

One and Two-Sample T-tests

Lectures 16, 17, & 18

Readings: GW 9 & 10 & SS 9 & 10

Single Sample Inference when True Variance is not known (almost always)

- Most typically, since we don't know μ , we don't know σ either.
- What do we know from our sample data that is an unbiased estimate of σ ?
- Sample standard deviation, s !
- Introduces additional uncertainty into test. Need to compensate by using a different statistic with more extreme critical values, to the extent that additional uncertainty is introduced.
- When will values of s be closer on average to the values of σ ?

Single Sample Inference when True Variance is not known (almost always)

- Estimated standard error of the mean

$$s_{\bar{x}} = \frac{s}{\sqrt{n}} \approx \sigma_{\bar{x}} = \frac{\sigma}{\sqrt{n}}$$

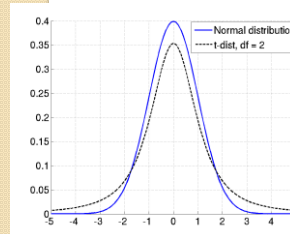
- Approximation depends on sample size
 - (actually $df = n - 1$)
- Computation of test statistic unchanged, but call it a t statistic with $df = (n - 1)$

$$t_{n-1} = \frac{\bar{x} - \mu}{s_{\bar{x}}} = \frac{\bar{x} - \mu}{s/\sqrt{n}}$$

- Critical value of Z was ± 1.96 . Critical value of t depends on df .

Distribution of t-statistic

$$t = \frac{M - \mu_0}{\frac{s}{\sqrt{n}}} \leftarrow \begin{array}{l} \text{magnitude} \\ \text{standard err} \end{array}$$



- This distribution is the t -distribution, and its shape depends on the degrees of freedom, $n - 1$.

- Write this as $t(df)$ or t_{df}

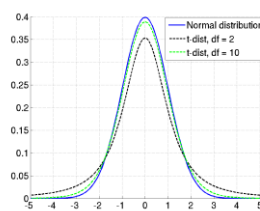
$$t(20) = 1.5$$

or

$$t_{20} = 1.5$$

Distribution of t-statistic

$$t = \frac{M - \mu_0}{\frac{s}{\sqrt{n}}} \leftarrow \begin{array}{l} \text{magnitude} \\ \text{standard err} \end{array}$$



- As df grows, $t(df)$ becomes more normal (SS 9.2.3).

- $t(\infty) = N(0, 1)$
= the Normal distribution

- Set a critical value based on the area under the t -distribution, just like we did with the normal dist. for Z
- Lookup on Table T

Critical values only.

We always do 2-tailed tests!

Notice at $df = \infty$,
crit t = crit z

Table D.6 Percentage Points of the t Distribution (Source: The entries in this table were computed by the author)

df	Level of Significance for One-Tailed Test									
	.25	.20	.15	.10	.05	.025	.01	.005	.001	.0005
1	1.000	1.078	1.155	1.250	1.378	1.638	2.000	2.306	3.078	3.453
2	0.985	1.054	1.119	1.200	1.318	1.578	1.943	2.179	2.748	3.007
3	0.973	1.043	1.107	1.183	1.287	1.549	1.900	2.132	2.689	2.945
4	0.962	1.033	1.096	1.169	1.269	1.533	1.881	2.116	2.661	2.917
5	0.952	1.023	1.085	1.157	1.255	1.520	1.867	2.103	2.648	2.903
6	0.943	1.014	1.075	1.145	1.241	1.507	1.853	2.089	2.639	2.894
7	0.935	1.006	1.066	1.135	1.230	1.492	1.840	2.076	2.629	2.884
8	0.928	0.998	1.058	1.126	1.220	1.483	1.828	2.064	2.619	2.875
9	0.921	0.991	1.051	1.118	1.211	1.474	1.817	2.053	2.609	2.866
10	0.915	0.985	1.045	1.112	1.204	1.465	1.807	2.043	2.599	2.857
15	0.903	0.973	1.033	1.099	1.189	1.451	1.793	2.028	2.583	2.841
20	0.896	0.966	1.026	1.092	1.181	1.443	1.785	2.020	2.576	2.835
25	0.891	0.961	1.021	1.087	1.176	1.437	1.779	2.015	2.571	2.830
30	0.887	0.957	1.017	1.083	1.171	1.432	1.774	2.011	2.567	2.826
40	0.883	0.953	1.013	1.079	1.166	1.427	1.769	2.007	2.563	2.822
50	0.880	0.950	1.010	1.076	1.163	1.424	1.766	2.004	2.560	2.819
60	0.878	0.948	1.008	1.074	1.160	1.422	1.764	2.002	2.558	2.817
70	0.876	0.946	1.006	1.072	1.158	1.420	1.762	2.000	2.556	2.815
80	0.875	0.945	1.005	1.071	1.156	1.419	1.761	2.000	2.555	2.814
90	0.874	0.944	1.004	1.070	1.155	1.418	1.760	2.000	2.554	2.813
100	0.873	0.943	1.003	1.069	1.154	1.417	1.759	2.000	2.553	2.812
150	0.871	0.941	1.001	1.067	1.152	1.415	1.757	2.000	2.551	2.810
200	0.870	0.940	1.000	1.066	1.151	1.414	1.756	2.000	2.550	2.809
300	0.869	0.939	1.000	1.065	1.150	1.413	1.755	2.000	2.549	2.808
400	0.868	0.938	1.000	1.064	1.149	1.412	1.754	2.000	2.548	2.807
500	0.868	0.938	1.000	1.064	1.149	1.412	1.754	2.000	2.548	2.807
600	0.868	0.938	1.000	1.064	1.149	1.412	1.754	2.000	2.548	2.807
700	0.868	0.938	1.000	1.064	1.149	1.412	1.754	2.000	2.548	2.807
800	0.868	0.938	1.000	1.064	1.149	1.412	1.754	2.000	2.548	2.807
900	0.868	0.938	1.000	1.064	1.149	1.412	1.754	2.000	2.548	2.807
1000	0.868	0.938	1.000	1.064	1.149	1.412	1.754	2.000	2.548	2.807

Example - Single Sample t test

- Does Drug A raise temperatures?
- Null hypothesis: $H_0: \mu = 98.6$
- Alternative hypothesis: $H_1: \mu \neq 98.6$
- Data:

99.2, 98.7, 99.3, 97.9, 100.3, 99.4, 98.9, 99.8, 100.1

$$\bar{X} = \frac{99.2 + 98.7 + 99.3 + 97.9 + 100.3 + 99.4 + 98.9 + 99.8 + 100.1}{9} = 99.3$$

$$s = \sqrt{\frac{(99.2 - 99.3)^2 + (98.7 - 99.3)^2 + (99.3 - 99.3)^2 + \dots + (100.1 - 99.3)^2}{8}} = 0.74$$

$$t_s = \frac{\bar{X} - \mu}{s/\sqrt{n}} = \frac{99.3 - 98.6}{0.74/\sqrt{9}} = \frac{0.7}{.247} = 2.83 \quad \text{crit}_{.05} t_s = \pm 2.306$$

- Reject H_0 : Patients taking Drug A have temperatures significantly above normal

Assumptions: One-sample t-test

- Independent observations (one observation doesn't influence another observation and knowing one score doesn't tell you anything about other scores)
- The scores from the populations are normally distributed
- What if the assumptions are violated?
 - Independence violated. Not good -- consider a different experiment or analysis method.
 - Normally distributed scores violated. Not a big deal, esp as sample size increases (e.g., $n > 30$)

Independent Samples t-test

- Is the mean in Group A different from the mean in Group B when there is no way to link up particular scores in one group with particular scores in another (the groups are independent)
- Random assignment of people to either the treatment or control conditions
- Are there gender differences in personality dimensions?
- Do CU in-state students have higher GPAs than CU out-of-state students?
- Do those who got the own-attitudes-first form of the questionnaire think about Obama differently from those who got the own-attitudes-later form of the questionnaire?
- Equal or unequal n's in the two groups
- Null hypothesis: $H_0: \mu_1 = \mu_2; \mu_1 - \mu_2 = 0$

Null hypothesis true: No mean difference

- Each group is actually sampled from one and the same population
- What then is the sampling distribution for each of the two group means?
 - Approximately normal
 - One true mean: μ (avg $\bar{X} = \mu$)
 - Standard error of mean $\sigma_{\bar{X}} = \frac{\sigma}{\sqrt{n}}$
 - estimated as $s_{\bar{X}} = \frac{s}{\sqrt{n}}$

Null hypothesis true: No mean difference

- We draw 2 samples from this one population, one of size n_1 and one of size n_2 .
- What does the sampling distribution for the difference between the two sample means look like? (Sampling distribution of mean differences)
 - Approximately normal
 - Average $\bar{X}_1 - \bar{X}_2 = \mu - \mu = 0$
 - Since each sample mean on average equals μ
 - Standard error of mean difference

$$\sigma_{\bar{X}_1 - \bar{X}_2} = \sqrt{\frac{\sigma^2}{n_1} + \frac{\sigma^2}{n_2}}$$

Null hypothesis true: No mean difference

- Sampling distribution of mean differences
 - Approximately normal
 - Average $\bar{X}_1 - \bar{X}_2 = 0$
 - Since each sample mean on average equals μ
 - Standard error of mean difference

$$\sigma_{\bar{X}_1 - \bar{X}_2} = \sqrt{\frac{\sigma^2}{n_1} + \frac{\sigma^2}{n_2}}$$
 - Note parallel to standard error of mean $\sigma_{\bar{X}} = \frac{\sigma}{\sqrt{n}} = \sqrt{\frac{\sigma^2}{n}}$
 - How estimated?
 - We have two different sample estimates of σ

Estimating the Standard Error of the Mean Difference

$$\sigma_{\bar{x}_1 - \bar{x}_2} = \sqrt{\frac{\sigma^2}{n_1} + \frac{\sigma^2}{n_2}}$$

$$s_{\bar{x}_1 - \bar{x}_2} = \sqrt{\frac{s_p^2}{n_1} + \frac{s_p^2}{n_2}}$$

$$s_p^2 = \frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{df_1 + df_2} = \frac{SS_1 + SS_2}{df_1 + df_2}$$

$$\text{If } n_1 = n_2 = n, \text{ then } s_p^2 = \frac{(n-1)s_1^2 + (n-1)s_2^2}{n+n-2} = \frac{(n-1)s_1^2 + (n-1)s_2^2}{2(n-1)} = \frac{s_1^2 + s_2^2}{2}$$

Independent Samples t-test: Testing the null hypothesis $H_0: \mu_1 = \mu_2$

$$t_{n_1+n_2-2} = \frac{(\bar{X}_1 - \bar{X}_2) - (\mu_1 - \mu_2)}{s_{\bar{x}_1 - \bar{x}_2}}$$

$$= \frac{(\bar{X}_1 - \bar{X}_2) - (\mu_1 - \mu_2)}{\sqrt{\frac{s_p^2}{n_1} + \frac{s_p^2}{n_2}}}$$

$$s_p^2 = \frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{df_1 + df_2} = \frac{SS_1 + SS_2}{df_1 + df_2}$$

Compare to crit $t_{n_1+n_2-2}; \alpha = .05$

Independent t-test: Data example

	Drug	Placebo
	6	8
	3	6
	5	4
	7	7
	5	6
	4	9
	3	7
	6	5
	4	6
		5
Mean	4.78	6.30
S	1.39	1.49
SS	15.56	20.1
n	9	10

$$H_0: \mu_p = \mu_d; \mu_p - \mu_d = 0$$

$$H_1: \mu_p \neq \mu_d; \mu_p - \mu_d \neq 0$$

$$s_p^2 = \frac{(n_p - 1)S_p^2 + (n_d - 1)S_d^2}{n_p + n_d - 2} = \frac{9(1.49)^2 + 8(1.39)^2}{17}$$

$$= \frac{9(2.22) + 8(1.90)}{17} = 2.09$$

$$= \frac{SS_p + SS_d}{df_1 + df_2} = \frac{15.56 + 20.1}{8 + 9} = 2.09$$

$$t_{n_p+n_d-2} = \frac{(\bar{X}_p - \bar{X}_d) - (\mu_p - \mu_d)}{s_{\bar{x}_p - \bar{x}_d}} = \frac{(\bar{X}_p - \bar{X}_d) - (\mu_p - \mu_d)}{\sqrt{\frac{s_p^2}{n_p} + \frac{s_d^2}{n_d}}}$$

$$= \frac{(6.30 - 4.78) - (0)}{\sqrt{\frac{2.09}{10} + \frac{2.09}{9}}} = \frac{1.52}{.66} = 2.29$$

$$\text{crit } t_{17} = \pm 2.11$$

Independent t-test: Data example

	Drug	Placebo
	6	8
	3	6
	5	4
	7	7
	5	6
	4	9
	3	7
	6	5
	4	6
		5
Mean	4.78	6.30
S	1.39	1.49
SS	15.56	20.1
n	9	10

$$H_0: \mu_p = \mu_d; \mu_p - \mu_d = 0$$

$$H_1: \mu_p \neq \mu_d; \mu_p - \mu_d \neq 0$$

$$t_{n_p+n_d-2} = \frac{(\bar{X}_p - \bar{X}_d) - (\mu_p - \mu_d)}{s_{\bar{x}_p - \bar{x}_d}} = \frac{1.52}{.66} = 2.29$$

$$\text{crit } t_{17} = \pm 2.11$$

Reject H_0

The Placebo group has significantly higher scores than the Drug group

Assumptions: Two-sample t-test

- Independent observations (one observation doesn't influence another observation and knowing one score doesn't tell you anything about other scores)
- The two populations from which samples are drawn have equal variance
- The scores from the two populations are normally distributed
- What if the assumptions are violated?
 - Independence violated. Not good -- consider a different experiment or analysis method.
 - Equal variance violated. No big deal. Use alternative formula
 - Normally distributed scores violated. Not a big deal, esp as sample size increases (e.g., $n > 30$)