

P-Values and NHPT

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 - ▶ Established what a test is
 - ▶ Discussed properties of a good test in terms of errors
- ▶ This class we:
 - ▶ Discuss p-values as a particular approach
 - ▶ Consider the Bayesian critique that maybe we should not be doing this at all

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So what does it mean?

Defining a p-value broadly

Suppose that for every $\alpha \in (0, 1)$ we have a size α test with rejection region R_α . Then,

$$\text{p-value} = \inf \{ \alpha : t(\mathbf{x}) \in R_\alpha \}$$

- In words this means that the p-value is the smallest level at which we can reject H_0 .

Getting down to business

- ▶ First we set up a null hypothesis.
- ▶ Then we assume that the null hypothesis is true.
- ▶ Then we consider a set of tests with size $\alpha \in (0, 1)$
- ▶ The p-value is the size of the largest test at which we can still reject H_0 .

A critical value perspective

- ▶ Suppose that the size α test is of the form “reject H_0 iff $t(\mathbf{x}) \geq c_\alpha$ ”
- ▶ In this case the p-value is

$$\sup_{\theta \in \Theta_0} P(t(\mathbf{X}) \geq t(\mathbf{x}))$$

where \mathbf{X} is the random variable and \mathbf{x} is the observed value.

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- ▶ It is the probability of observing a value of some statistic – ASSUMING THE NULL HYPOTHESIS IS TRUE – that is the same *or more extreme* than what was actually observed.

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- ▶ Third, we (kind of) conclude that our research hypothesis is true. This is usually called the alternative hypothesis.
- ▶ To do this, we first need to specify our hypotheses.

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- ▶ P-Values are very difficult for many people to understand.
- ▶ Smaller P-Values more strongly contradict the null.

How surprised would you have to be in order to conclude that the *null hypothesis* is false?

- ▶ Usually, $p \leq 0.05 \Rightarrow$ statistically significant result
- ▶ We would observe a test-statistic this extreme or more 1/20 times if the null hypothesis was true.
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- ▶ More generically, we want $p \leq \alpha$
- ▶ We “reject the null” and conclude that the evidence supports the alternative hypothesis.

Example

According to a union agreement, the mean income for all senior-level assembly-line workers in a large company equals \$525 per week. A representative of a women's group decides to analyze whether the mean income μ for female employees matches this norm. For a random sample of 36 female employees, $\bar{y} = \$495$ and $s = \$75$.

- ▶ Calculate the test using $\alpha = .01$.
- ▶ Draw a picture that represents the p – value.

Example

We flip a coin 20 times and observe 18 heads. Find the p-value for the null hypothesis that we have a fair coin.

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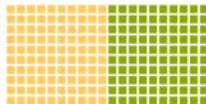
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 - ▶ You tested a lot of hypotheses
 - ▶ You estimated the sampling distribution wrong

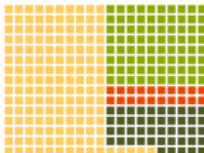
Unlikely results

How a small proportion of false positives can prove very misleading

False True False negatives False positives



1. Of hypotheses interesting enough to test, perhaps one in ten will be true. So imagine tests on 1,000 hypotheses, 100 of which are true.



2. The tests have a false positive rate of 5%. That means they produce 45 false positives (5% of 900). They have a power of 0.8, so they confirm only 80 of the true hypotheses, producing 20 false negatives.



3. Not knowing what is false and what is not, the researcher sees 125 hypotheses as true, 45 of which are not. The negative results are much more reliable—but unlikely to be published.

This is kind of a big deal

- ▶ We are increasingly aware that we are in a “replication crisis”
- ▶ P-values are at the heart of it (and there is no easy solution)
- ▶ As a practical matter:
 - ▶ Pre-registration
 - ▶ Lower acceptable p-value standards for new findings
 - ▶ Wait for the meta analysis
 - ▶ DO NOT TRUST UNDERPOWERED STUDIES
 - ▶ Publish replications
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 - ▶ Don't believe everything you read (but don't be a jerk about it)
- ▶ Maybe don't do hypothesis testing? But what could we do instead?

Bayes Factors

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- ▶ From a Bayesian perspective, we want to directly summarize the strength of the evidence for H_1 relative to H_0 .
- ▶ Using Bayes' rule, we get

$$\frac{\Pr(H_1|\mathbf{x})}{\Pr(H_0|\mathbf{x})} = \frac{f(\mathbf{x}|H_1)}{f(\mathbf{x}|H_0)} \times \frac{\pi(H_1)}{\pi(H_0)} \equiv \text{Bayes Factor} \times \text{Prior odds}$$

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- ▶ This can be re-written as:

$$\frac{L(H_1) \pi(H_1)}{L(H_0) \pi(H_0)}$$

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- ▶ Note that if $H_1 = MLE$, the first part is the inverse of the likelihood ratio and if we give the same prior odds to both theories it is exactly the same.
- ▶ Let's unpack that a bit:

$$\frac{\Pr(H_1|\mathbf{x})}{\Pr(H_0|\mathbf{x})}$$

Jefferry's proposed the following rules for comparing two models

$$BF(M_1 : M_2) = \frac{\Pr(M_1|x)}{\Pr(M_2|x)}$$

- ▶ $B(x) \geq 1 \rightarrow$ Model 1 supported
- ▶ $0.316 \leq B(x) < 1 \rightarrow$ Minimal evidence against Model 1 (Note $0.316 = 10^{-1/2}$)
- ▶ $0.1 \leq B(x) < 0.316 \rightarrow$ Substantial evidence against Model 1
- ▶ $0.01 \leq B(x) < 0.1 \rightarrow$ Strong evidence against Model 1
- ▶ $B(x) < 0.01 \rightarrow$ Decisive evidence against Model 1

Problems with Bayes factors

- ▶ The flaws with this paradigm open up when we consider the case where θ is a scalar and we are testing $H_0 : \theta = \theta_0$ against $H_1 : \theta \neq \theta_0$ where θ is a scalar that can take on many values.
- ▶ In these cases, improper (flat) priors can lead to non-defined Bayes factors

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- ▶ In these cases, improper (flat) priors can lead to non-defined Bayes factors
- ▶ Bayes factors can become seriously sensitive to priors especially when they are “vague.”
- ▶ We have to integrate over the entire parameter space which may not be tractable.
- ▶ For more, see: <http://www.stat.cmu.edu/~kass/papers/bayesfactors.pdf>

P-values and Bayes factors

- ▶ One of the nice things about this setup is that

$$P(M_0|\mathbf{x}) = \frac{BF(M_0 : M_1)}{1 + BF(M_0 : M_1)}$$

- ▶ Where the hell did that come from?

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- ▶ And what does that mean anyways?
- ▶ This number will usually *not* correspond well with a p-value

Simulation 1

- ▶ Generate 100000 experiments with two variables x and y
- ▶ Both should be random normal samples of size $n = 100$, $\mu = 100$, $\sigma = 20$.
- ▶ Perform a t-test and grab the p-value (difference of means)
- ▶ Plot a histogram of the p-values that result
- ▶ What does this mean? Are you surprised?

Simulation 2

- ▶ Generate 100000 experiments with two variables x and y
- ▶ X should be random normal samples of size $n = 100$,
 $\mu = 100$, $\sigma = 20$.
- ▶ Y should be random normal samples of size $n = 100$,
 $\mu = 103$, $\sigma = 20$.
- ▶ Perform a t-test and grab the p-value
- ▶ Plot a histogram of the p-values that result
- ▶ What does this mean? Are you surprised?

Simulation 3

- ▶ Let ϕ represent the proportion of cases where the null hypothesis is true
- ▶ Let α be the probability of rejecting the null hypothesis if it is false.
- ▶ Let $(1 - \beta)$ be the probability of rejecting given that the null hypothesis is false.
- ▶ If we test many hypotheses, the false positive rate is then:

$$\frac{\alpha\phi}{\alpha\phi + (1 - \beta)(1 - \phi)}$$

- ▶ If $\frac{\phi}{1-\phi}$ is 1/5, what is the false positive rate when $\alpha = .05$ and $\beta = .75$?
- ▶ If $\frac{\phi}{1-\phi}$ is 1/20, what is the false positive rate when $\alpha = .05$ and $\beta = .75$?
- ▶ If $\frac{\phi}{1-\phi}$ is 1/40, what is the false positive rate when $\alpha = .05$ and $\beta = .6$?

Exercise

If I, Prof. Montgomery, flipped a coin 20 times and it came up heads 18 times, what is the probability that it is a fair coin? - Set the problem up as a complete Bayesian problem. - Set the problem up as a choice of two discrete problems and solve explicitly.