Contents

1 Preamble 2

2 Not So Tapered Retirement 2

3 Benefits Of Retirement 2

4 Statistical Philosophies 3

5 What Does It Mean To ‘Do a Good Job’ in Statistics? 3

6 You (usually) Get What You Pay For 4

7 Computation Versus Contemplation 5

8 Sometimes Probability Isn’t Needed 5

9 Academic Culture & Organizational Context 6

10 Academe, Industry and Government 6

11 Perspectives On The Field and Profession of Statistics 7
Thoughts While Not Shaving: Revised

1 Preamble
In January 2018, after 45+ years of full-time teaching, advising, researching, writing grants, serving the profession; I decided it was time to cut back on my professional commitments, not to pull the plug completely, but to create additional space for other activities. The time-commitment and stress of commuting to JHU from DC and beyond influenced this decision, but it was by no means the sole generator. I’m working from home most days, shaving less often, and communicate ‘thoughts while not shaving.’

2 Not So Tapered Retirement
My retirement is most definitely a work in progress. Retirement, even partial, is challenging. E,ven with that heads-up I didn’t realize how difficult it would be substantially to reduce commitments and time in the office. Part of the challenge was generated by the delayed start of my 25% Inter-agency Personnel Agreement (IPA) with the FDA, but much of the challenge resulted from a too-rapid disconnect from JHU Biostatistics. Rather than gradually tapering the dose, I went instantaneously from about 120 percent-time to about 5 percent-time of Hopkins funding. Withdrawal symptoms are likely similar to those associated with a too-rapid reduction in the dose of a drug.

Challenges and issues in this new phase of my life include the need to adjust my professional and personal identities, and to acclimate to substantially reduced in-person social and professional interactions. My occasional days on-site at Hopkins help as do weekly Skype meetings with the Malaria project, with Sophie Berube (my last doctoral advisee), and my weekly presence at the FDA.

Tapering continues with a projected asymptote above zero. I don’t want to go to absolute zero, because I like statistics and will stay involved in appropriate roles for a 20th century statistician. However, moderation is key.

3 Benefits Of Retirement
There are benefits to retirement (in addition to retirement benefits!). With a reduced, official workload there is more time for professional recreation, for noodling an idea, for reading some literature that is a bit peripheral to a specific project, for not having to juggle so many obligations and deadlines.

On the personal front, I’m doing some volunteering at the Chesapeake Bay Maritime Museum, am trying to convince Ospreys not to build a nest on our boat lift, visiting children and grandchildren, now 7 in number, more often. Additional activities and benefits will accrue, but I need to create and activate them. So, this is not the time to be passive, as
time and aging move fast. As Wallace Stegner notes in *The Angle of Repose*, the transitions:

\[
\text{History} \leftarrow \text{Present} \leftarrow \text{Future}
\]

correct at warp speed,

“There is another physical law that teases me too: the Doppler Effect. The sound of anything coming at you—a train, say, or the future—has a higher pitch than the sound of the same thing going away. If you have perfect pitch and a head for mathematics you can compute the speed of the object by the interval between its arriving and departing sounds. I have neither perfect pitch or a head for mathematics, and anyway who wants to compute the speed of history? Like all falling bodies, it constantly accelerates.”

4 Statistical Philosophies

‘Pure’ Bayes, ‘pure’ frequentist, ‘pure’ any statistical philosophy, pairs nicely with Port, but when you leave port for the high seas of applications, some degree of impurity is usually necessary. Consequently, statisticians who engage in important studies use their philosophy as an aid to navigation, not as a straightjacket. The goal is to do a good job, and one can’t be (too) doctrinaire.

5 What Does It Mean To ‘Do a Good Job’ in Statistics?

I asked Hopkins Biostatistics colleagues for their take on what it means to do a good job, and here are consolidated responses.

*Response*

Interesting question! Without thinking too much about it here are some things I would include in ‘doing a good job’:

- Examining the data and doing basic descriptives to understand it (i.e., not just relying on some big fancy model)
- Not letting the results drive the analysis; being driven to use appropriate and the best methods possible, not by what the resulting scientific findings are
- Performing robustness checks/sensitivity analyses to probe the sensitivity of results to the underlying assumptions and how much the results might change with (reasonable) other analysis choices
- Trying to understand what the major sources of bias will be, and not necessarily worrying about the weeds (in part to avoid super fancy models that try to do too much and then fail, …)

*Response*

I am most (only?) convinced by studies that test the robustness of their conclusions to their choice of assumptions, methods, frameworks as thoroughly as possible. So I think “doing a good job” means taking multiple approaches to a problem and trying to see the problem from perspectives other than your own.

*Response*

It’s an excellent passage and being more in the translational world of statistical science (i.e., always on those high seas of applications) I agree with these sentiments 100%. How I would define ‘do a good job,’ both in general and specific terms, would involve the following.
• Address the questions, hypotheses and objectives of the application with sound defensible statistical analysis.
• Promote the use of statistical science within and beyond the applications. This can be done not only with the above comment, but to embed yourself enough within the applications so as to be able to propose additional hypotheses, use of advanced methods, improved design, etc. which advances both the substantive area application as well as statistics. As statisticians we always seem to have an educational role. Application PIs often do not know what else can be done and I think it’s part of our job when ‘doing a good job’ to use applications and collaborations as an opportunity to promote statistical science.
• Think about doing better science instead of spending too much time on the best science, as the latter is certainly an elusive subjective concept anyway.

Response
• Understand the relevant science/policy
• Understand the data,
  ◦ Sampling plans, including censoring
  ◦ Reference populations
  ◦ Measurement systems and their properties
• Target the appropriate estimand(s), don’t let a canned procedure dictate them
• Conduct protocol-driven, principal analyses, then explore
• Trade-off some efficiency for robustness
• Operate with a reproducible process
• Accommodate and quantify relevant uncertainties
• Conduct sensitivity analysis

Response
I read your question about purity. My response is in the context of clinical trials/regulatory and slightly different than I think you are looking for.

I think we must get away from the idea of one published analysis of clinical trial results. The publications we see in NEJM, JAMA, etc are highly influenced by regulators. We can call this analysis the “regulatory analysis” and it should be called such in publications. There is no reason why there cannot be other analyses in other journals e.g. “the physician analysis”, the “insurer analysis”, the “patient analysis” where Bayesian and causal inference methods could be used, alternatives to p-values. We could see cost-benefit, risk-benefit, analyses etc. These issues are important to other than the regulatory audience. I believe the “estimand era” that we have entered requires this approach to reporting. Surely different audiences have different estimands.

6 You (usually) Get What You Pay For
Risk/reward trade-offs permeate statistics in that additional assumptions increase both risks and rewards. Here are a few examples, with increasing risks and rewards.

Significance tests
Significance tests require a valid statistical model under the working (e.g., null) hypothesis (distribution, sampling plan, . . .), and some notion of distance of observed data from the null
so that ‘more extreme’ can be activated. The reward a P-value, nothing else; no estimates, confidence intervals, no posterior distributions, no . . . .

**Augment with a statistical model (a likelihood)**
Augmentation with a likelihood for all possible parameter values (at least for the observed data) buys the analyst estimates, confidence intervals, likelihood surfaces, likelihood ratios (aka, Bayes factors under a flat prior), . . . . However, model validity is more challenging than for significance test in that you need a likelihood for all parameters, not just for the null hypothesis.

**Augment with a prior distribution**
Now, you get the benefits of full probability modeling, the ability to make inferences for complex models and goals, freedom from analytic approximations (via MCMC, etc.). However, validity of the prior adds complexity and some contention, especially in clinical or public policy contexts.

7 **Computation Versus Contemplation**
I conjecture that reliance on P-values is explained in part by the laudable attempts for statisticians and others to make our field broadly accessible by focusing on computations rather than concepts. Surely, knowing how to compute a test, a confidence interval, a procedure more generally, is necessary (at least you need to know what ‘button’ to push), the most challenging aspects of statistics are the ‘whys,’ not the ‘whats’ and ‘hows.’ Understanding the ‘whys’ and how to use statistical results to inform science and policy are challenging and complex, but until we embrace these complexities, statistics will be viewed as a set of techniques rather than a discipline.

We need to make clear that computations are a means to a statistical end, by no means the end goal. Without question, the distinction between statistical means (pun intended) and ends is quite blurry, but for statistical goals simulation, MCMC, etc. are the means not the ends. The situation has analogues in many other fields. In music, one learns to read music and play the scales so you can then create and interpret. In soccer (football in most of the world), you must master the basic skills so you can rise above them with a creative deke and pass. In sailing, you must learn the basics, but then move on to the art of sailing and, in racing, optimization and tactics.

We shouldn’t hide the complexities, but also shouldn’t use them to exclude. Indeed, many excellent statistical ideas come from non-statisticians. We need to invite/encourage joint ownership of statistical issues; definitely avoid communicating the equivalent of, “Only historians are allowed to reminisce.”

8 **Sometimes Probability Isn’t Needed**
In the early 1970s, while I wasn’t involved in the early stages of a gender-related salary dispute at an university, I was asked my opinion by the female faculty near the end of the process. All parties, myself included, agreed with the statistical modeling, but the administration argued that gender effect wasn’t statistically significant (at 0.05). I stated

---

1 ‘More extreme’ may be motivated by a model-based alternative.
that if the goal was to indict the administration for malfeasance and predict that the situation would persist, then statistical significance was a relevant aspect. However, if the goal were to redress salary discrepancies without assigning blame, then the data analysis without any inferential decoration was the way to go. All parties agreed with the no-indictment approach, and salary adjustments were made.

9 Academic Culture & Organizational Context

Work environment and culture have notable effects on how we think and what we do. Two examples follow, but first a heads-up: the effects aren’t one-directional, because individuals are attracted to a culture/environment that aligns with their interests, skills and personality. So, the effects are a combination of selection and those associated with being in the environment; causal analysis in the workplace!

Theory and Applications

Though the distinction is increasingly fuzzy, it is still the case that individuals and groups interested primarily in statistical theory and methods have a culture different from those primarily focused on applications. The theory-focused have primary allegiance to the discipline; the application-focused have some loyalty to the discipline, but at least equal allegiance to application-specific science and policy. Relative to the applications-focused, the theory-focused more frequently honor disciplinary leaders, for example celebrating their notable birthdays and retirements through conferences and publications. In contrast, while not neglecting statistical leaders, the applications-focused also honor science and policy leaders.

Many groups, for example those in Biostatistics, occupy the middle ground with complementary allegiances. The prevalence of the middle ground is increasing, in my opinion good news. Many, possibly most, of the important statistical innovations are motivated by an application, and it has been the locus of my most satisfying professional engagements. While it is good news that the middle ground is expanding, meaningful statistical research and application also require contributions at the extremes: fundamental theory and fundamental application.

Statistics vis-à-vis Biostatistics; Arts & Science vis-à-vis Public Health

Simply stated, courses are the “currency” of Arts & Science (A&S) departments, whereas currency is the “currency” in schools of public health (SPH). Generally, in A&S there is institutional funding per course taught and some additional funds for advising and administration. Tuition and other income covering expenses for a 9-month period; research funding covers the remainder. In contrast, in SPH there is some funding for teaching, advising and administration, but most funding comes from extramural grants and contracts in a more business model. Properly administered, this setup empowers the public health mission, but success requires building in sufficient venture capital to mount an initial response to emerging issues (e.g., COVID) without relying on external funds. As for the theory/applications comparison, the distinction between the two contexts has blurred.

10 Academe, Industry and Government

Academe is losing some of its competitive advantages relative to industry, and to a lesser degree, to government. For example, it is increasingly difficult to get grants and teaching
loads are increasing in most institutions, all in the context of uncertainty of promotion and tenure. Increased bureaucratic requirements and a growing corporate culture move academic life towards the industry model. Creativity and breakthroughs in research and education depend on some degree of unruliness, and care is needed to preserve an empowering culture.

11 Perspectives On The Field and Profession of Statistics

My education, professional activities and placements over the past 55+ years have given me perspective on the technology and sociology of our field. Regarding technology, I’m a 20th century statistician, trying to keep up with the 21st century’s amazing creativity. Regarding sociology, I’ve had multiple ‘.edu’ one ‘.org,’ and two ‘.gov’ email addresses; would have had a ‘.com,’ if the internet had existed in the late 1960s.

Unifying elements and commonalities (some, possibly idealized)

As a discipline we are united by the ability, indeed the necessity, to think stochastically. We are comfortable dealing with uncertainty and with limits to what we know. Indeed, we consider knowing a probability distribution a full-knowledge state. In this stochastic environment, we develop and implement designs and analyses, delineate their properties. We aggressively identify fragilities and sensitivities, and develop procedures to address them. We provide advice on when and when not to use an approach.

We consider goal-identification a prerequisite to choosing a design and analysis, respect and highlight the importance of the sampling plan (even if it’s not known or knowable). By necessity, we engage in counterfactuals, and speak in the subjunctive mood.

Heterogeneities

Harmony is by no means universal amongst statisticians. There is considerable variation in strategic approaches, in philosophy, in what we think is most important. Data science, machine learning, models/algorithms, Bayes/frequentist, design-based/model-based, all generate considerable heat, and, thankfully, some light.

We have differing views on the role of statistics and statisticians; consultant, collaborator, (co)leader; communicator of ‘the facts’ (itself a vague concept) versus (co)interpreter of the information.

Challenges

The world approaches datafication of everything, and statisticians are no longer the only game in town. However, we do have some competitive advantages that with initiative will serve statistics and society well. Without question, no whining; amplify our competitive advantages, educate the next generation, carry on with our 21st century (bio)statistical business.

Statisticians in the stands and on the playing field

Our standards may be too high in some situations, especially when we are commentators and not collaborators, when we are risk-free rather than taking on some of the risk of ‘doing’ rather than ‘knowing.’ We do need to create, advocate and propagate state of the art statistical designs and methods; we need to promote respect and synergy between methods development and applications; maintain high standards. However, we also need to support
our discipline and our colleagues; not let the perfect drive out the very good in reviewing grants, in evaluating a research or educational portfolio, in advising on a project.

*We need to lead by example*

We must be scientifically and socially responsible, and not shy. The respect conferred by others to Statistics and Statisticians will be no greater than the respect we convey and confer.