

**Douglas Curran-Everett**

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D. Curran-Everett

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## Explorations in statistics: hypothesis tests and $P$ values

Douglas Curran-Everett

Division of Biostatistics and Bioinformatics, National Jewish Health, and Department of Biostatistics and Informatics and Department of Physiology and Biophysics, University of Colorado Denver, Denver, Colorado

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**Curran-Everett D.** Explorations in statistics: hypothesis tests and  $P$  values. *Adv Physiol Educ* 33: 81–86, 2009; doi:10.1152/advan.90218.2008.—Learning about statistics is a lot like learning about science: the learning is more meaningful if you can actively explore. This second installment of *Explorations in Statistics* delves into test statistics and  $P$  values, two concepts fundamental to the test of a scientific null hypothesis. The essence of a test statistic is that it compares what we observe in the experiment to what we expect to see if the null hypothesis is true. The  $P$  value associated with the magnitude of that test statistic answers this question: if the null hypothesis is true, what proportion of possible values of the test statistic are at least as extreme as the one I got? Although statisticians continue to stress the limitations of hypothesis tests, there are two realities we must acknowledge: hypothesis tests are ingrained within science, and the simple test of a null hypothesis can be useful. As a result, it behooves us to explore the notions of hypothesis tests, test statistics, and  $P$  values.

power; R; significance test; software; test statistic

THIS SECOND ARTICLE in *Explorations in Statistics* (see Ref. 8) provides an opportunity to explore test statistics and  $P$  values, two concepts integral to the test of a scientific hypothesis. What is a scientific hypothesis? An idea that can be tested. By tradition, this hypothesis is called the null hypothesis. The adjective null can be misleading: this hypothesis need not be one of no difference. In order to test a null hypothesis, we must first define the hypothesis. Using data from the subsequent experiment, we then compute the value of some test statistic and compare that observed value  $T$  to some critical value  $T^*$  chosen from the distribution of the test statistic that is based on the null hypothesis. If  $T$  is more extreme than  $T^*$ , that is unusual if the null hypothesis is true, and we are entitled—on statistical grounds—to question the null hypothesis.

Hypothesis tests pervade science, but statisticians have long stressed their limitations (1, 2, 5–7, 15–17, 19–24, 26–29, 31, 32, 42, 45, 49, 50). Despite these limitations, there are two practical considerations that have persisted: the simple test of a null hypothesis can be useful (10, 44), and hypothesis tests are ingrained within science. Before we explore the notions of hypothesis tests, test statistics, and  $P$  values, it behooves us to understand why hypothesis tests pervade science.

### A Brief History of Hypothesis Tests

The earliest known hypothesis test was the Trial of the Pyx, a periodic ritual<sup>1</sup> of the Royal Mint (London) that had become established by 1279 (47). Each time the Mint made coins, a

small number of them went into the Pyx, a wooden box. When a Trial was convened, an independent jury of goldsmiths compared these select coins to standards in order to assess whether the coins were within prescribed tolerances for weight and composition. In each Trial of the Pyx, the implicit null and alternative hypotheses,  $H_0$  and  $H_1$ , were

$H_0$ : The coins are within the prescribed tolerances.

$H_1$ : The coins are outside the prescribed tolerances.

By the 1700s, astronomers routinely used hypothesis tests to decide if discrepant celestial measurements should be discarded (18, 46). At issue: precise information about the position of the moon for purposes of navigation (46). To do one of these hypothesis tests, an astronomer compared the discrepant value to the *law of errors*, the distribution of errors about the true lunar position (18).<sup>2</sup> For each questionable measurement, the implicit null and alternative hypotheses were

$H_0$ : The measurement is within the limits of error.

$H_1$ : The measurement is outside the limits of error.

As in the Trial of the Pyx, each astronomical hypothesis test had a binary outcome: the measurement either was or was not within some allowable deviation.

From the 1800s through the early 1900s, when a mathematician or physicist wrote about whether some event could be attributed to chance alone, he wrote about the odds of that event (18, 36, 46). The greater the odds, the more likely the event was due to something other than chance—random variation—alone (Fig. 1). Table 1 lists odds that were sufficient to pique scientific interest between 1837 and 1908.

In his landmark *The Probable Error of a Mean* (48), William Sealy Gosset, a chemist who wrote under the pseudonym Student because he worked for the Guinness brewery (40), outlined a procedure that would evolve into the one-sample  $t$ -test. To illustrate this procedure, Gosset used data from a paper published by Cushny and Peebles (11) in *The Journal of Physiology*:

First let us see what is the probability that [drug A] will on the average give increase of sleep. [Looking up the ratio of the sample mean to the sample standard deviation] in the table for ten experiments we find by interpolating. . . the odds are .887 to .113 that the mean is positive.

That is about 8 to 1 and would correspond to the normal curve to about 1.8 times the probable error. It is then very likely that [drug A] gives an increase of sleep, but would occasion no surprise if the results were reversed by further experiments.

Address for reprint requests and other correspondence: D. Curran-Everett, Div. of Biostatistics and Bioinformatics, M222, National Jewish Health, 1400 Jackson St., Denver, CO 80206 (e-mail: EverettD@NJHealth.org).

<sup>1</sup> In the past, a Trial was announced every 3–4 years. Today, the Trial is convened every year.

<sup>2</sup> The *law of errors* is just a normal distribution, a probability distribution developed independently by De Moivre, Laplace, Legendre, and Gauss (18).

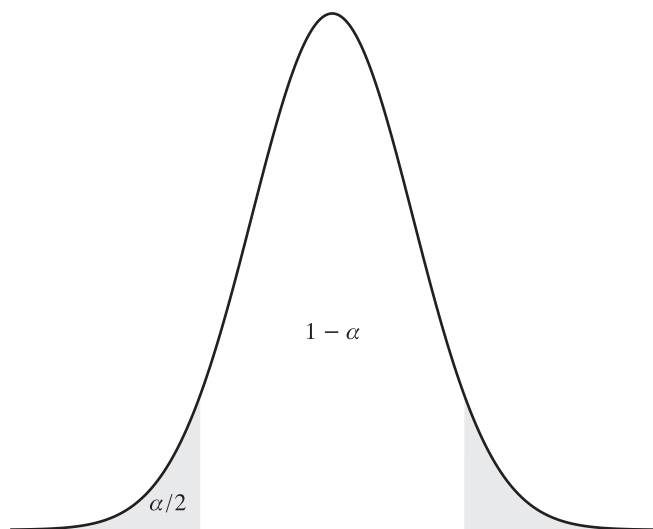


Fig. 1. Normal distribution. The critical significance level  $\alpha$  (gray area) is the probability we reject a null hypothesis when it is true. The ratio of  $1 - \alpha$  to  $\alpha$  is the odds against rejecting a true null hypothesis. Table 1 lists some critical significance levels and odds reported since 1837.

In current jargon, the phrase *1.8 times the probable error* means that  $t = 1.8$ .

Today, when a scientist writes about whether some event can be attributed to chance, she writes not about the odds but about the probability of that event if chance alone is at work. This convention can be traced to *Statistical Methods for Research Workers* (13), published in 1925 by Sir Ronald Aylmer Fisher (18, 52).<sup>3</sup> In 1919, after 4 years of teaching mathematics and physics in public schools, Fisher went to work as a statistician at the Rothamsted Experimental Station, a facility that conducted research in agronomy and biology (4, 40, 52). It was during his early tenure at Rothamsted that Fisher, inspired in part by Gosset's *The Probable Error of the Mean*, recognized that scientists needed a practical guide to statistical methods. *Statistical Methods for Research Workers* gave them what they needed (35).

Just as others defined the magnitude of a deviation that they regarded as beyond chance, so too did Fisher in *Statistical Methods for Research Workers*. Fisher opted for 1 in 20: only 5% of possible values of the event are more extreme than this benchmark. In *Statistical Methods for Research Workers*, Fisher cites his 0.05 benchmark three times. The latter two, on p. 79 and 101–102, allude to this first (p. 46–47):

In practical applications we do not so often want to know the frequency at any distance from the centre as the total frequency beyond that distance; this is represented by the area of the tail of the curve cut off at any point. . . A deviation exceeding the standard deviation occurs about once in three trials. Twice the standard deviation is exceeded only about once in 22 trials, thrice the standard deviation only once in 370 trials. . . The value for which  $P = .05$ , or 1 in 20, is 1.96 or nearly 2; it is convenient to take this point as a limit in judging whether a deviation is to be considered significant or not. Deviations exceeding twice the standard deviation are thus formally re-

<sup>3</sup> The impact of Fisher on statistics and science is legendary (3, 18, 25, 30, 34, 35, 43, 51–53). His collected papers are posted at <http://www.adelaide.edu.au/library/special/digital/fisherj/>.

garded as significant.

In our guidelines for reporting statistics (Ref. 9, *guideline 2*), Dale Benos and I wrote that most researchers adhere to tradition and define the critical significance level  $\alpha$ —the benchmark for the limits of random variation—to be 0.05. It is this passage in *Statistical Methods for Research Workers* that was the genesis of the tradition.

*Statistical Methods for Research Workers* filled such a void within the scientific community that two things happened. First, researchers started to use statistical procedures from the book, but without fully understanding the underlying concepts, they sometimes misused the procedures (18, 53). And second, the notion of a significance level of 0.05 approached the level of doctrine despite subsequent but less obvious elaborations by Fisher:

If one in twenty does not seem high enough odds, we may, if we prefer it, draw the line at one in fifty (the 2 per cent. point), or one in a hundred (the 1 per cent. point). Personally, the writer prefers to set a low standard of significance at the 5 per cent. point, and ignore entirely all results which fail to reach this level. A scientific fact should be regarded as experimentally established only if a properly designed experiment *rarely fails* to give this level of significance.

[Ref. 14 (1926)]

The attempts that have been made to explain the cogency of tests of significance in scientific research. . . seem to miss the essential nature of such tests. A [person] who ‘rejects’ a hypothesis provisionally, as a matter of habitual practice, when the significance is at the 1% level or higher, will certainly be mistaken in not more than 1% of such decisions. For when the hypothesis is correct he will be mistaken in just 1% of these cases, and when it is incorrect he will never be mistaken in rejection. . . However, the calculation is absurdly academic, for in fact no scientific worker has a fixed level of significance at which from year to year, and in all circumstances, he rejects hypotheses; he rather gives his mind to each particular case in the light of his evidence and his ideas. Further, the calculation is based solely on a hypothesis, which, in the light of the evidence, is often not believed to be true at all, so that the actual probability of erroneous decision, supposing such a phrase to have any meaning, may be much less than the frequency specifying the level of significance.

[Ref. 16 (1956)]

In contrast to Fisher who defined a null hypothesis but no alternative hypothesis (18), Jerzy Neyman and Egon Pearson advocated a paradigm of hypothesis testing that involved making a decision about competing null and alternative hypotheses (18, 33, 38, 39). In this paradigm, power, the probability that we reject some null hypothesis given that it is false, plays a prominent role. Neyman and Pearson argued that the

Table 1. *Significance levels between 1837 and 1908*

Year	Person	$1 - \alpha$	$\alpha$	Odds	Reference
1837	Poisson	0.9953	0.0047	212	Matthews (36)
1874	Hirschberg	0.916	0.084	11	
1877	Liebermeister	0.8333	0.1667	5	
1885	Edgeworth	0.93	0.07	13	Edgeworth (12)
	Edgeworth	0.997	0.003	332	
1908	Gosset	0.9801	0.0199	49	Student (48)
	Gosset	0.887	0.113	8	

The odds against rejecting a true null hypothesis is  $(1 - \alpha)/\alpha$  (see Fig. 1).

selection of the critical significance level  $\alpha$ , the probability that we reject a true null hypothesis, and  $\beta$ , the probability that we fail to reject a false null hypothesis, depended on the costs associated with committing each kind of error (18, 33).

Although the philosophical differences between the Fisher and Neyman-Pearson strategies led to some fierce exchanges between the protagonists, from a practical perspective, the strategies are complementary (18, 33). In fact, in science, these strategies have been blended (18). Despite their philosophical difference, it is fitting that Fisher, Neyman, and Pearson all believed that statistics provided a means by which to learn (33).

With this brief history, we are ready to begin our explorations of contemporary hypothesis tests, test statistics, and P values.

*The Null Hypothesis: Controlling Mistakes*

When we make an inference about a null hypothesis, we can make a mistake. We can reject a true null hypothesis, an error of the first kind, or we can fail to reject a false null hypothesis, an error of the second kind (37, 38).<sup>4</sup> Our challenge is to balance two conflicting objectives: reduce the risk that we find an experimental effect when it does not exist but maintain the likelihood that we detect an experimental effect when it does exist.

The chance that we make an error of the first kind is just the probability that we reject the null hypothesis  $H_0$  given that  $H_0$  is true:

$$\Pr\{\text{reject } H_0 \mid H_0 \text{ is true}\} .$$

We control the chance that we make this kind of error when we define the critical significance level  $\alpha$  because

$$\alpha = \Pr\{\text{reject } H_0 \mid H_0 \text{ is true}\} .$$

When we define  $\alpha$ , we declare that we are willing to reject a true null hypothesis 100 $\alpha$ % of the time. *Guideline 2* (9) discusses the choice of  $\alpha$  so it is appropriate to the goals of your study.

The chance that we make an error of the second kind is the probability that we fail to reject  $H_0$  given that  $H_0$  is false:

$$\Pr\{\text{fail to reject } H_0 \mid H_0 \text{ is false}\} .$$

We control the chance that we make this kind of error when we define the error rate  $\beta$ :

$$\beta = \Pr\{\text{fail to reject } H_0 \mid H_0 \text{ is false}\} .$$

Rather than define  $\beta$  per se, we usually define power, the probability that we reject  $H_0$  given that  $H_0$  is false:

$$\text{power} = 1 - \beta = \Pr\{\text{reject } H_0 \mid H_0 \text{ is false}\} .$$

In general, four things affect power: the critical significance level  $\alpha$ , the standard deviation  $\sigma$  of the underlying population,

the sample size  $n$ , and the magnitude of the difference that we want to be able to detect.<sup>5</sup>

Before we begin our actual exploration of test statistics and P values, we need to review the software we will use to help us learn about these concepts.

*R: Basic Operations*

In the inaugural article (8) of this series, I summarized R (41) and outlined its installation. The APPENDIX here reviews this process. For this exploration, there is just one additional step: download the script *Advances\_Statistics\_Code\_P.R*<sup>6</sup> to your *Advances* folder.

If you use a Mac, highlight the commands in *Advances\_Statistics\_Code\_P.R* you want to submit and then press  $\text{⌘}+\text{↵}$ . If you use a PC, highlight the commands you want to submit, right-click, and then click Run line or selection. Or, highlight the commands you want to submit and then press  $\text{Ctrl}+\text{R}$ .

*The Simulation: Observations and Sample Statistics*

When we explored the distinction between standard deviation and standard error (8) we drew a total of 1000 random samples—each with 9 observations—from our population, a standard normal distribution with mean  $\mu = 0$  and standard deviation  $\sigma = 1$  (Fig. 2). These were the observations—the data—for *samples 1, 2, and 1000*:

```
> # Sample Observations
[1] 0.422 1.103 1.006 1.034 0.285 -0.647 1.235 0.912 1.825
[2] 0.154 -0.654 -0.147 1.715 0.720 0.804 0.256 1.155 0.646
⋮
[1000] 0.560 -1.138 0.485 -0.864 -0.277 2.198 0.050 0.500 0.587
```

Each time we drew a random sample, we calculated the sample statistics listed in Table 2. These were the statistics for *samples 1, 2, and 1000*:

<sup>5</sup> In light of its importance to hypothesis testing and grant applications, we will explore power in a future installment of *Explorations*.

<sup>6</sup> This file is available through the Supplemental Material link for this article at the *Advances in Physiology Education* website.

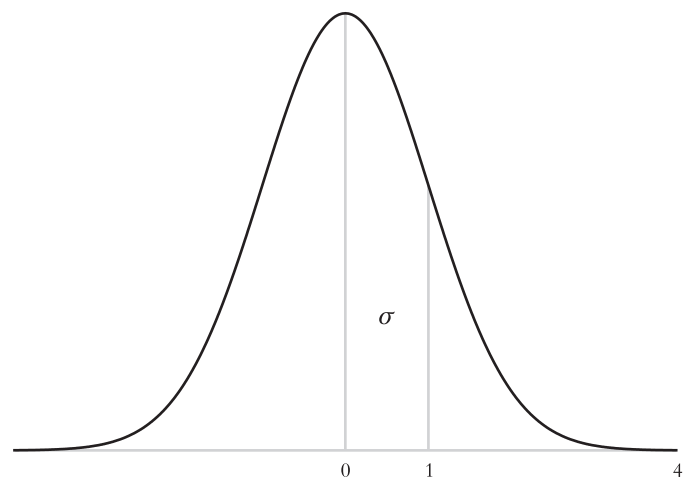


Fig. 2. The population. We can generate a standard normal distribution by transforming some random variable  $Y$  to  $z$  by the relationship  $z = (Y - \mu)/\sigma$ , where  $z$  represents the number of standard deviations  $Y$  is from the mean  $\mu$ . [Reprinted from Ref. 8.]

<sup>4</sup> Errors of the first kind and second kind are known also as type I and type II errors.

Table 2. Sample statistics calculated for each random sample

Column	Heading	Sample Statistic
1	Sample	Sample number
2	Mean	Mean $\bar{y}$
3	SD	Standard deviation $s$
4	SE	Standard error of the mean $SE\{\bar{y}\} = s/\sqrt{n}$
5	t	Observed value of $t = \bar{y}/SE\{\bar{y}\}$
6	LCI	Lower confidence interval bound
7	UCI	Upper confidence interval bound

[Reprinted from Ref. 8.]

```

> # Sample Mean SD SE t LCI UCI
  [,1] [,2] [,3] [,4] [,5] [,6] [,7]
1 0.797 0.702 0.234 3.407 0.362 1.232
2 0.517 0.707 0.236 2.193 0.079 0.955
:
1000 0.233 0.975 0.325 0.718 -0.371 0.838
    
```

The commands in lines 35–63 of `Advances_Statistics_Code_P.R` generate the observations and compute the sample statistics. These commands are identical to those in the first script (8).

With these 1000 sets of sample statistics, we are ready to explore hypothesis tests, test statistics, and  $P$  values.

*Hypothesis Tests: Test Statistics and P Values*

When we began our statistical explorations, we wanted in part to estimate  $\mu$ , the mean of our population (see Ref. 8). Only because we defined our population do we know that  $\mu = 0$ . Had this been a real experiment, we might have wanted to learn if some intervention affected the physiological thing<sup>7</sup> we cared about. In this case, we would have constructed the null and alternative hypotheses,  $H_0$  and  $H_1$ , as

$H_0$ : The intervention has no effect.

$H_1$ : The intervention has an effect.

More formally, we would have written these hypotheses as

$$H_0: \mu = 0$$

$$H_1: \mu \neq 0$$

which translate to these statements: the sample observations are consistent with having come from a population that has a mean  $\mu$  of 0, and the sample observations are consistent with having come from a population that has a mean  $\mu$  other than 0. This is silly, right? We know that  $\mu = 0$ . We can use our knowledge that the null hypothesis is true, however, to explore the concepts behind test statistics and  $P$  values.

The basis for some test statistic is a comparison between what we observe in the experiment and what we expect if the null hypothesis is true. In our first theoretical experiment, what we observed was the sample mean  $\bar{y} = 0.797$ . Now the question is, what do we expect if the null hypothesis is true? We already know the answer. When we took 1000 samples from a population with  $\mu = 0$ , the sample means varied (see Ref. 8, Fig. 5), but a typical sample mean differed from the

population mean by a distance of 1 SD  $\{\bar{y}\}$ , the standard deviation of the sample means (8). This is identical to the standard error of the mean  $SE\{\bar{y}\}$ . Therefore, if the null hypothesis is true, we expect the typical variation in the sample mean to be  $SE\{\bar{y}\}$ .

One test statistic with which we can assess whether our sample observations are consistent with having come from a population with  $\mu = 0$  is the familiar  $t$  statistic:

$$t = \frac{\bar{y}}{SE\{\bar{y}\}}, \text{ where } SE\{\bar{y}\} = s/\sqrt{n}$$

$s$  is the sample standard deviation, and  $n$  is the number of observations in the sample.<sup>8</sup> In a manner similar to the statistic  $z$  (8),  $t$  represents the number of standard deviations the sample mean  $\bar{y}$  is from the population mean  $\mu$ . If the sample mean  $\bar{y}$  is far enough away from the population mean  $\mu$ , then that is unusual if the null hypothesis is true.

In our first sample,

$$t = \frac{\bar{y}}{SE\{\bar{y}\}} = \frac{0.797}{0.234} = 3.407$$

That’s fabulous, but exactly how do we interpret a  $t$  value of 3.407? We interpret it within the context of a true null hypothesis: if the null hypothesis is true, how usual is this value of  $t$ ? If the null hypothesis is true, we expect to observe a value of

<sup>8</sup> We can use a  $t$  statistic to also assess whether two sets of sample observations are consistent with having come from the same or different populations. In this situation, we calculate  $t$  in the same manner but replace the single sample mean  $\bar{y}$  with the difference between sample means,  $\bar{y}_2 - \bar{y}_1$  (see Ref. 44).

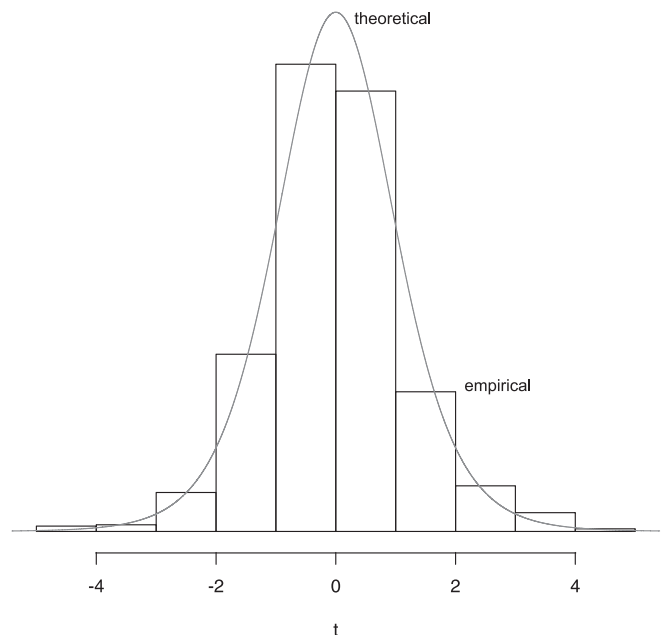


Fig. 3. Empirical (black) and theoretical (gray) distributions of  $t$  for 9 observations. The empirical distribution is composed of 1000 values of  $t$ . The commands in lines 89–90 of `Advances_Statistics_Code_P.R` calculate the theoretical distribution of  $t$ , and the commands in lines 92–101 create this data graphic. To generate this data graphic, highlight and submit the lines of code from Figure 3: first line to Figure 3: last line.

<sup>7</sup> For example, L-ascorbic acid transport, differential gene expression, TNF- $\alpha$ , or venous capacitance in trout (see Ref. 8).

$|t|$  at least as big as 3.407 just 1 time in 200 ( $P = 0.005$ ).<sup>9</sup> By virtue of our simulation, we have 1000 values of  $t$ ; the magnitudes of 14 values are at least as extreme as 3.407:

```
> # Sample      Mean      SD      SE      t      LCI      UCI
[.1]  [.2]  [.3]  [.4]  [.5]  [.6]  [.7]
  1  0.797  0.702  0.234  3.407  0.362  1.232
 28  0.790  0.507  0.169  4.681  0.476  1.104
 34 -0.668  0.451  0.150 -4.442 -0.948 -0.389
215  1.100  0.880  0.293  3.751  0.555  1.646
238  0.923  0.736  0.245  3.763  0.467  1.379
283 -0.576  0.387  0.129 -4.465 -0.816 -0.336
536  0.826  0.682  0.227  3.635  0.404  1.249
616 -0.633  0.487  0.162 -3.895 -0.935 -0.331
645  0.671  0.558  0.186  3.607  0.325  1.017
800 -0.981  0.726  0.242 -4.053 -1.431 -0.531
804  1.037  0.707  0.236  4.405  0.599  1.475
880  0.804  0.674  0.225  3.581  0.387  1.222
925 -0.801  0.574  0.191 -4.182 -1.157 -0.445
981 -0.744  0.610  0.203 -3.663 -1.122 -0.366
```

The commands in *lines 81–83* of *Advances\_Statistics\_Code\_P.R* print the statistics for the samples in your simulation. Your number of samples will differ.

If we treat these 1000 values of  $t$  as observations, their empirical distribution is centered at  $-0.04$  (median), just less than the theoretical value of 0 (Fig. 3). Five percent of the 1000 values of  $t$  are less than  $-1.773$  and five percent are greater than  $1.979$ , close to the theoretical percentiles of  $-1.860$  and  $1.860$ . The commands in *lines 109–110* of *Advances\_Statistics\_Code\_P.R* return these values. Your values will differ slightly.

In most experiments, we use a single sample and calculate a single test statistic in order to make inferences about some null hypothesis. Suppose we established beforehand a critical significance level—a benchmark for uncommonness—of  $\alpha = 0.10$  (9). If the null hypothesis is true, the test statistic  $t = 3.407$  ( $P = 0.005$ ) from our first sample is more unusual—less likely to occur—than our benchmark. As a result, we would reject the null hypothesis and conclude that the sample observations were consistent with having come from a population that had a mean  $\mu$  other than 0. And we would be wrong. We know the null hypothesis is true: we drew our observations from a population that had a mean of 0 (see Fig. 2).

So how can we make sense of this? By realizing that when we draw a single random sample from some population—when we do a single experiment—we can have enough unusual observations so that it just appears the observations came from a different population.

### Summary

As this exploration has demonstrated, a test statistic compares what we observe in an experiment to what we expect to see if the null hypothesis is true. The  $P$  value associated with the magnitude of that test statistic answers the question, if the null hypothesis is true, what proportion of possible values of the test statistic are at least as extreme as the one I got? Although the statistical test of a null hypothesis is useful—it helps guard against an unwarranted conclusion, or it helps argue for a real experimental effect (7, 44)—the only question it can answer is a trivial one: is there anything other than random variation going on here? The answer to this question is a simple yes or no. Science is less yes-or-no and more how-much.

<sup>9</sup> The commands in *lines 75–76* of *Advances\_Statistics\_Code\_P.R* return this value.

In the next installment of this series, we will explore confidence intervals. A confidence interval provides the same statistical information as the  $P$  value from a hypothesis test, but it circumvents the drawbacks inherent to a hypothesis test. In essence, a confidence interval helps answer the question, is the experimental effect big enough to be relevant?

### APPENDIX

Regardless of whether you use a Mac or a PC, there are two preliminary steps to perform: first, on your Desktop, create a folder called *Advances*, and second, download and install R.


If you use a Mac, download R from

<http://cran.us.r-project.org/bin/macosx/> .

After you have installed R, double-click on *Advances\_Statistics\_Code\_P.R* to open it.

If you use a PC, download R from

<http://cran.us.r-project.org/bin/windows/base/> .

After you have installed R, a shortcut for R will exist on your Desktop. To simplify the process of starting R from within your *Advances* folder, move this shortcut into your *Advances* folder, right-click on the shortcut, and then click *Properties*. Paste the full address (path) of your *Advances* folder—this path will vary depending on the Windows operating system you use—into the *Start in:* location (see Ref. 8, Fig. 1) and then click *OK*. Now double-click on the R shortcut to open R. To open *Advances\_Statistics\_Code\_P.R*, click *File | Open script. . .* or click the *Open script* icon , select the script filename, and then click *Open*. *Advances\_Statistics\_Code\_P.R* will open in the R Editor.

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