

Statistical Reasoning 101

Ryan Martin¹
North Carolina State University
Researchers.One

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¹www4.stat.ncsu.edu/~rmartin

- Statistics is hard, for various reasons.
- One is that we never know if we're right.
- So we're guided by *statistical principles*.
- Principles for an effective statistical analysis:²
 - data must be relevant
 - model must be sound
 - inference must be valid
- My focus here is mostly on the third principle.

²Crane & M. (2018), <https://researchers.one/articles/18.08.00011>

- Setup
- What is validity? Why is it important?
- Simple comparative example
 - Bayes and probability
 - Fisher and p-value/plausibility
- General comments beyond the example
 - Bayes vs non-Bayes?
 - resolving some confusion about them
- Conclusions

- Data Y .
- Some unknown θ of interest.
- Connect Y and θ with a model \mathcal{P} :
 - classical: $\mathcal{P} = \{Y \sim \mathbb{P}_\theta : \theta \in \Theta\}$
 - Bayesian: $\mathcal{P} = \{(Y, \theta) \sim \mathbb{P} = \text{"}\mathbb{P}_\theta \times \pi\text{"}\}$
- Goal is to use observed $Y = y$ to make inference about θ .
- For concreteness, consider testing³ a hypothesis H about θ .
- Methods to use:
 - Bayes and (conditional) probability
 - Fisher and p-value/plausibility
 -

³These considerations are general, even beyond inference to prediction:
Cella and M. (2020), <https://researchers.one/articles/20.01.00010>

- Statistician can choose any test, $\text{TEST}_H(Y)$.
- Why trust $\text{TEST}_H(Y)$ in a given application?
- We can't evaluate based on it being right/wrong.
- Effectiveness hinges on the method being reliable, or *valid*.
- Very, very roughly: the test is valid, relative to \mathcal{P} , if

$$\max_{\mathbb{P} \in \mathcal{P}} \mathbb{P}\{\text{TEST}_H(Y) \text{ is wrong}\} \leq \text{small.}$$

General observation.

Without validity, there's no reason to trust the conclusions drawn based on the method applied to the given data.

- Clearly, validity depends on both the method and model.
- That is:
 - one is free to choose any method, but...
 - whether the chosen method is valid depends on the model, i.e., on what one is willing to assume.
- So the goal is to establish validity under a *justifiable* model.
- Obviously, weaker assumptions are easier to justify...

- Standard cancer screening example:

$Y = 1\{\text{patient tests positive}\}$ (observable)

$\theta = 1\{\text{patient has cancer}\}$ (unknown)

- Scanning procedure is such that

$$Y \sim \mathbb{P}_\theta = \begin{cases} \text{Ber}(0.03) & \text{if } \theta = 0 \\ \text{Ber}(0.99) & \text{if } \theta = 1. \end{cases}$$

- Model is $\mathcal{P} = \{\mathbb{P}_\theta : \theta = 0, 1\}$.
- *If a patient tests positive, i.e., $y = 1$, do they have cancer?*
- Goal is to test the hypothesis $H : \theta = 0$.

- Given $y = 1$, a p-value/plausibility of $H : \theta = 0$,

$$\bar{\pi}_y(H) = \mathbb{P}_0(Y = 1) = 0.03.$$

- The “doesn’t have cancer” hypothesis is *implausible*.
- Fact: relative to this model, the following test is valid:

$$\text{TEST}_H(Y) = \text{“reject } H \text{ if } \bar{\pi}_Y(H) \text{ is small”}.$$

- However, the *implausible* conclusion is rather weak:
 - certainly doesn’t prove they have cancer
 - doesn’t even imply they’re “likely” to have cancer
 - only says that $y = 1$ implies having cancer is plausible

- Bayesian solution is to use conditional probability.
- This requires an extra model assumption:
 - patient is randomly chosen from a population
 - in that population, 99% don't have cancer
- Bayes model: $\mathbb{P} = “\theta \sim \text{Ber}(0.01) \text{ and } Y \mid \theta \sim \mathbb{P}_\theta”$.
- If $y = 1$, then Bayes's theorem says

$$\pi_y(H) = \mathbb{P}(\theta = 0 \mid Y = 1) = 0.75.$$

- Fact: relative to the Bayes model, the following is valid:

$$\text{TEST}_Y(H) = “\text{reject } H \text{ if } \pi_Y(H) \text{ is small}”$$

- Probability claim is stronger than plausibility.

- Two analyses come up with different answers:
 - non-Bayesian analysis implies H is *implausible*
 - Bayesian analysis implies H is *probable*
- More specifically:
 - former commits to the data: $Y = 1 \rightarrow$ cancer plausible
 - latter ignores the data: $Y = 0, 1 \rightarrow$ cancer improbable
- Which one is better? It depends...
 - If the stronger assumptions of the Bayes model are justified, then the Bayes method is valid—and stronger;
 - otherwise, the Bayes method is not valid so the non-Bayes method is preferred despite the weaker conclusions.
- Not a philosophical choice, it's about being justifiably valid.

Beyond this example

- The considerations in the above example are typical.
- That is, one is faced with the question: Bayes or not?
- The cancer screening example is a special one:
 - real/reliable prior information is available
 - so Bayes model is justifiable, and validity follows
- But perhaps most scientific applications have no genuine prior information available.
- Brad Efron: *Scientists want to work on new problems.*

- A common criticism of p-values is that they don't measure **the** probability of the hypothesis.
- This complaint assumes “probability of H ” is real.
- Bruno de Finetti: *Probability does not exist*.
- Therefore: “probability of H ” is only in the statistician's mind
- Is what's in the statistician's mind practically relevant?
 - only if its connection to the real world is established
 - that's what validity/reliability aims to do.

- Can't fake it with default/non-informative priors...
- That is, one can't both have and eat cake:
 - stronger probabilistic conclusions aren't free
 - price is making stronger assumptions, harder to justify
- Don Fraser:
 - *Bayes's theorem does not create real probabilities from hypothetical probabilities.*
 - *Any serious mathematician would ask how you could use a lemma with one premise missing by making up an ingredient and thinking that the lemma's conclusions were still available.*

- Fact: Under the Bayes model for Y , based on prior π ,

$$\mathbb{E}\{\pi_Y(H)\} = \pi(H)$$

- Therefore, under the Bayes model, validity follows because the posterior is near the real prior.
- Alternatively, under the non-Bayes model, \mathbb{P}_{θ^*} ,
 - the posterior can learn (e.g., consistency)
 - but generally isn't valid, i.e., a risk of *false confidence*⁴⁵

⁴Balch, M., and Ferson (2019), arXiv:1706.08565

⁵M. (2019). <https://researchers.one/articles/19.02.00001>

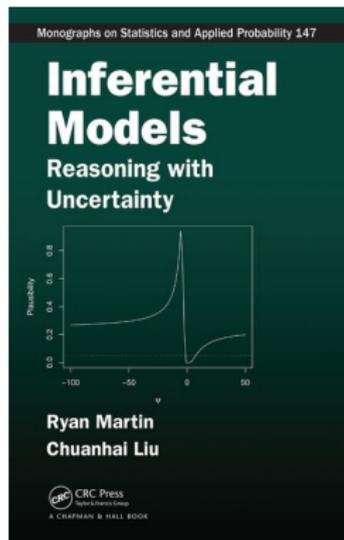
- Fisher/p-values/significance are misunderstood.
- A small p-value...
 - *does not imply a scientific discovery*
 - suggests a notable finding, worthy of further investigation.
- The “plausibility” interpretation makes this clear:
 - small p-value means H is implausible
 - not- H being plausible is far from scientific proof of not- H .
- Fisher was clear that p-values are not probabilities, but there was no alternative to probability at that time...

- Plausibility theory isn't something I made up:
 - mathematically rigorous framework for UQ
 - part of *imprecise probability*
- Plausibility provides a convenient way to interpret p-values and confidence intervals.
- I teach this to students in my classes:

"...your discussion of plausibility in ST503 made it easier for me to explain what a p-value is at my job interview. Thank you for the new perspective on the subject!"
- Strong validity results, no prior necessary.
- Conclusions based on plausibility are weaker
 - but p-values do exactly what they advertise to do
 - do data suggest that not- H is worth investigating further?

- Take-away messages:
 - validity is crucial to statistical reasoning
 - any method can be valid
 - valid or not depends on assumptions one is willing to make
- Bayes and probability
 - strong probabilistic conclusions
 - no validity guarantees without strong assumptions
- Fisher and p-values/plausibility
 - validity under weaker assumptions
 - weaker plausibility-based conclusions
- Remember: statistics is hard.
- So we have to calibrate our expectations:
 - nobody can say that one approach is always right
 - validity under justifiable assumptions can't be wrong

- Some recent work about these ideas:
 - <https://researchers.one/articles/19.02.00001>
 - <https://researchers.one/articles/21.01.00002>
- How I got started thinking about these things:



- Questions? Email me at rgmarti3@ncsu.edu.
- Papers, etc. at www4.stat.ncsu.edu/~rmartin/
- Check out *Researchers.One*:
 - <https://researchers.one>
 - www.twitter.com/ResearchersOne

Thanks for your attention!