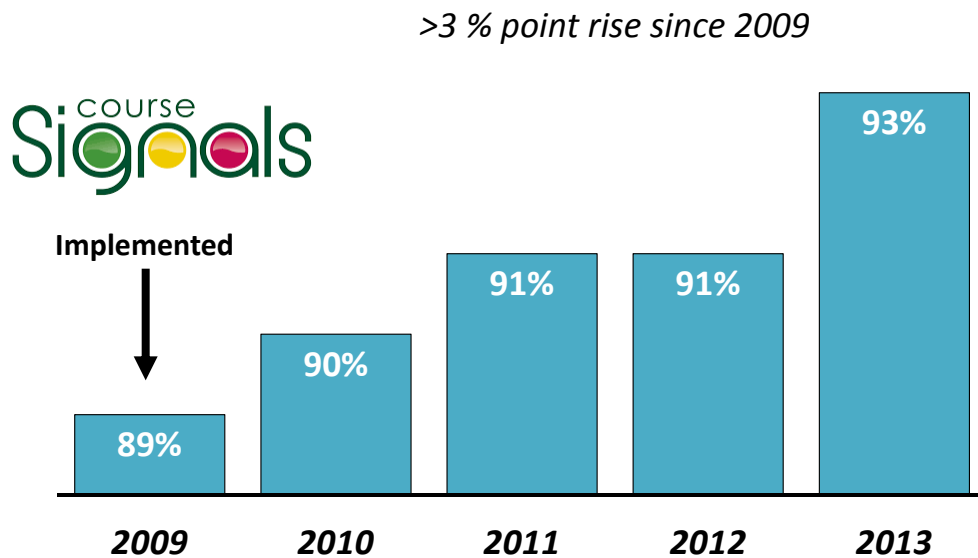
| Student | Int.1 | Int.2 | Int.3 | Int.4 | Int.5 | Int.6 | Int.7 | Course Int.15 |
|---------------|-------|-------|--------|-------|-------|--------|-------|---------------|
| Smith, Angela | Red | Green | Yellow | Green | Green | Yellow | Green | Yellow |
| Jones, Bobby | Green | Green | Yellow | Green | Green | Yellow | Green | Yellow |
| Duncan, Chris | Green | Green | Red | Red | Green | Yellow | Green | Yellow |

PURDUE UNIVERSITY

Purdue University, West Lafayette, IN 47907 USA, (765) 494-4600
© 2009 Purdue University. An equal access, equal opportunity university.

<http://www.nbcnews.com/id/3032619/vp/32634348#32634348>

Student Retention at Purdue



Other Noteworthy Examples

1. Rio Salado College - "RioPACE"
2. University of Michigan - "Ecoach"
3. University of Maryland, Baltimore – "Blackboard Learn"

...See syllabus for more references

Challenges to using analytics

Affordability

- Infrastructure
- Technology
- People/Expertise
- Opportunity Costs

Data availability

- Student Information System
- Learning Management System
- Budget/ Human Resource Silos

Predictive data

- Culture change
- Wary of misuse of data
- Questions about data used to generate scores
- Students' access to risk scores
- Self-fulfilling prophecy

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Combined Activity + Break

Think – Pair – Share Activity

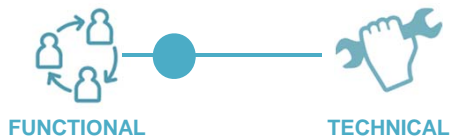
5 minute discussion over break

1. What are some challenges at your institution to supporting a culture for analytics (**i.e., affordability, data availability, expertise, etc**)?
2. What strategies may be helpful for overcoming these challenges?

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Analytics Application #1

Program Review and Assessment



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Process and Purpose

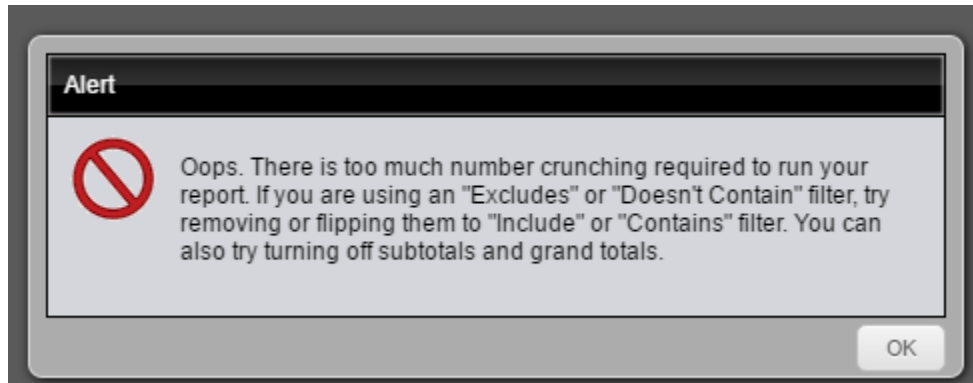
- Process of Program Review on campus
- Variable skillset of faculty and staff
- Curriculum mapping and rubric assessment
- Collecting assessment data
- Purpose
 - **Bringing it all together**
 - **Using the data to make changes where needed - “closing the loop”**
- Power BI examples



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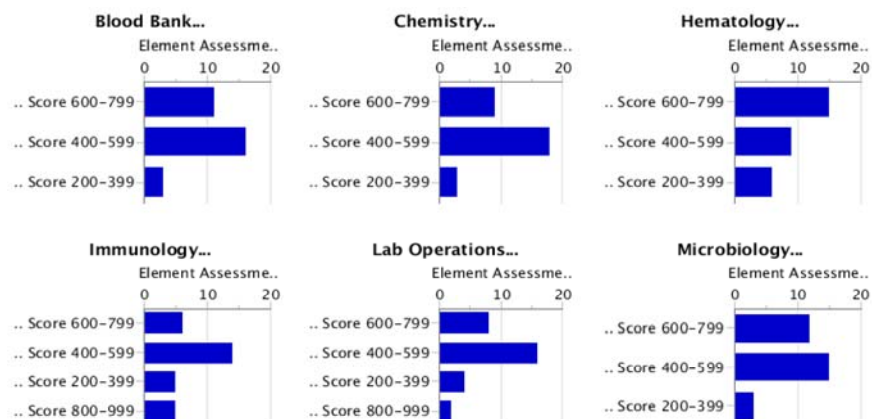
Rubric Element Scoring – Institution Example

- Challenge –
 - Assessment software couldn't provide average rubric value
 - Assessment software didn't allow complete data extract
 - Attempting to use the assessment software built-in analytics resulted in:



Rubric Element Scoring – Institution Example

- Challenge –
 - Extract needed student IDs
 - Rudimentary analytics provided by assessment software



Rubric Element Scoring – Institution Example

- Solution –
 - Create small reports in the assessment software
 - Download csv of created report
 - Recombine using Power BI query editor

The screenshot shows the Power BI Query Editor interface. On the left, a 'Queries [9]' pane lists 'Rubric Scoring', 'people', 'SN', 'SP', and 'SR'. The main area displays a table with columns: Institution, Academic Year, College, Department, and Major. The table contains 6 rows of data for Loma Linda University in 2014. The 'Query Settings' pane on the right shows 'Name' as 'SM' and a list of 'APPLIED STEPS' including Source, Navigation, Promoted Headers, Changed Type, Renamed Columns, Changed Type1, Replaced Errors, Changed Type2, and Replaced Errors1. Below the table is a ribbon with various data manipulation options like Transpose, Reverse Rows, Detect Data Type, Fill, Pivot Column, etc.

Rubric Element Scoring – Institution Example

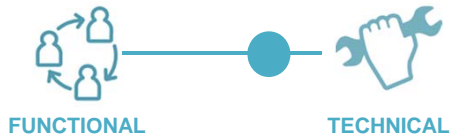
The screenshot shows the 'Rubric Element Scoring' assessment tool interface. At the top left is the LLU logo with the motto 'MANY STRENGTHS. ONE MISSION.' The title is 'Rubric Element Scoring' and the assessment tool is 'Assessment Tool: LLU Quantitative Reasoning Metarubric Official'. There are two dropdown menus: 'Students' showing '49' and 'Student' showing 'All'. A blue arrow points to the 'Student' dropdown. Below this is a horizontal bar chart titled 'Rubric Element - Average Score' with the following data:

| Rubric Element | Average Score |
|---|---------------|
| APPLICATION / ANALYSIS: Ability to ... | 3.55 |
| ASSUMPTIONS: Ability to make and ... | 3.92 |
| CALCULATION... | 3.88 |
| COMMUNICATION: Expressing quant... | 3.90 |
| INTERPRETATION: Ability to explain L... | 3.63 |
| REPRESENTATION: Ability to convert ... | 3.94 |

To the right is a circular gauge chart titled 'Average Overall Rubric Score' showing a score of 3.80 on a scale from 1 to 4. Below the charts is a section for 'Assessment for:' with various filters: Race/Ethnicity (checkboxes for American Indian or Alaska Native, Asian, Black or African American, Hispanic, Multiple Races, Native Hawaiian or Other Pacific Islander, Nonresident Alien, White), School (All), Age Group (All), Program (checkboxes for Biochemistry, Biology, Biostatistics, Clinical Laboratory Science), Rubric (checkboxes for LLU Critical Thinking Metarubric Official, LLU Information Literacy Metarubric Official, LLU Oral Communication Metarubric Official, LLU Quantitative Reasoning Metarubric Official (checked), LLU Service Learning Grading Rubric, LLU Written Communication Metarubric Official), Degree ((Blank)), and a 'Set' button. There are also checkboxes for SDA (Y/N), Gender (M/F), and Year (All). A blue arrow points to the 'Rubric' section.

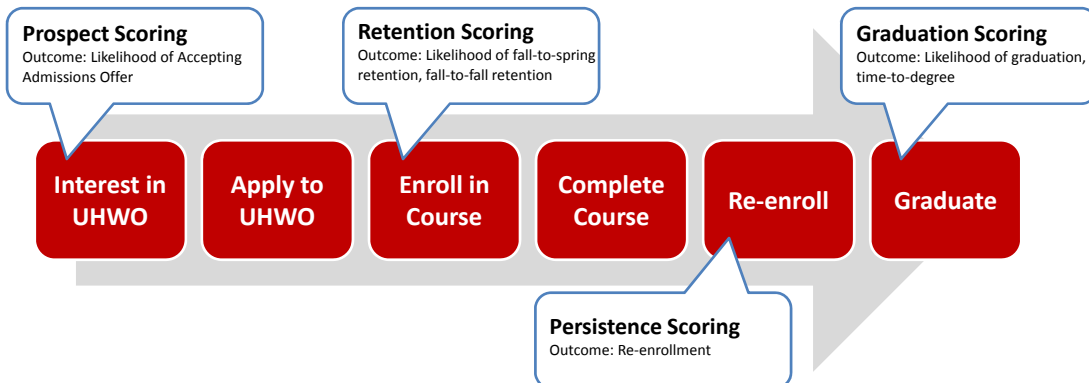
Analytics Application #2

Enrollment Management



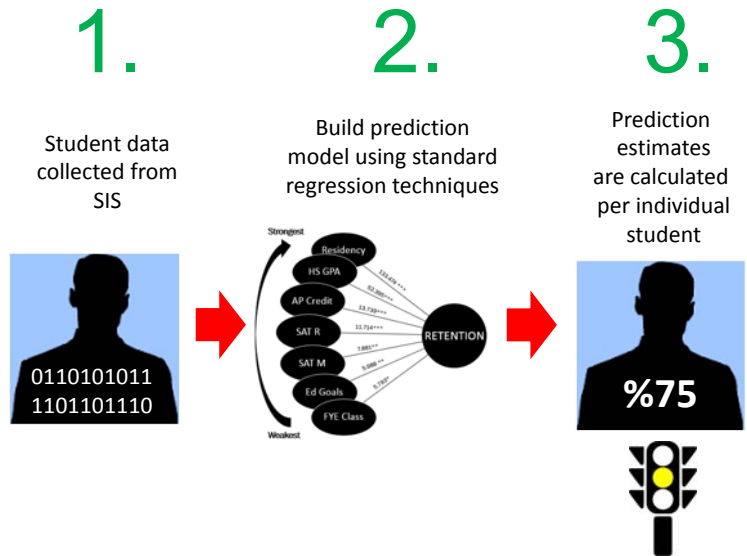
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Predictive analytics for the enrollment funnel



How does predictive modeling work?

Student Dropout Risk Example



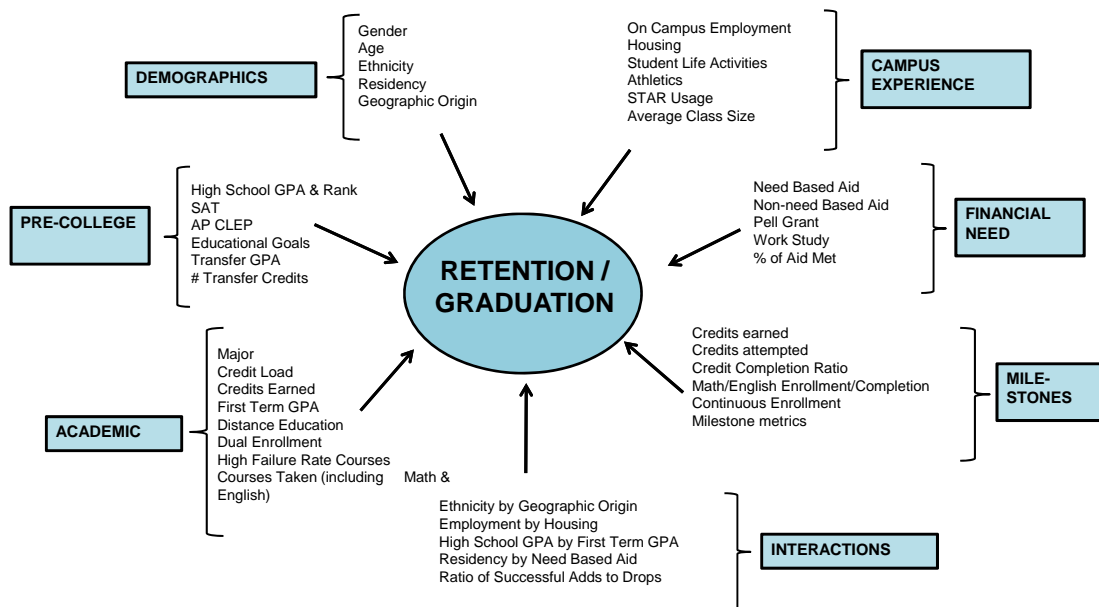
Student John Doe at the beginning of the semester:

- First Generation Student
- < Average high school GPA (3.00)
- Attempting 12 credits (12)
- Low % of financial need met (65%)
- Undeclared major
- Not enrolled in a campus learning community
- No educational goals in survey
- Not working on campus

Probability of Dropping Out:
75%

45

A taxonomy of SIS data available for prediction



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Sample data for advisors/success coaches

| ID | LAST NAME | FIRST NAME | EMAIL | CURRENT CREDITS | RESIDENT | AP/ CLEP | HS GPA | WORK ON CAMP | 1 st YR EXP CLASS | % FIN NEED MET | STAR LOGINS | ADVISOR PREVIOUS CONTACT |
|-----|-----------|------------|-------|-----------------|----------|----------|--------|--------------|------------------------------|----------------|-------------|--------------------------|
| 001 | | | | 15 | HI | 6 | 3.80 | Y | Y | 77% | 5 | Y |
| 002 | | | | 14 | HI | 0 | 3.33 | N | Y | 63% | 3 | N |
| 003 | | | | 12 | CA | 6 | 3.00 | N | N | 45% | 0 | N |

| ID | AGE | GENDER | ETHNICITY | COLLEGE | MAJOR | DEGREE | Ed Goal Specified | Relative Risk Value | Risk Level |
|-----|-----|--------|-----------|---------|-------|--------|-------------------|---------------------|------------|
| 001 | 18 | F | CH | CA&H | ART | BA | Yes | 14.92 | LOW |
| 002 | 18 | F | HW | CSS | SOC | BA | Yes | 36.88 | MEDIUM |
| 003 | 18 | M | UNDEC | UNDEC | UNDEC | UNDEC | No | 89.18 | HIGH |

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Academic advising intervention example

John



- First Generation
- SAT-M/SAT-R = 900
- H.S. GPA = 3.00
- 85% Unmet Financial Need
- Undeclared
- 12 credits registration

- Dropout risk probability: **60%**
- Risk group: **6 of 10**

Intervention strategy:

- Proactive advising
- Meta major pathway mapping
- Revisit financial aid support and other support
- Check for possible ill-advised registration choices

Ken



- SAT-M/SAT-R = 1100
- H.S. GPA = 3.50
- Declared major (Accounting)
- Local address within 5 miles
- 15 credits registration
- Educational Goals = "Earn B.A."

- Dropout risk probability: **15%**
- Risk group: **1 of 10**

Intervention strategy:

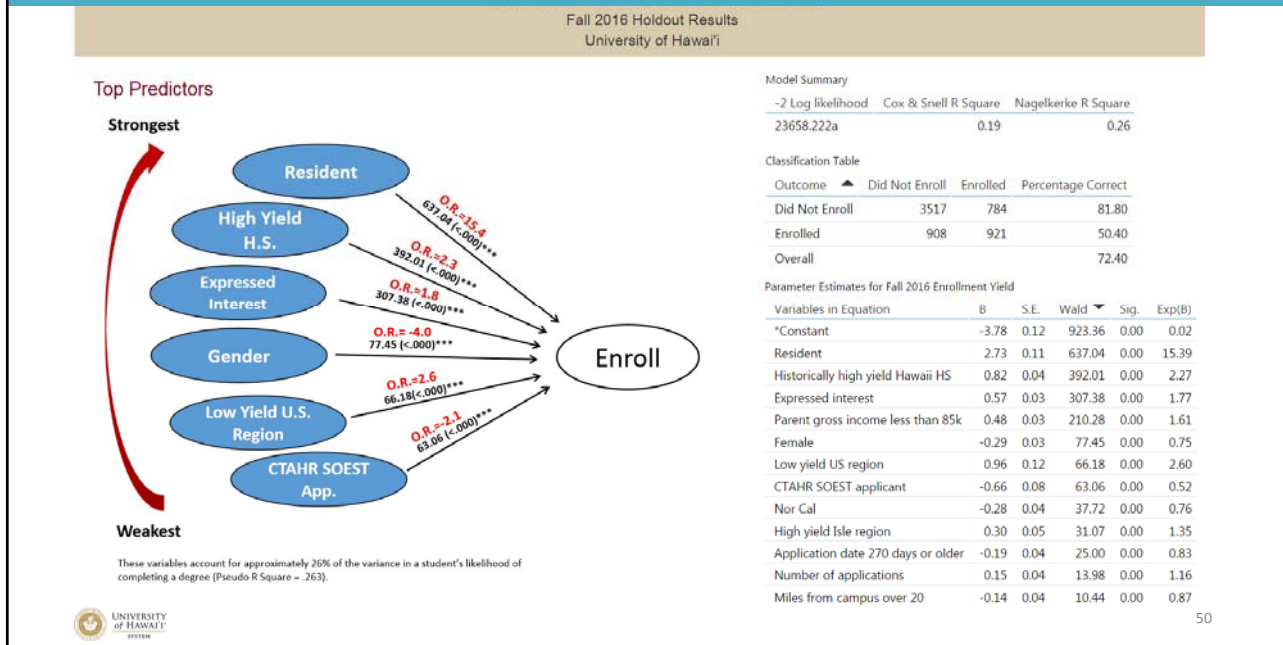
- Monitor *Starfish* reporting
- Mid-semester check-in
- Re-assess dropout risk at end-of-semester

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Analytics system for enrollment mgmt.



Predictive analytics



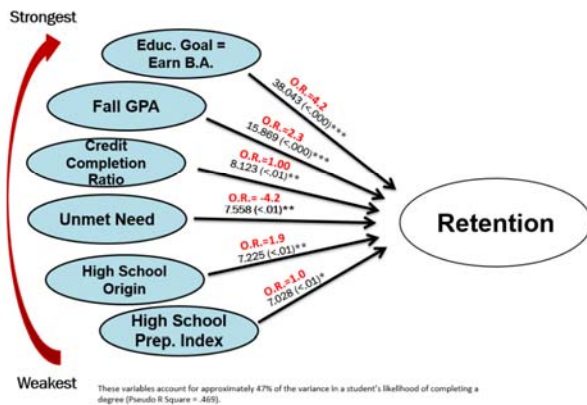
A prediction system for retention



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Predictive analytics

UNIVERSITY of HAWAII WEST OAHU Retention Prediction Model Fall 2015 Cohort Holdout Results



-2 Log likelihood Cox & Snell R Square Nagelkerke R Square
491,806a 0.34 0.47

| Outcome | Did Not Enroll | Enrolled | Percentage Correct |
|----------------|----------------|----------|--------------------|
| Did Not Enroll | 44 | 18 | 71.00 |
| Enrolled | 33 | 136 | 80.50 |
| Overall | | | 77.90 |

| Variables in Equation | B | S.E. | Wald | Sig. | Exp(B) |
|--|-------|------|-------|------|--------|
| *Constant | -2.73 | 1.30 | 4.40 | 0.04 | 0.07 |
| Age less 18 Flag | 0.29 | 0.27 | 1.16 | 0.28 | 1.34 |
| Dual Enrolled UH Campus Flag | 0.63 | 0.32 | 3.92 | 0.05 | 1.89 |
| End-of-semester Fall CCR | 0.03 | 0.01 | 8.12 | 0.00 | 1.03 |
| End-of-semester Fall GPA | 0.85 | 0.21 | 15.87 | 0.00 | 2.34 |
| Historically High Retained HS | 0.66 | 0.25 | 7.22 | 0.01 | 1.94 |
| HS Prep Index | -0.05 | 0.02 | 7.03 | 0.01 | 0.95 |
| Immed Ed Goal Earn BA End-of-Semester Flag | 1.43 | 0.23 | 38.04 | 0.00 | 4.20 |
| Math First Term Flag | 0.30 | 0.24 | 1.54 | 0.21 | 1.34 |
| STAR Usage End-of-semester | 0.03 | 0.01 | 6.46 | 0.01 | 1.03 |
| Total Offer Amount | 0.00 | 0.00 | 6.59 | 0.01 | 1.00 |
| Undeclared Major Flag | -0.42 | 0.24 | 2.99 | 0.08 | 0.66 |
| Unmet Need Percent | -1.44 | 0.52 | 7.56 | 0.01 | 0.24 |

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Prescriptive analytics

UNIVERSITY of HAWAII
WEST OAHU

Stanley, John 4. x

Time to Degree Status

Stanley, John 4.
jstanley@hawaii.edu
Senior
157806569
Education

Top 5 Factors

Cumulative GPA

3.67

Goal: 3 (+22.5%)

Credit Completion Ratio

100.0

Goal: 80 (+25%)

Percent Unmet Need

0.00

Goal: 0.50 (+100%)

HS Preparation Index

74.0

Goal: 75 (-1.3%)

Total Offer Amount

5500

Goal: 0

Drop Risk Level

1

Starfish advisor notes

05/05/2013 contacted student per phone re: NH merit scholarship, student will apply; 05/15/2013 End-of-semester kudos message;

05/15/2014 End-of-semester kudos message

05/15/2015 End-of-semester kudos message

05/15/2016 End-of-semester kudos message

07/15/2013 NH Merit Scholarship awarded; 12/15/2013 End-of-semester kudos message

12/15/2012 End-of-semester kudos message

Immediate Educational Goal

Earn a bachelor's degree

Quarterly Review

| Term # | Term | Units | GPA | Cumulative Units | Cumulative GPA | Registration Status | Academic Status |
|--------|------|-------|------|------------------|----------------|---------------------|-----------------|
| 9 | FA16 | 12 | 3.83 | 133 | 3.50 | RG | GOOD |
| 8 | SP16 | 16 | 3.74 | 121 | 3.47 | RG | GOOD |
| 7 | FA15 | 15 | 3.62 | 105 | 3.43 | RG | GOOD |
| 6 | SP15 | 15 | 2.74 | 90 | 3.40 | RG | GOOD |
| 5 | FA14 | 15 | 3.08 | 75 | 3.53 | RG | GOOD |
| 4 | SP14 | 15 | 3.48 | 57 | 3.66 | RG | GOOD |
| 3 | FA13 | 15 | 3.68 | 42 | 3.72 | RG | GOOD |

Current Schedule

| Subject | Course Number | Crn | Distance Ed | Day | Week | Room |
|---------|---------------|-------|-------------|-----|------|------|
| BUSA | 313 | 66046 | N | TR | | D146 |
| | 319 | 66053 | N | S | | B233 |
| | | | | | | D140 |
| | 416 | 66055 | Y | | | |
| | 435 | 66612 | Y | | | |

Contact System
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Technical training available for predictive analytics

SIGN IN ▶

MAY 29

MONDAY (FULL DAY)
8:00 A.M. – 4:00 P.M.

A Step-by-Step Introduction to Building a Student-at-Risk Prediction Model (\$220)

Presenters: Serge Herzog (University of Nevada-Reno), John Stanley (University of Hawaii-West Oahu)

Full Description:

To improve student retention, and thus net tuition revenues, institutional research offices are asked to help identify which students are likely to drop out. The purpose of this workshop is to teach IR professionals how to effectively build and implement a predictive model for student dropout and retention using standard regression methods with IBM SPSS. Participants will follow along on their laptops while instructors demonstrate step-by-step instructions (via overhead projection) on how to build a model with start-of-semester data that yield the relative dropout risk for each student. The workshop highlights how dropout risk data are used by academic support services to measurably improve student retention. Knowledge of statistical variance, correlation, and regression is recommended.

Participants in this workshop will:

- Develop a conceptual understanding of how predictive models developed by an IR office can improve institutional effectiveness;
- Learn how to set up a matriculation system (or census warehouse) data file in IBM SPSS that can be used to develop a predictive statistical model to identify students at risk;
- Learn how to use historical data to develop predictor coefficients to estimate (score) the dropout risk for students in future cohorts, and
- Learn how to translate the student dropout risk into a relative percentile risk score to assist student support services with actionable information.

Note: Participants attending this workshop are required to bring a laptop capable of running IBM SPSS software. AIR will provide participants with a link to download a trial version of this software in advance of the workshop.

AIR Workshop: A Step-by-Step Introduction to Building a Student-at-Risk Prediction Model

Instructors: Serge Herzog (University of Nevada-Reno) and John Stanley (University of Hawai'i – West Oahu)

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Prescriptive analytics activity

Post hoc Activity

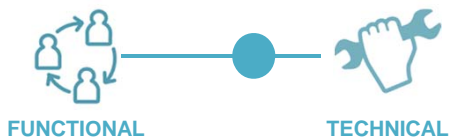
Read *Retention data use . . .*, see spreadsheet, and then

- A. Generate list of reasons from multiple perspectives.
- B. Draft techniques/strategies to address reasons.
- C. Share with a neighboring table.

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Analytics Application #3

Surveys




56

Power BI Solution for Qualtrics Survey Data

- Challenge – each row contained individual data elements
- Columns by individual numbered question or numbered answer
- Report needs to be updated as students continue to take survey
- Report needs to be disaggregated by school and program
- Comments need to be organized

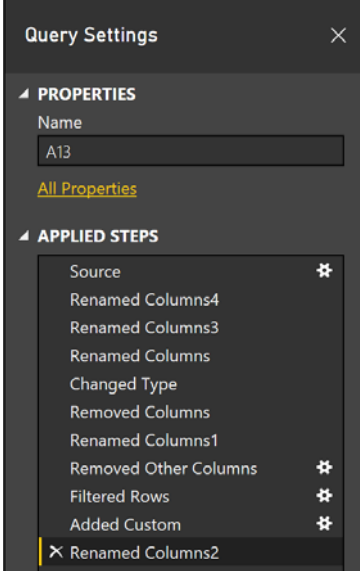
```

SELECT TOP
  [Q11Quality]
  [A11QualityScore]
  [A28QualityComment]
  [Q12Values]
  [A12ValuesScore]
  [A30ValuesComment]
  [Q13Balance]
  [A13BalanceScore]
  [A31BalanceComment]
  [Q14Journey]
  [A14Journey]
  [Q15Experience]
  [A15Experience]
  [Q16Interprofessional]
  [A16InterprofessionalScore]
  [A32InterprofessionalComment]
  [Q17Respected]
  [A17RespectedScore]
  [A33RespectedComment]
  [Q18Overall]
  [A18OverallScore]
  [A34OverallComment]
  [Q21Recommend]
  [A21RecommendScore]
  [A35RecommendComment]
  [Q22Courses]
  [A22Courses]
  [Q24Socially]
  [A24Socially]
  [Q25Academically]
  [A25Academically]
  [Q26Professionally]
  [A26Professionally]
  [Q27Faculty]
  [A27FacultyScore]
  [A36FacultyComment]
FROM [commonTablesV2].[dbo].[ex33Survey]
    
```



Power BI Solution for Qualtrics Survey Data

- Dataset is duplicated for each question
- Extra columns (other answers) deleted
- New columns for filters are added
- Columns renamed for clarity
- Each step is recorded, can be “played back” and edited at any time



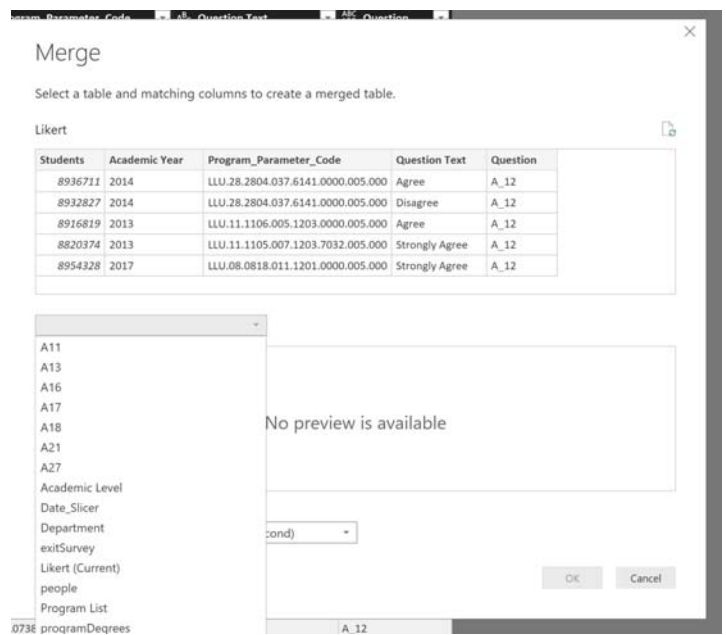
The screenshot shows the 'Query Settings' window for a query named 'A13'. Under the 'APPLIED STEPS' section, the following steps are listed from top to bottom:

- Source
- Renamed Columns4
- Renamed Columns3
- Renamed Columns
- Changed Type
- Removed Columns
- Renamed Columns1
- Removed Other Columns
- Filtered Rows
- Added Custom
- Renamed Columns2

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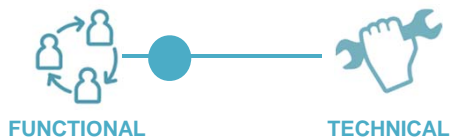
Power BI Solution for Qualtrics Survey Data

- Each copied table is then merged
- Power BI has options that will automate this each time source table is updated
- Resultant merged table now ready to be used for developing visualization



Analytics Application #4

What-if Analysis



Tuition revenue what-if planner

Alphabet University

Total Cost Estimator Based on Per Unit Fee

Selected Enrollment
289

| Enrollment Charges by Degree | | | | | | |
|------------------------------|---------------|--------------------|-----------------------|----------------------|-----------------------|------------------|
| Degree Abbr | Total Units | Other Fees | Tuition Charges | Proposed Fee Revenue | Student Payment | Percent Increase |
| BS | 4313.0 | \$26,043.00 | \$1,170,159.00 | \$127,215.00 | \$1,223,417.00 | 10.8% |
| Cert | 45.0 | \$3,940.00 | \$19,800.00 | \$2,475.00 | \$26,215.00 | 10.4% |
| DPHI | 391.0 | \$3,622.00 | \$37,276.00 | \$21,505.00 | \$362,403.00 | 6.3% |
| MPH | 456.0 | \$12,148.00 | \$32,140.00 | \$25,080.00 | \$419,388.00 | 8.4% |
| MS | 170.0 | \$600.00 | \$116,676.00 | \$9,350.00 | \$126,626.00 | 8.0% |
| MSRC | 80.0 | \$988.00 | \$60,079.00 | \$4,400.00 | \$65,467.00 | 7.2% |
| MSRS | 237.0 | \$9,716.00 | \$145,524.00 | \$13,035.00 | \$168,275.00 | 8.4% |
| NONE | 39.0 | \$0.00 | \$14,446.08 | \$2,145.00 | \$16,591.08 | 14.8% |
| OTD | 144.0 | \$3,965.00 | \$100,800.00 | \$7,920.00 | \$112,685.00 | 7.6% |
| SCH CERT | 90.0 | \$6,544.00 | \$41,940.00 | \$4,950.00 | \$53,434.00 | 10.2% |
| Total | 4139.0 | \$67,786.00 | \$2,519,349.88 | \$227,645.00 | \$2,814,771.88 | 8.8% |

Average Percent Increase

8.9%

Proposed Per Unit Fee

\$10 \$15 \$20
\$25 \$30 \$35
\$40 \$45 \$50
\$55 \$60 \$65

Tuition Revenue Trend

Percent Increase in Total Cost to Student by Degree

| Degree | Percent Increase |
|----------|------------------|
| BS | 10.8% |
| Cert | 10.4% |
| DPHI | 6.3% |
| MPH | 8.4% |
| MS | 8.0% |
| MSRC | 7.2% |
| MSRS | 8.4% |
| NONE | 14.8% |
| OTD | 7.6% |
| SCH CERT | 10.2% |
| SCHD | 10.2% |

Academic Year

2017 2018 2019

Gender

F M

Academic Level

Graduate

Quarter

Summer Autumn Winter

Financial Aid

Above Need Below Need

Additional Revenue

\$228,965.00

Estimated Tuition Revenue

\$2,816,091.88

Degree

- BS
- Cert
- DPHI
- MPH
- MS
- MSRC
- NONE

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What-if activity

Final Activity

Read *Cost Estimator Worksheet*. . . , see dashboard, and then

- A. Generate a research question to answer using the parameters in the dashboard.
- B. Discuss which parameters need to be checked and unchecked in order to visualize the answers.
- C. Share with a neighboring table.

Institutional benchmarking using what-if

New WASC comparative dashboard under development. Compare actual versus predicted rates and perform what-if analyses.

ARC Session: Thursday, April 20, 2:15-3:15

Thank You



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