RECIPE FOR A COBB SALAD IN A TIME OF EASY COMPUTABILITY

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Technology continues to change not only how we teach, but also what we teach in the introductory course. Recently there has been lively discussion about which topics belong in the course. George Cobb has challenged us to rethink the curriculum in light of the computational power of our technologies. This paper proposes a framework for structuring a course using JMP, omitting some traditional topics, leaving space for emphasis on concepts, on data production, on visualization, and on topics that are rarely included in an introductory course. Through such a structure, we can more directly connect statistics education to students' disciplinary contexts in business, engineering, social and natural sciences, etc. Additionally, we can strengthen students' conceptual foundations in the field so that, in their roles as citizens and professionals, they can become more critical consumers of statistical arguments.

INTRODUCTION

In a recent rethinking of our introductory courses, George Cobb reminds us just how pervasive have been the accommodations to problems of computability. Many of our core topics are progressively complex adjustments to approximations that we rely on because more direct methods were not previously practically computable. But now we have cheap and powerful computing that permits us to remove the normal distribution from the center of our universe and instead replace it with the fundamental logic of inference at the center. Liberated from the "tyranny of computability" we can "emphasize the 3R's of inference: Randomize, Repeat, Reject any model that puts your data in its tail" (Cobb, 2007).

In statistics education we have a long history of questioning what we should teach, when we should teach it, and how we should teach it (Federer, 1978; Hogg, 1991; Meng, 2009; Moore, Cobb, Garfield, & Meeker, 1995; Vere-Jones, 1995). There is an equally rich history of adapting to new technologies, from calculators to computers (Friedman & Stuetzle, 2002; Phillips, 2001; Schatzoff, 1968; Tukey, 1972). This paper takes up Cobb's exhortation and offers a recipe for a course in the spirit of his article.

In 1937 Robert Cobb introduced a salad at the Brown Derby restaurant in Hollywood, California featuring an assortment of vegetables, meat, eggs and cheese with each ingredient chopped and artistically arranged in adjacent mounds on a dinner plate. A Cobb salad is a full meal in itself—rich in nutrients and flavor. It is loaded with proteins and fats providing the diner with a substantial meal of bite-sized elements, unified with a savory dressing.

Our standard emphasis on technique has too often produced introductory statistics courses that are green salads: an enormous amount of space on the plate is occupied by bulky greens that have relatively little flavor or nutritional value, take a long time to chew, and ultimately leave the diner unsatisfied. The recipe outlined here reduces some of the space-filling and watery leafiness and adds substantial ingredients that will fortify students and remain with them for a long time.

A FRAMEWORK: CONSTRAINED OPTIMIZATION

We begin building the course within a framework of multi-objective constrained optimization. The animating idea in Cobb's article is that an ancient constraint has been lifted; we can productively think about our objective function(s) and our constraints. What are we optimizing, and what are the critical constraints?

Cobb includes the "logic of inference" as a key term in the objective function. Though there is enormously consequential national variation on this score, I suggest that we emphasize the logic of inference in order to maximize our students' preparedness for world citizenship. We live in an age when statistical thinking is one major modality of truth-seeking, policy development and decision-making. Scholars from various nations and cultures have cited the idea of "statistics for citizenship" for years (Bartholomew, 1995; Gal, 2003; Utts, 2003; Wild, 1994). If we are to educate for world citizenship, we also must pursue the objective of *statistical thinking*; indeed our

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literature often points to it as the objective *par excellence*. One recent discussion notes that "Statistical thinking uses probabilistic descriptions of variability in (1) inductive reasoning and (2) analysis of procedures for data collection, prediction, and scientific inference" (Brown & Kass, 2009). The authors go on to note that "Statistical models of regularity and variability in data may be used to express knowledge and uncertainty about a signal in the presence of noise, via inductive reasoning."

What of constraints? This section briefly outlines the proposed constraint set:

- *Important problems*: Statistical thinking is brought to bear on problems of great importance and therefore illustrative problems and cases presented in our courses should be real and important.
- *Best practices*: Follow GAISE (or comparable) guidelines.
- *One semester*: the introductory course is often the terminal course, and we have roughly one quarter of the year at our disposal (in the U.S. a 14-week course is typical).
- *Infrastructure*: We must recognize national differences in statistical infrastructure and student preparation in secondary in schools (Peres, Morettin, & Narula, 1985).
- *Barriers to reform*: We must also recognize the social, political, economic hurdles to curricular reform (Kerr, 1989; Obanya, 1995).
- *SOS disciplines*: Many courses serve the needs of programs in engineering, social sciences, business, or natural science. At each institution we must meet the needs of the disciplines with whom we cooperate in offering Subject-Oriented Statistics (SOS) courses (Altman & Bland, 1991; Love & Hildebrand, 2002; McAlevey, Everett, & Sullivan, 2001; Meng, 2009; Smeeton, 1997; Yasar & Landau, 2003).
- *Non-negativity*: Here we might be inspired by the Hippocratic Oath: do no harm. Better still, keep the affect positive, so that on net we offer "Happy Courses" (Meng, 2009).

Cobb's original point is that some long-standing constraints have been substantially relaxed or effectively dropped. We should note that in many nations we no longer assume an absence of prior background knowledge (Holmes, 2003).

AN OUTLINE FOR A 14-WEEK COURSE

Much as we think of data as a mixture of signal and noise (Konold & Pollatsek, 2002) we may do well to reexamine our course outlines similarly with an eye to improving the signal-to-noise ratio. Activities and lessons that advance statistical thinking and the logic of inference are signal, as is any content that satisfies SOS-related needs or other constraints. All other potential course elements are noise.

The course design should follow principles of good study design, following the essential structure of a Plan-Do-Report cycle (Sharpe, De Veaux, & Velleman, 2010), iterating the cycle several times within the course. *Planning* involves raising theory- and data-driven questions, specifying variables, and planning for data collection. *Doing* is about methods and techniques. This course proposal presents methods that satisfy constraints and/or increase facility with the logic of inference and statistical thinking. For each "doing" segment, a micro P-D-R cycle will repeat according to the conventions of the technique. *Reporting* focuses on resolution of those important problems, assessing the extent to which conclusions can be drawn, and with direct attention to language suited to communicating within our allied disciplines (Radke-Sharpe, 1991; Samsa & Oddone, 1994; Wild, 1994).

In keeping with the Cobb salad metaphor, let's treat the four P-D-R cycles as four nutritious elements arranged artfully in *mounds*, and describe the topics that form ingredients for each mound. This section presumes use of JMP software, but other programs can also serve the purpose.

Mound 1: *Populations and Variability* (4 weeks): We begin with a vivid presentation of an important international problem relevant to the SOS discipline; rich areas might involve social justice, public health, or quality of life (Lesser, 2007). How do we study and describe the dimensions of such problems? What do we mean by variation and to what extent is variation at the root of such problems? How do we measure and characterize variation (concepts, constructs, measures)? Here the students first meet concepts of study design for experimental, observational, survey research.

Today, genuine population data truly are available and manageable. This mound presents one real population dataset and introduces data sources, discussing their credibility and reliability. In JMP we can demonstrate simple database queries and data management concepts, opening the door to enormous databases typically available to governments and industry. We can use JMP's visual interface to develop deeper understanding of data types, of distributions and density, and how graphs and summary measures represent distributions.

Mound 2: *Samples and Variability* (3 weeks): Why do we sample at all? At this stage we move on to concepts related to samples including sampling methods, sampling error, and the idea of representativeness. We present techniques and conventions for describing sample data, for gleaning insights and for generating hypotheses. Here, too, is the place for the foundations of experimental design and survey research (depending on SOS allies). This is also a place for the unglamorous but critical processes for data cleaning, dealing with missing data, and other forms of data preparation. As appropriate, we can also selectively teach how to design experiments and/or to design simple and complex samples for survey research. In this mound we introduce proper habits of speaking and writing about sample results.

Mound 3: *The Logic of Inference* (4 weeks): This mound begins with reinforcement of the scientific method and the logic of inference from sample data. The permutation test is introduced as the canonical technique, first with manipulatives then with software, emphasizing visualization of sampling distributions. We continue with further use of software to simulate random, non-random, and complex samples. Hypothesis generation was previously introduced and now there is more formal coverage of the subject. The course presents inference as consisting of estimation and significance testing—and builds these concepts with resampling and permutation tests, emphasizing the concept of a P-value. We then cover conventional *t*-tests and interpretation of confidence intervals. As appropriate to the SOS-partners, we can also teach simple modeling using theoretical distributions (e.g., normal, Poisson), and expand communication skills to encompass speaking and writing about inferences results. Especially in SOS courses allied with social sciences, a brief treatment of the concept and use of sampling weights is appropriate here.

Mound 4: *Further Applications of Inference* (3 weeks): Depending on the allied disciplines partners, such topics might include ANOVA, Regression, or another technique commonly required by the discipline. In this part of the course, one should include student projects that stepping all the way through the process of a statistical study. Finally, the course concludes with a more sophisticated treatment of the same important problem with which it began.

DISCUSSION

The course described here is ambitious and deliberately provocative. Some recommendations are more feasible than others, and some reflect an orientation to social science and business. It is my hope that the framework of constrained optimization is a useful one, and that this proposal is both constructive and in keeping with the spirit of George Cobb's challenge. There is a marked reduction in the coverage of specific methods and techniques, and greater attention to foundational concepts and to real problems that can yield to statistical analysis.

Once the ingredients have been selected from the freshest and most delectable locally available, they should be cut into lesson-sized cubes, and arrayed pleasingly into mounds. Finally, the salad should be gently tossed in a dressing that blends important and engaging problems, our enthusiasm for our discipline, and good humor.

REFERENCES

Altman, D. G., & Bland, J. M. (1991). Improving Doctors' Understanding of Statistics. *Journal of the Royal Statistical Society. Series A (Statistics in Society)*, *154*(2), 223-267.

Bartholomew, D. J. (1995). What is Statistics? *Journal of the Royal Statistical Society. Series A (Statistics in Society)*, *158*(1), 1-20.

Brown, E. N., & Kass, R. E. (2009). What is Statistics? *The American Statistician*, *63*(2), 105-110.

Cobb, G. (2007). *The Introductory Statistics Course: A Ptolemaic Curriculum?* Online: http://repositories.cdlib.org/uclastat/cts/tise/vol1/iss1/art1.

Federer, W. T. (1978). Some Remarks on Statistical Education. *The American Statistician, 32*(4), 117-121.
Friedman, J. H., & Stuetzle, W. (2002). John W. Tukey's Work on Interactive Graphics. *The Annals of Statistics, 30*(6), 1629-1639.
Gal, I. (2003). Teaching for Statistical Literacy and Services of Statistics Agencies. *The American Statistician, 57*(2), 80-84.
Hogg, R. V. (1991). Statistical Education: Improvements are Badly Needed. *The American Statistician, 45*, 342-343.
Holmes, P. (2003). 50 Years of Statistics Teaching in English Schools: Some Milestones. *Journal of the Royal Statistical Society. Series D (The Statistician), 52*(4), 439-474.
Kerr, S. T. (1989). Reform in Soviet and American Education: Parallels and Contrasts. *The Phi Delta Kappan, 71*(1), 19-28.
Konold, C., & Pollatsek, A. (2002). Data Analysis as the Search for Signals in Noisy Processes. *Journal for Research in Mathematics Education, 33*(4), 259-289.
Lesser, L. M. (Ed.). (2007). *Critical Values and Transforming Data: Teaching Statistics with Social Justice* (Vol. 15).
Love, T. E., & Hildebrand, D. K. (2002). Statistics Education and Making Statistics More Effective in Schools of Business Conferences. *The American Statistician*, *56*(2), 107-112.
McAlevey, L., Everett, A. M., & Sullivan, C. (2001). Evolution in Business Statistics Curricula: Learning from the ‘Making Statistics More Effective in Schools of Business’ Conference. *Journal of the Royal Statistical Society. Series D (The Statistician), 50*(3), 321-333.
Meng, X.-L. (2009). Desired and Feared-What Do We Do Now and Over the Next 50 Years. *The American Statistician, 63*(3), 202-210.
Moore, D. S., Cobb, G. W., Garfield, J., & Meeker, W. Q. (1995). Statistics Education Fin de Siecle. *The American Statistician*, *49*(3), 250-260.
Obanya, P. (1995). Case Studies of Curriculum Innovations in Western Africa. *International Review of Education, 41*(5), 315-336.
Peres, C. A., Morettin, P. A., & Narula, S. C. (1985). Educating and Training Undergraduate Applied Statisticians. *Journal of Educational Statistics*, *10*(3), 283-292.
Phillips, B. (2001). David Vere-Jones’s Influence on Statistical Education. *Journal of Applied Probability, 38A*, 6-19.
Radke-Sharpe, N. (1991). Writing as a Component of Statistics Education. *The American Statistician, 45*(4), 292-293.
Samsa, G., & Oddone, E. Z. (1994). Integrating Scientific Writing into a Statistics Curriculum: A Course in Statistically Based Scientific Writing. *The American Statistician, 48*(2), 117-119.
Schatzoff, M. (1968). Applications of Time-Shared Computers in a Statistics Curriculum. *Journal of the American Statistical Association*, *63*(321), 192-208.
Sharpe, N., De Veaux, R. D., & Velleman, P. F. (2010). Business Statistics. Boston: Addison-Wesley.
Smeeton, N. (1997). Statistical Education in Medicine and Dentistry. *Journal of the Royal Statistical Society. Series D (The Statistician)*, *46*(4), 521-527.
Tukey, J. W. (1972). *How Computing and Statistics Affect Each Other*. Paper presented at the Babbage Memorial Meeting: Report of Proceedings, London.
Utts, J. (2003). What Educated Citizens Should Know about Statistics and Probability? *The American Statistician, 57*(2), 74-79.
Vere-Jones, D. (1995). The Coming of Age of Statistical Education. *International Statistical Review / Revue Internationale de Statistique, 63*(1), 3-23.
Wild, C. J. (1994). Embracing the “Wider View” of Statistics. *The American Statistician, 48*(2), 163-171.
Yasar, O., & Landau, R. H. (2003). Elements of Computational Science and Engineer Education. *SIAM Review, 45*(4), 787-805.