I can see clearly now: reinterpreting statistical significance

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Abstract

1. Null hypothesis significance testing (NHST) remains popular despite decades of concern about misuse and misinterpretation. There are many recent suggestions for mitigating problems arising from NHST, including calls for abandoning NHST in favor of Bayesian or information-theoretic approaches. We believe that NHST will continue to be widely used, and can be most usefully interpreted as a guide to whether a certain effect can be seen *clearly* in a particular context (e.g. whether we can clearly see that a correlation or between-group difference is positive or negative).

2. We believe that much misinterpretation of NHST is due to language: significance testing has little to do with other meanings of the word ``significance''. We therefore suggest that

researchers describe the conclusions of null-hypothesis tests in terms of statistical ``clarity'' rather than ``significance''. We illustrate our point by rewriting common misinterpretations of the meaning of statistical tests found in the literature using the language of ``clarity''.

3. The meaning of statistical tests become easier to interpret and explain when viewed through the lens of ``statistical clarity''.

4. Our suggestion is mild, but practical: this simple semantic change could enhance clarity in statistical communication.

Key Words

Statistical philosophy; Statistical clarity; Hypothesis testing; p-value

Introduction

Statisticians and scientists have bemoaned the shortcomings of null hypothesis significance testing (NHST) for nearly a century (Cohen, 1994). Books and articles proposing the de-emphasis or abandonment of the p-value have been cited thousands of times (Cohen, 1994, Goodman, 1999, Wilkinson, 1999, Ziliak and McCloskey, 2008, Wasserstein and Lazar, 2016). These works plead for a focus on effect sizes and confidence intervals, and point out that null effects that truly have zero magnitude are unrealistic or impossible in most fields outside of the hard physical sciences (Meehl, 1990, Tukey, 1991, Cohen, 1994). Yet, p-values without confidence intervals (or even effect sizes) and references to null effects still pervade the scientific literature at all levels up to and including articles in high-impact journals.

In a meta-analysis of 356 studies Bernardi et al. (2017) found that 72% of studies contained an ambiguous use of the term ``significant'', 49% interpreted non-significant effects as zero effects, and 44% failed to report a comprehensible effect size. The misuse and misinterpretation of NHST is so frequent that there have been recent calls for drastically reducing (Szucs and Ioannidis, 2017) or abandoning (McShane et al., 2017) its use. Other prescriptions have included the complete abandonment of frequentist statistics (The, 2011), or the use of a stricter significance threshold (e.g. $p < 0.005$: Benjamin et al. (2018)); however, the former seems impractical, while the latter is unlikely to reduce the misuse and misinterpretation of p-values, or the publication bias imposed by any p-value threshold (Ridley et al., 2007).

We believe that NHST can be useful as a simple criterion for evaluating whether a data signal is clear (see Abelson (1997) for arguments for NHST), and that pervasive misuse can be reduced through a linguistic change: using the language of statistical ``clarity'' instead of statistical ``significance''.

The null hypothesis is false

In most biological studies, the null hypothesis is known *a priori* to be false. Even in cases where the null hypothesis is sensible (e.g., particle physics, Staley (2017)), NHST does not provide evidence that a difference is exactly zero. This being the case, it is worth asking how NHST has survived ``if it is as idiotic as ...long believed'' Ziliak and McCloskey (2008, cited in Krämer (2011)).

Part of the answer is that asking whether we can reject the null hypothesis is a proxy for asking whether we see clearly *how* our data differs from it. For example, in a t-test, we are nominally asking whether we can see a *difference* between two means, but the scientific question is whether we are confident which of the two means is *larger*; similarly, tests for whether two values are correlated are a proxy for whether we are confident about the *sign* of the correlation coefficient (Robinson and Wainer, 2001). In other cases (e.g., a one-way ANOVA), it may not be simple to describe the difference we see, but NHST is still a reasonable, widely accepted way to evaluate whether an effect has been seen clearly.

The ``idiocy'', if any, comes in the interpretive step. A statistical fact (``we have *seen* a difference between the groups'', which should immediately prompt the question ``what have you learned *about* that difference?'') is interpreted as a scientific fact (``there *is* a 'significant' difference between the groups''), which is often seen as an end in itself: ``we showed that the groups differ''.

The p-value is a property of the study

Researchers often write sentences like, ``X et al. showed that there is no significant effect of Y on Z'' with the implication that this effect can now be assumed to be absent (or unimportant). In fact, the sentence is erroneous even before we get to the implication: significance tests provide information about *a data set* -- that is, about a study, not about the study system (Hoenig and Heisey, 2001). A very small effect can lead to $p < 0.05$ when data is abundant (or noise is small); or a very large one can lead to $p > 0.05$ when the sample is small or noisy.

The statement ``X et al. showed that Y has a statistically significant effect on Z'' is similarly misleading. Frequentist statistics effectively assume that the effect is present (or at least admit that it can't be disproven). The question is whether it is seen in a particular data set. The statement ``X et al. were able to see the effect of Y on Z'' is not only more accurate, but it appropriately implies that something is missing: *What* effect did they see?

Statistical clarity

The language of ``statistical clarity'' could help researchers escape various logical traps while interpreting the results of NHST, allowing for the continued use of NHST as a simple, robust method of evaluating whether a data signal is clear. The use of ``significance'' to describe the results of hypothesis tests is deeply, and sometimes subtly, misleading, because it is at odds with other meanings of the word: the p-value is not an accurate gauge of whether a result is large in magnitude, biologically important, or relevant. ``Clarity,'' on the other hand, is an apt term for what NHST actually evaluates. Jones and Tukey (2000) and Robinson and Wainer (2001) suggest that researchers should report $p > 0.05$ using language such as ``the direction of the differences among the treatments was undetermined''. This is a step in the right direction. Replacing ``significance'' with ``clarity'' takes this idea further, and has the potential to improve statistical communication.

For example, the sentence ``X et al. showed that the effect of Y on Z is statistically unclear'', is noticeably awkward. It seems less like a statement about the study system, and suggests the more straightforward ``did not find a statistically clear effect.'' Similarly, ``We did not find a clear difference in response between the control and sham groups'' is both more colloquial and harder to transform into a misleading statement than ``We did not find a significant difference ...''. Bernardi et al. (2017) complained that ``...sociological and social significance are sacrificed on the altar of statistical significance''. Describing statistical tests in terms of clarity would allow ``significant'' to reclaim its common English definition and reduce conflation between statistical results and substantive significance.

Descriptions of statistical results using the language of clarity should begin with reference to the effect. For example, ``The difference between the control and treatment group was not statistically clear.'' Table 1 shows published examples of statements that misinterpret p-values in three different ways and demonstrates how to rephrase them in the language of clarity. We have attempted to do this thoughtfully, and therefore the language on the right differs from the language on the left by more than a simple substitution of ``significance'' to ``clarity''. We do not claim that executing a search-and-replace operation will automatically improve statistical practice; rather, we think it can prompt rethinking and reinterpretation. We also hope that, by drawing attention to effects, the language of clarity will encourage more reporting of effect sizes and confidence intervals.

Caveats

If widely adopted, ``statistical clarity'' could eventually come to be seen as an end in itself, the way that ``significance'' is now. We hope this can be avoided, but in any event we feel that the unthinking use of ``clarity'' would be (marginally) better than the current unthinking use of ``significance''. If there is a transition it will also be important to communicate clearly when ``clarity'' is being used in a technical sense; we have found that in particular that understanding is improved by explicitly connecting clarity statements to statements about P values.

Conclusions

We believe that NHST is useful as a simple, robust way to ask whether an effect can be seen clearly in a particular data set (Robinson and Wainer, 2001), and that careful, clarity-based language can reduce misinterpretation and miscommunication.

We agree with Cohen (1994) and others (Goodman, 1999, Ziliak and McCloskey, 2008, Wasserstein and Lazar, 2016), that scientific communication and understanding will be improved by a shift away from p-values to effect sizes and confidence intervals. The use of ''statistical clarity'' should reinforce the need for confidence intervals and effect sizes by making bald statements about p-values more obviously insufficient. The statement ''The difference between our control and treatment groups was not statistically clear $(p = 0.30)$'' is noticeably incomplete; an effect size and confidence interval are required to complete the story.

Improving language will not by itself solve all of the known problems with current statistical practice. We echo previous statements in favor of ''neglected factors'' (prior and related evidence, plausibility of mechanisms, study design and data quality, real world benefits, novelty, etc.) (McShane et al., 2017) and reporting of *a priori* analysis of statistical power to avoid emphasis on implausibly large effects given low statistical power (the ''winner's curse'' Gelman and Carlin, 2014, Szucs and Ioannidis, 2017, Bernardi et al., 2017). Additionally, we support the writing of statistical journals that chronicle all of the steps in the analytical process (Kass et al., 2016), and clearly delineating the boundary between inferences based on *a priori* hypotheses and discoveries from *post hoc* data exploration. These procedures help to avoid the ''garden of forking paths'' by which cryptic multiple testing amplifies noise to make it look like a signal of biologically interesting processes (Gelman and Loken, 2014)).

Whether or not our recommendations are broadly adopted by authors, reviewers, and editors, they can be useful for individual researchers who want to help themselves think clearly about NHST results. We have found that rephrasing NHST statements that we encounter (in the literature, or in seminar presentations) in terms of clarity has already helped us with both interpretation and communication.

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Author contributions

JD conceived the main idea of the paper. All authors helped to develop it. JD and MPK outlined the MS. MPK led the literature review and wrote the first draft. All authors wrote and revised later drafts.

Data accessibility

No data was used in the production of this manuscript.

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Language from published articles	**Rewritten using “clarity”**
Accepting the null hypothesis ($p > 0.05$ no effect)	
Toxins accumulate after acute exposure but have no effect on behaviour	Toxins accumulate after acute exposure but their effects on behaviour are statistically unclear
There was no effect of elevated carbon dioxide on reproductive behaviors	The effect of elevated carbon dioxide on reproductive behaviors was statistically unclear
The finding that species richness showed no significant relationship with the area of available habitat is surprising because richness is usually strongly influenced by landscape context	Although species richness is usually strongly influenced by landscape context, we were unable to find a statistically clear relationship in this study
Inferring weak effects from large p-values (Wasserstein and Lazar, 2016)	
. . . differences between treatment and control groups were nonsignificant, with P values of at least 0.3, and most in the range $0.7 \leq P \leq 0.9$.	. . . differences between treatment and control groups were not statistically clear (all $P > 0.05$) [*since smallness is no longer implied the authors might now think of adding confidence intervals.*]
The difference between “clear” and “not clear” is not clear (Gelman and Stern, 2006)	
This correlation was significant in males ($\rho = 0.35$, P <0.05) but not females ($\rho = 0.35$, NS). . . . [*The authors later write as though they have demonstrated a difference between males and females*]	Although males and females show the same correlation coefficient ($\rho = 0.35$), the sign of the coefficient is statistically clear only in males . . . [*Again, this phrasing may suggest to the authors that confidence intervals are called for.*]
. . . risk of low BMD [bone mineral density] remained greater in HCV-coinfected women versus women with HIV alone (adjusted OR 2.99, 95% CI 1.336.74), but no association was found between HCV coinfection and low BMD in men (adjusted OR 1.26, 95% CI 0.752.10). . . . The precise mechanisms for the association between viral hepatitis and low BMD in HIV-infected women but not men remain unclear.	. . . risk of low BMD [bone mineral density] remained greater in HCV-coinfected women versus women with HIV alone (adjusted OR 2.99, 95% CI 1.336.74), but the association between HCV coinfection and low BMD in men was not statistically clear (adjusted OR 1.26, 95% CI 0.752.10). . . . Pursuing biological differences between women and men in the effect of HIV on BMD would be premature given these results.

Table 1: Examples of misleading language in peer-reviewed papers (citations available by request), and revisions using our proposed language of clarity.