

# More hypothesis testing p-values

Lecture 15

# Different results for different $\alpha$

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

## Example: left-tailed test



**Failed to reject  $H_0$**  at  
significance level  $\alpha_1$



**Reject  $H_0$**  at a different  
significance level  $\alpha_2$

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

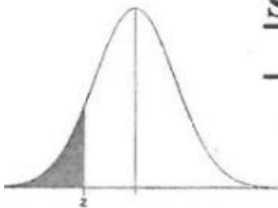
# Hypothesis testing using p-values

- *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  $\alpha$ -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  $\leq 0.009$
- This is a very low probability, and we should probably reject  $H_0$

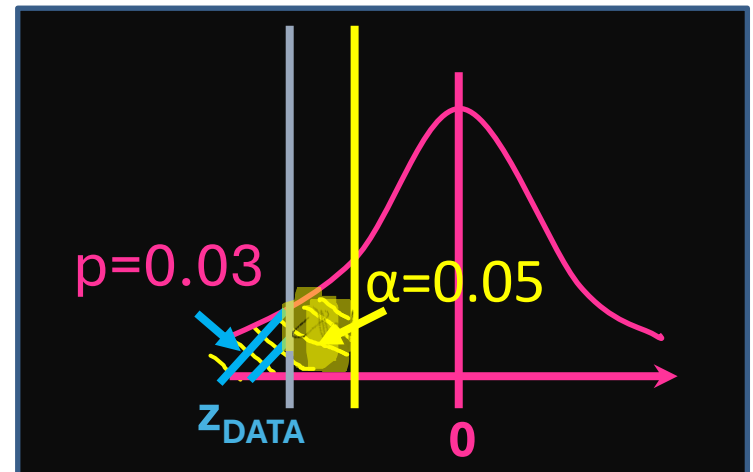
Ex. 8:

hypothesis testing with p-value and alpha

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

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

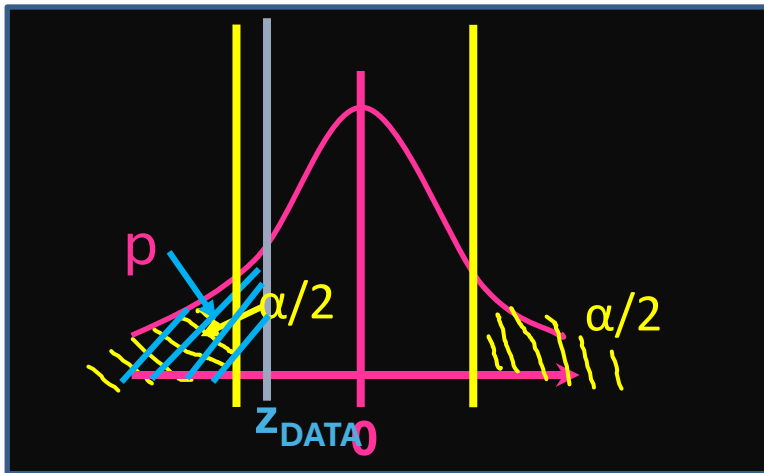
- $H_0: \mu \geq 409$   $z_{DATA} = -1.87$
- $H_a: \mu < 409$   $\alpha = 0.05$
- $p(z < -1.87) = 0.0307$  (from z-table)



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  $H_0$



- $H_0: \mu = 2$                        $z_{DATA} = -2.28$
- $H_a: \mu \neq 2$                        $\alpha = 0.02$

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

Failed to reject  $H_0$

# 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
7	1.415	1.895	2.365	2.517	2.998	3.499
8	1.397	1.860	2.306	2.449	2.896	3.355
9	1.383	1.833	2.262	2.398	2.821	3.250
10	1.372	1.812	2.228	2.359	2.764	3.169
11	1.363	1.796	2.201	2.328	2.718	3.106
12	1.356	1.782	2.179	2.303	2.681	3.055
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

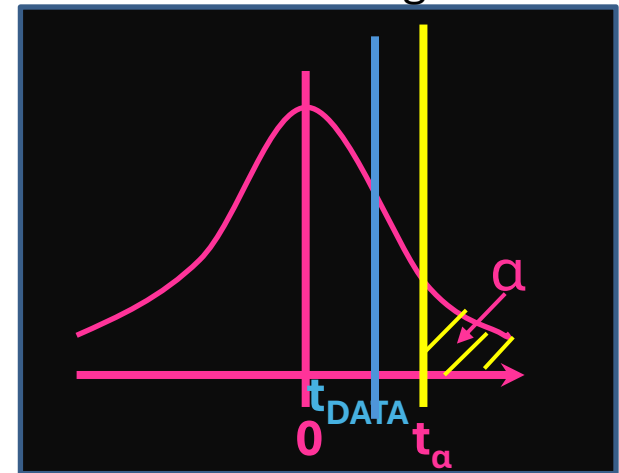
$n=29$ ,  $\text{DOF} = 28$   
 $\alpha = 0.01$

# Ex. 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  $t_\alpha$   
for  $\alpha$  to the right



Method of rejection regions

# Finding p-value from t-table

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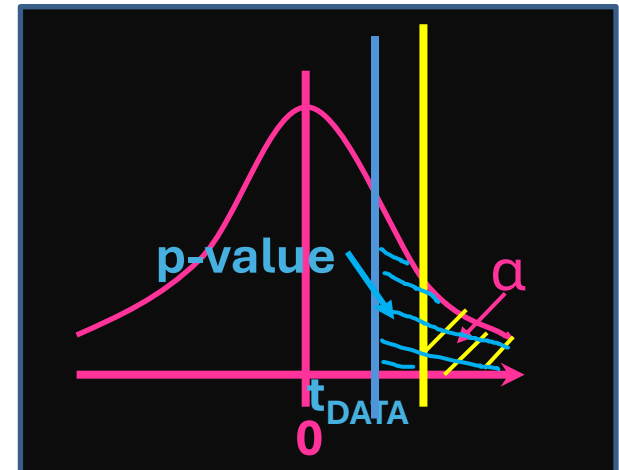
$n=29$

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

# 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  $H_0$

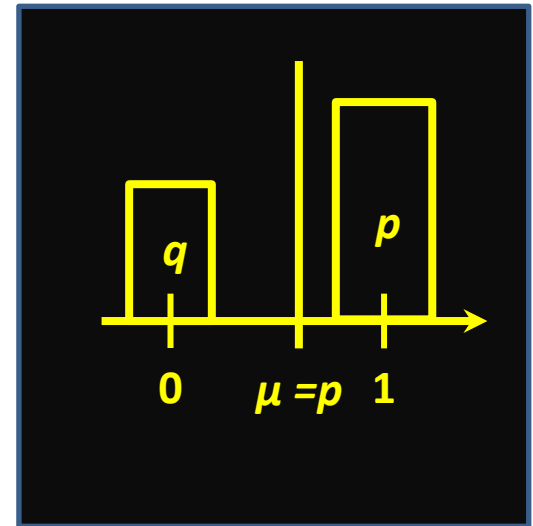


Using p-value

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  $\hat{p}$ ,  $\mu$  points to  $p$ , and  $\sigma^2$  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:

- $\mu_1$  – population mean 1
- $\mu_2$  – 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

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

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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  $\mu_1$  and  $\mu_2$  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:  $\bar{p} = \frac{x_1}{n_1} + \frac{x_2}{n_2}$

# 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  $\mu_d$  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).