Hypothesis Testing

Inductive v. Deductive Reasoning

Inductive Inference: Small pieces of evidence are used to shape a larger theory.

Deductive Inference: A larger theory is used to devise many small tests.

How Do we Derive Truth from Data?

Null Hypothesis Tests & Popper

- 1. Frequentist inference correct conclusion drawn from repeated experiments
 - Null Hypothesis Tests
 - falsify a null hypothesis
 - Likelihood/Information Theoretic evaluate weight of evidence
- 2. Bayesian probability of belief that is constantly updated

Deductive vs. Inductive



Falsification of hypotheses is key!

A theory should be considered scientific if, and only if, it is falsifiable.

Deductive Reasoning and Null Hypothesis Tests	Common Uses of Null Hypothesis Tests
A null hypothesis is a default condition that we can attempt to falsify.	 Ho: Two groups are the same Ho: An estimated parameter is not different from 0 Ho: The slopes of two lines are the same Etc
Ho and Ha	Null Distributions
Ho and Ha There are often many alternate hypotheses. Rejection of the null does not imply acceptance of any single alternative hypothesis.	Null Distributions

Null Distributions



Evaluation of a Test Statistic

We can use our data to calculate a test statistic that maps to a value of the null distribution. We can then calculate the probability of observing our data, or of observing data even more extreme, given that the null hypothesis is true.

Evaluation of a Test Statistic



The P Value

P-value: The Probability of making an observation or more extreme observation given that the null hypothesis is true.



R. A. Fisher

The P Value



p=0.0227,Note - this is a one-tailed test!

1-Tailed v. 2-Tailed Tests

 $1\mathchar`-Tailed Test:$ We are explicit about whether Ha implies that our sample is greater than or less than our null value.

2-Tailed Test: We are make no assumption about the sign or direction of our alternative hypotheses.

Two-Tailed P Value





p=0.0454 from pnorm(-2)*2

When should you use a 1-Tailed Test?

Exercise: Evaluate Support for Null Hypothesis	Exercise: Evaluate Support for Null Hypothesis
 Typically, the number of warts on a toad is Poisson distributed with a λ of 54 You survey a lake suspected to contain high PAH levels. You pick up a toad, and it has 40 warts. What is your null hypothesis? What is the probability of making this observation, given your null? Challenge: How does your p value change with # of warts, say, from 1 to 108 warts? 	2 * ppois(40, 54) ## [1] 0.05755 # OR! p <- 0 1 1:40) { p <- p + dpois(i, 54) } p * 2 ## [1] 0.05755
Exercise: Evaluate Support for Null Hypothesis	Exercise: Evaluate Support for Null Hypothesis
	<pre>p <- 0 for (i in 0:54) { p[i + 1] <- 2 * pnorm(i, 54) } for (i in 55:108) { p[i + 1] <- 2 * pnorm(i, 54, lower.tail = F) } plot(0:108, p)</pre>

Neyman-Pearson Hypothesis Testing and Decision Making



Jerzy Neyman



Egon Pearson

Neyman-Pearson Hypothesis Testing

Rejection of a null hypothesis if the p-value is below some critical level - α

If $\mathsf{p} \leq \alpha$ then we reject the null. There is strong support for the null to be falsified. This result is sometimes termed being statistically significant.

 α is often 0.05, but, set it according to your a priori reasoning (including what you assume your power to be)

Types of Errors in a NHST framework

Statistical Significance is NOT Biological Sigficance.

Should we even use the word "significant"? Why or why not just talk about level of support for rejecting the null?

	Ho is True	Ho is False
Reject Ho	Type I Error	Correct OR Type S error
Fail to Reject Ho	-	Type II Error

- Possibility of Type I error regulated by choice of α
- Probability of Type II error regulated by choice of β
- Probability of Type III error is called δ

Type S Error

Power

Correctly rejecting the null hypothesis for the wrong reason

This is a Type S, or Type III error - a mistake of sign. Often inherent in an experiment's design, or possible by change. Can determine by mechanistic simulation or a redesigned study.

- \blacktriangleright If β is the probability of comitting a type II error, 1- β is the power of a test.
- The higher the power, the less of a chance of comitting a type II error.
- We typically want a power of 0.8 or higher.

Power via Simulation

We can assess the power of a test via simulation. We simulate a test statistic, and assuming a particular Ha is true, evaluate whether we falsely fail to reject Ho.

Sample Size and Power via Simulation

Ho is that the average effect of a drug on heart rate is 0. Actually, is speeds it up by 15 beats per minute. What is the effect of sample size of patients on power, assuming a SD of 6?



Sample Size and Power via Simulation

We can get the p value of each simulation using pnorm - and, remember, this is two-tailed!

pvec <- pnorm(abs(vec), sd = simSD, lower.tail = FALSE) * 2
plot(pvec ~ n, ylab = "p")</pre>



Sample Size and Power via Simulation

```
Power is 1 - the fraction of those tests which \mathsf{p} \leq \alpha. So, we loop over all sample sizes to get...
```

```
power < rep(NA, 10)
for (i in 1:10) {
    nVec < vec[which(n == i)]
    power[i] <- 1 - sum(nVec <= 0.05)/length(nVec)
}
plot(power ~ I(1:10), xlab = "n", ylab = "power", type = "b")</pre>
```

Sample Size and Power via Simulation

Power is 1 - the fraction of those tests which $\mathsf{p} \leq \alpha.$ So, we loop over all sample sizes to get...



Challenge: How will this relationship be affected as you change alpha?

Exercise: Power and Simulation



Exercise: Power and Simulation

