Undergraduate data science: Biological connections and assessing impacts

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National Institute for STEM Evaluation and Research

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Kelly Sturner - former NIMBioS Education and Outreach Coordinator

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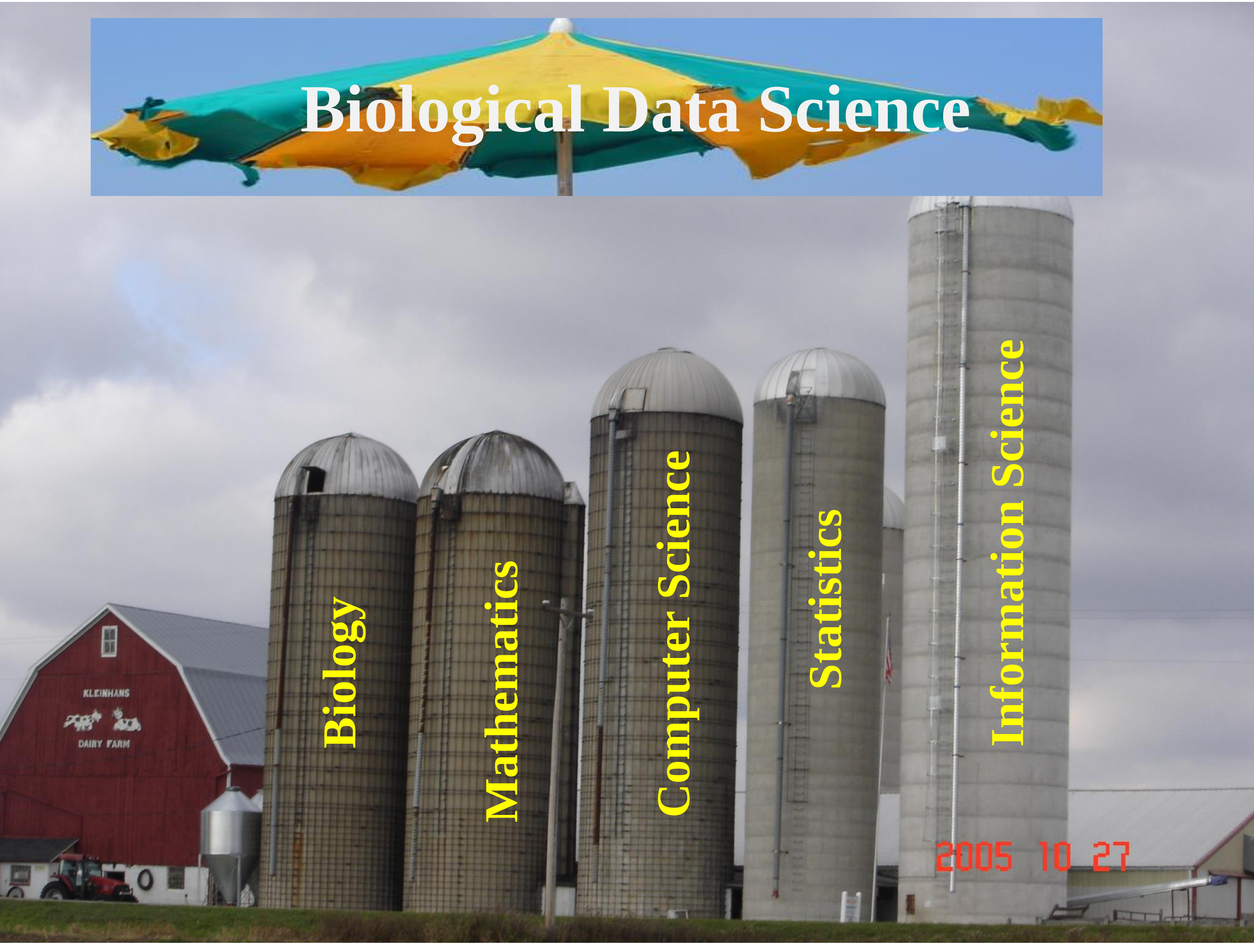
National Academies Committee on Envisioning the Data Science Discipline: The Undergraduate Perspective

http://sites.nationalacademies.org/CSTB/CurrentProjects/CSTB_175246

Look for a report soon


Biological Data Science
Biology
Mathematics
Computer Science
Statistics
Information Science
KLEINHANS
DAIRY FARM
2005 10 27

Dynamical systems

Optimization

Networks

Graph theory

Calculus

Modeling

Linear algebra

Stochastics

Inference

Distributions

Dynamical systems

Optimization

Networks

Likelihood

Graph theory

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Hypothesis testing

Regression

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ANOVA

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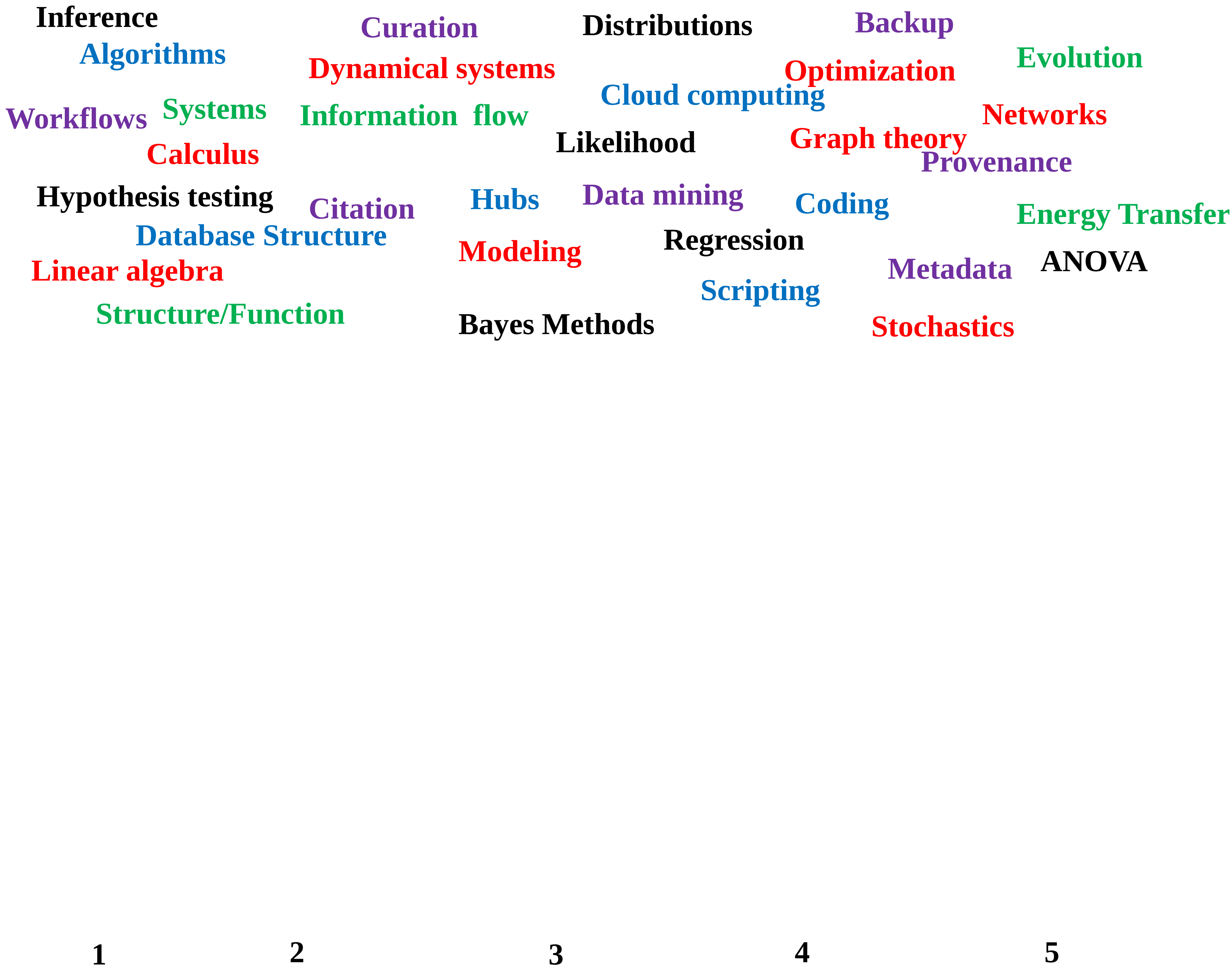

Inference
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Stochastics
1
2
3
4
5

Curricular Organization as a Data-science Problem

- Prioritization of concepts/skills
- Use of education research to guide pedagogy
- Borrowing/adapting existing materials (downscaling, not dumbing-down)
- Sequencing coverage of concepts/skills
- Enhancing high priority concepts/skills through repetition
- Assessing success

Training Fearless Biologists: Quantitative Concepts for all our Students

1. Rate of change
2. Modeling
3. Equilibria and stability
4. Structure
5. Interactions
6. Data and measurement
7. Stochasticity
8. Visualizing
9. Algorithms

Slide presented at Bio2010 public release - Sept. 10, 2002
Listing arose from Workshops at UTK in 1992 and 1994.
See *Bio2010: Transforming Undergraduate Education for Future Research Biologists* (NRC, 2003)

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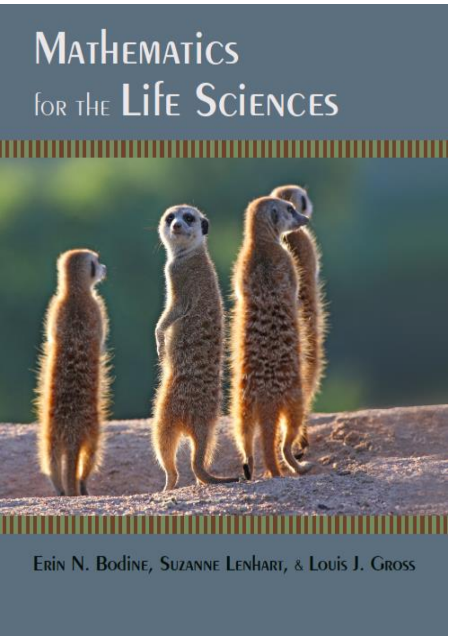
Mathematics for the Life Sciences – Princeton U. Press

Rule of Five- **different learning styles to meet needs of diverse students: Symbolically, Graphically, Numerically, Verbally, Data-driven**

We use this approach throughout the text which includes descriptive statistics (regression, semi-log, log-log), matrix algebra (eigenvalues, eigenvectors), discrete probability, discrete dynamical systems, basic calculus, differential equations, emphasizing data and hypothesis formulation (math and biological) using Matlab and R.



Erin Bodine

Suzanne Lenhart

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What evidence is there that indeed introducing and/or motivating quantitative concepts through inclusion of data and models from the life sciences actually enhances learning of these concepts by our students?

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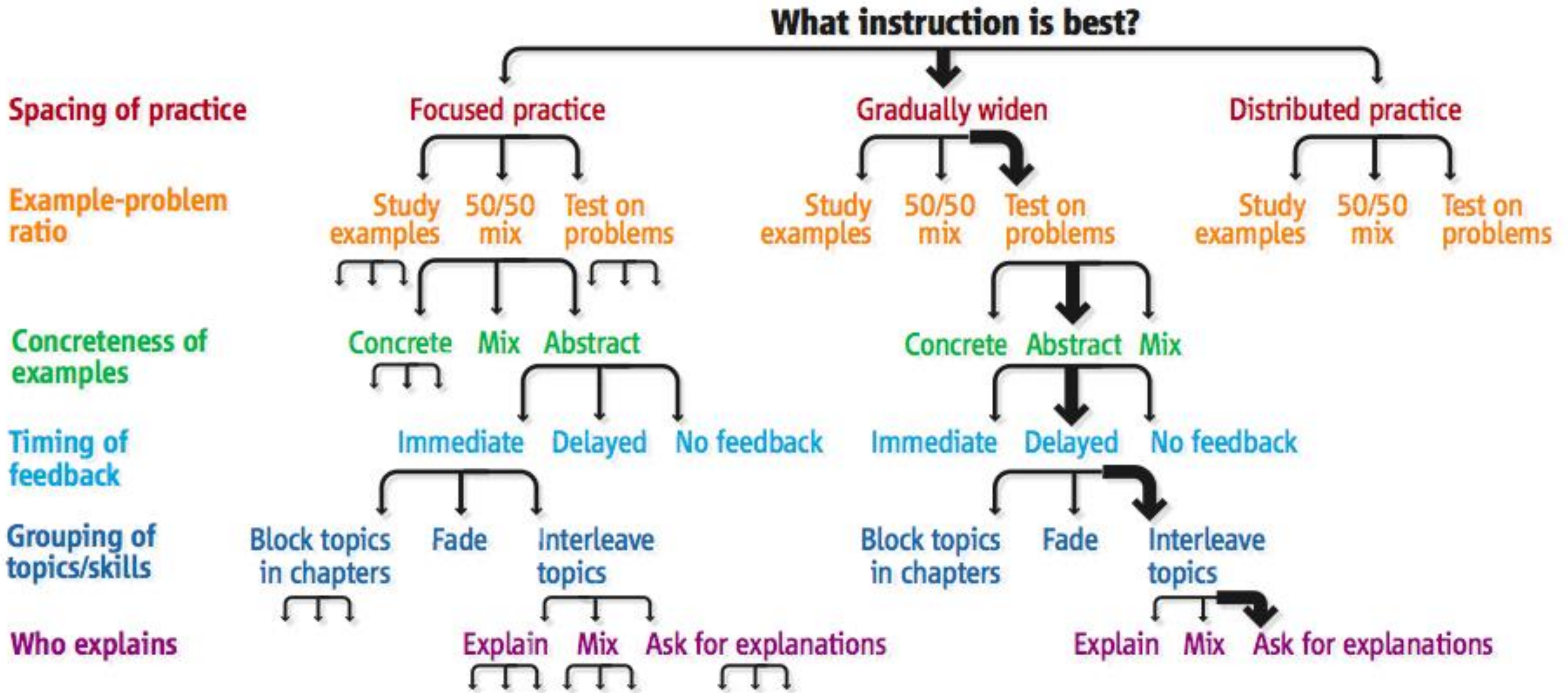

Instructional design choices. Different choices along different instructional dimensions can be combined to produce a vast set of instructional options. The path with thicker arrows illustrates one set of choices within a space of trillions of such options.

Koedinger, K. R., J. L. Booth, and D. Klahr1 Instructional Complexity and the Science to Constrain It. *Science* 342:935-7 (2013)

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Evidence for the effectiveness of learning quantitative concepts through concrete examples and real data over abstract methods is mostly anecdotal. Very few studies investigate learning gains in mathematics arising from the use of scientific examples.

A first step towards evaluating the potential impact of biological examples on mathematics comprehension is to develop a robust assessment instrument designed for college-level math concepts.

Quantitative Biology Concept Inventory (QBCI)

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Quantitative Biology Concept Inventory Construction

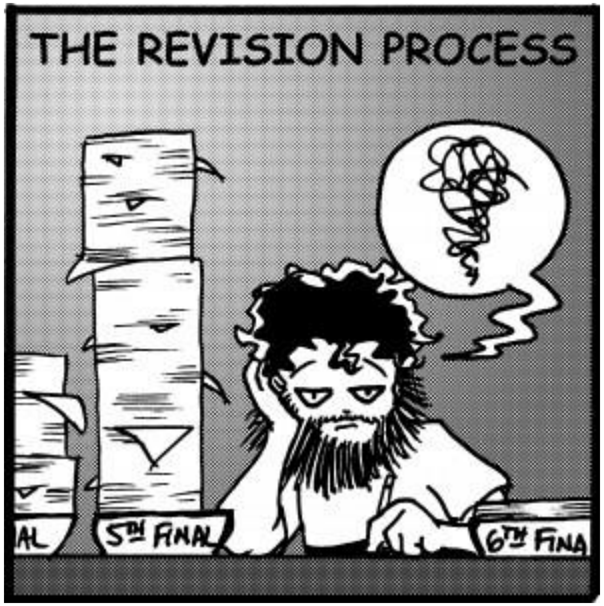
Objectives/ Planning

Content Specification

Item Development

Test administration

Validity Analysis



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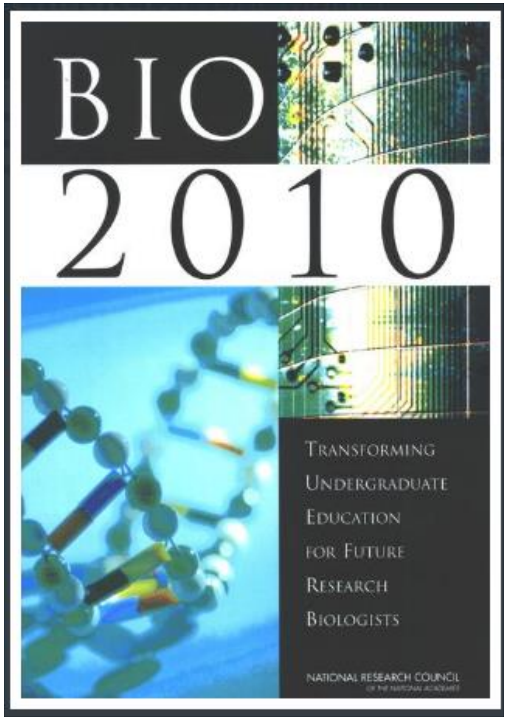
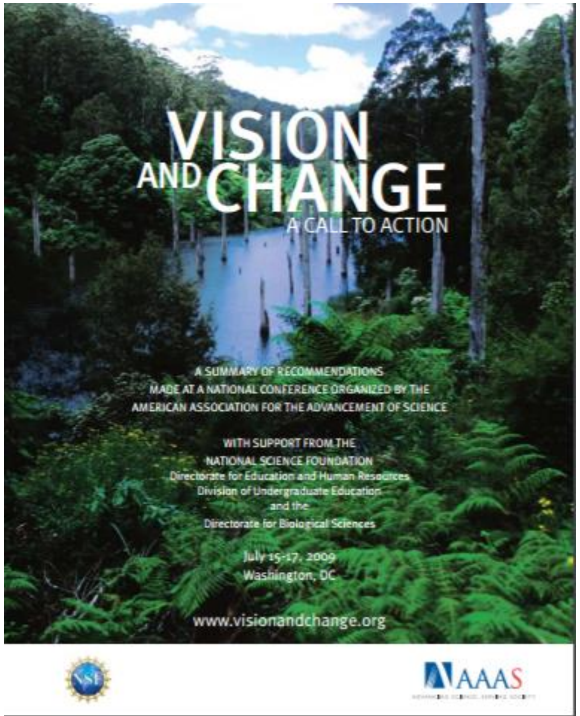
Objectives/Planning





Literature review of concept inventories

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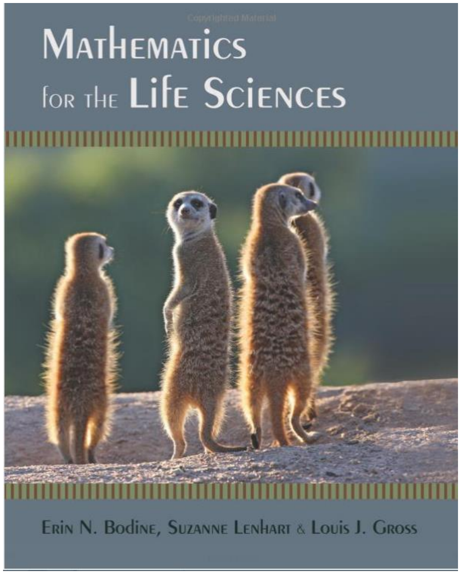
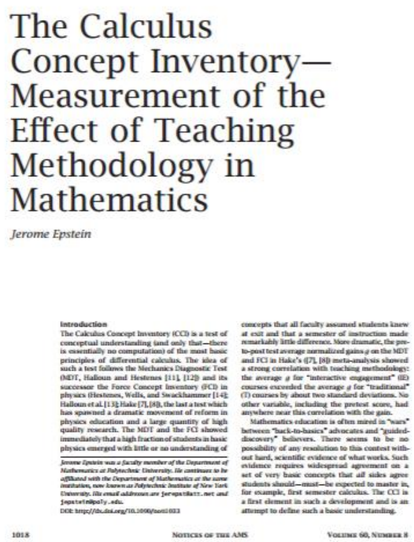
Content Specification

- Calculus
  - Rates of change
  - Sums and Integration
  - Modeling
  - Interpreting Graphs and Data





The Calculus Concept Inventory—Measurement of the Effect of Teaching Methodology in Mathematics

Jerome Epstein

Introduction

The Calculus Concept Inventory (CCI) is a test of conceptual understanding (and only that—there is essentially no computation) of the most basic principles of differential calculus. The idea of such a test follows the Mechanics Diagnostic Test (MDT, Halloun and Hestenes [11], [12]) and its successor the Force Concept Inventory (FCI) in physics (Hestenes, Wells, and Swackhammer [14]; Halloun et al. [13]; Hake [7], [8]), the last a test which has spawned a dramatic movement of reform in physics education and a large quantity of high quality research. The MDT and the FCI showed immediately that a high fraction of students in basic physics emerged with little or no understanding of concepts that all faculty assumed students knew at exit and that a semester of instruction made remarkably little difference. More dramatic, the pre-to-post test average normalized gains g on the MDT and FCI in Hake's ([7], [8]) meta-analysis showed a strong correlation with teaching methodology: the average g for "interactive engagement" (IE) courses exceeded the average g for "traditional" (T) courses by about two standard deviations. No other variable, including the pretest score, had anywhere near this correlation with the gain.

Mathematics education is often mired in "wars" between "back-to-basics" advocates and "guided-discovery" believers. There seems to be no possibility of any resolution to this contest without hard, scientific evidence of what works. Such evidence requires widespread agreement on a set of very basic concepts that all sides agree students should—must—be expected to master in, for example, first semester calculus. The CCI is a first element in such a development and is an attempt to define such a basic understanding.

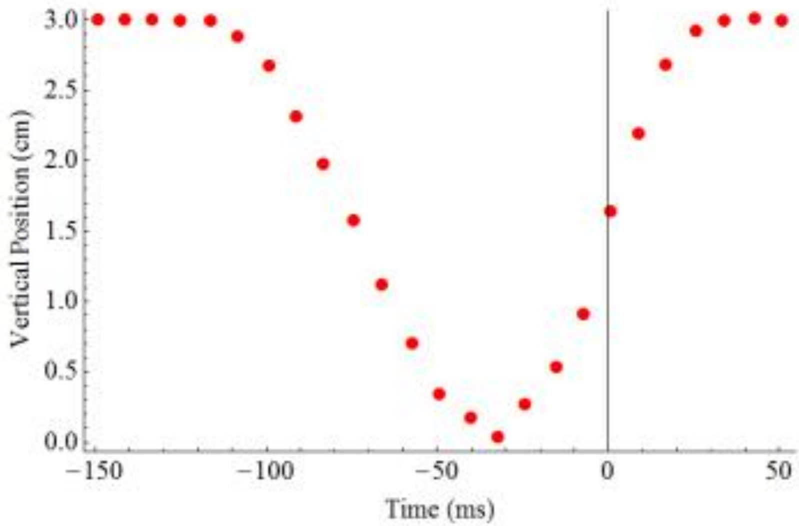
Jerome Epstein was a faculty member of the Department of Mathematics at Polytechnic University. He continues to be affiliated with the Department of Mathematics at the same institution, now known as Polytechnic Institute of New York University. His email addresses are [illegible] *and* [illegible].

DOI: http://dx.doi.org/10.1090/noti1033

1018 Notices of the AMS Volume 60, Number 8

Item Development (Example 1)

2. Slow motion videos were used to collect time-series data on the vertical position of a cat's tongue as it drank water. The graph below shows the vertical position of the cat's tongue above a bowl of water during one lap of the tongue.



Over what interval is the vertical position increasing?

(a) [−150, 30]

(b) [−70, 0]

(c) [−50, 30]

(d) [−30, 10]

(e) [−100, −60]

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Test Review and Administration

- Expert review → REVISE
- Student focus group completion → REVISE
- Fall 2016 Administration → REVISE
  - Calculus I, Calculus II, Math for Life Sciences
  - Pre-post testing

- Spring 2017 administration (n ~ 200) → REVISE
  - Calculus I, Calculus II, Math for Life Sciences
  - Pre-post testing

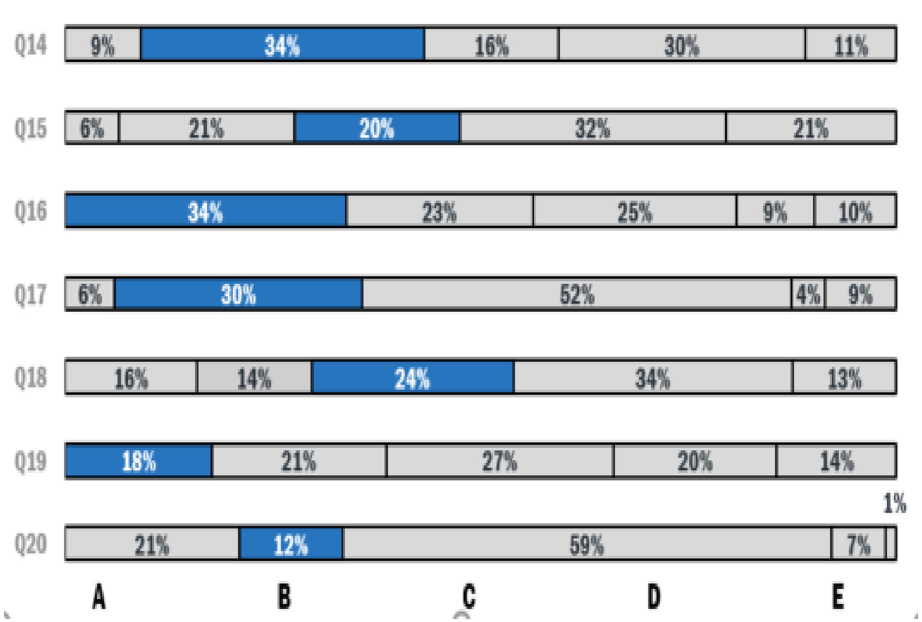
Validity Analysis

- Item Response Theory (IRT): family of latent trait models used to establish psychometric properties of items and scales
- Rasch Modeling: Demonstrate relationship between item difficulty and person ability
  - Probabilistic unidimensional model
    - Easier test question, higher likelihood of a correct response
    - More capable the student, higher likelihood of getting questions correct versus less capable (or able) student
  - Assumes probability a student correctly answers a question is a logistic function of the difference between the student's ability and the difficulty of a question
- **PROVIDES A LOT OF INFORMATION ABOUT TEST QUESTIONS TO HELP EXAMINE THE QUALITY OF TEST CONSTRUCTION**

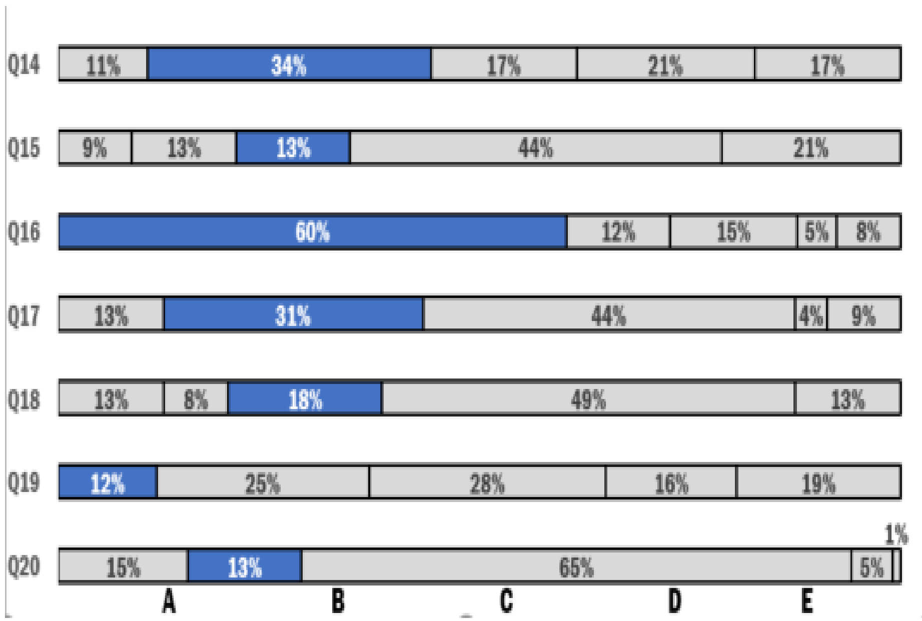
Example distribution of QBCI responses

Correct responses are in blue

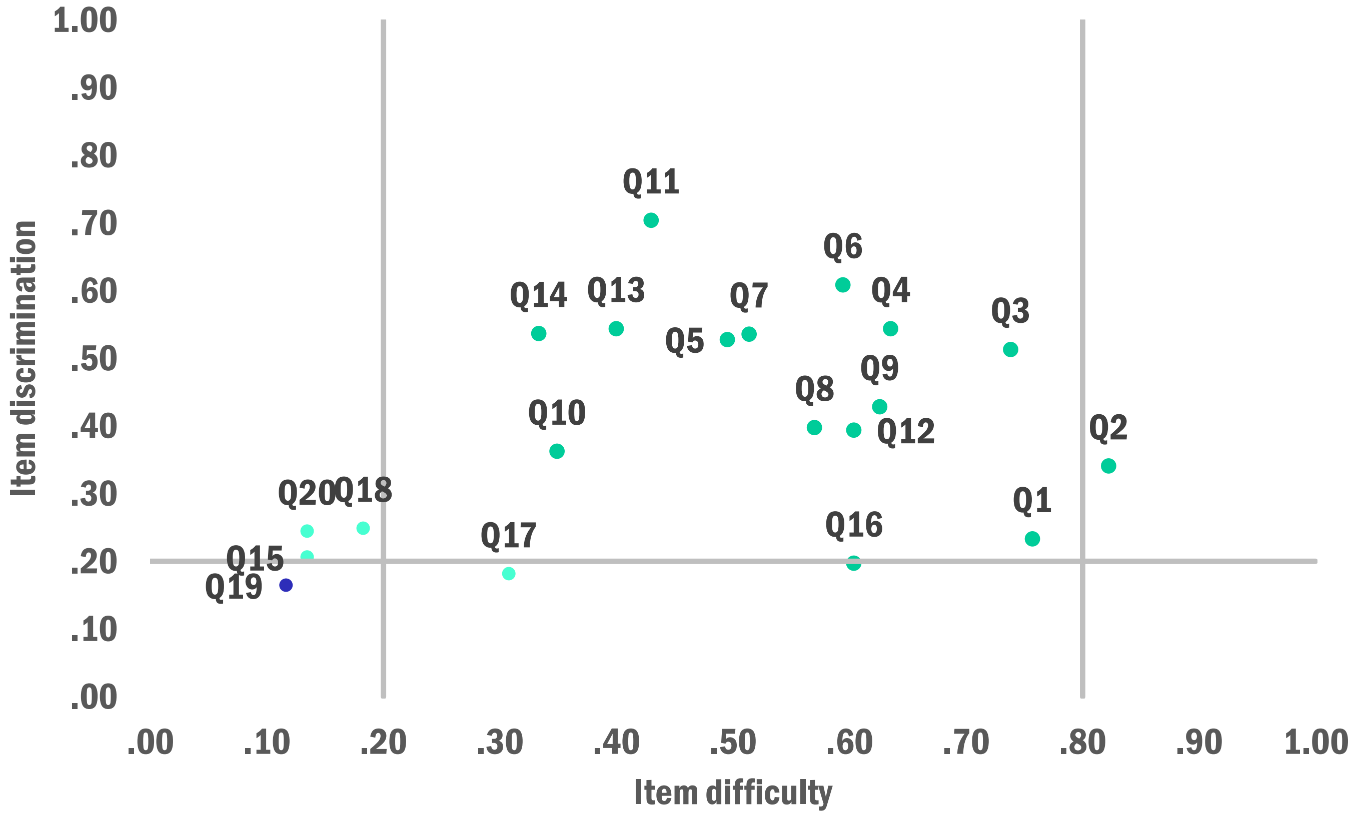
Pre-administration of the QBCI



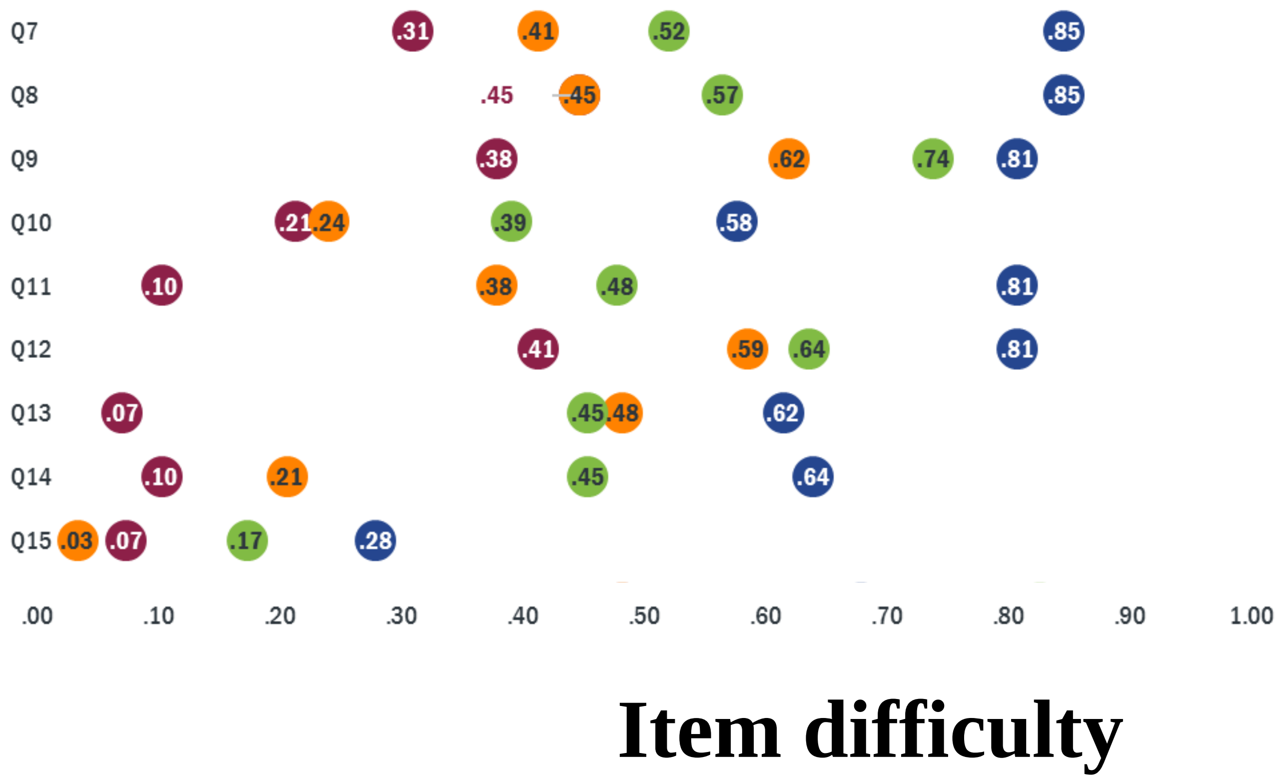
Post-administration of the QBCI



Item discrimination by item difficulty for QBCI



Item difficulty by groups of overall test performance



Low performers (<=7 correct)

Mid-Low Performers (8 or 9 correct)

Mid-High performers (10 and 11 correct)

High performers (>= 12 correct).

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There is some, but not much, evidence that quantitative education of life science students can be enhanced by incorporating biological examples and data in quantitative courses. ***Many (likely fundable) projects on this remain to be done by education researchers.***

There is some, but not much, evidence that quantitative education of life science students can be enhanced by incorporating quantitative ideas in biology courses. ***Many (likely fundable) projects on this remain to be done by education researchers***.

STEMeval.org

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References and Further Reading

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  - TEAMS Project Webinars: Diagnosing Your Survey Using Rasch Modeling (Level 1/2): Karen Drill and Erin Stack: http://teams.mspnet.org/