# Hypothesis Testing

Basics and Tests

### Hypothesis Testing

- Introduction to Hypothesis
- Type I and Type II Errors
- Test of Hypothesis





#### **Example 1:**

Pepsico India sells a soft drink in a can container having 250ml of the drink.

Since this information is on the label, we assume it to be true.

But is it really true?





#### Example 1:

Pepsico India sells a soft drink in a can container having 250ml of the drink.

#### As a customer:

We want the volume to be at least 250ml. Quantity of Drink >= 250ml

#### As a manufacturer:

We want the volume of the drink to be exactly 250ml. No more, no less Quantity of Drink = 250ml





So we collected 100 Pepsi cans from all over India (to randomize the sample)

Then we measured the quantity of soft drink in each can in the sample and find the mean quantity for all 100 cans.

Using those sample means or measurements, we can TEST THE ASSUMPTION (i.e. the STATUS QUO)





#### Example 2:

An auto manufacturer had designed a new engine which claims to reduce the fuel consumption. It claims that the new engine makes more efficient use of fuel and performs better than the old engine which used to run at 30 miles per gallon.

Company now need to run some tests to look for statistical evidence to support the **claim** that the new engine offers better fuel efficiency.





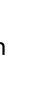
#### **Company Claim:**

Fuel Efficiency > 30

But it cold be well above or below 30 mpg.

The manufacturer is making a claim it wishes to test.

It is not testing an assumption (i.e. Status Quo)







When trying to formulate a statistical hypothesis, think about the following:

Are we testing an assumption (status quo) that already exists? (Pepsi Can)
Or

Are we testing a claim (assertion) which may be true, if not then truth is something else? (New Engine)

Say, if the manufacturer now tested the engine and fix it in a car and rolled it out in the market saying the car performs 35 mpg; and now we want to test it, we will be testing an assumption here and not a claim.



#### Null Hypothesis:

The null hypothesis is the initial position. It is the status-quo position. It is the position that is rejected or fails to be rejected. It is the position that needs to be validated. It is the position that needs to be tested.

e.g.: Pepsi Can contains 250 ml of soft drink

#### Alternate Hypothesis:

The alternate hypothesis is the contrary position to NULL hypothesis. If there are statistically significant evidences that suggest that the alternate hypothesis is valid, then the NULL hypothesis is rejected.

e.g.: Pepsi Can does not contain 250 ml of soft drink (otherwise of NULL)

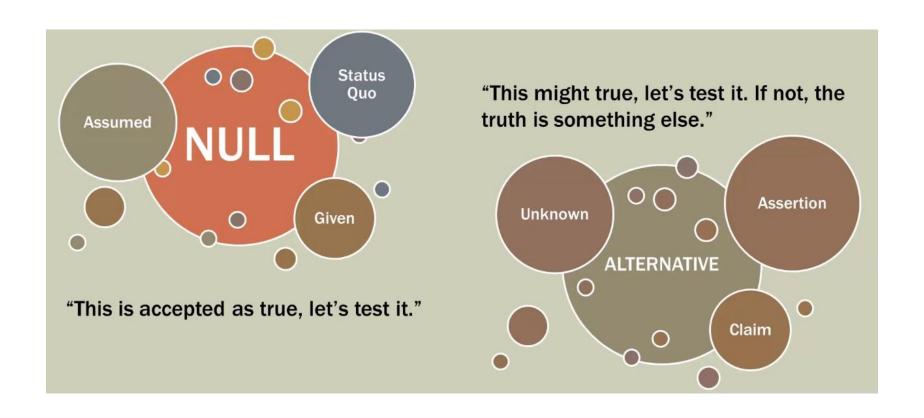


By Definition, null and alternate hypothesis are opposite; mutually exclusive. They both cannot be true.

The null is either rejected or not. Only if the null is rejected can we move with the alternate hypothesis.

Null and alternate hypothesis depends on the question we are trying to ask. A person can start with either the null hypothesis or the alternate hypothesis, and then form the other as a complement to the first.







Hypothesis testing can be used to determine whether a statement about the value of a population parameter should or should not be rejected.

<u>Null hypothesis:</u> denoted by  $H_0$ , is a tentative assumption about a population parameter.

<u>Alternate hypothesis:</u> denoted by  $H_a$ , is the opposite of what is stated in the null hypothesis.

e.g. Let's say a court room trial:

H<sub>0</sub>: The accused is innocent

H<sub>a</sub>: The accused is guilty



$H_0$	$H_a$
Assumption, status quo, nothing new	Rejection of an assumption
Assumed to be "true"; a given.	Rejection of an assumption or the given.
Negation of the research question	Research question to be "proven"
Always contains an equality $(=, \leq, \geq)$	Does not contain equality $(\neq, <, >)$

Based on the last property, we can derive the possible null/alternative pairs:

$$H_0$$
:  $\mu \ge \mu_0$ 

$$H_{\rm a}: \ \mu < \mu_0$$

$$H_0$$
:  $\mu \leq \mu_0$ 

$$H_{\rm a}: \ \mu > \mu_0$$

$$H_0$$
:  $\mu = \mu_0$ 

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



#### **Example:**

The NY city provides one of the most comprehensive emergency medical services in the world. Operating in a multiple hospital system with approximately 200 mobile medical units, the service goal is to respond to medical emergencies with a mean time of 12 minutes or less.

The director of medical services wants to formulate a hypothesis test that could use a sample of emergency response times to determine whether or not the service goal of 12 minutes or less is being achieved.



Hypothesis	Conclusion & Action
$H_0: \mu <= 12$	The response time goal is met by Emergency Service team. No action required
$H_a: \mu > 12$	The response time goal is not met by Emergency Service team. Appropriate follow up actions are required.

#### where,

 $\mu$  = mean response time for the population of medical emergency response unit.



#### **Few Important Guidelines:**

All statistical conclusions are made in reference to the null hypothesis.

We either **reject** the null hypothesis or **fail to reject** the null hypothesis; we **do not accept** the null hypothesis.

If we **reject** the null hypothesis, then we conclude the data supports the alternative hypothesis.

However, if we fail to reject the null hypothesis, it does not mean we have proven the null hypothesis is "true"



#### Example 1:

Is there anything we can assume to be true?

Yes. 250 ml in container can be assumed to be true

Which hypothesis pair to be selected?

$$H_0$$
:  $\mu = \mu_0$ 

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

$$H_0 = 250 ml$$

$$H_a \neq 250 \text{ ml}$$

If the cans are filled properly, then we **fail to reject** the null hypothesis.

We are not saying that we have proven the null. Just our assumption has held up.





#### Example 1:

According to the United States Department of Agriculture, in 2009 the average farm size in Texas was 2.3 sq. km. Due to large agriculture business in the past decade, the department wants to know if the current (2019) farm size is larger than it was in 2009.

Establish a null and alternative hypothesis.

#### **Solution:**

What is our assumption?

We assume that there has been no change in the farm size since 2009.

This is our null hypothesis.

$$H_0: \mu \le \mu_0$$
  
 $H_a: \mu > \mu_0$ 

 $H_0 \le 2.3 \text{ sq. km}$ 

 $H_a > 2.3 \text{ sq. km}$ 





Since hypothesis tests are based on sample data, we must allow for the possibility of errors.

#### Type I error: False Positive

This error occurs when we reject the assumption (null hypothesis) when it should not have been rejected.

#### **Type II error: False Negative**

When we fail to reject the assumption (null hypothesis) when it should have been rejected.



#### **Example: NY Medical Emergency Unit**

Our Hypothesis was:

 $H_0: \mu <= 12$ 

Our Alternate Hypothesis was:

 $H_a: \mu > 12$ 



	Population Condition	
Conclusion	<b>H</b> <sub>0</sub> True (μ <= 12)	$H_0$ False ( $H_a$ True) ( $\mu > 12$ )
Accept <b>H</b> <sub>0</sub>	True Positive	False Negative  Type II Error
Reject <b>H</b> <sub>0</sub>	False Positive <b>Type I Error</b>	True Negative



#### **Example:**







#### Case:

Let's say we have population mean  $\mu$  for a population under analysis. The hypothesized mean for the population under analysis is  $\mu_0$ . Test if the hypothesized mean comes from the same population under analysis.

$$H_0$$
:  $\mu = \mu_0$   $H_a$ :  $\mu \neq \mu_0$ 



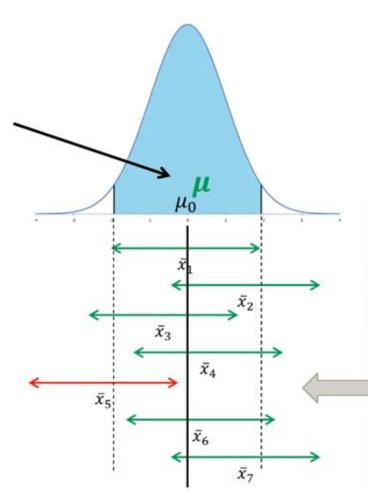
 $\alpha = .05$ 

95% of all sample means  $(\bar{x})$  are hypothesized to be in this region.

Fail to reject null hypothesis Fail to reject null hypothesis Fail to reject null hypothesis Fail to reject null hypothesis

#### Reject null hypothesis

Fail to reject null hypothesis Fail to reject null hypothesis



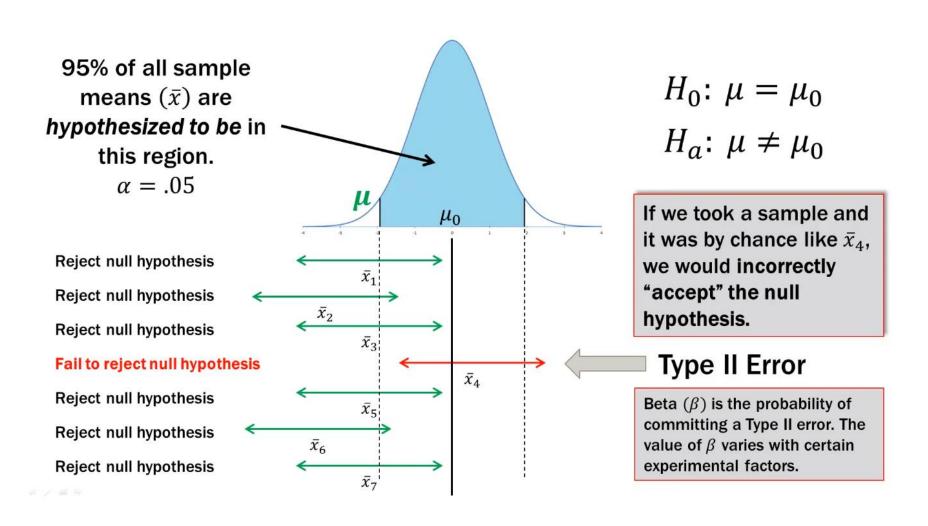
 $H_0$ :  $\mu = \mu_0$   $H_a$ :  $\mu \neq \mu_0$ 

If we took a sample and it was by chance like  $\bar{x}_5$ , we would incorrectly reject the null hypothesis.

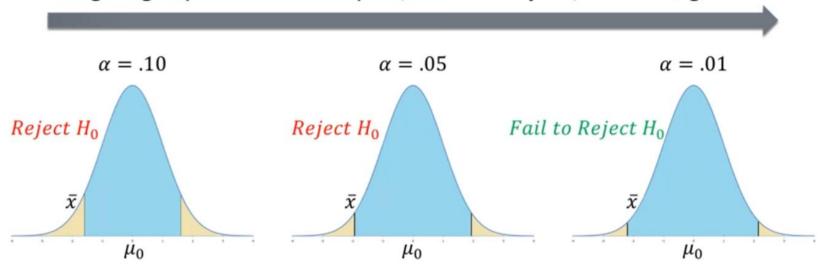
#### Type I Error

 $\alpha$  is the "level of significance" or our tolerance for making a Type I error.





As  $\alpha$  decreases so does the chance of Type I error. The critical value to reject the null hypothesis moves outward thus "capturing" more sample means. Kind of like moving the goal posts on a football pitch; the wider they are, more kicks go in.



However the move outward of the critical values may also "capture" a mean from a different population off to the side. We would fail to reject the null when indeed we should. Thus the chance of Type II error increases as  $\alpha$  decreases.

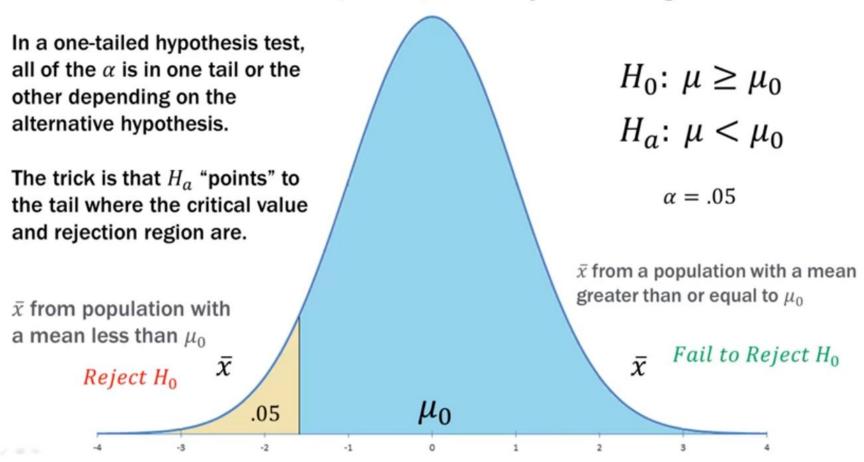


Visualizing One Tailed Test Rejection



### One Tailed Test Rejection

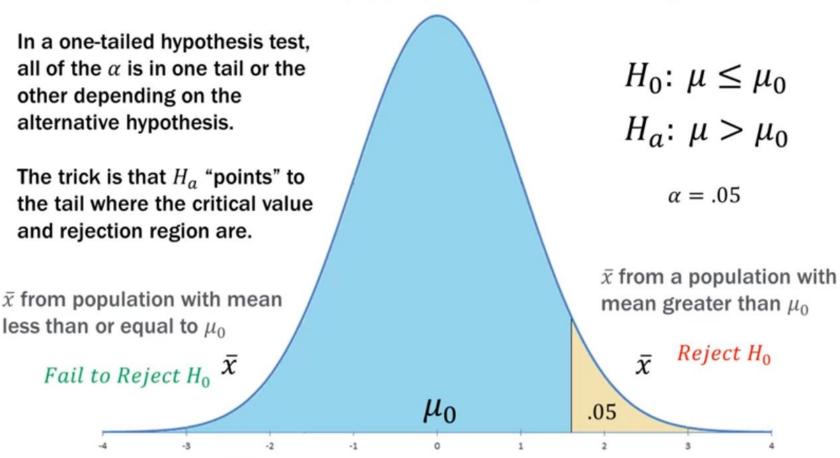
#### The One-tailed (Lower) Test Rejection Region





### One Tailed Test Rejection

#### The One-tailed (Upper) Test Rejection Region



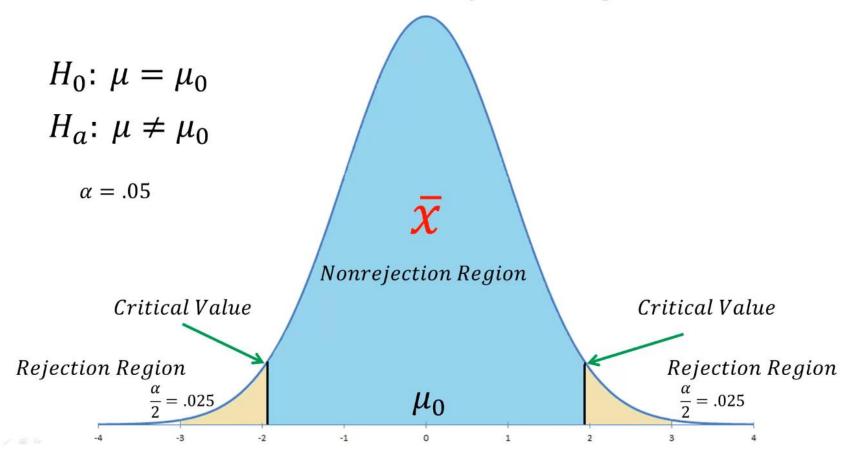


Visualizing Two Tailed Test Rejection



### Two Tailed Test Rejection

#### The Two-tailed Test Rejection Region



# Test of Hypothesis



### Test of Hypothesis

# Test of Hypothesis

Large Sample Tests

# Small Sample Test

Testing
Population
Mean
(One Sample)

Testing
Population
Mean
(Two Sample)

t-test

One Sample
Two Sample

Paired t-

Chisquare test

F - test



### Test of Hypothesis

#### **Large Sample Test**

- Tests are based on large sample on which hypothesis is test (sample size n at least >30)
- Exact Sampling Distributions are not available.
- Test are based on C.L.T distribution.

#### **Small Sample Test**

- Tests are based on small sample on which hypothesis is test
- Exact Sampling Distributions are available.

The **exact sampling distribution** is the sampling distribution of a statistic (estimator, e.g. sample mean x bar) over all the possible sample drawn from a population (finite or infinite).



### When to use z Vs t - distribution

When  $\sigma$  (sigma of population) is known -> use standard normal or z distribution

When  $\sigma$  (sigma of population) is unknown -> use t-distribution

#### **Important:**

Some books indicate the usage of z-distribution is acceptable any time when  $n \ge 30$ , irrespective of sigma known or unknown.

However you can use the t-distribution anytime you do not know sigma, irrespective of n.

**The reason behind this is,** as the sample size increases, the z-distribution and t-distribution actually converges.



# Large Sample Test



# Testing Population Mean (μ): One Sample

#### When to use?

If you want to test whether or not a given sample is taken from a population whose mean value is specified ( $\mu$ )

How to calculate statistics:

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

Where,

 $\overline{x}$  = Sample mean of 'n' observations.

 $\sigma$  = Population S.D. (known)

 $\mu$  = Population mean



### Testing Population Mean (μ): One Sample

$$z = \frac{\bar{x} - \mu_0}{\frac{\sigma}{\sqrt{n}}}$$

Standard Error of the Mean (standard deviation of the sampling distribution)

$$z = \frac{\bar{x} - \mu_0}{\sigma_{\bar{x}}}$$

 $\bar{x} =$ sample mean

 $\mu_o$  = hypothesized population mean

 $\sigma$  = population standard deviation (given)

n =sample size

Is this z-test value in the nonrejection region or the rejection region?



Here we test whether the given sample belongs to population having mean =  $\mu_0$ 

 $\mu_0$  =Specified value of mean

- $H_0$ : Mean is equal to  $\mu_0$
- $H_a$ : Mean is not equal to  $\mu_0$



#### Example

A report from 6 years ago indicated that the average gross salary for a business analyst was \$69,873. Since this survey is now outdated, the Bureau of Labor Statistics wishes to test this figure against current salaries to see if the current salaries are statistically different from the old ones.

Based on other studies, we will assume  $\sigma = \$13,985$ .

For this study, the BLS will take a sample of 112 current salaries.



#### Solution

Step 1: Establish Hypothesis

$$H_0$$
:  $\mu = $69,873$ 

$$H_0$$
:  $\mu = \$69,873$   $H_a$ :  $\mu \neq \$69,873$ 

Step 2: Determine Appropriate Statistical Test and Sampling Distribution

This will be a two-tailed test. Salaries could be higher OR lower.

Since  $\sigma$  is known, we will use the z-distribution.

$$z = \frac{\bar{x} - \mu_0}{\frac{\sigma}{\sqrt{n}}}$$

Step 3: Specify the Type I error rate (significance level)

$$\alpha = .05$$

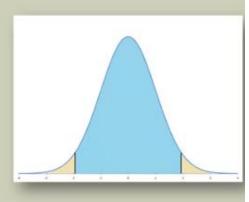
Step 4: State the decision rule

If 
$$z > 1.96$$
, reject  $H_0$ 

If 
$$z < 1.96$$
, reject  $H_0$ 

Step 5: Gather data

$$n = 112, \bar{x} = $72,180$$



The mean here (x bar) looks higher. But the question is: Is it high enough to be statistically significant ??

#### Solution

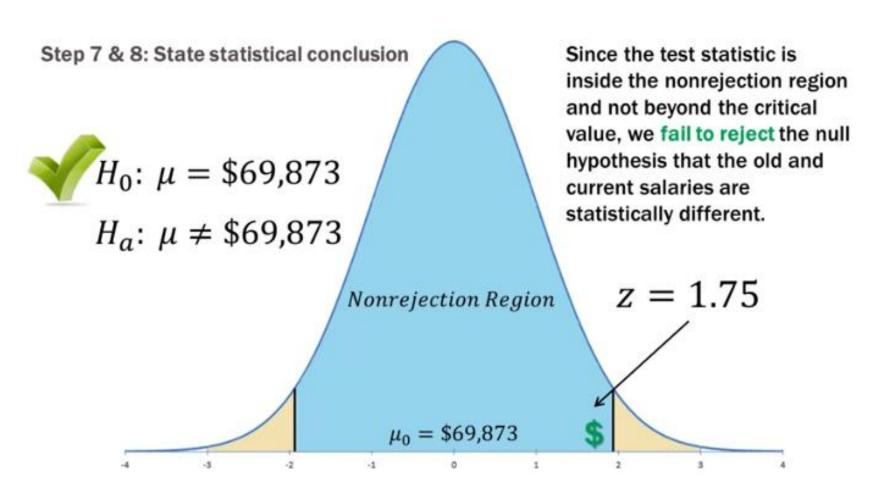
The mean here (x bar) looks higher. But the question is: Is it high enough to be statistically significant ??

$$\bar{x} = \$72,180$$
 $\mu_o = \$69,873$ 
 $\sigma = \$13,985$ 
 $n = 112$ 
 $z = \frac{\bar{x} - \mu_0}{\frac{\sigma}{\sqrt{n}}}$ 
 $z = \$72,180 - \$69,873$ 
 $z = \frac{\$13,985}{\sqrt{112}}$ 
 $z = 1.75$ 

The z value from the z – table for alpha = 0.05 and hence Confidence Interval is '1.96' and our z critical value is '1.75' which is less. Hence it falls within the non-rejection region. Hence, we fail to reject Null hypothesis that the old and current salaries are statistically different.



#### Solution



### Testing Population Mean (μ): Two Sample

#### When to use?

If you want to test whether if two population means are equal or unequal.

How to calculate statistics:

$$z = \frac{(\overline{x}_1 - \overline{x}_2) - (\mu_1 - \mu_2)}{\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}}$$

#### Where,

 $\overline{x}$  = Sample mean of 'n' observations.

 $\sigma 1$  = Population S.D. (known) of sample one

 $\mu$ 1 = Population mean of sample one

2 = Sample mean of 'n2' observations.

 $\sigma$ 2 = Population S.D. (known) of sample two

 $\mu$ 2 = Population mean of sample one



# **Small Sample Test**



### Small Sample Test

In small sample test, the sampling distribution that the test statistic follow are majorly classified in three distributions:

- X<sup>2</sup> distribution (chi-square)
- t-distribution
- F-distribution



#### When to use?

If you want to test whether a given sample is coming from a population or not, whose mean is specified value and population variance is unknown.

$$t = \frac{\overline{x} - \mu_0}{s / \sqrt{n}}$$

Where,

 $\overline{x}$  = Sample mean of 'n' observations.

s = S.D. of sample of 'n' observations (sample).

 $\mu_0$  = Population mean.



$$t = \frac{\bar{x} - \mu_0}{\frac{S}{\sqrt{n}}}$$

Standard Error of the Mean (standard deviation of the sampling distribution)

$$t = \frac{\bar{x} - \mu_0}{s_{\bar{x}}}$$

 $\bar{x} = \text{sample mean}$ 

 $\mu_o$  = hypothesized population mean

s =sample standard deviation

n =sample size

Is this t-test value in the nonrejection region or the rejection region based on df = n - 1?



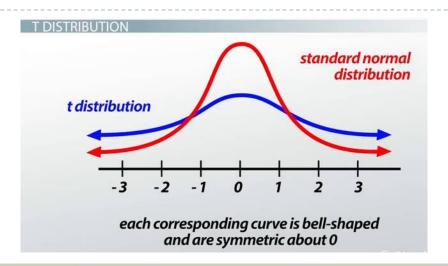
Here we test whether the given sample belongs to population having mean =  $\mu_0$ 

 $\mu_0$  =Specified value of mean

- $H_0$ : Mean is equal to  $\mu_0$
- $H_a$ : Mean is not equal to  $\mu_0$



### t – distribution properties



- A smaller sample size means more sampling error
- This sampling error due to small n means a higher probability of extreme sample means
- More probability in the tails means the center hump of the tdistribution must come downward.
- This process "squishes" the distribution slightly downward and outward thus taking the critical values along for the ride
- Given the same  $\alpha$  and s, a smaller n will push the critical values further outward in the tail(s) due to the uncertainty associated with small n



#### **Example:**

A report from 6 years ago indicated that the average gross salary for a business analyst was \$69,873. Since this survey is now outdated, the Bureau of Labor Statistics wishes to test this figure against current salaries to see if the current salaries are statistically different from the old ones.

Based on this sample, we found s = \$14,985. We do not know  $\sigma$  and will therefore have to estimate it using s.

For this study, the BLS will take a sample of 12 current salaries.



#### **Solution:**

Step 1: Establish Hypothesis

$$H_0$$
:  $\mu = $69,873$ 

$$H_0$$
:  $\mu = \$69,873$   $H_a$ :  $\mu \neq \$69,873$ 

Step 2: Determine Appropriate Statistical Test and Sampling Distribution

This will be a two-tailed test. Salaries could be higher OR lower.

$$t = \frac{\bar{x} - \mu_0}{\frac{S}{\sqrt{n}}}$$

Since  $\sigma$  is unknown and n is small, we will use the t-distribution.

#### Step 3: Specify the Type I error rate (significance level)

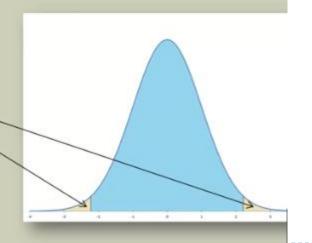
$$\alpha = .05$$

#### Step 4: State the decision rule

For 
$$df = 11$$
 If  $t > 2.201$ , reject  $H_0$  If  $t < -2.201$ , reject  $H_0$ 

Step 5: Gather data

$$n = 12, \bar{x} = $79,180$$



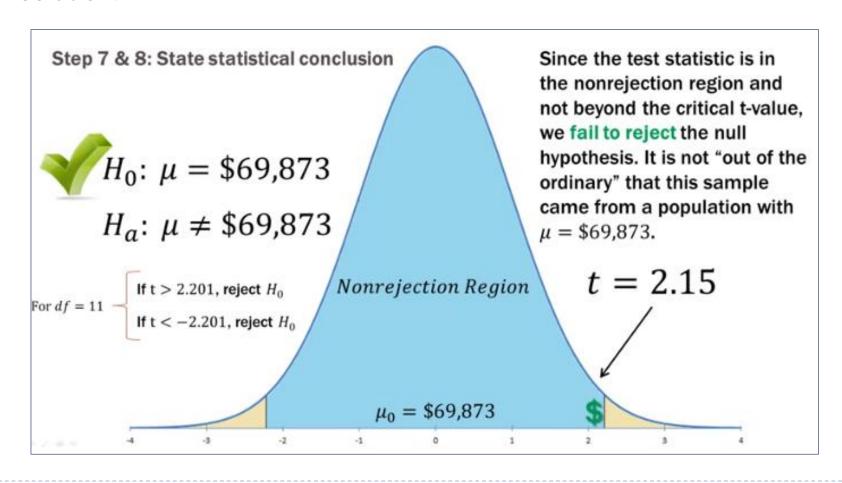
#### **Solution:**

Step 6: Calculate test statistic 
$$\bar{x} = \$79,180 \\ \mu_o = \$69,873 \\ s = \$14,985 \\ n = 12$$
 
$$t = \frac{\$79,180 - \$69,873}{\$14,985} \\ t = \frac{\$14,985}{\sqrt{12}}$$
 
$$t = 2.15$$

Since the t value is '2.15' which is lower than the t value of '2.201' for alpha of 0.05, hence we fail to reject the null hypothesis. Which means that this sample do come out of the sample with mean of \$69,873.



#### **Solution:**





#### When to use?

If you want to test whether given two samples belongs to same population or not. This can be tested by checking equality of means of two samples.

$$t = \frac{\overline{x}_1 - \overline{x}_2}{s_p * \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}}$$

Where,

 $\overline{x}_1$  = Sample mean of  $n_1$  observations

 $\overline{x}_2$  = Sample mean of  $n_2$  observations

 $S_p$  = Pooled S.D. of two samples



### Hypothesis on: Two Sample t test

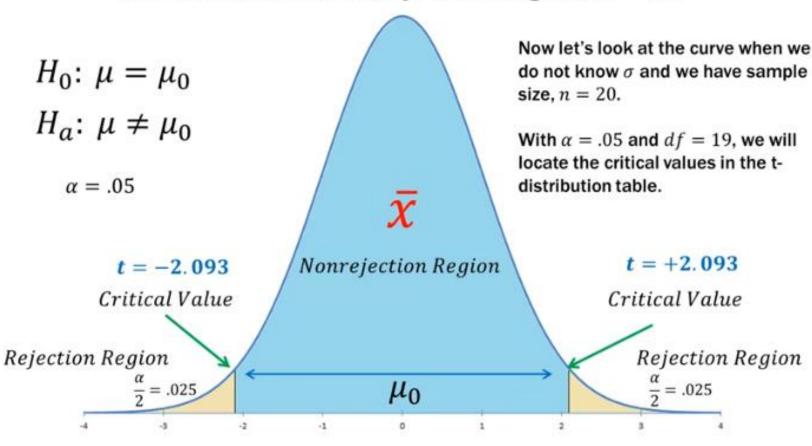
Here we test whether the given two sample belongs to same population.

- $H_0$ : Mean of two samples is same.
- H<sub>a</sub>: Mean of two samples is not same.
- $H_0$ : Two samples belongs to same population.
- H<sub>a</sub>: Two samples belongs to different population.



### Hypothesis on: Two Sample t test

### The Two-tailed t-Test Rejection Region, n=20





### Hypothesis on: Two Sample t test

### Looking up t-values

Now let's look at t-table when we do not know  $\sigma$  and we have sample size, n=20.

With  $\alpha = .05$  and df = 19, we will locate the critical values in the t-distribution table.

t Distribution						
			α			
Degrees of reedom	.005 (one tail) .01 (two tails)	.01 (one tail) .02 (two tails)	.025 (one tail) .05 (two tails)	.05 (one tail) .10 (two tails)	.10 (one tail) .20 (two tails)	.25 (one tail) .50 (two tails)
1	63.657	31.821	12.706	6.314	3.078	1.000
2	9.925	6.965	4.303	2.920	1.886	.816
3	5.841	4.541	3.182	2.353	1.638	765
4	4.604	3.747	2.776	2.132	1.533	741
5	4.032	3.365	2571	2.015	1.476	727
6	3.707	3.143	2,447	1.943	1.440	.718
7	3.500	2.998	2.365	1.895	1.415	.711
8	3.355	2.896	2.306	1,860	1.397	.706
9	3.250	2.821	2.262	1.833	1.383	.703
10	3.169	2.764	2.228	1.812	1.372	.700
11	3,106	2.718	2.201	1,796	1.363	,697
12	3,054	2.681	2.179	1.782	1.356	.696
13	3.012	2,650	2.160	1.771	1.350	.694
14	2.977	2.625	2.145	1.761	1.345	.692
15	2.947	2.602	2.132	1.753	1.341	.691
16	2.921	2.584	2.120	1.746	1.337	.690
17	2.898	2.567	2.110	1.740	1.333	.689
18	2.878	2.552	2.101	1.734	1.330	.688
19	2.861	2.540	(2.093)	1.729	1.328	.688
20	2.845	2.528	2,036	1.725	1.325	.687
21	2.831	2.518	2.080	1.721	1.323	.686
22	2.819	2.508	2.074	1.717	1.321	.686
23	2.807	2.500	2.069	1.714	1.320	.685
24	2.797	2.492	2.064	1.711	1,318	.685
25	2.787	2,485	2.060	1.708	1.316	.684
26	2.779	2.479	2.056	1.706	1.315	.684
27	2.771	2.473	2.052	1.703	1.314	.684
28	2.763	2.467	2.048	1.701	1.313	.683
29	2.756	2.462	2.045	1.699	1.311	.683
Large (z)	2.575	2.327	1.960	1.645	1.282	.675



### Small Sample Test: Paired t-test

#### When to use?

If you want to check, effectiveness of a new treatment, a new method employed or a training one can apply paired t-test. Here observations on every unit are made before and after applying the treatment or method. Hence if treatment or method is effective, there will be significant difference in observations before applying it and after applying it.

$$t = \frac{\overline{x}_D - \mu_0}{s_D / \sqrt{n}}$$

#### Where,

 $\overline{x}_D$  = Mean of differences of 'n' paired observations (samples).

 $S_D = S.D.$  of differences of 'n' paired observations (samples).

 $\mu_0$  = Mean of differences of 'n' paired observations under H<sub>0 (samples)</sub>.



### Hypothesis on : Paired t-test

Here we test whether the given two sample belongs to same population or not. This can also be taken as there is no significant difference in samples before and after applying some treatment or method.

- $H_0$ : Mean of samples before and after treatment is same.
- H<sub>a</sub>: Mean of samples before and after treatment is not same.



### Small Sample Test: Chi-square test

#### When to use?

If you have attribute data and if you want to test whether any two attributes are associated with each other or they are independent of each other, we can use Chi-Square test for checking independence of attributes.

$$\chi^2 = \sum \frac{(O_i - E_i)^2}{E_i}$$

Where,

O<sub>i</sub> = Observed frequency or Cell count

E<sub>i</sub> = Expected frequency or Cell count



### Hypothesis on : Chi-Square test

Here we test whether attributes in the given data are independent of each other or not.

- $H_0$ : Two attributes are independent of each other.
- H<sub>a</sub>: Two attributes are not independent of each other.



### Small Sample Test: F test

#### When to use?

If you have two different samples and you want to know whether these two sample have same population variance or not, one can use F test.

$$F = \frac{s_1^2}{s_2^2}$$

Where,

 $S_1^2$  = Sample variance of first sample of size  $n_1$ 

 $S_2^2$  = Sample variance of second sample of size  $n_2$ 



### Hypothesis on : F test

Here we test whether two samples have same variance or not.

- $H_0$ : Variance ratio is one
- H<sub>a</sub>: Variance ratio not equal to one

