Statistics: Description and inference

Part II: the t-test

Statistical theory and process control

- •Consider the problem facing Gossett or any quality control engineer. At a brewery (or any factory), beer (or widgets) are produced to meet certain specifications. There is a certain amount of variation from specifications that is acceptable, but you need to detect when something has gone wrong; i.e., when specifications are no longer being met. How can you tell if the product is being made up to specification?
- •Two basic cases: Large samples and small samples

Data = Model + Error

- Almost all of statistics can be summarized as finding how well a model fits the data.
- We need to specify a model, observe the phenomenon, and see how far off the model is from the data.
- Always ask: What is the model? How well does it fit? What are the alternatives? How well do they fit?

Normal distributions and the central limit theorem

• The distribution of sample means from a population with mean μ and variance σ^2 will tend towards a normal distribution with mean μ and variance σ^2/n

$$s^2 = \sum_{i=1}^n (X_i - \bar{X})^2 / (n-1)$$

$$s.e.=\sqrt{s^2/n}=s/\sqrt{n}$$

Distributions as f(sample size)



Basic Production process with mean = μ = 0 and σ = 1



distribution of production

Production can go bad



distribution of production from faulty system

Problem of estimating which state the brewery is in



Consider samples of size n



distribution of production with sample size = 8 and true difference = 3

Consider distribution of sample differences



distribution of sample differences with sample size = 8 and true difference = $\neg \pm 3$

Variation of group differences depend upon sample size



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Gossett and the t-test (compare differences of means to standard error of mean)

distribution of t differences with sample size = 4 and true difference = $\neg \pm 3$



A sample of 16, diff = 3



distribution of t differences with sample size = 16 and true difference = $\neg \pm 3$

Types of inferential errors failure to detect, failure to reject



Descriptions and inference

- Classical "Null Hypothesis Inference Statistical Test" NHIST
- Descriptive statistics with confidence intervals
 - expressed in units of measurement
 - expressed in "effect sizes"

Null Hypothesis Testing

- The Null or Nill hypothesis of no difference
- Alternative hypothesis is that Null is wrong
- What is the likelihood of observing differences this big or bigger if Null is true
- If likelihood given Null is small, then reject Null
- Error of false rejection when Null is True (Type I)
- Error of failure to reject when Null is false (Type II)

Critique of NHIST

- Null is never true
- It is not that something has an effect, but we want to know how big the effect is.
- Hookes Law is not that if you pull on a wire it gets longer but rather that the amount it stretches is proportional to the force.
- We need to estimate quantities, not just see if they are ≠ 0

Descriptive with confidence

- Standard error = s/\sqrt{N}
 - observed standard deviation/sqrt(sample size)
- Report observed mean and the standard error of the mean. Allows us to estimate the precision of the estimate.
- If population mean is X, then 68% of observed means will be within I se of X, 95% within 2 se of X

Effect size comparisons

- Effect (e.g., difference of means) depends upon the scale we use (meters, feet, inches)
- Standardized effect = effect/within group standard deviation
- Note that while t = effect/sqrt(n) and thus varies as a function of sample size,standardized effect size does not depend upon sample size and thus allows one to compare effects across studies

Consider multiple samples

> x<-matrix(rnorm(240),ncol=20)
>error.bars(x,xlab="sample",main="Means and Confidence Intervals")
>abline(h=0)



Means and Confidence Intervals

Another 20 samples of size 24



Means and Confidence Intervals

20 samples of size 50



Means and Confidence Intervals

20 samples of size 5



Means and Confidence Intervals

20 samples of size 4, 16, 32



Confidence Intervals and precision

- As sample size increases, the confidence intervals get smaller
- But the probability of being included in a 95% confidence interval remains 95%!

Finding t

The data			Analysis											
placebo 24 24 25 29 27 26	caffeine			Get	t th	e dat	a		spe	elling	<- re	ad.clipb	oard())
26 23 26 25 22 28 21 27	26 23 26 25 Describ 22 28 21 27				e the data					describe(spelling)				
22 24 23 27 25 28 25 27 25 26	placebo caffeine	var 1 2	n 12 12	mean 24.25 26.17	sd 1.86 1.85	median 25.0 26.5	mad 1.48 2.22	min 21 23	max 27 29	range 6 6	skew -0.33 -0.22	kurtosis -1.33 -1.33	se 0.54 0.53	

t.test in R

```
> attach(spelling)
> t.test(placebo,caffeine,equal.var=TRUE)
Welch Two Sample t-test
```

```
data: placebo and caffeine
t = -2.5273, df = 21.999, p-value = 0.01918
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
  -3.4894368 -0.3438965
sample estimates:
mean of x mean of y
  24.25000 26.16667
```

varnmeansdmedianmadminmaxrangeskewkurtosisseplacebo11224.251.8625.01.4821276-0.33-1.330.54caffeine21226.171.8526.52.2223296-0.22-1.330.53

Reporting the t.test

- Formally (and formerly!):
 - The hypothesis of no difference between the groups was rejected with a probability of p < .02
- More typical:
 - Caffeine (26.17, sd. = 1.85) led to an increase in spelling performance when compared to placebo (24.25, sd. = 1.86), t = 2.53, p < .02.
 - Some also report the probability of replication:
 - p.rep = .95