# <span id="page-0-0"></span>Two Group Differences

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Suppose that we have a diagnostic test for an infectious disease which has a Type I error rate of 5% and a Type II error rate of 1%. Answer the following:

- 1. What is the null hypothesis for a diagnostic test? What constitutes a Type I and Type II error?
- 2. Suppose we use it to test for the disease on a population of 1,000 people where 40% have the disease. Construct a table showing the number of correct and incorrect conclusions based on the truth of  $H_0$
- 3. Of individuals with a positive test, what percentage actually had the disease?
- 4. For testing for an infectious disease, is Type I or Type II error more important to control?

What we did before, we will do today:

- 1. Construct a null hypothesis,  $H_0$
- 2. Collect data and compute our statistic (i.e.,  $\overline{x}$ )
- 3. Evaluate that statistic in the context of a null distribution, i.e.,

$$
t = \frac{\overline{X} - \mu_0}{\hat{\sigma}/\sqrt{n}}
$$

- 4. Reject or fail to reject hypothesis
	- ▶ Type I errors
	- ▶ Type II errors

Often in statistical inference, we are interested in investigating the difference between two or more groups

For example, we may have two groups, A and  $B$ , with a mean value for each group,  $\mu_A$  and  $\mu_B$ 

Expressed in our null hypothesis, this equates to

 $H_0: \mu_A = \mu_B$  or  $H_0: \mu_A - \mu_B = 0$ 

Just as in the univariate case for testing the mean, we can use a  $t$ -test to evaluate the difference in means between two groups

There are a number of various assumptions about our data, all resulting in slightly different tests (degrees of freedom and standard error):

- 1. Independent, groups same size and have same variance
- 2. Independent, groups have unequal sizes and similar variance
- 3. Independent, groups have different sizes and different variances
- 4. Paired testing

In general, we will concern ourselves with (3) and (4)

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# Example

Consider our college data, where we might investigate the differences in median debt upon graduate for public and private schools



#### t-test, Independent samples, heterogeneous groups

Our t-statistic takes the form

$$
t = \frac{\overline{X}_1 - \overline{X}_2}{\sqrt{\frac{\hat{\sigma}_1^2}{n_1} + \frac{\hat{\sigma}_2^2}{n_2}}}
$$

This t-statistic only approximately follows a t-distribution, making the calculation of its degrees of freedom non-trival, usually approximated using  $n_1 + n_2 - 2$  (or with software)

Otherwise, the process for constructing confidence intervals or testing hypotheses is exactly the same

# Example

Again, we will use R to compute this, utilizing a special "formula" syntax when using data.frames (will cover in lab)

```
1 > t.test(Debt_median ˜ Private, college)
2
3 Welch Two Sample t-test
4
5 data: Debt_median by Private
6 t = 11.2, df = 1075, p-value <0.0000000000000002
7 alternative hypothesis: true difference in means between group
     Private and group Public is not equal to 0
8 95 percent confidence interval:
9 1981.0 2820.6
10 sample estimates:
11 mean in group Private
12 18028
13 mean in group Public
14 15627
```
The **paired t-test** or **paired difference test** is a test for assessing differences in group means where the groups consist of the same subjects with multiple observations

While it ostensibly shares many characteristics with a two-sample t-test, in practice it more closely resembles that of a one-sample test:

$$
t_{\text{paired}} = \frac{\overline{X}_D - \mu_0}{\hat{\sigma}_D / \sqrt{n}}
$$

where *n* represents the number of *unique* subjects and  $\overline{X}_D$  and  $\hat{\sigma}_D$ represent the mean and standard deviation of the *difference*, respectively Just as with the unpaired case, our null hypothesis is typically that

$$
H_0: \mu_0=0
$$

Paired testing between groups allows us to control for within-subject variation, effectively reducing variation and making it easier to detect a true difference (power)

This comes at a cost, however – for *n* subjects we are required to make  $2n$ unique observations

Consider the results of a summer institute program sponsored by the National Endowment for the Humanities to improve language abilities in foreign language high school teachers

Twenty teachers were given a listening test of spoken French before and after the program, with a maximum score of 36. We are interested in determining the efficacy of the summer institute

- 1. What is the null hypothesis for this study?
	- ▶ What would be a Type I error?
	- ▶ A Type II error?
- 2. How many total subjects do we have?
- 3. How many recorded observations do we have?



The results of the tests are as follows:



Plotted below is a boxplot of observed differences if people were randomly shuffled and repaired in each group



There are a few things to notice here:

- $\blacktriangleright$  The mean value for each arrangement is identical
- ▶ The groups that were randomly assigned show far greater variability
- $\blacktriangleright$  Less variability = more power



```
Results of the paired t-test
1 > t.test(post, pre, paired = TRUE)
2
3 Paired t-test
4
5 data: post and pre
6 t = 3.86, df = 19, p-value = 0.001
7 alternative hypothesis: true mean difference is
     not equal to 0
8 95 percent confidence interval:
9 1.1461 3.8539
10 sample estimates:
11 mean difference
12 2.5
```
Results of the unpaired t-test, no power to find difference

```
1 > t.test(post, pre, paired = FALSE)
2
3 Welch Two Sample t-test
4
5 data: post and pre
6 t = 1.29, df = 37.9, p-value = 0.2
7 alternative hypothesis: true difference in
    means is not equal to 0
8 95 percent confidence interval:
9 -1.424 6.424
10 sample estimates:
11 mean of x mean of y
12 28.3 25.8
```
- ▶ Hypothesis testing works nearly identically for two groups as it did with one group
- ▶ CLT applies for both difference in proportions as well as difference in group means
- ▶ Two-sample t-tests have a paired version
	- 1. Reduces variability
	- 2. Also reduces degrees of freedom
- $\triangleright$  We can use R to do most of these for us

# Difference in Proportions

Suppose we are interested in determining if the composition of public and private schools is the same between the Plains region and the Great Lakes



## Difference in Proportions





- $\triangleright$  H<sub>0</sub> :  $p_1 p_2 = 0$
- $\hat{p}_1 = 0.661, n_1 = 189$
- $\hat{p}_2 = 0.666, n_2 = 126$

#### Differences in Proportion

The central limit theorem gives

$$
\hat{p}_1 - \hat{p}_2 \sim N\left(p_1 - p_2, \ \sqrt{\frac{p_1(1-p_1)}{n_1} + \frac{p_2(1-p_2)}{n_2}}\right)
$$

The procedure for hypothesis testing is exactly the same:

- 1. State null hypothesis and construct distribution of values under the null
- 2. Create t-statistic using point estimate and standard error
- 3. Determine probability of observing t-statistic under the null, get p-value (prop.test() in R)
- 4. Reject or fail to reject  $H_0$



```
1 > prop.test(x = c(125, 84), n = c(189, 126))
2
3 2-sample test for equality of
4 proportions with continuity
5 correction
6
7 data: c(125, 84) out of c(189, 126)
8 X-squared < 3.74E-30
9 df = 1, p-value = 1
10 alternative hypothesis: two.sided
11 95 percent confidence interval:
12 -0.11701 0.1064313 sample estimates:
14 prop 1 prop 2
15 0.66138 0.66667
```