

Possibility measures for valid statistical inference based on censored data¹²

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¹Joint work with my student, Ms. Joyce Cahoon

²<http://www.isipta2019.ugent.be/contributions/cahoon19.pdf>

- Typical statistical inference problem: data is *fully observed*.
- However, in realistic situations, data may be *censored*.
- For example, in clinical trials:
 - patient may not show up to a post-treatment appointment
 - only a lower bound on patient's time to remission is available.
- This censoring element complicates a statistical analysis.
- In particular, *exact* inference is a challenge when nothing about the censoring mechanism is known.

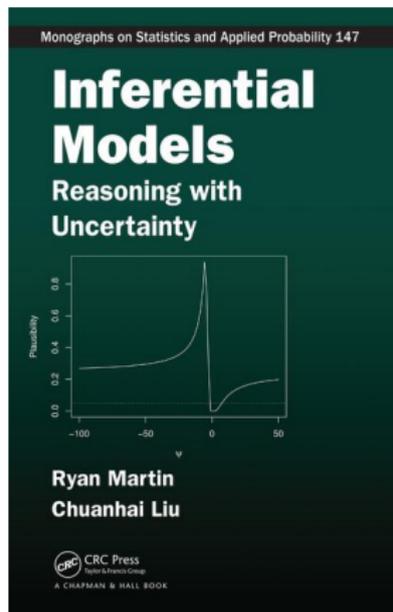
- Yesterday I described my IM construction, i.e.,
 - *association* links data, parameter, and auxiliary variables
 - user's random set predicts unobserved auxiliary variables
 - push random set through the association and compute the corresponding belief/plausibility on parameter space.
- Leads to *provably valid* inference.³
- Approach is general, but hard to write down an association without knowing the censoring mechanism.
- However:
 - can write a likelihood without such knowledge
 - then use likelihood to define a *generalized association*⁴⁵

³M. "False confidence, non-additive beliefs, and valid statistical inference," from my *BELIEF/SMPS 2018* lecture (arXiv:1607.05051 and *IJAR*)

⁴M. (arXiv:1203.6665, 1511.06733)

⁵Also related to M. (arXiv:1606.02352)

Wanna know more? What if it's still on sale, 20% off?



- Without censoring, we'd get iid samples (T_1, \dots, T_n) from a distribution depending on a parameter θ .
- Data consists of times/lower bounds and censoring indicators:

$$Y_i = (T_i \wedge C_i, 1_{T_i < C_i}), \quad i = 1, \dots, n.$$

- Likelihood doesn't depend on the censoring mechanism.
- Neither does the *relative likelihood*

$$(\vartheta, y) \mapsto R_{y, \vartheta} = L_y(\vartheta) / L_y(\hat{\theta}_y).$$

- But its *distribution* does!

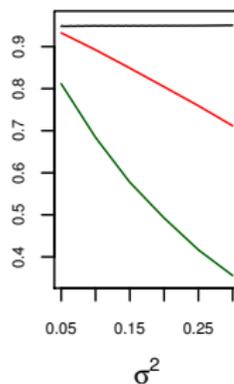
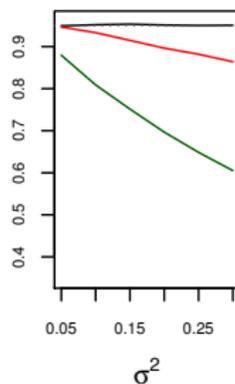
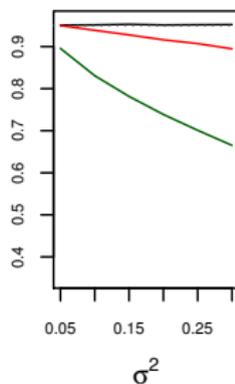
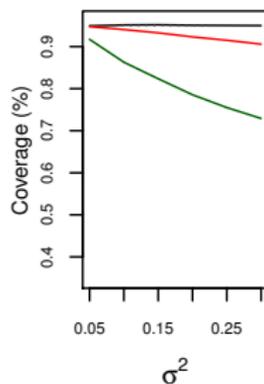
- Generalized IM is based on the distribution of $R_{Y,\theta}$, i.e.,

$$p_Y(\{\vartheta\}) = P_{Y|\vartheta, G}\{R_{Y,\vartheta} \leq R_{y,\vartheta}\}.$$

- Depends on the distribution G of censoring times C , which is generally completely unknown.
- Paper employs a tweak on Kaplan–Meier to estimate, G , the *censoring distribution* for evaluating $p_Y(\cdot)$.
- Numerical results suggest that the generalized IM is valid, or at least approximately so.
- We should be able to prove this formally...

Illustration

- Log-normal model, 95% intervals for $\psi = \exp\{\mu + \frac{1}{2}\sigma^2\}$
- Compare coverage probabilities for
 - generalized IM (black)
 - asymptotic normality of MLE (red)
 - Bayes (green)
- Varying σ^2 and $n = 15, 20, 25, 50$.



- Peer review + publish-or-perish is detrimental:
 - my livelihood depends on what reviewers think of my work
 - so I have to work on things reviewers will like
- Feedback from peers is important, but needs to be separate from how (junior) researchers are evaluated.
- H. Crane and I have created such a system:

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Thanks!

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