Many rules of statistics are wrong

There are two kinds of people who violate the rules of statistical inference: people who don't know them and people who don't agree with them. I'm the second kind.

The rules I hold in particular contempt are:

The interpretation of p-values: Suppose you are testing a hypothesis, H, so you've defined a null hypothesis, H0, and computed a p-value, which is the likelihood of an observed effect under H0.

According to the conventional wisdom of statistics, if the p-value is small, you are allowed to reject the null hypothesis and declare that the observed effect is "statistically significant". But you are not allowed to say anything about H, not even that it is more likely in light of the data.

I disagree. If we were really not allowed to say anything about H, significance testing would be completely useless, but in fact it is only mostly useless. As I explained in this previous article, a small p-value indicates that the observed data are unlikely under the null hypothesis. Assuming that they are more likely under H (which is almost always the case), you can conclude that the data are evidence in favor of H and against H0. Or, equivalently, that the probability of H, after seeing the data, is higher than it was before. And it is reasonable to conclude that the apparent effect is probably not due to random sampling, but might have explanations other than H.

Correlation does not imply causation: If this slogan is meant as a reminder that correlation does not *always* imply causation, that's fine. But based on responses to some of my previous work, many people take it to mean that correlation provides no evidence in favor of causation, ever.

I disagree. As I explained in this previous article, correlation between A and B is evidence of some causal relationship between A and B, because you are more likely to observe correlation if there is a causal relationship than if there isn't. The problem with using correlation for to infer causation is that it does not distinguish among three possible relationships: A might cause B, B might cause A, or any number of other factors, C, might cause both A and B.

So if you want to show that A causes B, you have to supplement correlation with other arguments that distinguish among possible relationships. Nevertheless, correlation is evidence of causation.

Regression provides no evidence of causation: This rule is similar to the previous one, but generalized to include regression analysis. I posed this question the reddit stats forum: the consensus view among the people who responded is that regression doesn't say anything about causation, ever. (More about that in this previous article.)

I disagree. It think regression provides evidence in favor of causation for the same reason correlation does, but in addition, it can distinguish among different explanations for correlation. Specifically, if you think that a third factor, C, might cause both A and B, you can try adding a variable that measures C as an independent variable. If the apparent relationship between A and B is substantially weaker after the addition of C, or if it changes sign, that's evidence that C is a confounding variable.

Conversely, if you add control variables that measure all the plausible confounders you can think of, and the apparent relationship between A and B survives each challenge substantially unscathed, that outcome should increase your confidence that either A causes B or B causes A, and decrease your confidence that confounding factors explain the relationship.

By providing evidence against confounding factors, regression provides evidence in favor of causation, but it is not clear whether it can distinguish between "A causes B" and "B causes A". The received wisdom of statistics says no, of course, but at this point I hope you understand why I am not inclined to accept it.

In this previous article, I explore the possibility that running regressions in both directions might help. At this point, I think there is an argument to be made, but I am not sure. It might turn out to be hogwash. But along the way, I had a chance to explore another bit of conventional wisdom...

Methods for causal inference, like matching estimators, have a special ability to infer causality: In this previous article, I explored a propensity score matching estimator, which is one of the methods some people think have special ability to provide evidence for causation. In response to my previous work, several people suggested that I try these methods instead of regression.

Causal inference, and the counterfactual framework it is based on, is interesting stuff, and I look forward to learning more about it. And matching estimators may well squeeze stronger evidence from the same data, compared to regression. But so far I am not convinced that they have any special power to provide evidence for causation.

Matching estimators and regression are based on many of the same assumptions and vulnerable to some of the same objections. I believe (tentatively for now) that if either of them can provide evidence for causation, both can.

Quoting rules is not an argument

As these examples show, many of the rules of statistics are oversimplified, misleading, or wrong. That's why, in many of my explorations, I do things experts say you are not supposed to do. Sometimes I'm right and the rule is wrong, and I write about it here. Sometimes I'm wrong and the rule is right; in that case I learn something and I try to explain it here. In the worst case, I waste time rediscovering something everyone already "knew".

If you think I am doing something wrong, I'd be interested to hear why. Since my goal is to test whether the rules are valid, repeating them is not likely to persuade me. But if you explain why you think the rules are right, I am happy to listen.