

# CSCI 3022 Intro to Data Science

## Testing Wrapup

A summary of our process:

1. State hypothesis:  $H_0$ : the baseline or "nothing is interesting result." For the coin: a fair coin, with  $p = .5$ .  
 $H_a$ : what we want to test or demonstrate. For the coin: an unfair coin, with  $p \neq .5$
2. Collect some data  $\rightarrow$  proportions? large/sample vs. small sample?  $\sigma$  or  $s$ .
3. Compute a *test statistic* from our data. Maybe a sample proportion of heads  $\hat{p}$ ?
4. Decide whether the *test statistic  $\hat{p}$*  is **too far** from it's assumed baseline value in  $H_0$ , and make a decision accordingly. E.g. was  $\hat{p}$  far enough from  $p = .5$  to actually assert that they're different?  
 $\rightarrow$  formula. that transforms data into  $z, t$
5.  $\alpha$  is the value that describes the probability of rejecting a null hypotheses given that the hypothesis was true.  
 $\rightarrow$  DO NOT memorize! know how to look them up.

# Announcements and Reminders

→ HW 5 probs posted tomorrow

- ▶ HW 1, HW2, Exam grades posted

→  $\bar{x} = 85$  ... review concept of MCQ #10  
(F unless f).

## Rejection Regions or Probabilities?

$\rightarrow \bar{x}$  for  $\mu$  proposed  $\mu$ .

How would we know when the test statistic is “sufficiently rare” under the null hypothesis such that we might regard the null as false? We could define a rejection region: a range of values that leads a researcher to reject the null hypothesis.

Today we discuss the second option. We can *either*:

1. Define a range of  $x$ -values in the *units* of the data - that correspond to  $z$ -values (on the standard normal) that represent “extremely far” from the hypothesized mean. Reject if they’re far enough, where far enough is beyond the  $z_{crit}$  value that depends on  $\alpha$   
 $\sim 1.96$  or  $< -1.96$ , if  $\alpha = .05$
2. Compute a probability: if the null hypothesis is true, exactly how “extreme” is our data, as a probability? If it’s in the  $\alpha$  proportion of most extreme or outlying outcomes when the null is true, maybe we should conclude the null *wasn’t* true.

## Test for Population Proportion

**Example** (continued):

Null hypothesis:

Test statistic value:

Alternative Hypothesis

Rejection Region for  $\alpha$  level test:

## Test for Population Proportion

**Example** (continued):

Null hypothesis:  $H_0 : p = p_0$

Test statistic value:

$$Z = \frac{\hat{p} - p_0}{\sqrt{\frac{p_0(1-p_0)}{n}}}$$

Alternative Hypothesis

Rejection Region for  $\alpha$  level test:

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Alternative Hypothesis

$$H_a : p > p_0$$

$$H_a : p < p_0$$

$$H_a : p \neq p_0$$

Rejection Region for  $\alpha$  level test:

# Test for Population Proportion

**Example** (continued):

Null hypothesis:  $H_0 : p = p_0$

Ex. test euro:  $p = .5$ ?

Test statistic value:

sample  $\downarrow$       vs. proposed baseline  $\downarrow$

$$Z = \frac{\hat{p} - p_0}{\sqrt{\frac{p_0(1-p_0)}{n}}}$$

$\rightarrow$  S.F. comes from proposed baseline  $p_0$

Alternative Hypothesis

$$H_a : p > p_0$$

$$H_a : p < p_0$$

$$H_a : p \neq p_0$$

Rejection Region for  $\alpha$  level test:

$$z > z_\alpha$$

$$z < -z_\alpha$$

$$z < -z_{\alpha/2} \text{ or } z > z_{\alpha/2}$$

half & half

## Test for Population Mean (known variance)

Null hypothesis:  $H_0 : \mu = \mu_0$

Test statistic value:

Alternative Hypothesis

Rejection Region for  $\alpha$  level test:



## Test for Population Mean (known variance)

Null hypothesis:  $H_0 : \mu = \mu_0$

Test statistic value:

Sample      Proposed

$$Z = \frac{\bar{X} - \mu_0}{\sigma/\sqrt{n}}$$

normalized

$\bar{X} > \mu_0$   
 $\bar{X} < \mu_0$   
 $\bar{X} \text{ "far" } \mu_0$

Alternative Hypothesis

Rejection Region for  $\alpha$  level test:

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# Test for Population Mean (known variance)

1)  $\sigma$  vs.  $s$

$\Rightarrow z$  or  $t$

Null hypothesis:  $H_0 : \mu = \mu_0$

Test statistic value:

$z$

$\bar{X}$  vs.  $\mu_0$

$\bar{X} - \bar{Y}$  vs. diff (o).

$$Z = \frac{\bar{X} - \mu_0}{\sigma / \sqrt{n}}$$

Alternative Hypothesis

Rejection Region for  $\alpha$  level test:

$$H_a : \mu > \mu_0$$

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$\sigma$  not  $s$ .

## Test for Population Mean (known variance)

**Example:** Suppose a company is considering putting a new type of coating on bearings that it produces. Let  $\mu$  denote the true mean life for the new coating. The company would not want to make any (costly) changes unless evidence **strongly** suggested that  $\mu$  exceeds 1000 hours.

Decision if true  $\mu > 1000$ .

State the null and alternative hypotheses:

$$H_0: \mu = 1000 \quad (\mu \leq 1000)$$

$$H_A: \mu > 1000 \quad (\mu_0 = 1000)$$

Now, suppose the company tests  $n = 25$  randomly selected bearings with the new coating, and finds that the sample mean for life of the new coating is 1090 hours. Suppose we know that the population standard deviation is 130 hours. Conduct a test for the mean.

$$\sigma = 130$$

$$\bar{x} = 1090$$

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Now, suppose the company tests  $n = 25$  randomly selected bearings with the new coating, and finds that the sample mean for life of the new coating is 1090 hours. Suppose we know that the population standard deviation is 130 hours. Conduct a test for the mean. Compare

$$Z = \frac{\bar{X} - \mu_0}{\sigma/\sqrt{n}} = \frac{1090 - 1000}{130/\sqrt{25}} = 3.45 \text{ to } z_{.01} = 2.32 \text{ and } \text{Reject}$$

(conclude:  $\mu > 1000$ , so use new coating.)

# Errors in Hypothesis Testing

**Definitions:** *Type One and Type Two Errors*

Handwritten decision matrix for hypothesis testing:

|           |             | Reality      |             |
|-----------|-------------|--------------|-------------|
|           |             | $H_0$ true   | $H_0$ false |
| Decision: | $H_0$ true  | $1 - \alpha$ | $\beta$     |
|           | $H_0$ false | $\alpha$     | $1 - \beta$ |

Handwritten notes: "WRONG" is written in red above the  $\alpha$  cell. To the right of the matrix, "Type II" is written in blue.

A *type I error* is when the null hypothesis is rejected, but it is true. (False Positive).

A *type II error* is not rejecting  $H_0$  when  $H_0$  is false. (False Negative)



# Errors in Hypothesis Testing

## **Definitions:** *Type One and Type Two Errors*

A *type I error* is when the null hypothesis is rejected, but it is true. (False Positive).

We commit type I errors at a rate of  $\alpha$ .

A *type II error* is not rejecting  $H_0$  when  $H_0$  is false. (False Negative)

We commit type II errors at a rate of  $\beta$ .

## Errors in Hypothesis Testing

Typically, we specify the largest value of a type I error,  $\alpha$ , that can be tolerated, and then find a rejection region with that  $\alpha$ .

The resulting value of  $\alpha$  is often referred to as the **significance** level of the test.

Traditional levels of significance are .10, .05, and .01, though the level in any particular problem will depend on the seriousness of a type I error. The more serious the type I error, the smaller the significance level should be.

## Errors in Hypothesis Testing

We can also obtain a smaller value of  $\alpha$  - the probability of a type I error - by decreasing the size of the rejection region. However, this results in a larger value of  $\beta$  - the probability of a type II error - for all parameter values consistent with  $H_a$ .

No rejection region will simultaneously make  $\alpha$  and  $\beta$  small at the same time. A region must be chosen to strike a **compromise** between these errors.

# Errors in Hypothesis Testing

$\alpha$ :  $P(\text{get procedure, but we didn't need it or it doesn't work})$

$\beta$ :  $P(\text{don't get procedure but we should have})$

Suppose we are evaluating a medical procedure. It has the following outcomes:

1. Procedure works: subject is cured!
2. Procedure doesn't work: subject dies.

Do we want our test - which compared this procedure as  $H_a$  to a null hypothesis of "don't get the procedure" - to focus on decreasing  $\alpha$  or  $\beta$ ?

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$\alpha$ : probability of endorsing the test when it doesn't actually work. Result: subjects die.

$\beta$ : probability of *not* endorsing the test when it really works! Result: (subjects don't get treated.)  $\Rightarrow$  then die "n"

# Errors in Hypothesis Testing

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1. Procedure works: subject is cured!
2. Procedure doesn't work: subject dies.

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$\alpha$ : probability of endorsing the test when it doesn't actually work. Result: subjects die.

*$\alpha$  is for ~~being~~: don't change how you plan work.*

**Where is your risk tolerance?**

## Large Sample HT Example

**Example** An inventor has developed a new, energy-efficient lawn mower engine. He claims that the engine will run continuously for more than 5 hours (300 minutes) on a single gallon of regular gasoline. (The leading brand lawnmower engine runs for 300 minutes on 1 gallon of gasoline.)

$$H_a: \mu > 300$$

$$H_0: \mu = 300$$

From his stock of engines, the inventor selects a simple random sample of 50 engines for testing. The engines run for an average of 305 minutes. The *sample* standard deviation (s) is found at 30 minutes.

$$s = 30$$

(denno  $\sigma$ )

Test the hypothesis that the mean run time is more than 300 minutes. Use a 0.01 <sup>$\alpha$</sup>  level of significance.

## Large Sample Testing

Same as CIs

When the sample size is large, the z tests are easily modified to yield valid test procedures without requiring either a normal population distribution or known standard deviation.

Earlier, we used the key result to justify large-sample confidence intervals:  
A large  $n (> 30)$  implies that the standardized variable

has approximately a standard normal distribution.



## Large Sample Testing

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Earlier, we used the key result to justify large-sample confidence intervals:  
A large  $n$  ( $> 30$ ) implies that the standardized variable

$$Z = \frac{\bar{X} - \mu}{s/\sqrt{n}}$$

has approximately a standard normal distribution.

## Test for Population Mean (Large Sample)

Null hypothesis:  $H_0 : \mu = \mu_0$

Test statistic value:

Alternative Hypothesis

Rejection Region for  $\alpha$  level test:

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Rejection Region for  $\alpha$  level test:

# Test for Population Mean (Large Sample)

$n > 30$

Null hypothesis:  $H_0 : \mu = \mu_0$

Test statistic value:

$$Z = \frac{\bar{X} - \mu_0}{s/\sqrt{n}}$$

*data proposed*  
*normalized*

Alternative Hypothesis

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**Example, cont'd:** An inventor has developed a new, energy-efficient lawn mower engine. He claims that the engine will run continuously for more than 5 hours (300 minutes) on a single gallon of regular gasoline. (The leading brand lawnmower engine runs for 300 minutes on 1 gallon of gasoline.)

$n = 50$ ;  $\bar{X} = 305$ ,  $s = 30$ . Is  $\mu > \overset{\text{proposed}}{300}$ ? at  $\alpha = .01$ ?

Test the hypothesis that the mean run time is more than 300 minutes. Use a 0.01 level of significance.

**Example, cont'd:** An inventor has developed a new, energy-efficient lawn mower engine. He claims that the engine will run continuously for more than 5 hours (300 minutes) on a single gallon of regular gasoline. (The leading brand lawnmower engine runs for 300 minutes on 1 gallon of gasoline.)

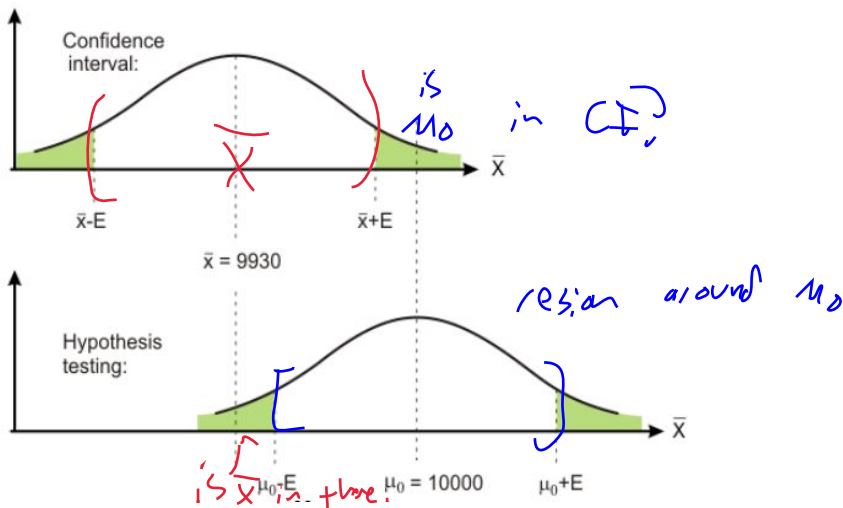
$n = 50$ ;  $\bar{X} = 305$ ,  $s = 30$ . Is  $\mu > 300$ ? at  $\alpha = .01$ ?

Test the hypothesis that the mean run time is more than 300 minutes. Use a 0.01 level of significance.

Compare  $Z = \frac{\bar{X} - \mu_0}{s/\sqrt{n}} = \frac{305 - 300}{30/\sqrt{50}} = 1.17$  to  $\underline{z_{.01}} = 2.32$  and **Fail to Reject**.

## Rejection Regions and CIs

Rejection regions have a lot in common with confidence intervals.





## p-values

The p-value measures the "extremeness" of the test statistic.

**Definition:** *p-value*:

A *p-value* is the probability, under the null hypothesis, that we would get a test statistic at least as extreme as the one we calculated.

or more.  $P(\text{random variable} \geq \bar{X} \text{ in "extremes"})$

**Idea:** So, the smaller the p-value, the more evidence there is in the sample data against the null hypothesis (so the story goes...).

So what constitutes "sufficiently small" and "extreme enough" to make a decision about the null hypothesis? : more extreme than  $\alpha$ .

## p-values: a Hypothesis Testing decision

1. Select a significance level (as before, the desired type I error probability), which would define the rejection region.

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2. Instead, calculate your test statistic (e.g. a  $z_{stat}$  or Z-score),

$$z = \frac{\bar{x} - \mu}{\sigma / \sqrt{n}}$$

Stats. norm. cdf ( $z$ )



## p-values: a Hypothesis Testing decision

1. Select a significance level (as before, the desired type I error probability), which would define the rejection region.
2. Instead, calculate your test statistic (e.g. a  $z_{stat}$  or  $Z$ -score),
3. ...and from it calculate the associated probability e.g.  $p = P(Z > z_{stat})$  - or the less than, two sided variant - and use that.

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4. decision rule is:

Reject if:  $p \leq \alpha$

*threshold*

*or 'extremeness'*

## p-values: a Hypothesis Testing decision

1. Select a significance level (as before, the desired type I error probability), which would define the rejection region.
2. Instead, calculate your test statistic (e.g. a  $z_{stat}$  or  $Z$ -score),
3. Compare the test statistic to the rejection region.
4. decision rule is:

$$\text{Reject if: } p \leq \alpha$$

Thus if the p-value exceeds the chosen significance level, the null hypothesis cannot be rejected at that level.

Note, the p-value can be thought of as the smallest significance level at which  $H_0$  can be rejected.

## p-values

The p-value measures the “extremeness” of the test statistic.

Note:

1. This probability is calculated assuming that the null hypothesis is true.
2. Beware: The p-value is not the probability that  $H_0$  is true, nor is it an (error probability!)
3. The p-value is between 0 and 1.

things don't  
happen

most central/  
common result

## p-values

The calculation of the p-value depends on whether the test is upper-, lower-, or two-tailed.

$\mu > \text{baseline}$

$\mu < \text{baseline}$

$\mu \neq \text{"far from" baseline}$

Each of these is the probability of getting a value at least as extreme as what was obtained (assuming  $H_0$  true).

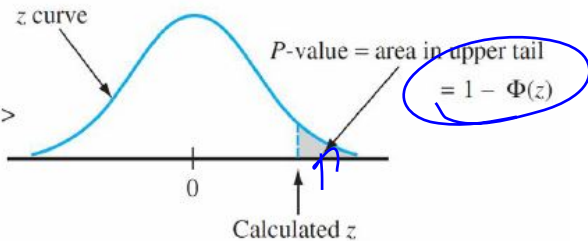


## p-values for Z tests

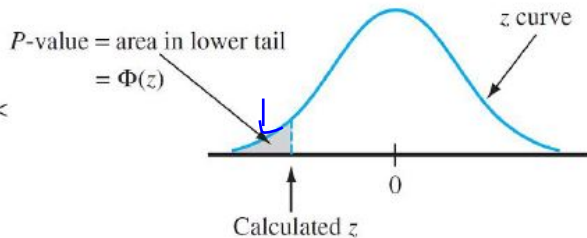
$$\Phi: \text{Stats.norm.cdf}(z)$$

1. **Upper-tailed test**

$H_a$  contains the inequality  $>$

2. **Lower-tailed test**

$H_a$  contains the inequality  $<$

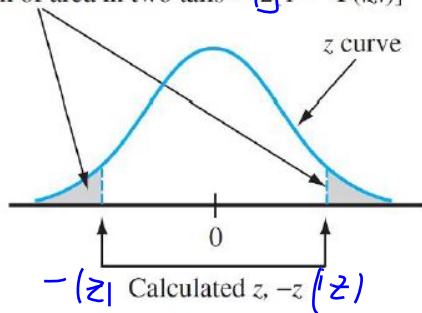


## p-values for Z tests

### 3. Two-tailed test

$H_a$  contains the inequality  $\neq$

P-value = sum of area in two tails =  $2[1 - \Phi(|z|)]$



## p-values for Z tests

Back to the lawnmower engine example: There, we had

$$H_0 : \mu = 300 \text{ vs } H_a : \mu > 300$$

and  $Z = 1.17$ .

What is the p-value for this result? What decision would you make?

## p-values for Z tests

Back to the lawnmower engine example: There, we had

$$H_0 : \mu = 300 \text{ vs } H_a : \mu > 300$$

and  $Z = 1.17$ .

What is the p-value for this result? What decision would you make?

Hopefully the same one! In particular,

$$P(Z > 1.17) = 1 - \text{stats.norm.cdf}(1.17) = .12 = p > \alpha$$

line 1:

$$Z = \frac{\bar{X} - \mu_0}{\sigma / \sqrt{n}}$$

line 2:

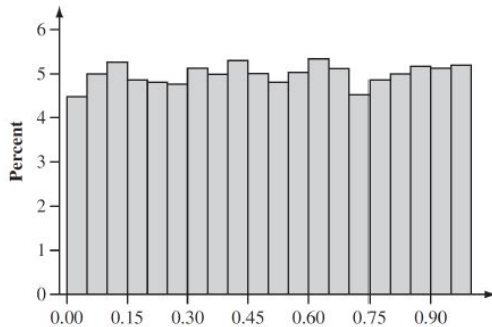
OR stats.norm.pdf  
(1.17)

12% of  
normals are  
 $\geq 1.17$ .

## Distribution of p-values

Figure below shows a histogram of the 10,000 P-values from a simulation experiment under a null  $\mu = 20$  (with  $n = 4$  and  $\sigma = 2$ ).

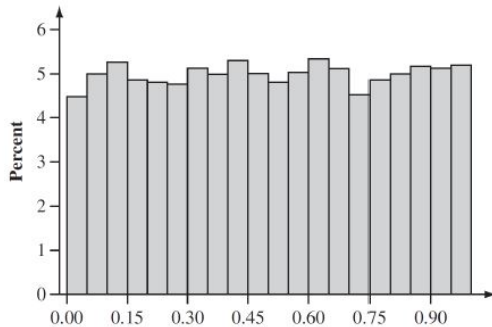
When  $H_0$  is true, the probability distribution of the P-value is a uniform distribution on the interval from 0 to 1.



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These data comes from a process where the null hypothesis is *TRUE*. Rejecting the null hypothesis would be an error.

## Distribution of p-values

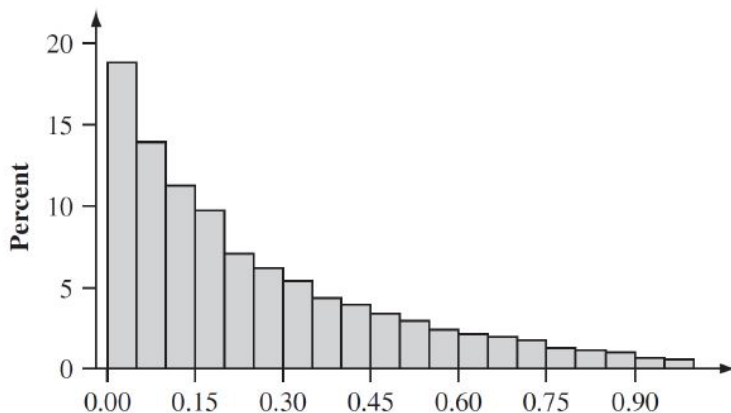
About 4.5% of these p-values are in the interval from 0 to .05.

Thus when using a significance level of .05, the null hypothesis is rejected in roughly 4.5% of these 10,000 tests.

If we continued to generate samples and carry out the test for each sample at significance level .05, in the long run, 5% of the p-values would be in the first class interval.

## Distribution of p-values

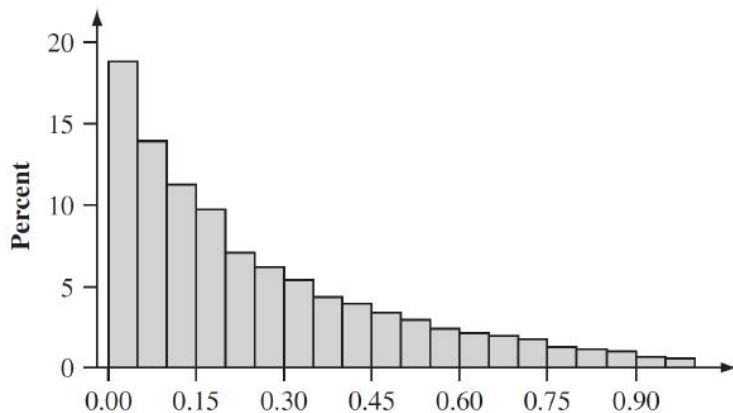
A histogram of the p-values when we simulate under an alternative hypothesis. There is a much greater tendency for the p-value to be small (closer to 0) when  $\mu = 21$  than when  $\mu = 20$





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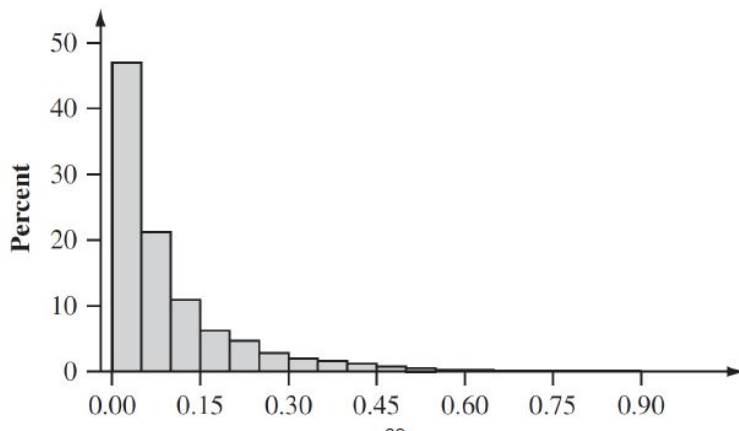
Again,  $H_0$  is rejected at significance level .05 whenever the p-value is at most .05 (in the first bin).

Unfortunately, this is the case for only about 19% of the p-values. So only about 19% of the 10,000 tests correctly reject the null hypothesis; for the other 81%, a type II error is committed.

The difficulty is that the sample size is quite small and 21 is not very different from the value asserted by the null hypothesis (the “effect size” is small).

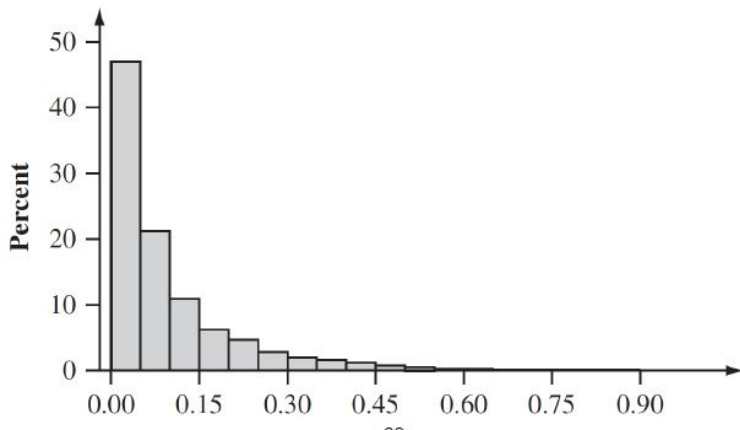
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The figure below illustrates what happens to the pvalue when  $H_0$  is false because  $\mu = 22$ .



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Again, these data come from  $H_a$ , but we reach the correct conclusion more often. The

## Distribution of p-values

The histogram is even more concentrated toward values close to 0 than was the case when  $\mu = 21$ .

In general, as  $\mu$  moves further to the right of the null value 20, the distribution of the p-value will become more and more concentrated on values close to 0.

Even here a bit fewer than 50% of the p-values are smaller than .05. So it is still slightly more likely than not that the null hypothesis is incorrectly not rejected. Only for values of  $\mu$  much larger than 20 (e.g., at least 24 or 25) is it highly likely that the p-value will be smaller than .05 and thus give the correct conclusion.

## Test for Population Mean (Small Sample)

When the sample size is small and the population is normal, we can use a t-test.

Null hypothesis:  $H_0 : \mu = \mu_0$

Test statistic value:

Alternative Hypothesis

Rejection Region for  $\alpha$  level test:

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## Test for Population Mean (Small Sample)

When the sample size is small and the population is normal, we can use a t-test.

Null hypothesis:  $H_0 : \mu = \mu_0$

*use s instead of  $\sigma$ .*

Test statistic value:

$$t = \frac{\bar{X} - \mu_0}{s/\sqrt{n}}$$

Alternative Hypothesis

$$H_a : \mu > \mu_0$$

$$H_a : \mu < \mu_0$$

$$H_a : \mu \neq \mu_0$$

Rejection Region for  $\alpha$  level test:

$$t > t_\alpha$$

$$t < -t_\alpha$$

$$t < -t_{\alpha/2} \text{ or } t > t_{\alpha/2}$$

## t example.

The Brinell scale is a measure of how hard a material is. An engineer hypothesizes that the mean Brinell score of all subcritically annealed ductile iron pieces is not equal to 170. It is known that these scores follow a normal distribution.

The engineer measured the Brinell score of 25 pieces of this type of iron and calculated the sample mean to be 174.52 and the sample standard deviation to be 10.31.

Perform a hypothesis test that the true average Brinell score is not equal to 170, as well as the corresponding confidence interval. Set  $\alpha = 0.01$ .

t sol:

We have:  $\bar{X} = 174.52$ ;  $n = 25$ ;  $s = 10.31$ , and underlying normal. That means that

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is normally distributed... but we need to use  $s$ ! It's  $t$ -time! That would give us a test statistic of

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From 'is not equal to,' we know we're testing the two sided  $H_a : \mu \neq 170$ , so we compared this to  $t_{\alpha/2} = \text{stats.t.ppf}(.995, 24) = 2.79$

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Our test statistic  $t$  is less than  $t_{\alpha/2}$ , so we **do not reject**, or there is not sufficient evidence to discount the null hypothesis.



"The Tortoise And The Hare" is actually  
a fable about small sample sizes.

## Comparing 2 Means

We now have the framework to finish asking most of the questions you'll most often see for binary decisions. We need to flesh out what to do with 2 samples for both Hypothesis testing and for  $t$  statistics.

**Spoilers:** The same way we could test a null of  $H_0 : \mu = \mu_0$  against a two-sided alternative by looking at the CI for  $\mu$  of our sample, we can look at a CI for  $\mu_1 - \mu_2$  to get similar inference to make a decision like  $\mu_1 \neq \mu_2$ .



# Comparing 2 Means

*Basic Assumptions:*

Note: We haven't made any distributional assumptions, for now.

## Comparing 2 Means

### *Basic Assumptions:*

1.  $X_1, X_2, \dots, X_n$  are a random sample from distribution 1 with mean  $\mu_1$  (or  $\mu_X$ ) and SD  $\sigma_1$ .
2.  $Y_1, Y_2, \dots, Y_m$  are a random sample from distribution 2 with mean  $\mu_2$  and SD  $\sigma_2$ .
3. The  $X$  and  $Y$  sample are independent of one another.

Note: We haven't made any distributional assumptions, for now.

## Comparing 2 Means: Review

The natural estimator of  $\mu_1 - \mu_2$  is \_\_\_\_\_.

Inferential procedures are based on standardizing estimators, so as before we need the mean and standard deviation of \_\_\_\_\_.

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Mean of  $\bar{X} - \bar{Y}$ :

$$E[\bar{X} - \bar{Y}] = E\left[\frac{\sum_i X_i}{n} - \frac{\sum_j Y_j}{m}\right] = \dots = \mu_1 - \mu_2$$

Variance/Standard Deviation of  $\bar{X} - \bar{Y}$ :

$$\begin{aligned} Var[\bar{X} - \bar{Y}] &= Var\left[\frac{\sum_i X_i}{n} - \frac{\sum_j Y_j}{m}\right] = Var[\bar{X}] + Var[\bar{Y}] = \dots \\ &= \frac{\sigma_1^2}{n} + \frac{\sigma_2^2}{m} \end{aligned}$$

## Comparing 2 Means

Normal Populations with known variances:

If both populations are normal and independent,  $\bar{X} - \bar{Y}$  is normally distributed with expected value  $\mu_1 - \mu_2$  and standard deviation:  $\sqrt{\frac{\sigma_1^2}{n} + \frac{\sigma_2^2}{m}}$ . So:

$$(\bar{X} - \bar{Y}) \sim N\left(\mu_1 - \mu_2, \frac{\sigma_1^2}{n} + \frac{\sigma_2^2}{m}\right)$$

Standardizing our estimator gives:

$$Z = \frac{(\bar{X} - \bar{Y}) - (\mu_1 - \mu_2)}{\sqrt{\frac{\sigma_1^2}{n} + \frac{\sigma_2^2}{m}}}$$

Therefore, the  $(1 - \alpha) \cdot 100\%$  confidence interval is:

$$(\bar{X} - \bar{Y}) \pm z_{\alpha/2} \sqrt{\frac{\sigma_1^2}{n} + \frac{\sigma_2^2}{m}}$$

## Test Procedures for Normal Populations with Known Variances

Null hypothesis:  $H_0 : \mu_1 - \mu_2 = \Delta_0$  (often 0)

Test statistic value:

Alt Hypothesis

Rejection Region

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## Large Sample Tests

The assumptions of normal population distributions and known standard deviations are fortunately unnecessary when both sample sizes are sufficiently large. WHY?

Furthermore, using \_\_\_\_\_ and \_\_\_\_\_ in place of \_\_\_\_\_ and \_\_\_\_\_ gives a variable whose distribution is approximately standard normal:

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## Large Sample Tests

### Example:

Data on daily calorie intake both for a sample of teens who said they did not typically eat fast food and another sample of teens who said they did usually eat fast food.

| Eat Fast Food | Sample Size | Sample Mean | Sample SD |
|---------------|-------------|-------------|-----------|
| No            | 663         | 2258        | 1519      |
| Yes           | 413         | 2637        | 1138      |

Does this data provide strong evidence for concluding that true average calorie intake for teens who typically eat fast food exceeds more than 200 calories per day the true average intake for those who don't typically eat fast food? Let's investigate by carrying out a test of hypotheses at a significance level of 0.05.

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$$H_0 : \mu_2 - \mu_1 = 200; \quad H_a : \mu_2 - \mu_1 > 200$$

Plan: Reject if  $p < .05$ .



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$$z_{stat} = \frac{(2637 - 2258) - (200)}{\sqrt{\frac{1519^2}{663} + \frac{1138^2}{413}}} = 2.20 \quad P(Z < 2.20) = .987$$

## Comparing 2 Means: Small Sample

For large samples, the CLT allows us to use these methods we have discussed even when the two populations of interest are not normal.

In practice, it can happen that at least one sample size is small and the population variances have unknown values.

Without the CLT at our disposal, we proceed by making specific assumptions about the underlying population distributions.

## Comparing 2 Means: Small Sample

When the population distributions are both normal, the standardized variable

has approximately a  $t$  distribution with df  $\nu$  estimated from the data by:

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$$\nu = \frac{\left( \frac{s_1^2}{m} + \frac{s_2^2}{n} \right)^2}{\frac{(s_1^2/m)^2}{m-1} + \frac{(s_2^2/n)^2}{n-1}}$$

## Comparing 2 Means: Small Sample

The two-sample  $t$  confidence interval for  $\mu_1 - \mu_2$  with confidence level  $(1 - \alpha) \cdot 100\%$  is then:

$$(\bar{X} - \bar{Y}) \pm t_{\alpha/2, \nu} \sqrt{\frac{s_x^2}{n} + \frac{s_y^2}{m}}$$

## Test Procedures for Normal Populations with Unknown Variances

Null hypothesis:  $H_0 : \mu_1 - \mu_2 = \Delta_0$  (often 0)

Test statistic value:

Alt Hypothesis

Rejection Region

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## Test for Equivalence of Proportions

Theoretically, we know that:

has approximately a standard normal distribution.

When  $H_0 : p_1 - p_2 = 0$  is true, we have  $p_1 = p_2$ , which simplifies this:

However, this  $Z$  cannot serve as a test statistic because the value of  $p$  is unknown;  $H_0$  asserts only that there is a common value of  $p$ , but does not say what that value is.

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Under the null hypothesis, we assume that  $p_1 = p_2 = p$ , instead of separate samples of size  $m$  and  $n$  from two different populations (two different binomial distributions).

So, we really have a single sample of size  $m + n$  from one population with proportion  $p$ .

The total number of individuals in this combined sample having the characteristic of interest is  $X + Y$ .

The estimator of  $p$  is then:

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Using  $\hat{p}$  and  $1 - \hat{p}$  in place of  $p$  and  $1 - p$  in our old equation gives a test statistic having approximately a standard normal distribution when  $H_0$  is true.

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Alt Hypothesis

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## Now what?

We're almost done talking about CI's and Hypothesis tests. Where are our gaps?

1. We can compare samples or do inference on a single sample when one of the following conditions is met:
  - 1.1 The sample or samples are  $n > 30$  (or success/fail  $> 10$ ) (use  $Z$ !)
  - 1.2 The sample or samples are small and underlying normal (use  $t$ !)
2. What are we missing?
  - 2.1 The samples are small and *not normal*
  - 2.2 We aren't trying to do inference on means at all, but something else!
  - 2.3 We will cover 2 cases of this next lecture: variances and bootstrapping.

# Daily Recap

Today we learned

1. Intro and Basics of Hypothesis Tests

Moving forward:

- nb day Friday for HTs

Next time in lecture:

- More Hypotheses!