SCHOOL OF INFORMATION
UNIVERSITY OF MICHIGAN

Learning Analytics (680)

Office Hour 1

N. Sheltrown

About Nick Sheltrown

My family

My profession

Education:

- Michigan State University: MA, Ph.D.
- University of Michigan: MBA
- Northwestern University: MS

Experience:

- COO / VP of Analytics (BI and Data Science) in Grand Rapids, Michigan
- 20+ years in data science/technology management
- Passions: Data Science and Education

Learning Analytics:
A (mostly) K-12 Perspective

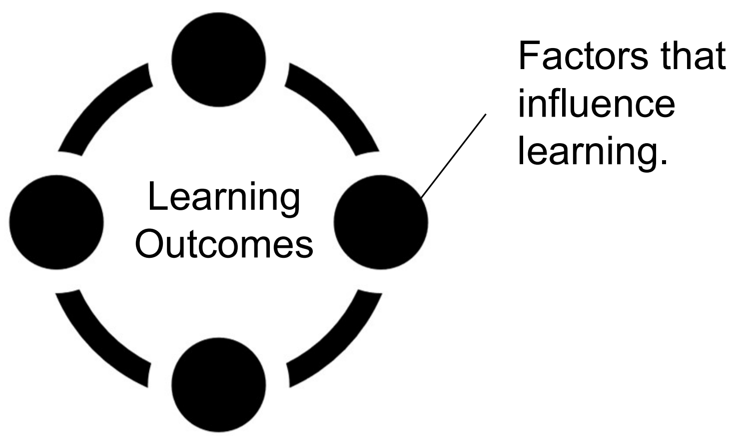
The 1st International Conference on Learning Analytics and Knowledge defined learning analytics as “the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs.”

“If statistics are boring, then you’ve got the wrong numbers.”

@EdwardTufte, *The Visual Display of Quantitative Information*, p. 80.

Many interested parties in learning analytics have made a distinction between learning analytics and academic analytics. Phil Long and George Siemens provide an excellent discussion illustrating the difference between these two. In summarizing it, academic analyses benefit the educational organization rather than learners and teachers. They liken it to "business intelligence" practices. I, however, would encourage learning analysts to embrace business intelligence and processes as part of their work. Making organizations more effective benefits students. If a principal receives an analysis of parent satisfaction finding that teachers are unresponsive to parents' calls or emails, s/he may act on that information and institute systematic processes to facilitate the communication between the two groups. Such an initiative will make parents more informed and effective at home, and empower a stronger partnership between parents and educators. This benefits student learning outcomes. *Learning analytics must be narrow in its focus on learning outcomes; it should be broad in considering those factors that can influence student learning.*

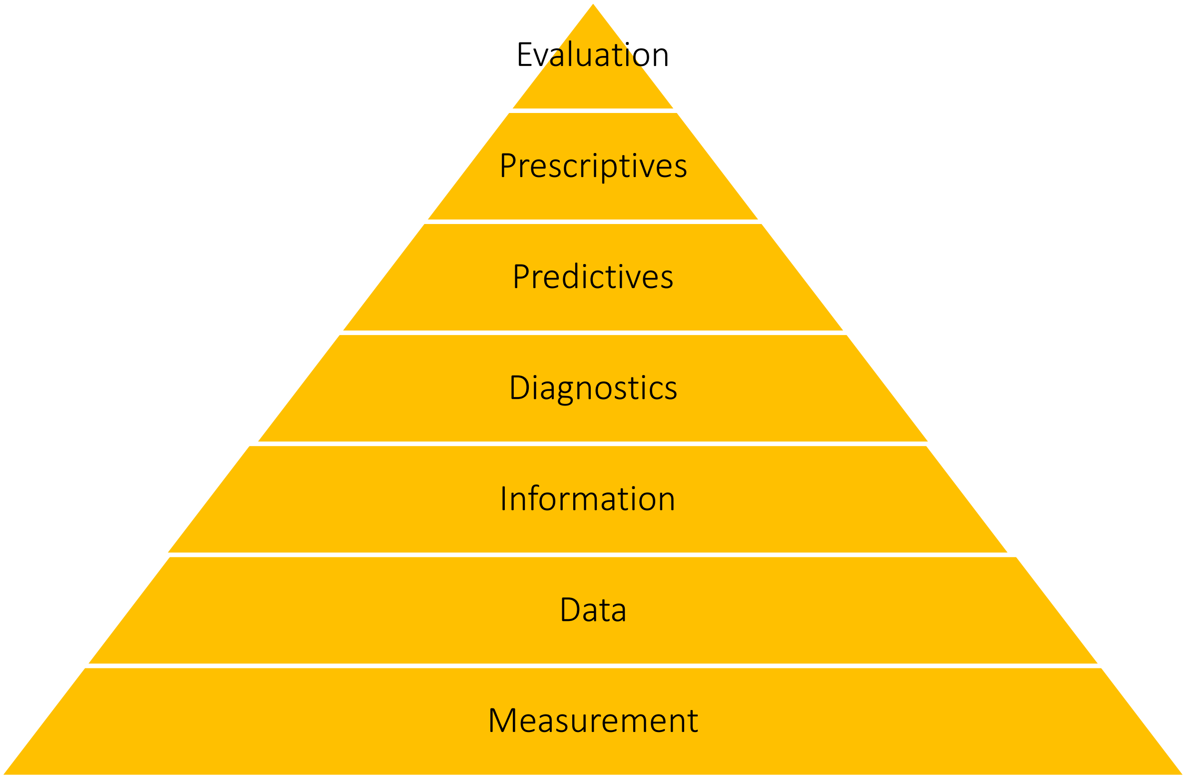
Long, P. and Siemens, G. (2011). [“Penetrating the Fog: Analytics in Learning and Education.”] *Educause Review*. September/October.



Kinds of Analytics Projects We Do

Academic Analytics	Learning Analytics
Teacher Turnover Prediction Model	Student Proficiency Prediction
Over-enrollment Model	Student Performance Diagnostics
Student Attrition Model	Evaluation for Academic Programs

The Data Science Pyramid



Another way to think about learning analytics

			Scope						
			Microscopic						Macroscopic
			Learning process data	Skills/objectives	Sub-standards	Standards	Domains	Subject	Learning Constructs
		Examples:	Time-on-task, number of learning activities, clicks.	Distinguish between whole numbers, integers, and rational numbers.	Determine whether a given whole number in the range 1-100 is a multiple of a given one-digit number.	CCSS.MATH.CONTENT.4.OA.B.4: Find all factor pairs for a whole number in the range 1-100. Recognize that a whole number is a multiple of each of its factors. Determine whether a given whole number in the range 1-100 is a multiple of a given one-digit number. Determine whether a given whole number in the range 1-100 is prime or composite.	Operations & Algebraic Thinking	Math	College Readiness
Telescopic:	Past	Understand	descriptive analytics						
	Present	Explore	diagnostic/prescriptive analytics						
	Future	Predict	predictive analytics/data mining						

Measurement

"…if I had to reduce all of educational psychology to just one principle,
I would say this: 'The most important single factor influencing learning
is what the learner already knows. Ascertain this and teach him accordingly."

- Professor David Ausubel
Thorndike Award Winner
from the American Psychological Association

Measurement in learning is a complex domain.

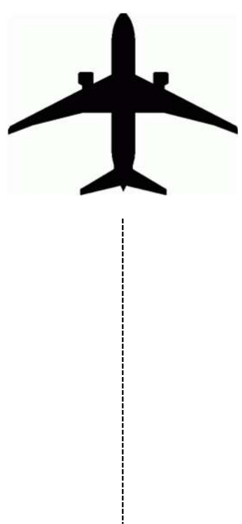
			What you measure	
			Content Knowledge	Growth
How you measure	Frame of reference	criterion	knowledge relative to standards	expected growth/gts
		normative	knowledge relative to others	typical growth
	form of assessment	fixed form	same questions for all students	
		computer adaptive	custom configuration of questions	
		item types	closed response vs. open response	
Why you measure	Intended action	placement	appropriate placement	
		diagnostic	diagnose needs	
		predictive	forecast outcomes	
		formative	adjust instruction	
		summative	evaluate knowledge	evaluate learning

To simplify, we need to consider the what, why, and how of measurement.

1. <u>What of measurement</u>: aptitude, content knowledge, or growth.
2. <u>Why of measurement</u>: to place, diagnose, predict, inform/monitor, or summarize.
3. <u>How of measurement</u>: frame of reference, form, and frequency.

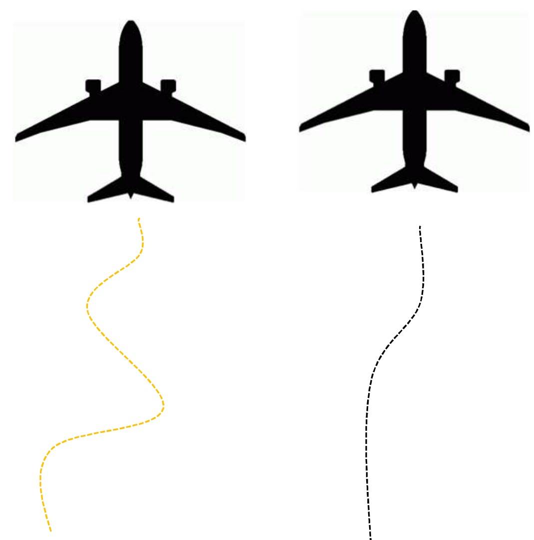
What of measurement: content knowledge or growth.

Content knowledge



Can you fly the plane?
Y/N

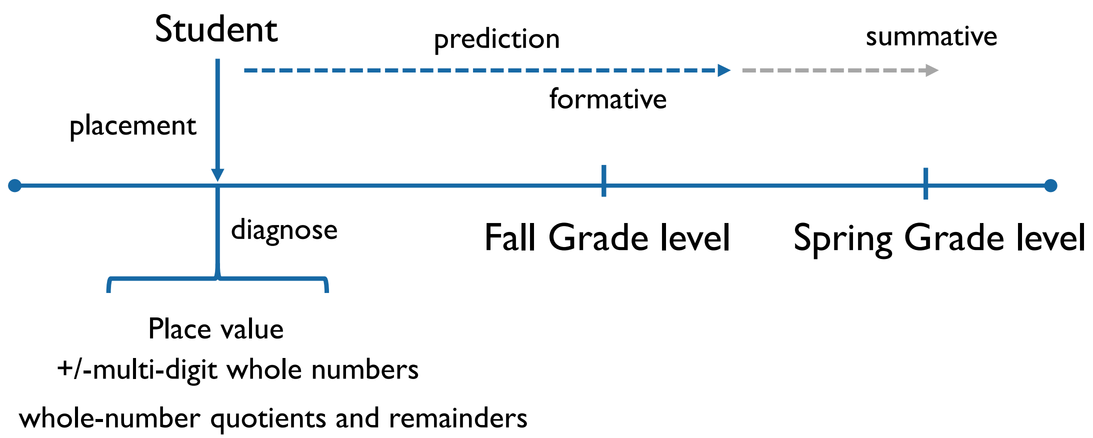
Growth



Before After

How much improvement in flying?

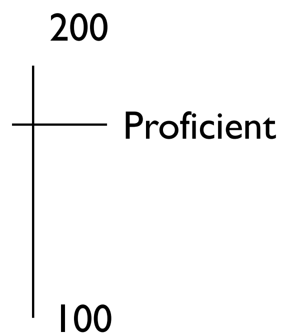
The Why: Assessments can serve multiple purposes.



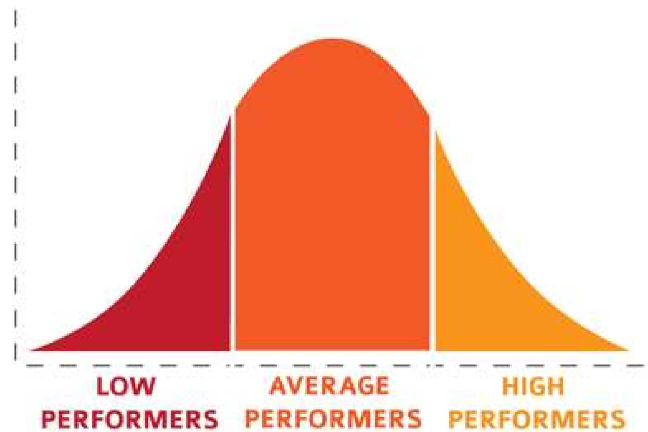
1. Place students *into grades, programs, interventions.*
2. Diagnose *student learning needs and opportunities.*
3. Predict *future student outcomes.*
4. Inform/monitor *learning.*
5. Summarize *learning.*

How of measurement: frame of reference, frequency, and form of assessment.

Criterion

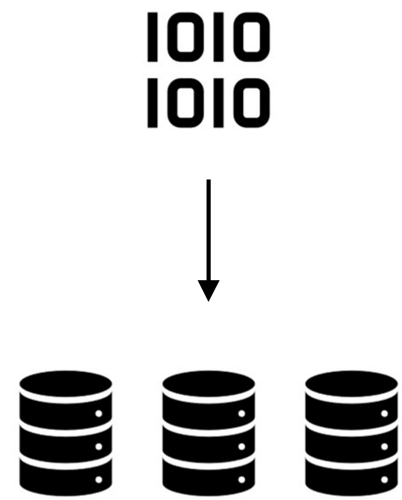


Normative



Data

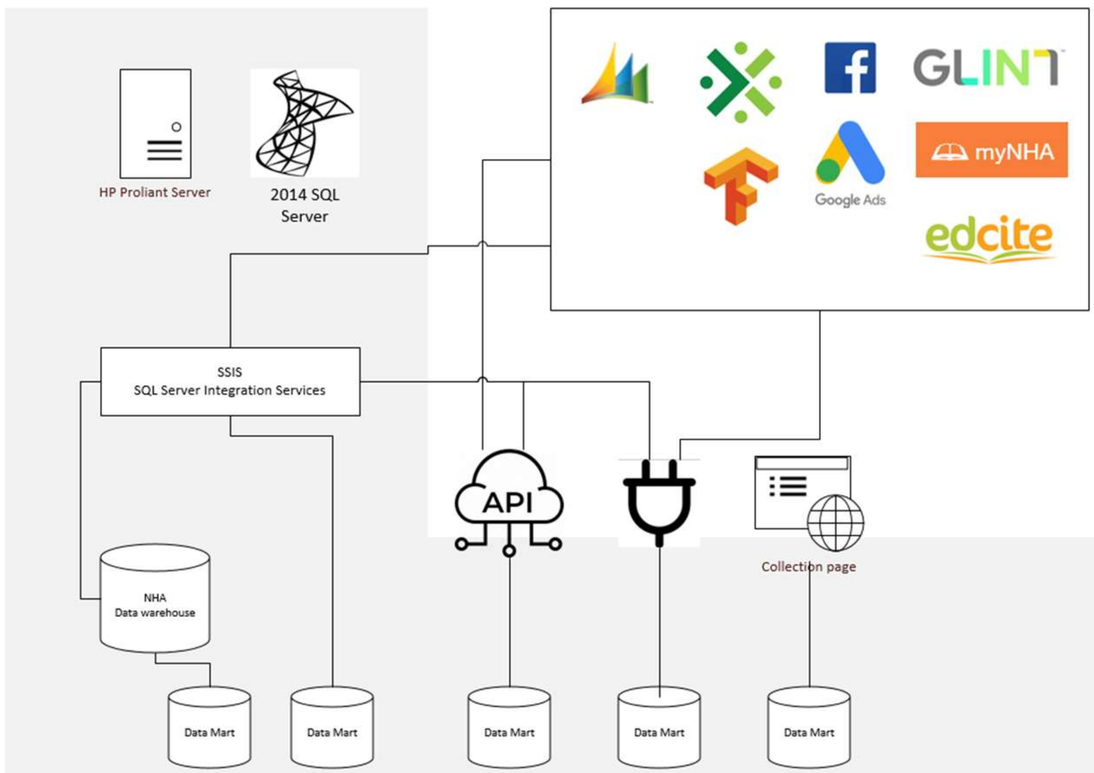
The purpose of measures is to produce data. Data are the DNA of all analytical work. The importance of a comprehensive, reliable set of data, systematically stored in a data warehouse optimized for reporting and analysis cannot be overstated. The data layer is one focused on engineering; that is, systematically collecting and combining data in a way that analytical work can be done. As organizations become more mature in their use of data, needs become more elaborate. Identifying a reliable data warehouse solution early will head off problems later.



Data warehouse

A Data warehouse

A large store of data accumulated from a wide range of sources within a company and used to guide management decisions.



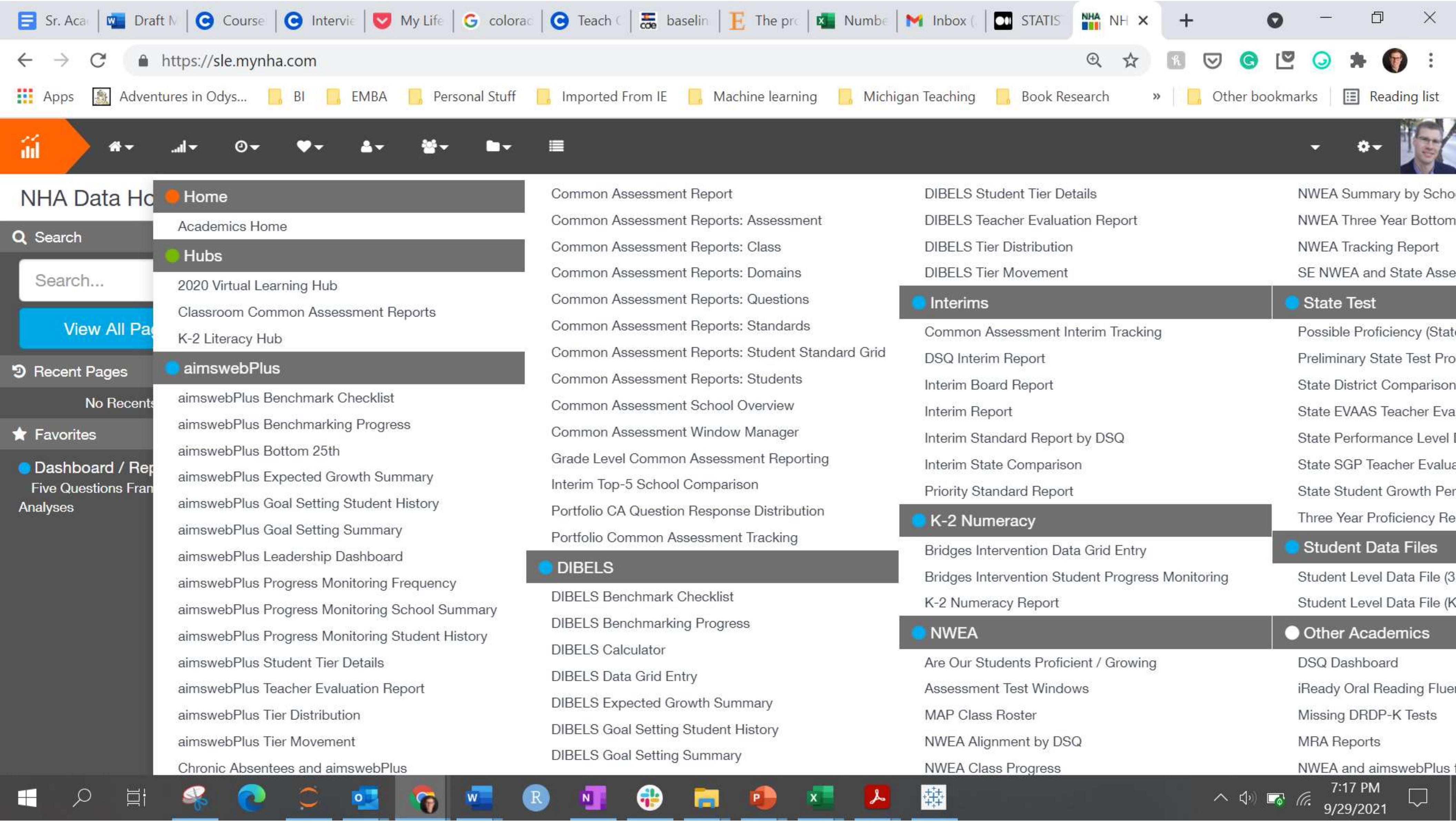
The Information Layer

In its raw form, most data does not tell you much. For example, if you were told that the Massachusetts Avenue bridge between Boston and MIT is approximately 364.4 smoots long, would that mean much to you? Unless you are a MIT graduate or particularly well-read on measurement idiosyncrasies, it probably won't mean much. The point is that data divorced from some kind of context lacks meaning. And even if the data are more familiar to us, full meaning can still be illusive. For example, Harpers Index cited in February of 2014 that the estimated per capita federal spending on programs for children annually is $3,822. We all understand how much $3,822 dollars are; however, when we compare the amount spent per capita by US government on programs for the elderly - $25,455 – we develop a different appreciation. *Context changes value of data, even though the values of data do not change in the process.*

BTW --- A smoot is a unit of length equal to 5 feet 7 inches long. It is named after Oliver Smoot, a 1962 MIT graduate standing 5'7" who was used by his classmates to measure the distance from the Boston fraternities to MIT's main campus. (Source: Susan Curran, "Smoot makes his mark in standards and measurements" on http://web.mit.edu/spotlight/smoot-salute/.)

Harper's Index, February 2014, from http://harpers.org/archive/2014/02/harpers-index-358/

ibid


https://sle.mynha.com
Apps
Adventures in Odys...
BI
EMBA
Personal Stuff
Imported From IE
Machine learning
Michigan Teaching
Book Research
Other bookmarks
Reading list
NHA Data Ho
Search
Search...
View All Pa
Recent Pages
No Recents
Favorites
Dashboard / Rep
Five Questions Fran
Analyses
Home
Academics Home
Hubs
2020 Virtual Learning Hub
Classroom Common Assessment Reports
K-2 Literacy Hub
aimswebPlus
aimswebPlus Benchmark Checklist
aimswebPlus Benchmarking Progress
aimswebPlus Bottom 25th
aimswebPlus Expected Growth Summary
aimswebPlus Goal Setting Student History
aimswebPlus Goal Setting Summary
aimswebPlus Leadership Dashboard
aimswebPlus Progress Monitoring Frequency
aimswebPlus Progress Monitoring School Summary
aimswebPlus Progress Monitoring Student History
aimswebPlus Student Tier Details
aimswebPlus Teacher Evaluation Report
aimswebPlus Tier Distribution
aimswebPlus Tier Movement
Chronic Absentees and aimswebPlus
Common Assessment Report
Common Assessment Reports: Assessment
Common Assessment Reports: Class
Common Assessment Reports: Domains
Common Assessment Reports: Questions
Common Assessment Reports: Standards
Common Assessment Reports: Student Standard Grid
Common Assessment Reports: Students
Common Assessment School Overview
Common Assessment Window Manager
Grade Level Common Assessment Reporting
Interim Top-5 School Comparison
Portfolio CA Question Response Distribution
Portfolio Common Assessment Tracking
DIBELS
DIBELS Benchmark Checklist
DIBELS Benchmarking Progress
DIBELS Calculator
DIBELS Data Grid Entry
DIBELS Expected Growth Summary
DIBELS Goal Setting Student History
DIBELS Goal Setting Summary
DIBELS Student Tier Details
DIBELS Teacher Evaluation Report
DIBELS Tier Distribution
DIBELS Tier Movement
Interims
Common Assessment Interim Tracking
DSQ Interim Report
Interim Board Report
Interim Report
Interim Standard Report by DSQ
Interim State Comparison
Priority Standard Report
K-2 Numeracy
Bridges Intervention Data Grid Entry
Bridges Intervention Student Progress Monitoring
K-2 Numeracy Report
NWEA
Are Our Students Proficient / Growing
Assessment Test Windows
MAP Class Roster
NWEA Alignment by DSQ
NWEA Class Progress
NWEA Summary by Scho
NWEA Three Year Bottom
NWEA Tracking Report
SE NWEA and State Asse
State Test
Possible Proficiency (Stat
Preliminary State Test Pro
State District Comparison
State EVAAS Teacher Eva
State Performance Level
State SGP Teacher Evalua
State Student Growth Per
Three Year Proficiency Re
Student Data Files
Student Level Data File (3
Student Level Data File (K
Other Academics
DSQ Dashboard
iReady Oral Reading Flue
Missing DRDP-K Tests
MRA Reports
NWEA and aimswebPlus
7:17 PM
9/29/2021

The Diagnostic Layer

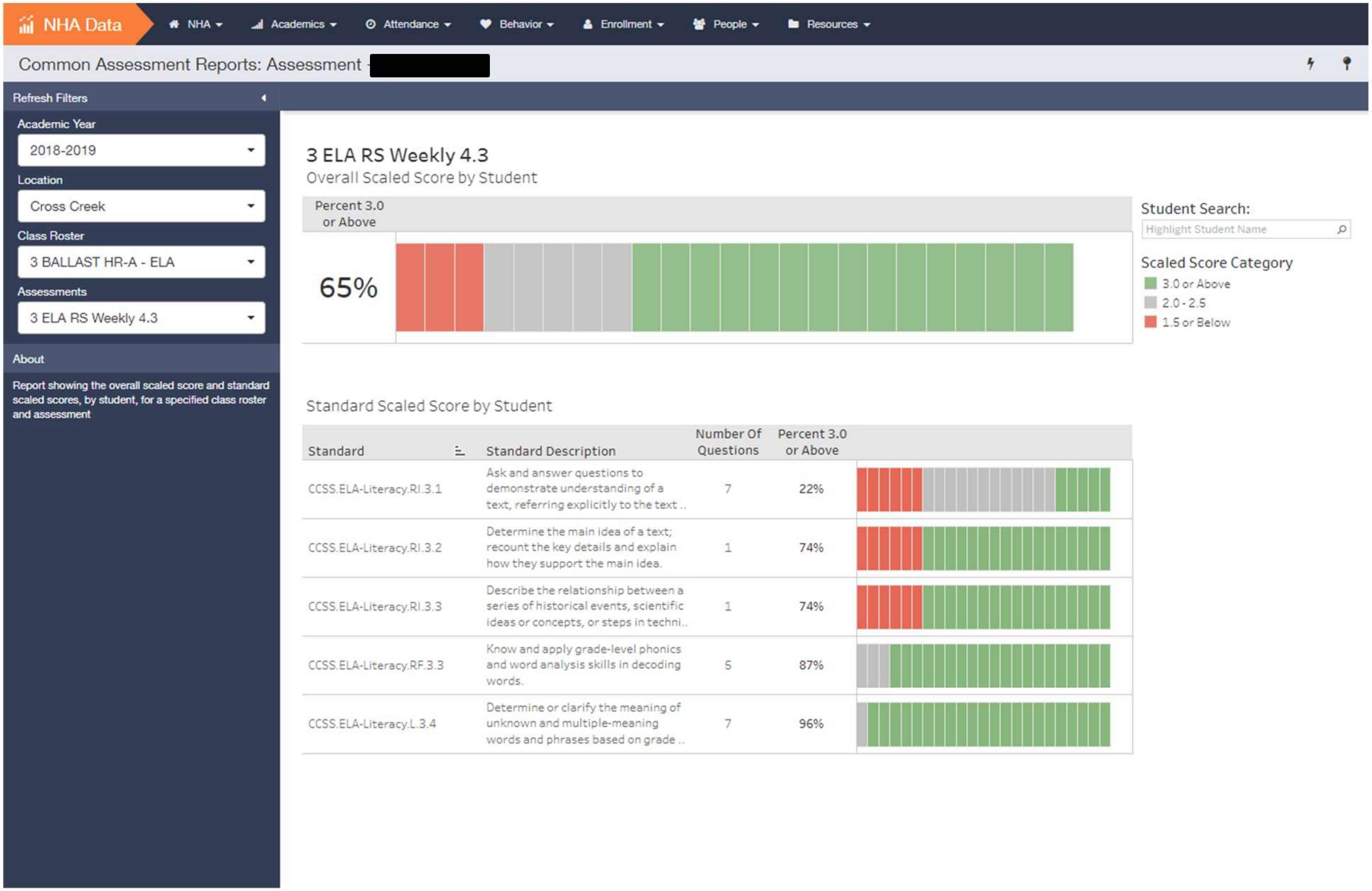
Diagnostics is analyzing the information we have for either positive or negative aberrations that should lead us to adjust our course of action. A blood test may reveal that your body has a problematically low vitamin D level, which may present a problem to your health. Such a diagnosis should lead to an adjusted course of action (take vitamin D pills or spend more time in the sunshine). In learning analytics, we seek to diagnosis challenges (deficiencies in student learning) and opportunities (situations where students are ready for above grade-level content) that should lead to a material adjustment of the student's instructional treatment. Similar to medical diagnosis, the primary focus of the activity is to identify abnormalities that can lead to suboptimal outcomes. Information from the diagnostic layer may lead an educator to adjust a student's learning path to more appropriately reflect his/her particular strengths and weaknesses.

Item Analysis

- Provides information about what students do and do not know
- Highlights different response patterns that will require different instructional strategies (whole class, small group)

CORRECT ANSWER	2	1	4	2	3	4	4
POINTS POSSIBLE	1	1	1	1	1	1	1
%CORRECT	60%	58%	53%	65%	26%	40%	32%
ITEM ANALYSIS							
% Choosing A or (1)	32%	58%	9%	13%	32%	13%	18%
% Choosing B or (2)	60%	26%	23%	65%	10%	23%	8%
% Choosing C or (3)	4%	14%	13%	13%	26%	22%	40%
% Choosing D or (4)	3%	0%	53%	8%	30%	40%	32%

- Item Analyses appear at the bottom of all **roster** reports



NHA Data | NHA | Academics | Attendance | Behavior | Enrollment | People | Resources

Common Assessment Reports: Assessment - [redacted]

Refresh Filters

Academic Year
2018-2019

Location
Cross Creek

Class Roster
3 BALLAST HR-A - ELA

Assessments
3 ELA RS Weekly 4.3

About

Report showing the overall scaled score and standard scaled scores, by student, for a specified class roster and assessment

3 ELA RS Weekly 4.3

Overall Scaled Score by Student

Percent 3.0 or Above

65%

Student Search:
Highlight Student Name

Scaled Score Category
3.0 or Above
2.0 - 2.5
1.5 or Below

Standard Scaled Score by Student

Standard	Standard Description	Number Of Questions	Percent 3.0 or Above
CCSS.ELA-Literacy.RI.3.1	Ask and answer questions to demonstrate understanding of a text, referring explicitly to the text ..	7	22%
CCSS.ELA-Literacy.RI.3.2	Determine the main idea of a text; recount the key details and explain how they support the main idea.	1	74%
CCSS.ELA-Literacy.RI.3.3	Describe the relationship between a series of historical events, scientific ideas or concepts, or steps in techni..	1	74%
CCSS.ELA-Literacy.RF.3.3	Know and apply grade-level phonics and word analysis skills in decoding words.	5	87%
CCSS.ELA-Literacy.L.3.4	Determine or clarify the meaning of unknown and multiple-meaning words and phrases based on grade ..	7	96%

The Predictive Layer

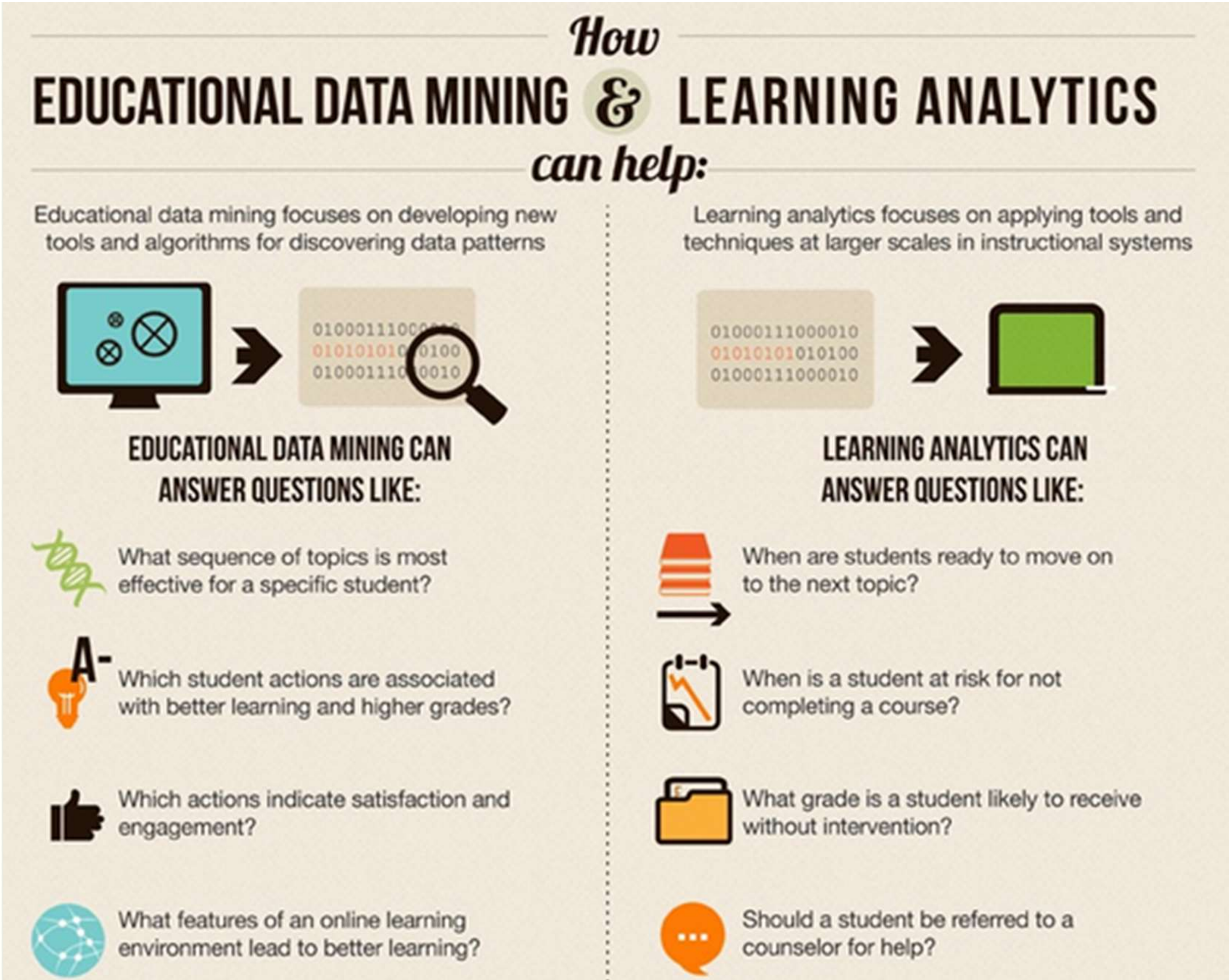
Predictive analytics is a much discussed (though less often realized) layer of analytics. In predictive analytics, we consider where a student is (drawn from the information and diagnostic layer). Given the students pattern of learning over time and present condition, where do we think the student will be at some future point in time? For example, we may build a prediction for students on state test outcomes in the spring by using a fall interim assessment. Predictions are built to give insight into where outcomes will land absent atypical intervention. It is no surprise that this form of analysis has gathered so much attention in recent years as the implications for such analyses are clear: if we do nothing, here's what we think may happen. Of course, we say "may" quite intentionally, as there are many sources of error that obscure the quality of a prediction.

Multiple-R	.48	.37	.46	.46
Standardized betas				
SAT I	.02	.34	.22	.25
High school GPA	.28		.30	.30
SAT II	.24			
Family income	.03	.01	.03	
Parental education	.06	.04	.05	

The Prescriptive Layer

Prescriptive analytics holds the highest position of the analytics pyramid for good reason; it answers the most important question: what do I do next? In prescriptive analysis, the learning analyst identifies what should happen with a student (or collection of students) given their diagnosis and direction (prediction). If, for example, we think that a given population of students may not reach key learning outcomes by the end of the school year in reading, prescriptive analytics will provide key insights into what should happen next.

The focus of prescription is optimization of student learning outcomes. What should we change to improve on these data or the outcomes associated with them? Prescriptive analytics essentially leverage the entirety of the pyramid to identify an empirical basis for what the next step should be.


How
EDUCATIONAL DATA MINING & LEARNING ANALYTICS
can help:
Educational data mining focuses on developing new tools and algorithms for discovering data patterns
Learning analytics focuses on applying tools and techniques at larger scales in instructional systems
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01010101010100
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EDUCATIONAL DATA MINING CAN ANSWER QUESTIONS LIKE:
What sequence of topics is most effective for a specific student?
A-
Which student actions are associated with better learning and higher grades?
Which actions indicate satisfaction and engagement?
What features of an online learning environment lead to better learning?
LEARNING ANALYTICS CAN ANSWER QUESTIONS LIKE:
When are students ready to move on to the next topic?
When is a student at risk for not completing a course?
What grade is a student likely to receive without intervention?
Should a student be referred to a counselor for help?