

Testing hypothesis about the population using sample statistics

Lecture 14

Recap: consequences of Central Limit Theorem

- If a **population** parameter that we are sampling over is **normally distributed**, then the distribution of **sample means** also follows a **normal distribution** with mean $\mu_{\bar{x}} = \mu$ and standard deviation of $\sigma_{\bar{x}} = \sigma / \sqrt{n}$
- If the parameter in the **population** is **not normally distributed**, but the sample size $n \geq 30$, then the distribution of **sample means** still is close to the same **normal distribution**

Statistical hypothesis testing

- A hypothesis test is a method for evaluating a claim, or hypothesis, about a population parameter by examining the statistical evidence **against** the claim based on a sample.
- We state **null** and **alternative hypotheses** about parameters.
- The null hypothesis, H_0 , is typically the by-chance or no-effect explanation
- The alternative hypothesis, H_a , is typically the explanation of an effect, or difference.

Recap

Level of confidence

- **C** – how confident we are in our decision (of rejecting H_0):
90%, 95%, 99%
- The larger C the more confident we are in our decision

Level of significance

- **α** – the probability that the reported result happened by chance (insignificant) : $1 - C$
- The smaller the α (probability that it happened by chance), the more confident we are in our decision

Hypothesis

- A premise or a claim that we want to test
- Null hypothesis H_0 – a currently accepted value of a population parameter
- Alternative hypothesis H_a – research hypothesis, a claim to be tested

Ex. A candy machine in this factory makes chocolate bars that weigh on average 5 g.

A worker claims that the machine after maintenance no longer makes 5-g bars.

Hypothesis testing

Step 1: Formulate H_0 and H_a

Ex. A candy machine in this factory makes chocolate bars that weigh on average 5 g.

A worker claims that the machine after maintenance no longer makes 5-g bars.

- $H_0: \mu = 5$
- $H_a: \mu \neq 5$

Hypothesis testing

Step 2: collect evidence (sample)

Ex. A candy machine in this factory makes chocolate bars that weigh on average 5 g.
A worker claims that the machine after maintenance no longer makes 5-g bars.

- $H_0: \mu = 5$
- $H_a: \mu \neq 5$
- Measure 50 bars
- Calculate test statistic: \bar{x} 5.3? 4.95? 5.83?

Hypothesis testing

Step 3: is the difference statistically significant?

Ex. A candy machine in this factory makes chocolate bars that weigh on average 5 g.

A worker claims that the machine after maintenance no longer makes 5-g bars.

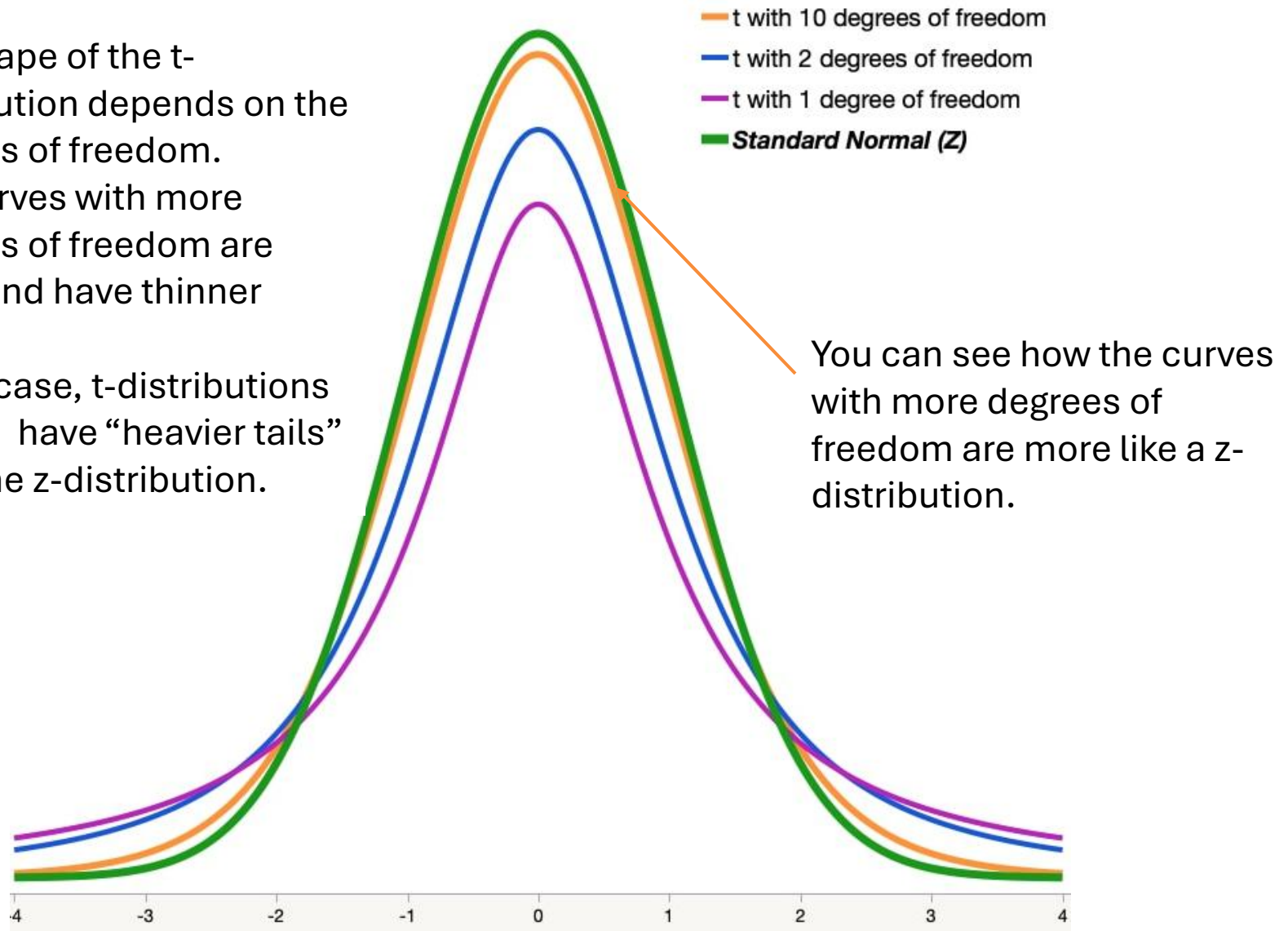
- $H_0: \mu = 5$
- $H_a: \mu \neq 5$
- Measure 50 bars
- Calculate test statistic: \bar{x}
- Determine if this sample mean is statistically significantly different from $\mu = 5$

Small sample sizes: t-distribution

- If the variable in the population is believed to be normally distributed, but if the sample size is < 30 – the sampling statistics follows a **t-distribution** (sample means are t-distributed)
- In general, we should always use the t-distribution if the standard deviation σ of the population parameter is unknown
- The **t-distribution** is defined by the degrees of freedom DOF. These are related to the sample size: **DOF = n-1**
- At higher degrees of freedom ($n \geq 30$), the t-distribution becomes practically indistinguishable from the normal distribution

T-distributions for different DOFs

- The shape of the t-distribution depends on the degrees of freedom.
- The curves with more degrees of freedom are taller and have thinner tails.
- In any case, t-distributions always have “heavier tails” than the z-distribution.



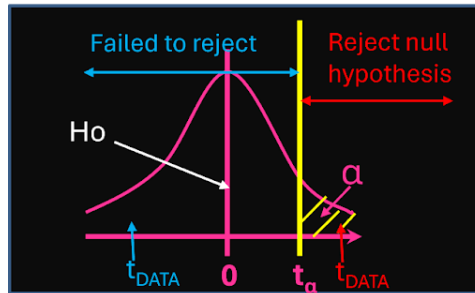
Statistical hypothesis testing: theory

- The null hypothesis H_0 describes the accepted belief about the population parameter: μ
- We formulate alternative hypothesis H_a and try to reject null hypothesis based on a sample statistic \bar{x}
- We know that sample means are t-distributed (normally distributed)
- We want to know how far our sample mean \bar{x} should be from μ to conclude that the difference is statistically significant (at a given significance level)
- If \bar{x} is statistically significantly different from μ we reject null hypothesis H_0
- If not: we fail to reject H_0

Types of tests

$H_0: \mu < 5$

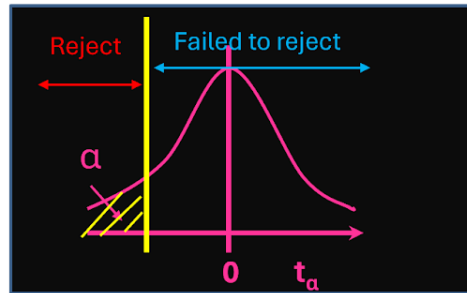
$H_a: \mu \geq 5$



Right-tailed

$H_0: \mu \geq 5$

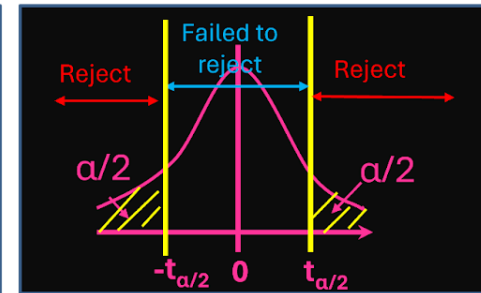
$H_a: \mu < 5$



Left-tailed

$H_0: \mu = 5$

$H_a: \mu \neq 5$



Two-tailed

Hypothesis testing process (small samples)

Given:

- H_0, H_a
- Significance level α
- DOF (from sample size n : $DOF = n-1$)
- Test statistics computed from a sample: t_{DATA}

To reject H_0

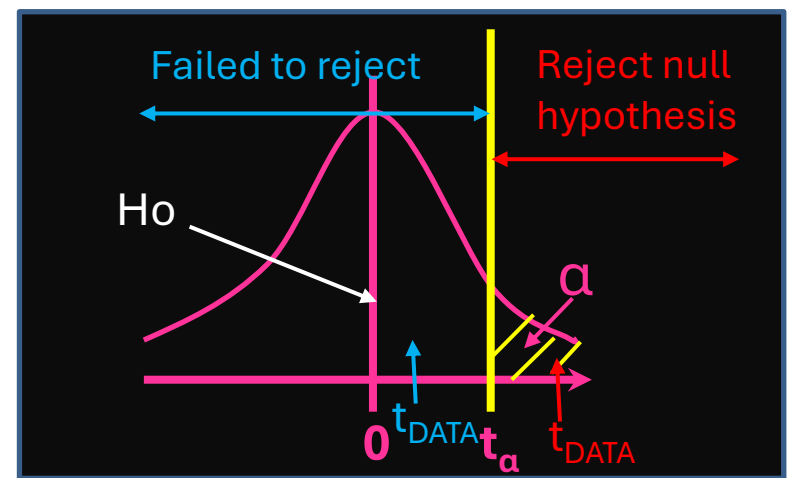
- Find t_α (from a t-table)
- Depending on the problem see if t_{DATA} passes the threshold for rejecting H_0

Method of rejection regions

Right Tail test

$$H_0: \mu < 5$$

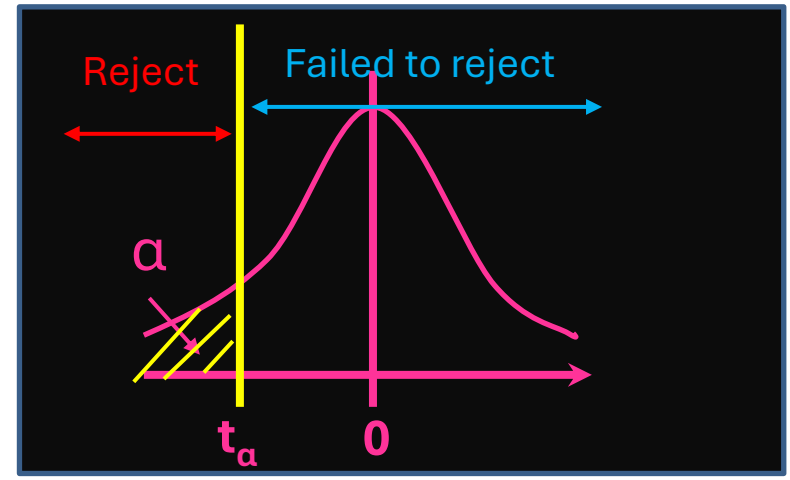
$$H_a: \mu \geq 5$$



Left Tail test

$$H_0: \mu \geq 5$$

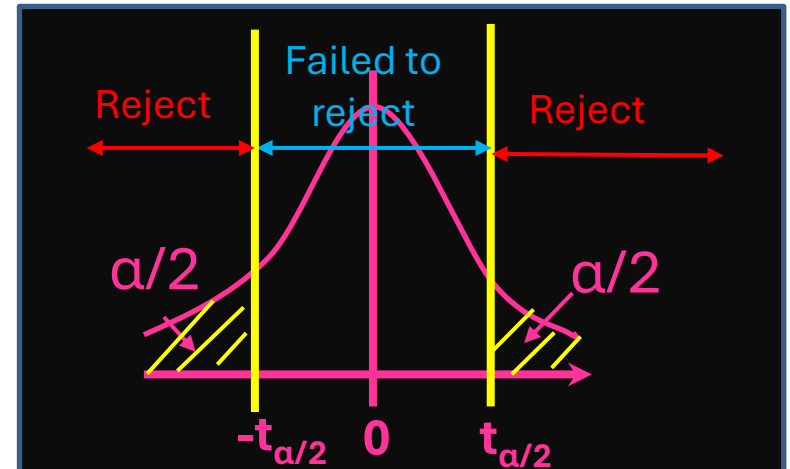
$$H_a: \mu < 5$$



Two Tail test

$$H_0: \mu = 5$$

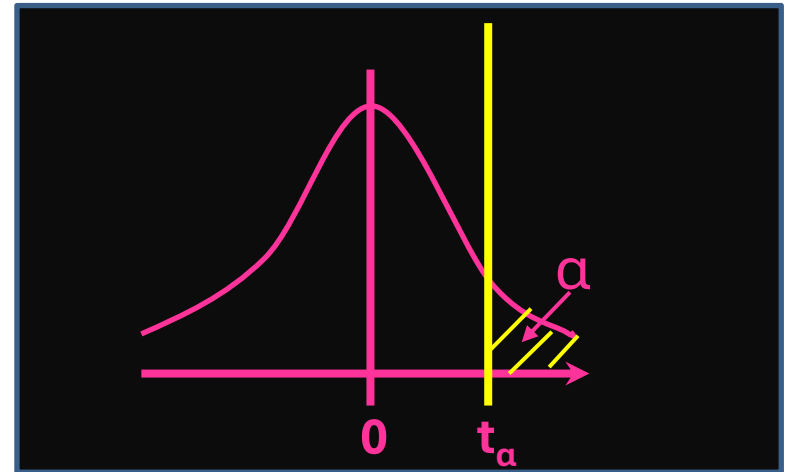
$$H_a: \mu \neq 5$$



Finding $t_{\alpha, \text{DOF}}$ from t-table

df	0.1	0.05	0.025	0.02	0.01	0.005
1	3.078	6.314	12.706	15.895	31.821	63.657
2	1.886	2.920	4.303	4.849	6.965	9.925
3	1.638	2.353	3.182	3.482	4.541	5.841
4	1.533	2.132	2.776	2.999	3.747	4.604
5	1.476	2.015	2.571	2.757	3.365	4.032
6	1.440	1.943	2.447	2.612	3.143	3.707
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13	1.350	1.771	2.160	2.282	2.650	3.012
14	1.345	1.761	2.145	2.264	2.624	2.977
15	1.341	1.753	2.131	2.249	2.602	2.947
16	1.337	1.746	2.120	2.235	2.583	2.921
17	1.333	1.740	2.110	2.224	2.567	2.898
18	1.330	1.734	2.101	2.214	2.552	2.878
19	1.328	1.729	2.093	2.205	2.539	2.861
20	1.325	1.725	2.086	2.197	2.528	2.845
21	1.323	1.721	2.080	2.189	2.518	2.831
22	1.321	1.717	2.074	2.183	2.508	2.819
23	1.319	1.714	2.069	2.177	2.500	2.807
24	1.318	1.711	2.064	2.172	2.492	2.797
25	1.316	1.708	2.060	2.167	2.485	2.787
26	1.315	1.706	2.056	2.162	2.479	2.779
27	1.314	1.703	2.052	2.158	2.473	2.771
28	1.313	1.701	2.048	2.154	2.467	2.763

$n=29$, $\text{DOF} = 28$
 $\alpha = 0.01$



Ex. 1: mean, small samples

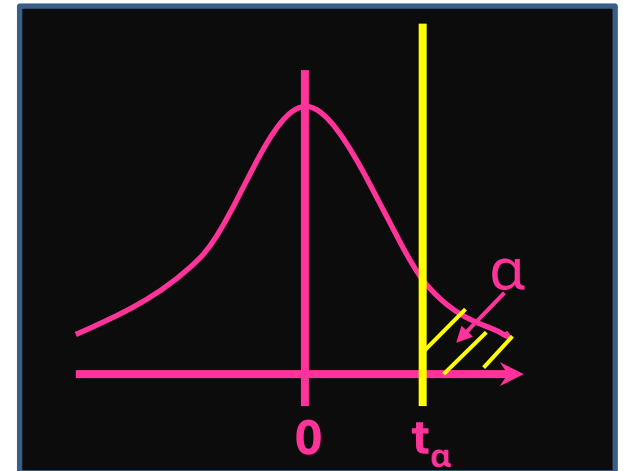
Right-tailed test

- $H_0: \mu \leq 28$ $n=29$ $t_{\text{DATA}} = 1.99$
- $H_a: \mu > 28$ $\alpha = 0.01$

- $\text{DOF} = n-1 = 28$
- $t_\alpha = t_{0.01}$ @ 28 DOF => [t-table](#)
(see prev. slide)

- $t_{0.01} = 2.47$ Failed to reject H_0

T-table always gives the t_α
for α to the right



The higher the significance, the lower is the confidence, and the easier it is to reject the null hypothesis

Calculating test statistics t_{DATA} from a sample

$$t_{DATA} = \frac{\bar{x} - \mu}{\sqrt{\frac{s^2}{n}}}$$

Sample mean

Mean according to H_0

Sample variance

Sample size

We are trying to show that the difference between the sample mean and the population mean is not zero

t_{DATA} computes the number of standard deviations of sample mean from the population mean

Ex. 4

$$t = \frac{\bar{x} - \mu}{\sqrt{\frac{s^2}{n}}}$$

- Doctors at a hospital believe they see on average at least 8 patients per day. Management claims that they did not see this many patients consistently. They sample 19 doctors who report a sample mean of 7.5 patients seen per day with standard deviation of 1.1 patients.
- Test management's claim at 0.025 level of significance

Ex. 4

$$t = \frac{\bar{x} - \mu}{\sqrt{\frac{s^2}{n}}}$$

- Doctors at a hospital believe they see on average at least 8 patients per day. Management claims that they did not see this many patients consistently. They sample 19 doctors who report a sample mean of 7.5 patients seen per day with standard deviation of 1.1 patients.
- Test management's claim at 0.025 level of significance

$$H_0: \mu \geq 8$$

$$H_a: \mu < 8$$

Sample mean: 7.5

$$\mu = 8$$

$$s = 1.1$$

$$t_{\text{DATA}} = -1.98$$

$$t_{\alpha=0.025 @ \text{DOF}=18} = -2.10$$

Fail to reject H_0

Hypothesis testing: means, **large samples** ($n > 30$)

- When n grows – the t-distribution approaches the normal distribution
- We can use normal distribution for hypothesis testing when $n \geq 30$
- Test statistics Z_{DATA} :

$$Z = \frac{\bar{x} - \mu}{\sqrt{\frac{s^2}{n}}}$$

The shape of normal distribution does not change with n (no DOF)

C	α	One-tailed test	Two-tailed test
0.90	0.10	1.28	± 1.645
0.95	0.05	1.645	± 1.96
0.98	0.02	2.05	± 2.33
0.99	0.01	2.33	± 2.575

Ex 5: means, large samples

$$z = \frac{\bar{x} - \mu}{\sqrt{\frac{s^2}{n}}}$$

- For a standard test: records show that students on average score less than or equal to 850.
- A test prep company claims that students who take their course will score on average higher than this.
- To test, they sample 1000 students who score on average 856 with standard deviation of 98 after taking their course. At 0.05 level of significance, test the company's claim.

Ex 5: means, large samples

$$z = \frac{\bar{x} - \mu}{\sqrt{\frac{s^2}{n}}}$$

- For a standard test: records show that students on average score less than or equal to 850.
- A test prep company claims that students who take their course will score on average higher than this.
- To test, they sample 1000 students who score on average 856 with standard deviation of 98 after taking their course. At 0.05 level of significance, test the company's claim.

Ho: $\mu \leq 850$

Ha: $\mu > 850$ right-tailed

$\alpha=0.05$, C=0.95

$z_C = 1.645$

$z_{DATA} = 1.94$

Reject Ho

C	α	One-tailed test	Two-tailed test
0.90	0.10	1.28	± 1.645
0.95	0.05	1.645	± 1.96
0.98	0.02	2.05	± 2.33
0.99	0.01	2.33	± 2.575

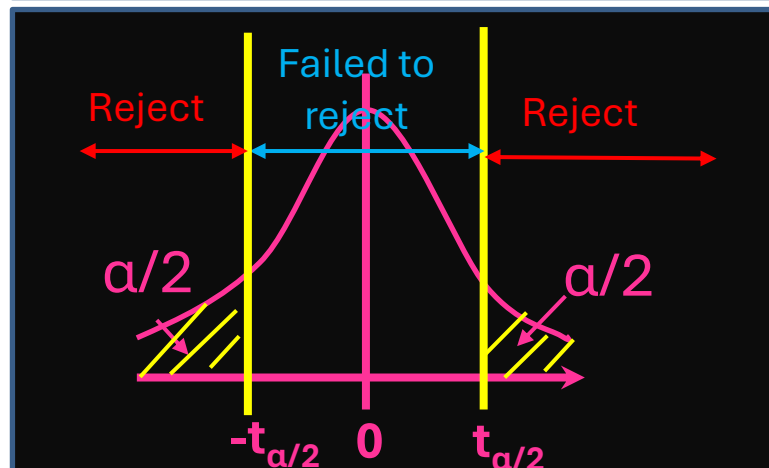
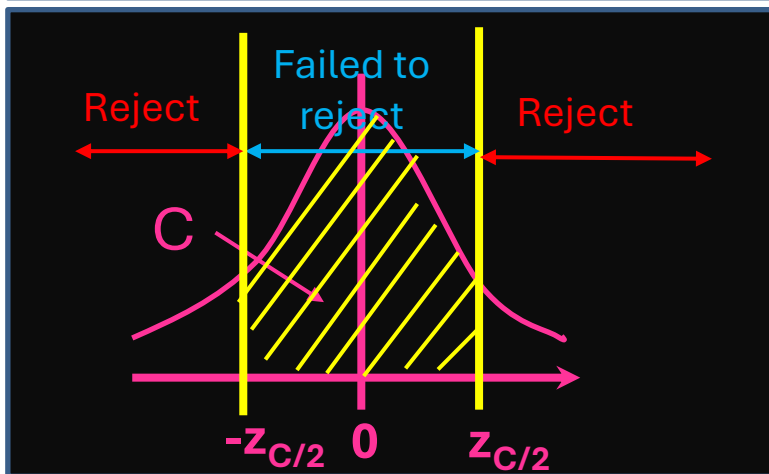
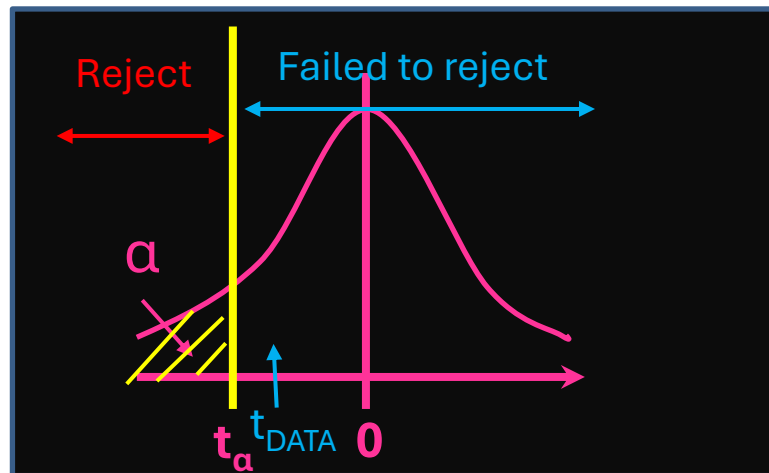
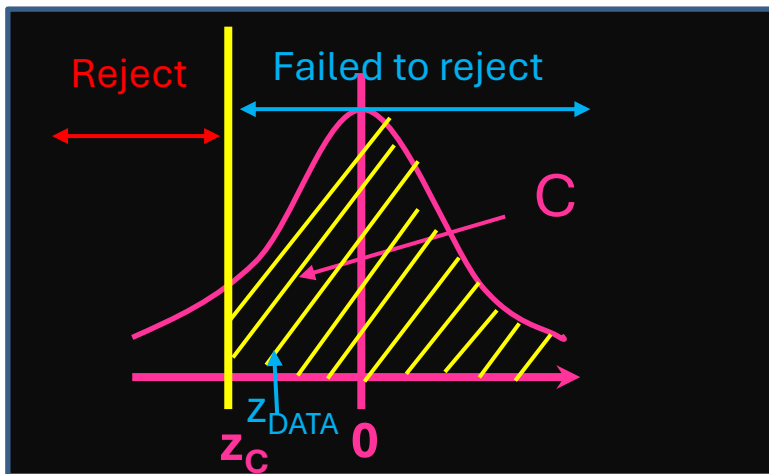
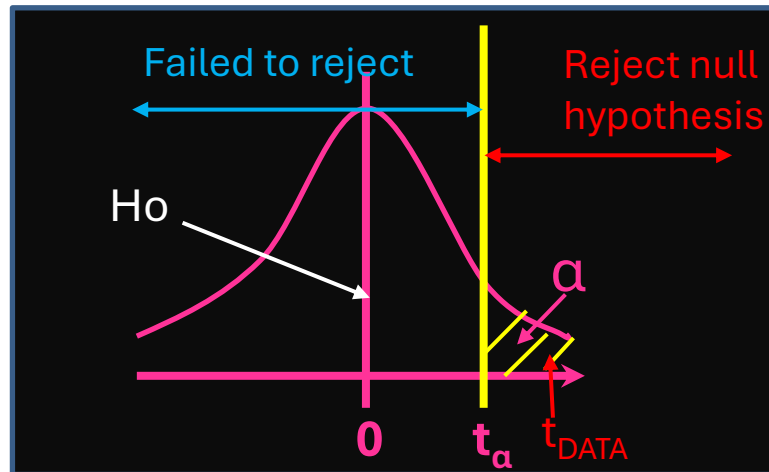
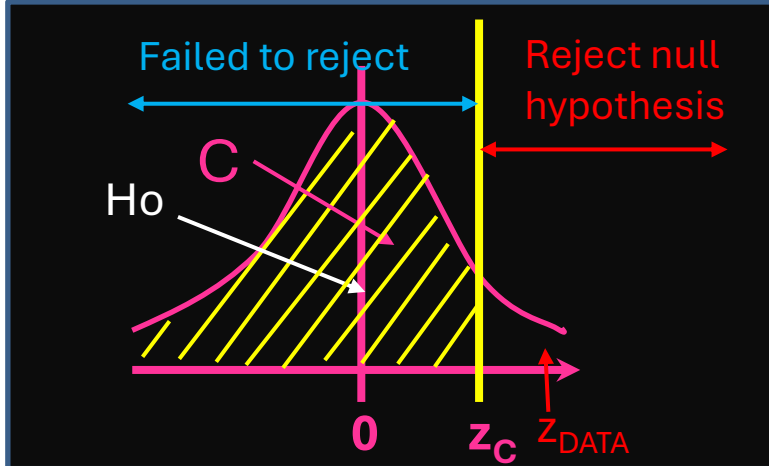
Hypothesis testing with rejection regions: summary

Given:

- H_0, H_a
- Significance level α
- Sample of size n collected with the purpose to reject H_0
- Test statistics computed from a sample: t_{DATA} or z_{DATA}

To reject H_0

- The goal is to show that the difference between population parameter claimed in H_0 and the statistics observed in a sample is statistically significant (not by chance)
- Find $t_{\alpha, \text{DOF}=n-1}$ (from a t-table) or z_c (from a z-table)
- Depending on the test type (right-tailed, left-tailed, two-tailed): see if test statistics passes the threshold



p-values

Different results for different α

- Sometimes we are not sure what value of significance to use

Example: left-tailed test



Failed to reject H_0 at
significance level α_1



Reject H_0 at a different
significance level α_2

For the same sample

Hypothesis testing using p-values

- *p-value* - probability of obtaining a sample more extreme than the current data assuming that H_0 is true
- How likely your data and beyond is observed under a null hypothesis

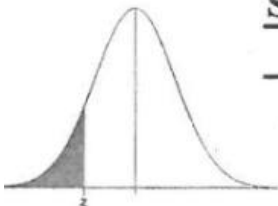
Hypothesis testing using p-values

- *p-value* - probability of obtaining a sample more extreme than the current data assuming that H_0 is true
- How likely your data and beyond is observed under a null hypothesis

Example: left-tailed test



p-value lets you specify the level of significance **from data**, instead of testing current data with different α -thresholds



STANDARD NORMAL DISTRIBUTION: Table Values Represent AREA to t

Z	.00	.01	.02	.03	.04	.05	.06
-3.9	.00005	.00005	.00004	.00004	.00004	.00004	.00004
-3.8	.00007	.00007	.00007	.00006	.00006	.00006	.00006
-3.7	.00011	.00010	.00010	.00010	.00009	.00009	.00008
-3.6	.00016	.00015	.00015	.00014	.00014	.00013	.00013
-3.5	.00023	.00022	.00022	.00021	.00020	.00019	.00019
-3.4	.00034	.00032	.00031	.00030	.00029	.00028	.00027
-3.3	.00048	.00047	.00045	.00043	.00042	.00040	.00039
-3.2	.00069	.00066	.00064	.00062	.00060	.00058	.00056
-3.1	.00097	.00094	.00090	.00087	.00084	.00082	.00079
-3.0	.00135	.00131	.00126	.00122	.00118	.00114	.00111
-2.9	.00187	.00181	.00175	.00169	.00164	.00159	.00154
-2.8	.00256	.00248	.00240	.00233	.00226	.00219	.00212
-2.7	.00347	.00336	.00326	.00317	.00307	.00298	.00289
-2.6	.00466	.00453	.00440	.00427	.00415	.00402	.00391
-2.5	.00621	.00604	.00587	.00570	.00554	.00539	.00523
-2.4	.00820	.00798	.00776	.00755	.00734	.00714	.00695
-2.3	.01072	.01044	.01017	.00990	.00964	.00939	.00914
-2.2	.01390	.01355	.01321	.01287	.01255	.01222	.01191
-2.1	.01786	.01743	.01700	.01659	.01618	.01578	.01539
-2.0	.02275	.02222	.02169	.02118	.02068	.02018	.01970
-1.9	.02872	.02807	.02743	.02680	.02619	.02559	.02500
-1.8	.03593	.03515	.03438	.03362	.03288	.03216	.03144
-1.7	.04457	.04363	.04272	.04182	.04093	.04006	.03920
-1.6	.05480	.05370	.05262	.05155	.05050	.04947	.04846
-1.5	.06681	.06552	.06426	.06301	.06178	.06057	.05938
-1.4	.08076	.07927	.07780	.07636	.07493	.07353	.07215
-1.3	.09680	.09510	.09342	.09176	.09012	.08851	.08691
-1.2	.11507	.11314	.11123	.10935	.10749	.10565	.10383

Finding probability
of observing
sample
 $\leq z_{\text{DATA}} = -1.34$

Ex. 7: hypothesis testing with p-value

- $H_0: \mu \geq 0.15$
- $H_a: \mu < 0.15$

$$z_{\text{DATA}} = -1.34$$

- $p(z < -1.34) = 0.00901$ (see prev. slide)



- This means that if H_0 is true then probability of observing this sample is ≤ 0.009
- This is a very low probability, and we should probably reject H_0

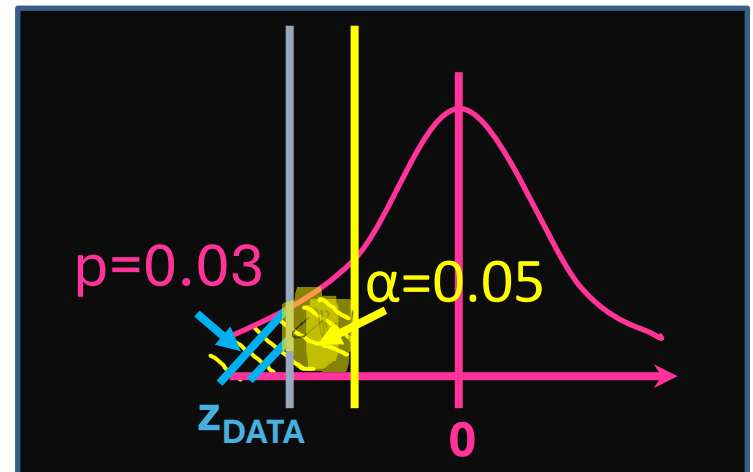
Ex. 8:

hypothesis testing with p-value and alpha

If $p \leq \alpha \Rightarrow$ reject H_0

If $p > \alpha \Rightarrow$ failed to reject H_0

- $H_0: \mu \geq 409$ $z_{DATA} = -1.87$
- $H_a: \mu < 409$ $\alpha = 0.05$
- $p(z < -1.87) = 0.0307$ (from z-table)

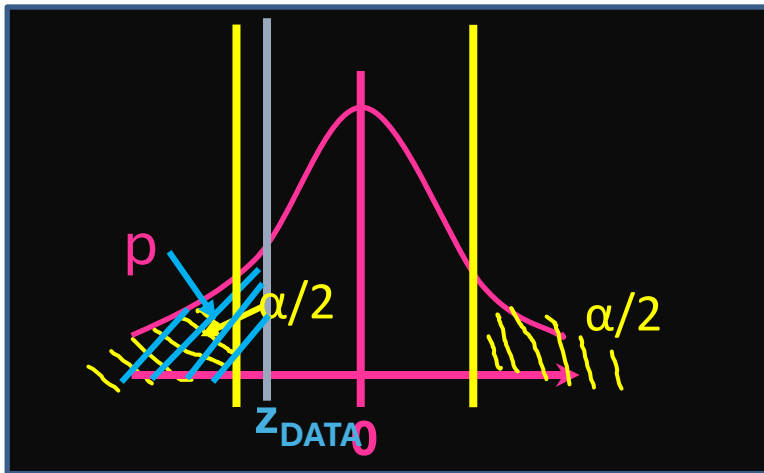


Reject H_0

Ex. 8: p-value for a two-tailed test

If $p \leq \alpha/2 \Rightarrow$ reject H_0

If $p > \alpha/2 \Rightarrow$ failed to reject H_0



Failed to reject H_0

• $H_0: \mu = 2$ $z_{DATA} = -2.28$

• $H_a: \mu \neq 2$ $\alpha = 0.02$

$p(z < -2.28) = 0.013$ (from z-table)

Finding $t_{\alpha, \text{DOF}}$ from t-table

df	0.1	0.05	0.025	0.02	0.01	0.005
1	3.078	6.314	12.706	15.895	31.821	63.657
2	1.886	2.920	4.303	4.849	6.965	9.925
3	1.638	2.353	3.182	3.482	4.541	5.841
4	1.533	2.132	2.776	2.999	3.747	4.604
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28	1.313	1.701	2.048	2.154	2.467	2.763

$n=29$, $\text{DOF} = 28$
 $\alpha = 0.01$

Ex. 9: mean, small samples, rejection regions

Right-tailed test

- $H_0: \mu \leq 28$ $n=29$ $t_{\text{DATA}} = 1.99$
- $H_a: \mu > 28$ $\alpha = 0.01$

- $\text{DOF} = n-1 = 28$
- $t_\alpha = t_{0.01 @ 28 \text{ DOF}} = 2.47$ (see prev. slide)

- Failed to reject H_0

T-table always gives the t_α
for α to the right



Method of rejection regions

Finding p-value from t-table

df	0.1	0.05	0.025	0.02	0.01	0.005
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13	1.350	1.771	2.160	2.282	2.650	3.012
14	1.345	1.761	2.145	2.264	2.624	2.977
15	1.341	1.753	2.131	2.249	2.602	2.947
16	1.337	1.746	2.120	2.235	2.583	2.921
17	1.333	1.740	2.110	2.224	2.567	2.898
18	1.330	1.734	2.101	2.214	2.552	2.878
19	1.328	1.729	2.093	2.205	2.539	2.861
20	1.325	1.725	2.086	2.197	2.528	2.845
21	1.323	1.721	2.080	2.189	2.518	2.831
22	1.321	1.717	2.074	2.183	2.508	2.819
23	1.319	1.714	2.069	2.177	2.500	2.807
24	1.318	1.711	2.064	2.172	2.492	2.797
25	1.316	1.708	2.060	2.167	2.485	2.787
26	1.315	1.706	2.056	2.162	2.479	2.779
27	1.314	1.703	2.052	2.158	2.473	2.771
28	1.313	1.701	2.048	2.154	2.467	2.763

n=29

$t_{\text{DATA}} = 1.99$

Ex. 9A: mean, small samples, p-value

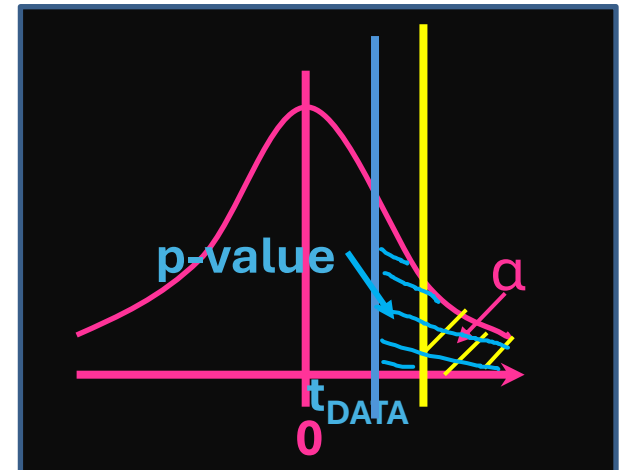
Right-tailed test

- $H_0: \mu \leq 28$ $n=29$ $t_{\text{DATA}} = 1.99$
- $H_a: \mu > 28$ $\alpha = 0.01$

- $\text{DOF} = n-1 = 28$
- $\text{p-value} (t_{1.99, \text{DOF} = 28}) \approx 0.03$ (see prev. slide)

- $\text{p-value} > \alpha$

- Failed to reject H_0

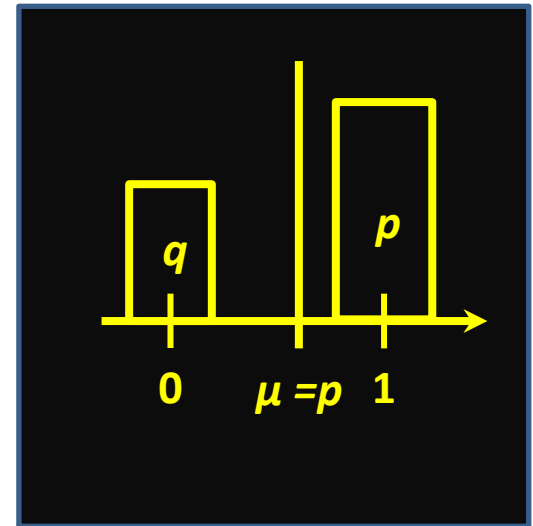


Using p-value

Population proportions

Population proportions

- Population proportion is a percentage of Bernoulli experiments with an outcome “yes”(success) - a percentage of a population behaving a certain way
- The proportion (the probability of success) is denoted by small letter p . The probability of failure by letter $q = 1-p$
- The expected value (mean) of this distribution: $\mu = p$
- The variance $\sigma^2 = pq$,
- The standard deviation $\sigma = \sqrt{p(1 - p)}$



Hypotheses with population proportions

- Proportion of a sample is denoted as: \hat{p}
- We can approximate the distribution of proportions (Bernoulli means) using normal distribution when:
 - $np \geq 5$
 - $n(1-p) \geq 5$

Then the hypothesis **test statistic** is:

$$Z_{DATA} = \frac{\hat{p} - p}{\sqrt{\frac{\hat{p}(1 - \hat{p})}{n}}}$$

\bar{x} points to \hat{p} , μ points to p , and σ^2 points to $\hat{p}(1 - \hat{p})$.

Compare to:

$$Z_{DATA} = \frac{\bar{x} - \mu}{\sqrt{\frac{s^2}{n}}}$$

For population **proportion**

For population **mean**

Ex. 10: proportions, p-value

$$Z_{DATA} = \frac{\hat{p} - p}{\sqrt{\frac{\hat{p}(1 - \hat{p})}{n}}}$$

- A report states that at least 75% of women like red roses.
- Alice claims this figure is too high.
- She asks 125 women and finds that 92 do like red roses.
- At a 0.10 level of significance test the claim.

Ex. 10. proportions, p-value

$$Z_{DATA} = \frac{\hat{p} - p}{\sqrt{\frac{\hat{p}(1 - \hat{p})}{n}}}$$

- A report states that at least 75% of women like red roses.
- Alice claims this figure is too high. She asks 125 women and finds that 92 do like red roses.
- At a 0.10 level of significance test the claim.

Ho: $p \geq 0.75$

Ha: $p < 0.75$

Left-tailed test

From a sample:

$$\hat{p} = \frac{92}{125} = 0.736,$$

$$s^2 = 0.736 * (1 - 0.736) = 0.19$$

Can we use z-distribution?

$$np = 92 \geq 5$$

$$n(1-p) = 125 * 0.264 = 33 \geq 5 \text{ Yes!}$$

$$Z_{DATA} = -0.362$$

$$p\text{-value} = p(z < -0.362) = 0.3594 > \alpha = 0.1$$

Failed to reject Ho

Comparing two populations

Comparing **means** of **two** populations: large independent samples

- If $n \geq 30 \Rightarrow$ use normal distribution

We want to compare:

- μ_1 – population mean 1
- μ_2 – population mean 2

Hypotheses of type:

- $H_0: \mu_1 \leq \mu_2$
- $H_a: \mu_1 > \mu_2$

Usually written as:

- $H_0: \mu_1 - \mu_2 \leq 0$
- $H_a: \mu_1 - \mu_2 > 0$

Then the test-statistic is:

$$z = \frac{(\bar{x}_1 - \bar{x}_2) - (\mu_1 - \mu_2)}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}}$$

Ex. 11

$$z = \frac{(\bar{x}_1 - \bar{x}_2) - (\mu_1 - \mu_2)}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}}$$

A company believes that employees who drink coffee **do not complete** more tasks per day than those who don't drink coffee.

- Sample 1 (Non-coffee drinkers): $n_1 = 40$, $\bar{x}_1 = 16.9$ tasks, $s_1 = 3.2$
- Sample 2 (Coffee drinkers): $n_2 = 45$, $\bar{x}_2 = 18.2$ tasks, $s_2 = 3.5$

At $\alpha = 0.05$, test if coffee drinkers are more productive.

Ex. 11

$$z = \frac{(\bar{x}_1 - \bar{x}_2) - (\mu_1 - \mu_2)}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}}$$

A company believes that employees who drink coffee **do not complete** more tasks per day than those who don't drink coffee.

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- Sample 2 (Coffee drinkers): $n_2 = 45$, $\bar{x}_2 = 18.2$ tasks, $s_2 = 3.5$

At $\alpha = 0.05$, test if coffee drinkers are more productive.

- $H_0: \mu_1 \geq \mu_2 \Leftrightarrow \mu_1 - \mu_2 \geq 0$ (no difference in drinkers-non-drinkers)
- $H_a: \mu_1 < \mu_2 \Leftrightarrow \mu_1 - \mu_2 < 0$ (left-tailed test)
- Since under H_0 the difference between μ_1 and μ_2 should be zero, the formula is simplified and we compute:
- $z_{\text{DATA}} = -1.79$
- $z_C = -1.645$
- Since $z_{\text{DATA}} < z_C$ we **reject H_0** — coffee drinkers are indeed more productive.

Comparing **two proportions**: large independent samples

- Independent (non-overlapping) samples
- For both samples:
 - $n\hat{p} \geq 5$
 - $n(1 - \hat{p}) \geq 5$
- Test statistic:

$$z = \frac{(\hat{p}_1 - \hat{p}_2) - (p_1 - p_2)}{\sqrt{\bar{p}(1 - \bar{p})\left(\frac{1}{n_1} + \frac{1}{n_2}\right)}}$$

where: $\bar{p} = \frac{p_1}{n_1} + \frac{p_2}{n_2}$

Ex. 12: Vaccine Effectiveness

In a study, 400 people receive a new vaccine and 400 receive a placebo.

- Vaccine group: 18 people get sick ($p_1=18/400$)
- Placebo group: 45 people get sick ($p_2=45/400$)

At $\alpha = 0.05$, test whether the vaccine reduces the infection rate.

Ex. 12: Vaccine Effectiveness

$$z = \frac{(\hat{p}_1 - \hat{p}_2) - (p_1 - p_2)}{\sqrt{\bar{p}(1 - \bar{p})\left(\frac{1}{n_1} + \frac{1}{n_2}\right)}}$$

In a study, 400 people receive a new vaccine and 400 receive a placebo.

- Vaccine group: 18 people get sick ($p_1=18/400$)
- Placebo group: 45 people get sick ($p_2=45/400$)

At $\alpha = 0.05$, test whether the vaccine reduces the infection rate.

- $H_0: p_1 \geq p_2 \Leftrightarrow p_1 - p_2 \geq 0$
- $H_a: p_1 < p_2 \Leftrightarrow p_1 - p_2 < 0$

- For a **left-tailed** test at $\alpha = 0.05$: $z_c = -1.645$

- $z_{DATA} = -3.55 < -1.645$

- **Reject H_0**

- There is strong evidence ($p \approx 0.0002$) that the **vaccine significantly reduces infection rates** compared to placebo.

Dependent samples: paired data

- In many studies we have the statistics about **the same** group of people: clinical studies, before/after
- Hypothesis testing with **paired data**

Ex. 13: paired data, small samples

weight loss drug

	Person 1	2	3	4	5	
Population 1	Before	160	175	182	180	160
Population 2	After	155	158	179	179	159
	d	-5	-17	-3	-1	-1

- What is important here is the **difference**, not absolute values:
 $d = \text{after} - \text{before}$

- We study **mean of paired differences**: $\bar{d} = \frac{\sum d}{n}$
- The means of differences follow t-distribution

- The test statistic is : $t = \frac{\bar{d} - \mu}{\frac{s_d}{\sqrt{n}}}$ DOF = n-1 Use rejection regions

Ex. 13: solution

- We test whether the drug reduces weight on average.
- $H_0: \mu_d \geq 0$ (*no decrease in mean weight*)
- $H_a: \mu_d < 0$ (*weight decreases after treatment*)

where μ_d is the population mean of the paired differences (After – Before).

- Compute sample mean: $\bar{x}_d = -5.4$
- Compute sample standard deviation: $s_d = 6.69$
- $t_{\text{DATA}} = (-5.4 - 0)/(6.69/\text{sqrt}(5)) = -1.81$
- $t_{\alpha=0.05 @ \text{DOF}=4} = -2.132$
- $t_{\text{DATA}} = -1.81 > -2.132 \Rightarrow$ We **failed to reject** H_0

There isn't enough evidence to conclude that the drug causes significant weight loss (at the 5% level of significance).