Who's gotta p?

Tripping up statistics in the garden of forking paths

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What's a *p*-value?

Let's get the hard part done up front

Definition

The p-value is the probability under the null hypothesis of a result at least as extreme as the observed result.

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A whole other can of worms: NHST

- the p-value is useless as soon as we reject the null hypothesis
- the p-value is uniformly distributed under the null hypothesis (Murdoch, Tsai, and Adcock 2008)

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For better or worse, there are a lot of p-values out there and we have to deal with them (cf. Gelman 2013).

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So what do we have to watch out for?

Assume makes an ass out of u and me

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- *p*-values deeply intertwined with error estimates
- *p*-values now effectively garbage

How are *p*-values actually computed?

0. Under the null hypothesis, test statistics have a known distribution
   - either analytic: t, F, χ^2, etc.
   - or empirically determined: bootstrapping and other resampling methods
1. Compute the test statistic
   - t-test: mean divided by standard error
   - F-test: between vs. within group variance
   - degrees of freedom compensate for small samples
2. Compare it to the reference distribution
   - Old way: use a table and find out what your p-value is less than
   - New way: have the computer figure out a precise value

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- the error term is wrong
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BAD NEWS BEARS

- We no longer know the proper reference distribution.
- And so we know longer know what null hypothesis (whether or not meaningful!) the p-value corresponds to.

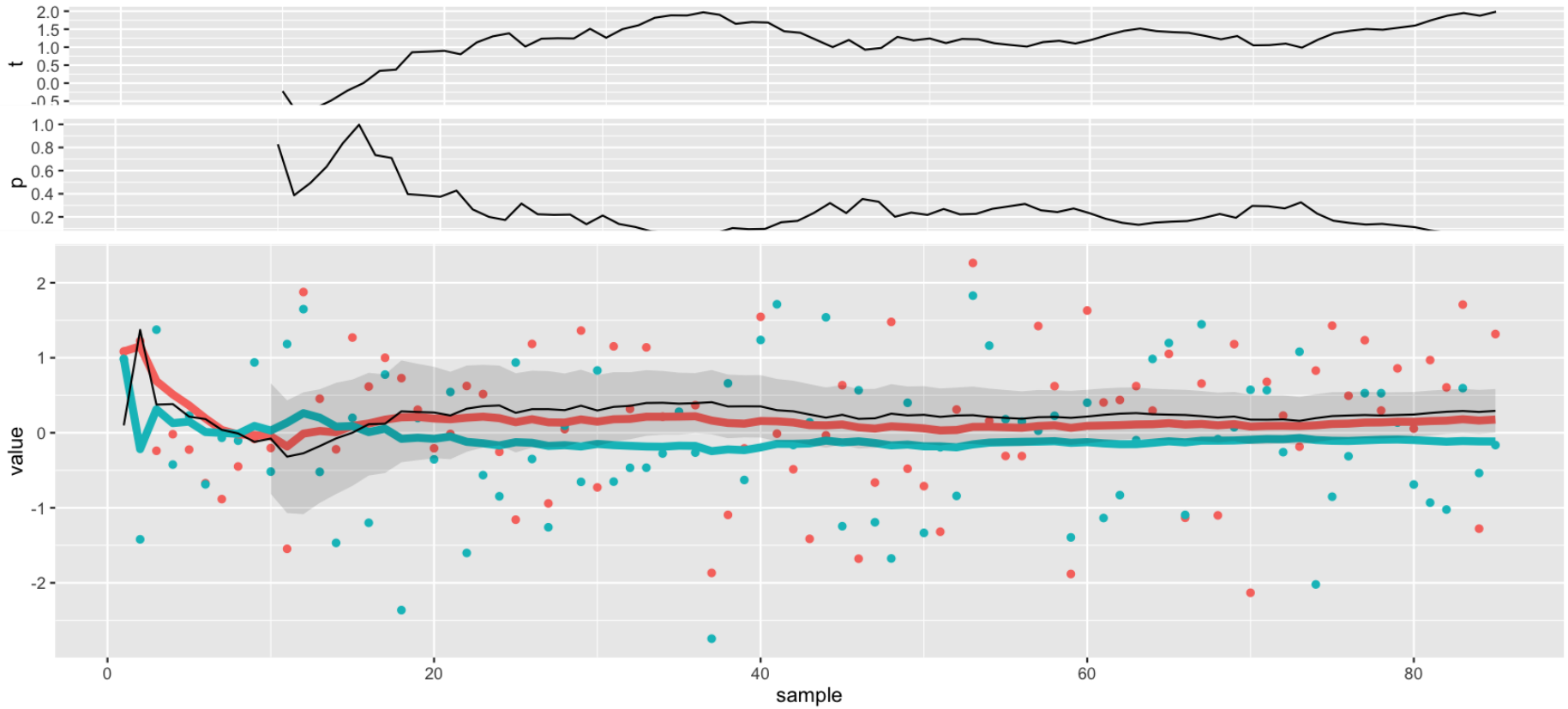
What I really want to say is

Don't use t / F / traditional ANOVA for accuracy data (Jaeger 2008; Allefeld, Görgen, and Haynes 2016).

Don't use inferential statistics for comparing non-randomly sampled, closed populations such as stimuli or experimental groups (Sassenhagen and Alday 2016).

Optional Stopping

We're not so different



try it yourself at `https://tinyurl.com/optionalstopping`

Optional stopping is a great way to guarantee a significant yet meaningless result

If you're going to play the significance game, play by the rules.

- Set your α-threshold ahead of time
  - no "trending towards significance"
  - no "marginal signficance"
- Determine your stopping rule ahead of time
  - power analysis
  - rules of thumb
  - "until we run out of money"
- But don't base it on peeking at *p*-values
- Only claim the significance you test (the difference between significant and not significant is not itself significant; cf. Gelman and Stern 2006; Nieuwenhuis, Forstmann, and Wagenmakers 2011)

Never forget

The *p*-value is a random variable under the null hypothesis.

- *p*-hacking and "fishing expeditions" will always succeed
- And if you're not careful, you'll find yourself far out at sea

Welcome to the garden of forking paths

Blurring the distinction exploratory and confirmatory makes interpretable *p*-values hard to find

- There is (almost) always a significant result lurking in any given dataset just by chance
  - "researcher degrees of freedom" (Simmons, Nelson, and Simonsohn 2011)
  - "garden of forking paths" (Gelman and Loken 2013)

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And that's what counts.

The End

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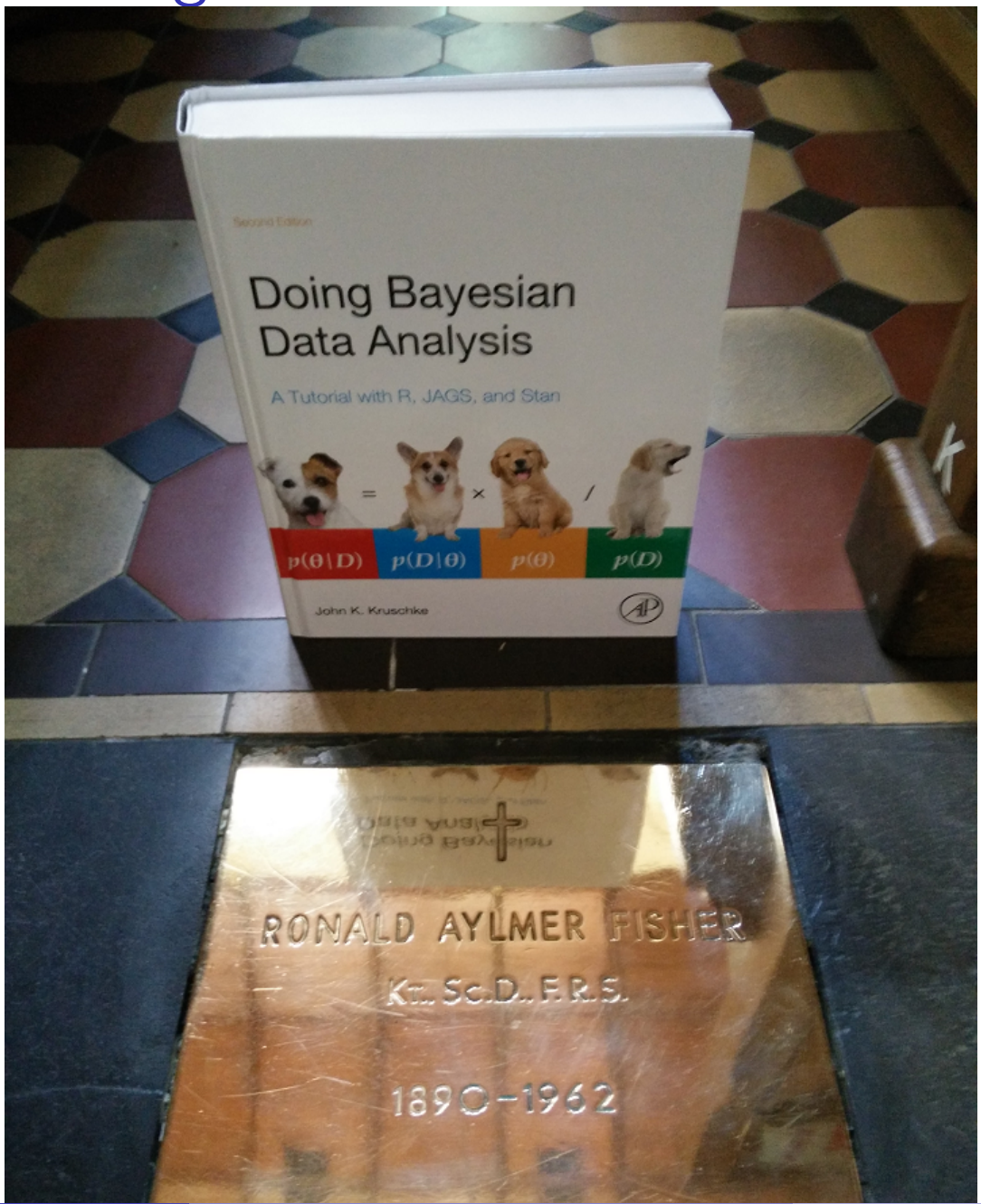

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