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# Teaching Statement

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## Motivation

Today's students are tomorrow's doctors, lawyers, politicians, entrepreneurs, patients, parents, volunteers, neighbors, retirees, etc.; all of whom will use data to make personal and group decisions. It is crucial that our educational institutions prioritize teaching everyone, not just students who excel in quantitative majors, how to learn from data and consider uncertainty in judgements for decision making. For this reason, I have an abiding interest in teaching statistics, modernizing current statistics curricula to overlap expectations in data science, and developing data science programs that bring analytic methods to the masses.

An irony in teaching statistics and data science methods is that, as toddlers, humans already have skills to weigh options and make data-supported choices [e.g., Kushnir and Gopnik 2007; Waisman et al. 2012]. So, it is ironic that we need to *teach* skills explicitly that are quite possibly innate to humans. As a society, however, we tend to accept new principles and policies easier when they are supported by data than when they are not. Thus, if we want personal inferences to be accepted by others, it is important to incorporate mathematical rigor or "objectivity" into analyses and communicate the logic in the analytical approaches. In statistics and other analytics classes, we teach the mathematics and offer good approaches for communicating data informed judgements. Alas, students are graduating with a misunderstanding of what the application of statistics entails. For example, students often conceptualize statistical solutions as right or wrong outcomes to set procedures, when, really, statistical solutions develop from creative, application-specific problem solving strategies. Consequently, students avoid using, or fail to realize when to use, rigorous statistical methods in their personal and professional lives and often make comments, such as, "I am terrible at statistics" [Williams 2010, 2015]. Yet, if indeed we all are natural statisticians, no one can truly be terrible at statistics.

## In the Classroom

In light of cognitive research in how humans use data and my passion for education in statistics and data science, I have two main principles that I apply when I teach: 1) start with what the students know and 2) focus on aspects of critical thinking to guide lessons. Thinking statistically is thinking critically, in my opinion.

When introducing new concepts in class, starting with what students know initiates constructivist learning, an accepted pedagogical strategy [e.g., Von Glasersfield 1987; Garfield 1995; Piaget 1928]. The idea is that, from the beginning, students use their intuition, maintain self confidence, and assimilate new information with old to construct their understanding of concepts. I take three different opportunities in a course to "start with what they know". First, at the beginning of every semester, I work through key concepts from previous classes that will apply in the current course. For example, in my undergraduate Applied Bayesian Methods class, I start with defining random variables, developing the role of probability in inference, deriving likelihood functions, and finding maximum likelihood estimators - all concepts that students have seen before. Second, I start every lecture with a review from the previous lecture. This has the added bonus to reinforce retention via repetition [Graham 2000] and offer more time for questions. Third, I use data in examples, labs, and projects to which the student can relate. For example, to teach Principal Component Analysis (PCA), my favorite dataset to use is one created by the students; e.g., students answer a 25-question survey with personal questions, such as "On average, how many hours of sleep do you get per week?" and "On a scale from 1 to 100, how much do you love statistics?". Students then consider their judgements about people in the class, while learning how to formulate high-dimensional distance functions and interpret PCA plots.

The second principle I keep in mind as I design my lessons is to emphasize critical thinking when learning and applying statistical concepts. In 2011, Arum and Roksa wrote the book *Academically Adrift* and used data to support the claim that U.S. college graduates do not practice thinking critically during their first two years of college [Arum and Roksa 2011]. However, the application of statistical principles is fundamentally a form of thinking critically about a problem, as defined in the eight "Elements of Thoughts" (EoT) [Elder and Paul 2010] shown in Figure 1. That is, contrary to many peoples' perceptions of statistics, comprehensive statistical analyses result from a creative, thoughtful process that relies on both analytical tools and self reflection about what is known about the problem, how to interpret analyses, and honest assessments of both assumptions and implications, including personal biases. Also, good analyses define the research problem by clear research questions that have the opportunity to be answered by relevant data. All of these features of statistical analyses are also included in the EoT. Hence, to think statistically is also to think critically.

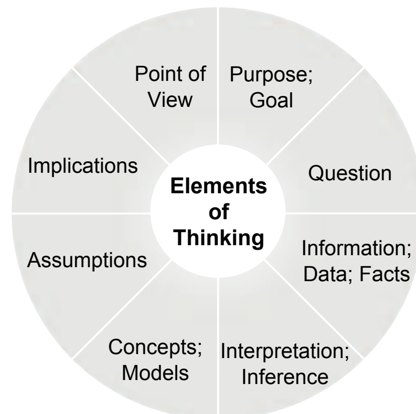


Figure 1: *Eight Elements of (Critical) Thinking (EoT) [Elder and Paul 2010] that also correspond to aspects of comprehensive statistical analyses.*

One way to emphasize the EoT in a course is to provide opportunities for students to apply all eight elements in assignments and to devote lessons to individual or sets of elements. For example, in a new course called *Data in Our Lives* that I developed, I have students break into groups and read contradicting articles about controversial topics; e.g., the necessity of college, health risks of diet soda, mandating HPV vaccinations, etc. Each article uses data to support opposing points of view. The students are asked to state the EoT from the authors' perspectives of each article, as well as to apply the EoT and select articles with which the students agree.

Also, in collaboration with colleagues, I developed lessons that rely on interactive data visualization software that we innovated [e.g., Kodali et al. In progress; Chen et al. 2017, 2016; Self et al. 2016; Leman and House 2012]. By using the software, students start with their own understandings of the data and explore real-world, high-dimensional datasets based on personal questions and data discoveries. Thus, without distractions from technicalities of analytical methods, students have opportunities to complete the EoT while conducting exploratory data analyses.

— *L. House, 2017, Teaching Statement*

My teaching principles apply to all levels of students and in a variety of settings. For example, the principles apply in large introductory statistics classes, upper level graduate classes, and in one-on-one collaborations with PhD advisees or colleagues. However, even with common principles, what classes and collaborators need to build from what they know and have the freedom to think critically may change. Thus, it is up to me to adjust accordingly and provide safe environments for diverse learners to develop their own forms of statistical thinking.

**Courses Taught**

The table below lists the courses I have taught at Virginia Tech, the number of times I taught them, and the course levels.

| **Course** | **Course Name** | **# Times Taught** | **Level** |
|---|---|---|---|
| STAT 1984 | Data in Our Lives | 1 | Undergraduate |
| STAT 2004 | Introductory Statistics | 1 | Undergraduate |
| COS 2984/ ISC 111X/ ISC 211X | Integrated Science Curriculum† | 3 | Undergraduate |
| CMDA/ STAT/ CS 3654 | Introduction to Data Analytics and Visualization† | 1 | Undergraduate |
| STAT 4214/ 5214G | Methods of Regression Analysis | 2 | Undergraduate/ Graduate |
| STAT 4444/ 5444G | Applied Bayesian Analysis | 7 | Undergraduate/ Graduate |
| STAT 5365/ 5984 | Hierarchical Modeling | 3 | Graduate |
| STAT 5104 | Probability and Distribution Theory | 3 | Graduate |

† Team Taught

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