Assessment and evaluation tools for the undergraduate statistics major

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Overview

- **Goal: Evaluate student outcomes upon completion of undergraduate statistics program (e.g. major)**
  - comprehensive scope
  - snapshot of student outcomes
  - cohort comparisons
- Constraints
  - faithful to (2014) ASA Curriculum Guidelines[1]
  - applicable across institutions, instructors, years
- Assessment instruments
  - student assessment instruments
    - indirect assessment (i.e., survey)
    - direct assessment (i.e., test)
    - multi-year pilot data collection ongoing
  - faculty survey–proxy for program emphasis
    - new in Spring 2020

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[1] American Statistical Association Undergraduate Guidelines Workgroup (2014). *Curriculum guidelines for undergraduate programs in statistical science.*

(2014) ASA Guidelines for Undergraduate Programs in Statistical Sciences

data. Such skills underpin strategies for assessing and ensuring data quality as part of data preparation and are a necessary precursor to many analyses[43].

- Use of one or more professional statistical software environments[44]
- Data management using software in a well-documented and reproducible way[45], data processing in different formats, and methods for addressing missing data
- Basic programming concepts (e.g., breaking a problem into modular pieces, algorithmic thinking[46], structured programming[47], debugging, and efficiency)
- Computationally intensive statistical methods (e.g., iterative methods, optimization, resampling, and simulation/Monte Carlo methods)[48]
- Use of multiple data tools[49], so graduates are not wedded to one and are better able to learn new technologies[50]

Mathematical Foundations

The study of mathematics lays the foundation for statistical theory. Undergraduate statistics majors should have a firm understanding of why and when statistical methods work. They should be able to communicate in the language of mathematics and explain the interplay between mathematical derivations and statistical applications.

- Calculus (e.g., integration and differentiation)[51]
- Linear algebra (e.g., matrix manipulations, linear transformations, projections in Euclidean space, eigenvalues/eigenvectors, and matrix decompositions)

- Probability (e.g., properties of univariate and multivariate random variables, discrete and continuous distributions)[52]
- Emphasis on connections between concepts in these mathematical foundations courses and their applications in statistics[53]

Statistical Practice

Strong communication skills complement technical knowledge and are particularly necessary for statisticians; graduates need technical skills to perform analyses and communication skills to understand clients' needs and then effectively discuss results and conclusions. Important practical skills include the following:

43 See Zhu et al. (2013) "Data acquisition and pre-processing in studies on humans: What is not taught in statistics classes," *The American Statistician*, 67(4):235–241, which includes a series of skills: (1) get to know the study; (2) assess the validity of variable coding; (3) assess data entry accuracy; (4) perform data cleaning; and (5) edit identified data errors.

44 Although we acknowledge that Microsoft Excel is a common platform for data exchange, we do not recommend it as a primary analysis environment.

45 Appropriate environments could include R, Python, and SAS, complemented by tools including shell scripts and knitr.

46 Futschek (2006) defines algorithmic thinking as a set of abilities related to constructing and understanding algorithms: (1) the ability to analyze a given problem; (2) the ability to precisely specify a problem; (3) the ability to find the basic actions that are adequate to the given problem; (4) the ability to construct a correct algorithm to a given problem using basic actions; (5) the ability to think about all possible special and normal cases of a problem; and (6) the ability to improve the efficiency of an algorithm. Futschek, G. (2006). "Algorithmic thinking: The key for understanding computer science," in R. Mittermeir (Ed.), *Informatics Education–The Bridge Between Using and Understanding Computers* (Vol. 4226, pp. 159–168). Berlin/Heidelberg: Springer. We consider this to be a necessary, but not sufficient component of "computational thinking."

47 We define structured programming as the ability to use functions and control structures (e.g., "for" loops).

48 This recommendation is consistent with the efforts of Conrad Wolfram and the Computer-Based Math initiative, *www.computerbasedmath.org* and *www.tinyurl.com/ted-wolfram*. The incorporation of these tools may be particularly valuable at the bachelor's level, since students will generally have less technical knowledge (and need to be able to simulate to generate insights and/or check analytic results).

49 Students should develop the capacity to manipulate formats such as CSV, JSON (JavaScript Object Notation, a data-interchange format that is easy to read, parse, and generate; see Nolan and Temple Lang (2014) *XML and Web Technologies for Data Sciences with R*), XML, databases (see, for example, Ripley (2001) "Using databases with R," *R News*, 1(1):18–20 and Wickham (2011) "ASA 2009 Data Expo," *Journal of Computational and Graphical Statistics*, 20(2):281–283), and text data. Because many faculty were not trained in these technologies, continuing education in this area needs to be made a priority.

50 We are not prescriptive regarding which technologies are incorporated into the curriculum, as long as they are sufficiently flexible and powerful. Many undergraduate statistics students develop expertise in environments such as R/RStudio, Python, and SAS.

51 Multivariate calculus is recommended.

52 Markov chains are a useful topic for undergraduate majors in statistics.

53 This linkage includes topics such as the delta method. In addition, many students might benefit from exposure to modeling and simulation in their mathematics courses as a way to reinforce their computational skills.

Comprehensive Undergraduate Statistics Program (CUSP) Assessment Strategy

# Competencies	(2014) ASA Guidelines Areas of Emphasis
37	Statistical Methods & Theory
16	Data Wrangling, Computing, & Data Science
11	Mathematical Foundations
18	Statistical Practice
9	Problem Solving
4	Discipline-Specific Knowledge

- 95 competencies cited in 2014 ASA Guidelines
- Single assessment tool likely not sufficient
- Test blueprint (Link to resource page)

Comprehensive Undergraduate Statistics Program (CUSP) Assessment Map

- CUSP Survey–Indirect assessment (students)
  - self-evaluated survey
  - all 95 competancies in (2014) ASA Guidelines
  - $\sim$ 10-15 minutes duration
  - single institution w. multiple cohorts
- CUSP Test–Direct assessment (students)
  - selected response test
  - prioritized subset of the 95 competencies
  - $\sim$ 1 hour duration
  - multiple institutions w. single cohort
  - single institution w. multiple cohorts
- Faculty Perception of SPECs–Indirect assessment (program)
  - program emphasis self-reported by faculty
  - all 95 competancies in (2014) ASA Guidelines
  - single institution; single implementation (Spring 2020)
  - scale: {incidental; T shows; S does; Assessed}

Indirect assessment–CUSP Survey

- **Benefits**
  - easy implementation
  - may administer multiple times
  - no problem if topics haven't been taught
  - includes demographics that can be linked to other instruments
- **Risks/Issues**
  - lexical ambiguity issues
  - over/underconfidence with content exposure
  - reflection of affect vs knowledge? (Sitzman et al., 2010)

Excerpt

Statistical Theory

(scale: [1] very low / never learned; [2] low; [3] fair; [4] good; [5] very good; [6] excellent; [7] exceptional)

Please rate your **current level of knowledge/competency** related to:

	1	2	3	4	5	6	7
Distributions of random variables	O	O	O	O	O	O	O

Example Use

- Indirect assessment tool (i.e., Survey) administered at key program milestones
    - first-year course
    - midpoint course(s)–if possible
    - beginning & end of capstone course
- Informative for annual program evaluation data
    - due caution about interpretation (e.g., Sitzman et al., 2010)
    - most effective when corroborated by other tools

Comprehensive Undergraduate Statistics Program (CUSP) Assessment Map

- *Indirect assessment–CUSP Survey*
- **Next: Direct assessment–CUSP Test**
  - selected response test
  - $\sim$ 1 hour duration
  - multiple institutions w. single cohort
  - single institution w. multiple cohorts
- Indirect assessment–Faculty Perception of SPECs
- Future work

Direct assessment–CUSP Test

- Selected response assessment tool with broad coverage
- 33 tasks; some with multiple parts
  - 9 testlets
  - 24 conventional MC questions
- several tasks/subtasks assess multiple competancies
  - score adjustment for successive competancies
  - 86 'points possible'
- some tasks adpted from other instruments (with permission)
  - 2 from the REGRESS assessment (Enders, 2013)
  - 9 from the CAOS assessment (delMas et al., 2007)

CUSP Test

- Instructor Preview (link)
  - **preview is not for classroom use**
  - password protected

Excerpt (partial item)

driver or passenger side.

Study design dictates appropriate statistical analysis, but often there is more than one reasonable approach to the analysis. Evaluate whether each of the following analysis suggestions is VALID or NOT VALID for testing and estimating the difference in durability for the two brake pad materials:

	Valid	NOT Valid
paired t-test for brake pad difference of each car (DriverSide - PassengerSide)	○	○
paired t-test for brake pad difference of each car (Experimental - Standard)	○	○
ANOVA with car as a blocking variable	○	○

CUSP Test

- **Benefits**
  - test statistical “reflexes” of students
  - built-in “CAOS” subtest
  - objective measure of student competancies
    - for individual students
    - for a cohort of students
    - aggregate useful for program evaluation
  - selected response implementation
- **Risks/Issues**
  - variable use conditions jeopardize comparisons
  - implementation logistics restrict scope
    - duration/content coverage
    - selected response
  - includes topics we don’t necessarily teach (yet)
  - too lengthy/difficult to implement without incentive

Example Use Cases

- Penn State
  - Indirect assessment (i.e., survey) administered multiple times
  - Direct assessment (i.e., test) as midterm in capstone course
  - benchmarking student skills and competancies against ASA Guidelines
  - identify & prioritize cohort needs before graduation
  - program feedback & annual evaluation data
- Other Institutions
  - no course credit
  - homework, extra credit, etc
  - resource constraints (or not)

Preliminary Item Analysis

- Heuristics[2]
  - unidimensionality: assumed by common methods of assessment evaluation
  - reliability: coefficient alpha > 0.8
  - descrimination $r_{it(i)} > 0.15$ preferred
  - $0.6 <$ proportion correct < 0.9
- Results
  - PCA evidence supports unidimensionality
  - coefficient alpha $= 0.802$
  - $30/33$ items with discrimination $r_{it(i)} > 0.15$
  - $9/33$ items in recommended difficulty range
  - $21/33$ items with $> 50\%$ correct

[2] Haladyna & Rodriguez (2013); Thorndike & Thorndike-Christ (2010)

Comprehensive Undergraduate Statistics Program (CUSP) Assessment Map

- *Indirect assessment–CUSP Survey*
- *Direct assessment–CUSP Test*
- **Next: Indirect assessment–Faculty Perception of SPECs**
    - program emphasis self-reported by faculty
    - same 95 topics from ASA Guidelines
    - scale: {incidental; T shows; S does; Assessed}
- Future work

Indirect assessment–Faculty Perception of SPECs

- Statistics Program Emphases and Contents (SPECs)
- Indirect assessment
  - program emphasis self-reported by faculty/administrator
  - same 95 topics from ASA Guidelines

Computationally Intensive Statistical Methods

(scale: 0-none, 1-incidental, 2-teacher, 3-student, 4-assessed)

	Learning Outcome Exposure Scale					Course
	0- None	1- Incidental	2- Teacher	3- Student	4- Assessed	
Iterative methods	○	○	○	○	○	
Optimization	○	○	○	○	○	
Resampling	○	○	○	○	○	
Simulation/Monte Carlo methods	○	○	○	○	○	

Comprehensive Undergraduate Statistics Program (CUSP) Assessment Map

- *Indirect assessment–CUSP Survey*
- *Direct assessment–CUSP Test*
- *Indirect assessment–Faculty SPECs*
- **Next: Future work**

Future work

Shorter term goals

- Post-graduation follow-up for validation evidence
- Link CUSP Survey data to CUSP Test outcomes
- Streamline logistics for wider implementation
- Expand item bank for direct assessment

Longer term goals

- Experimentation with short/long forms
- Alternative or additional tools for more complete alignment to ASA Guidelines

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References

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Q & A

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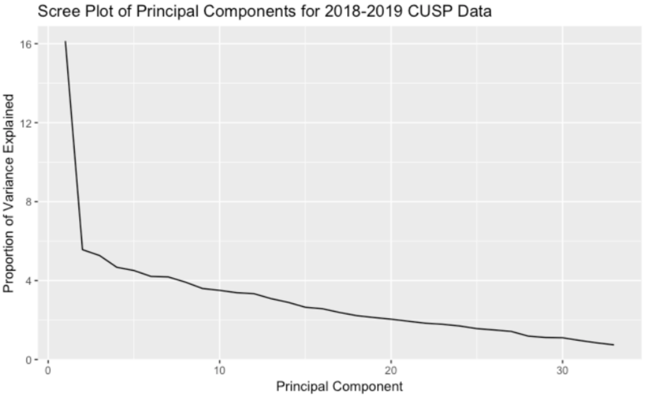
https://mdbeckman.github.io/2020-UMN-Colloquium/

CUSP Test blueprint alignment to ASA Guidelines

Section	Subsection	Target Weight (%)
Statistical Methods and Theory	Statistical Theory	18.0
Statistical Methods and Theory	Exploratory Data Analysis	6.0
Statistical Methods and Theory	Design of Studies	18.0
Statistical Methods and Theory	Statistical Models	18.0
Data Wrangling Computation and Data Science	Software and Tools	0.0
Data Wrangling Computation and Data Science	Accessing and Wrangling Data	4.5
Data Wrangling Computation and Data Science	Basic Programming Concepts	1.5
Data Wrangling Computation and Data Science	Computationally Intensive Statistical Methods	4.0
Mathematical Foundations	Calculus	0.0
Mathematical Foundations	Linear Algebra	0.0
Mathematical Foundations	Probability	2.5
Mathematical Foundations	Connecting mathematical foundations & applications in statistics	2.5
Statistical Practice	Communication	0.0
Statistical Practice	Collaboration	0.0
Statistical Practice	Ethical Issues	5.0
Statistical Practice	Opportunities for Authentic Practice	0.0
Problem Solving	Complex open-ended problems	2.2
Problem Solving	Scientific method and statistical problem-solving cycle	12.8
Discipline-Specific Knowledge	Discipline-Specific Knowledge	5.0

Scree plot of CUSP test data



Item discrimination results

- Item-total correlations $r_{it(j)} < 0.15$
  - (21% correct; $r_{it(j)} = 0.11$) Validity of models aligned to a study design
  - (40% correct; $r_{it(j)} = -0.04$) CAOS task about CI interpretation
  - (3.6% correct; $r_{it(j)} = -0.10$) Strategies to maximize likelihood
- Highly discriminating items
  - ($r_{it(j)} = 0.59$) Probability distributions task
  - ($r_{it(j)} = 0.50$) CAOS Histograms & std deviation task
  - ($r_{it(j)} = 0.46$) OLS regression assumptions task

Q20. Choose the **most** appropriate probability distribution from the list below for each of the scenarios described. Each distribution may be used more than once or not at all.

X = how many of the next 20 cars that pass you on the highway are silver colored. [Binomial]

X = how much time until the next diet coke is purchased from a vending machine.

X = birth weights of infants born within one week of their due date at a given hospital.

X = the total number of goals scored during a randomly selected match in the FIFA World Cup soccer tournament.

✓
Bernoulli
Binomial
Continuous Uniform
Discrete Uniform