

Fundamentals of Statistics for Language Sciences LT2206



Jixing Li

Lecture 5: t-tests

Slides adapted from Cecilia Earls

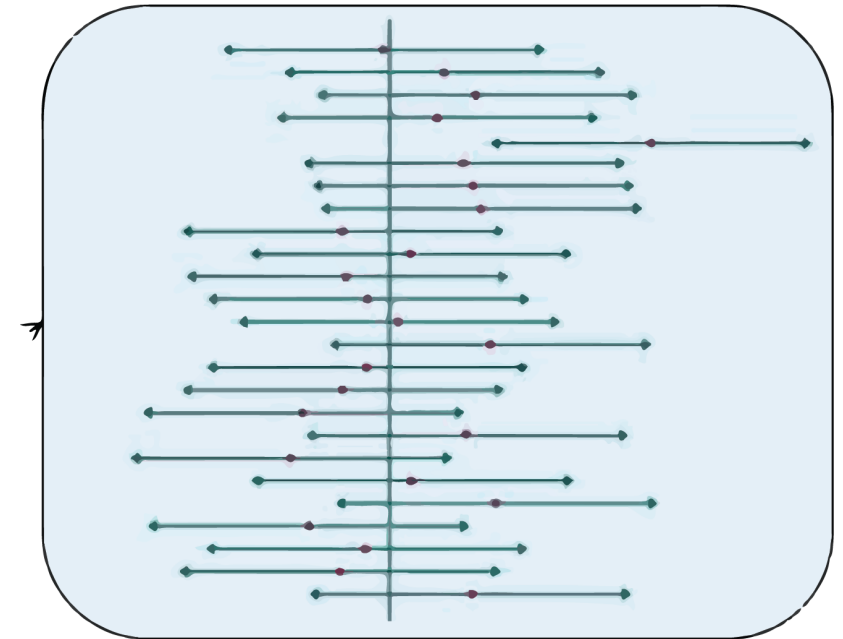
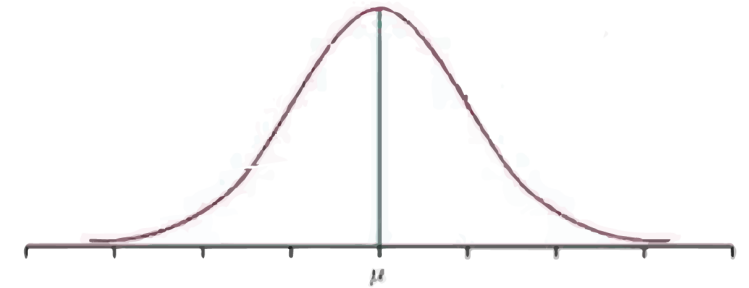
Inference for μ

Scenario: Often we would like to say **SOMETHING** about the mean of a population we are sampling from.

What do we have to work with?

- Take one SRS from this population
 - $X_i, i = 1, \dots, n$
 - $E(X_i) = \mu, \text{Var}(X_i) = \sigma^2$
- } Basic Assumptions (might have more)
- From our sample, we get an outcome: \bar{x}_n (e.g., 17)

Often know the standardized **sampling distribution of \bar{X}_n** (at least approximately)



Hypothesis Testing

- **First steps:**

- Set type I error rate, $\alpha = P(\text{Reject } H_0 \mid H_0 \text{ is true})$
- H_a (\neq or $>$ or $<$) & H_0 ($=$ or \leq or \geq)
- Determine sample size to control $\beta = P(\text{Fail to reject } H_0 \mid H_a \text{ is true})$
- Collect SRS

- **Determine:**

- Distribution of **standardized test statistic** under H_0
- Using this distribution make a **decision**:
 - Reject H_0 ? or Fail to reject H_0 ?
 - Decision can be based on **rejection region**
 - Decision can be based on a ***p*-value**

Suppose under H_0 :

$$\frac{\bar{X}_n - \mu_0}{\sigma/\sqrt{n}} \sim N(0,1)$$

standardized
test statistic standard
normal
distribution

Critical value: z_α

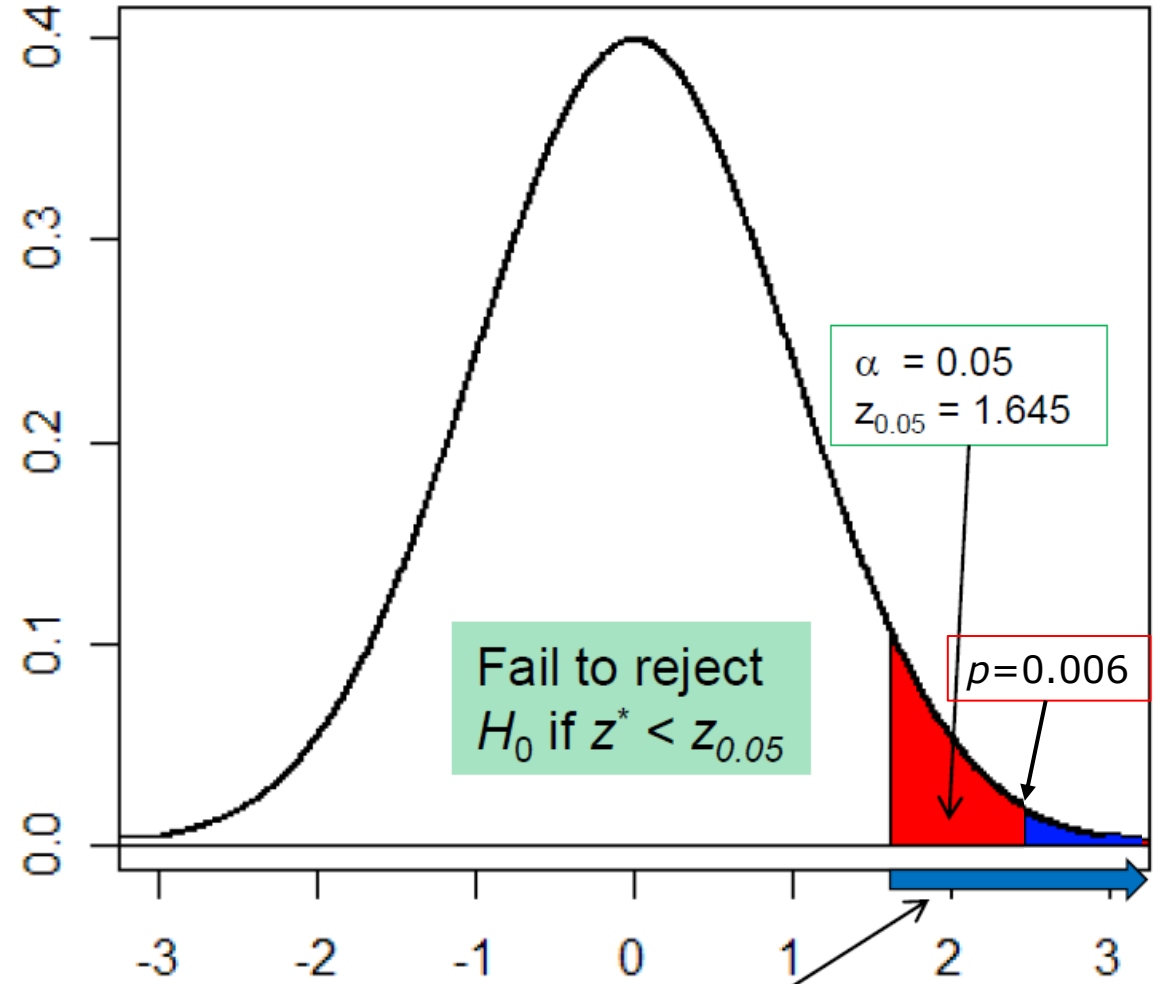
(1 - α)100th percentile of $N(0,1)$

In R: $z_{0.05} = \text{qnorm}(1-0.05)=1.645$

p-value: $P(z_\alpha > z^*)$

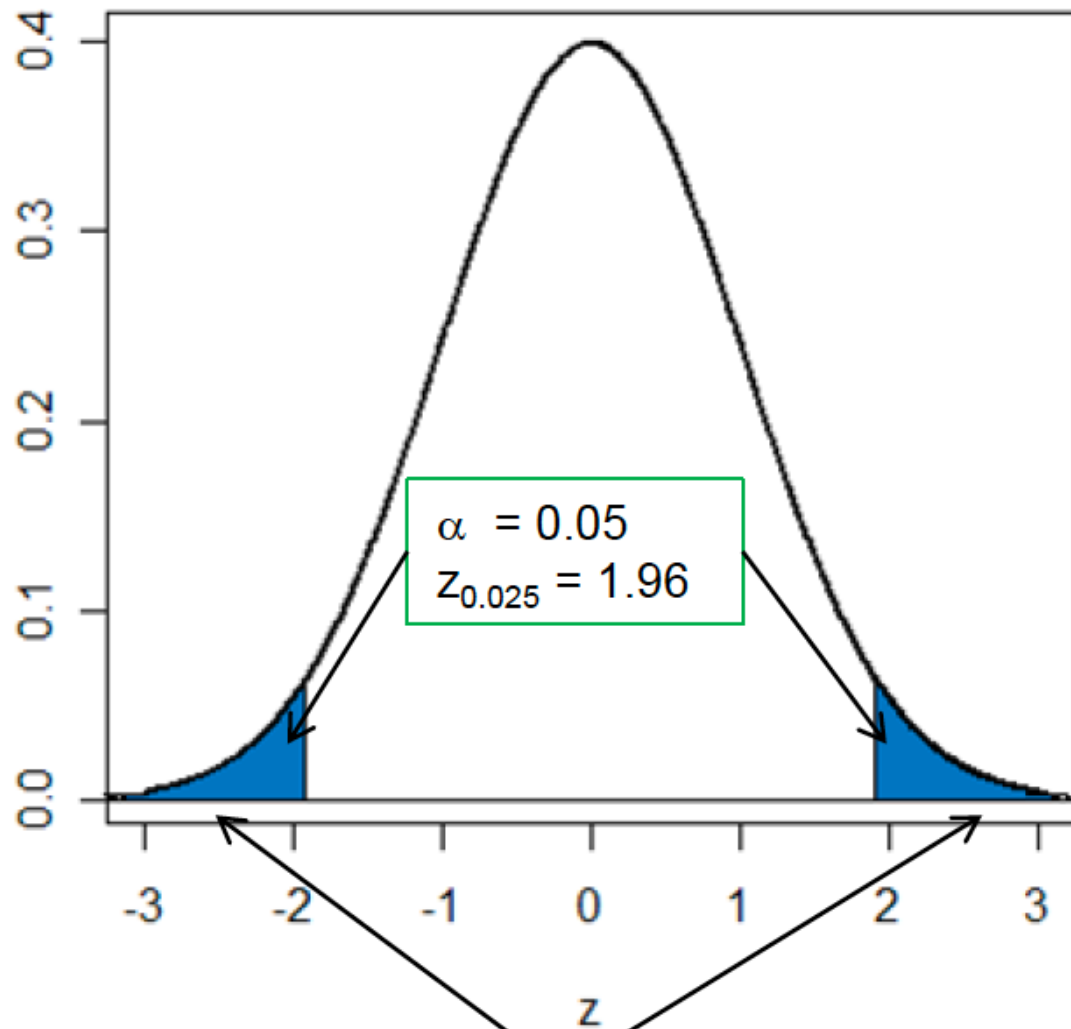
In R: $p = 1-\text{pnorm}(z^*)$

$\alpha = 0.05$, one-sided



Reject H_0 if $z^* > z_{0.05}$ or $p < \alpha$

two-sided test



$$|z^*| > z_{\alpha/2}$$

Example

Reading comprehension in L1 and L2

Mean accuracy of L1: 0.85

	L2
N	46
Mean	0.8
SD	0.2

Are L2 speakers' accuracy lower than L1?

Are L2 speakers' accuracy different than L1?

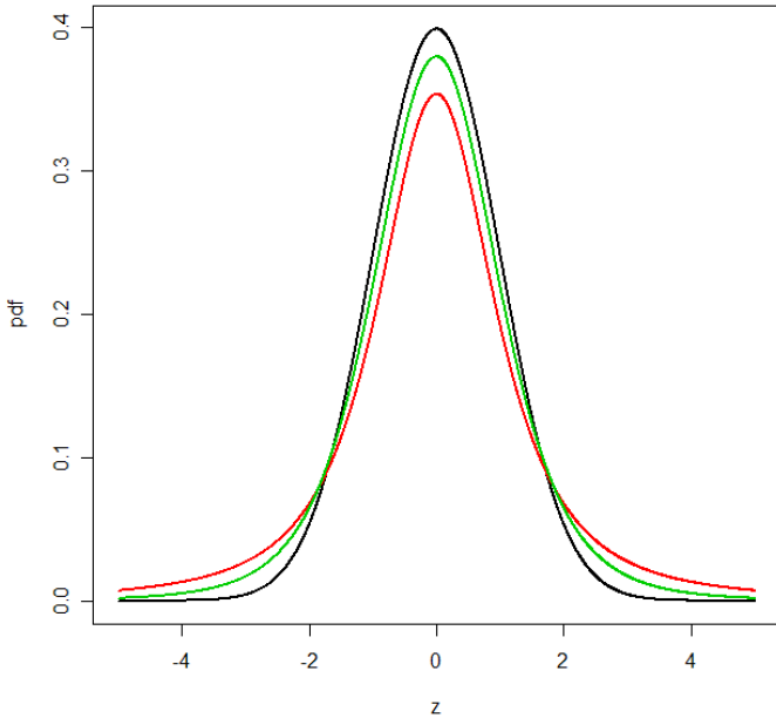
t-distribution

$$\frac{\bar{X}_n - \mu}{\sigma/\sqrt{n}} \sim N(0,1) \text{ does not } \longrightarrow \frac{\bar{X}_n - \mu}{S/\sqrt{n}} \sim N(0,1)$$

Reason: There is extra variability introduced when we replace a fixed σ by a varying, sample-dependent s .

Sampling distribution of $\frac{\bar{X}_n - \mu_0}{S/\sqrt{n}} \sim t_{\boxed{n-1}}$
degrees of freedom

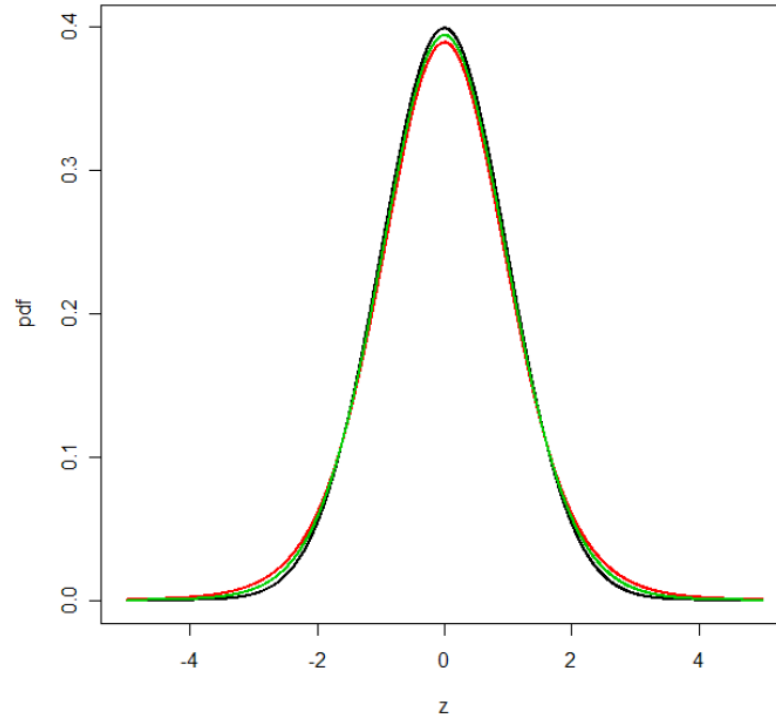
How different is a t_{df} distribution from a $N(0,1)$ distribution?



Black: $N(0,1)$

Green: t_5

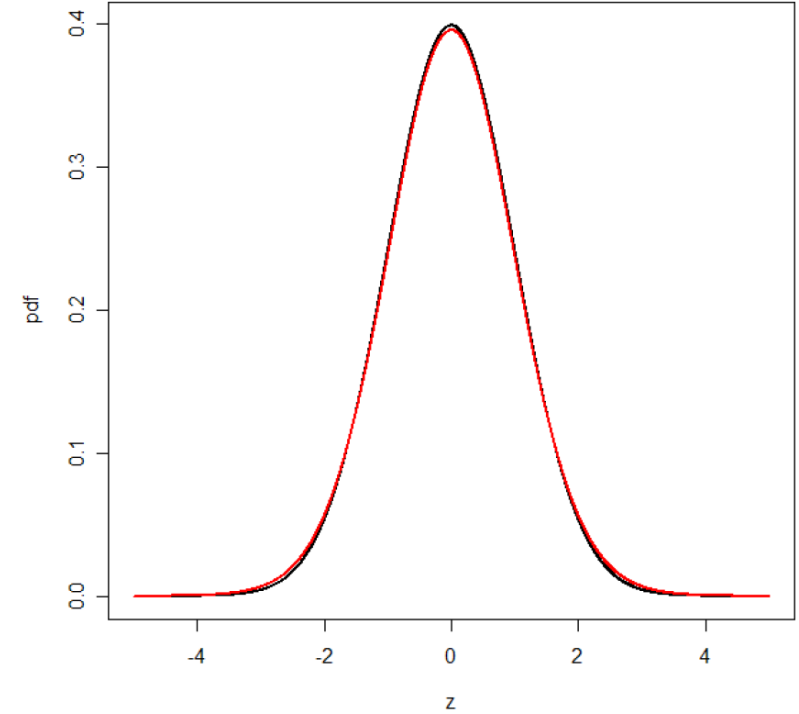
Red: t_2



Black: $N(0,1)$

Green: t_{20}

Red: t_{10}



Black: $N(0,1)$

Red: t_{30}

Hypothesis Testing: Normal Samples, σ Unknown

Example: $H_0: \mu \leq \mu_0$
 $H_a: \mu > \mu_0$

T.S. $t^* = \frac{\bar{X}_n - \mu_0}{s/\sqrt{n}}$

R.R. $t^* > t_{n-1, \alpha}$

p -value $p = P(t_{n-1} > t^*)$

For the two other forms of H_a , the relevant p -values are:

$$H_a: \mu < \mu_0 \leftrightarrow p = P(t_{n-1} < t^*)$$

$$H_a: \mu \neq \mu_0 \leftrightarrow p = 2 P(t_{n-1} > |t^*|)$$

Example: Students quiz score

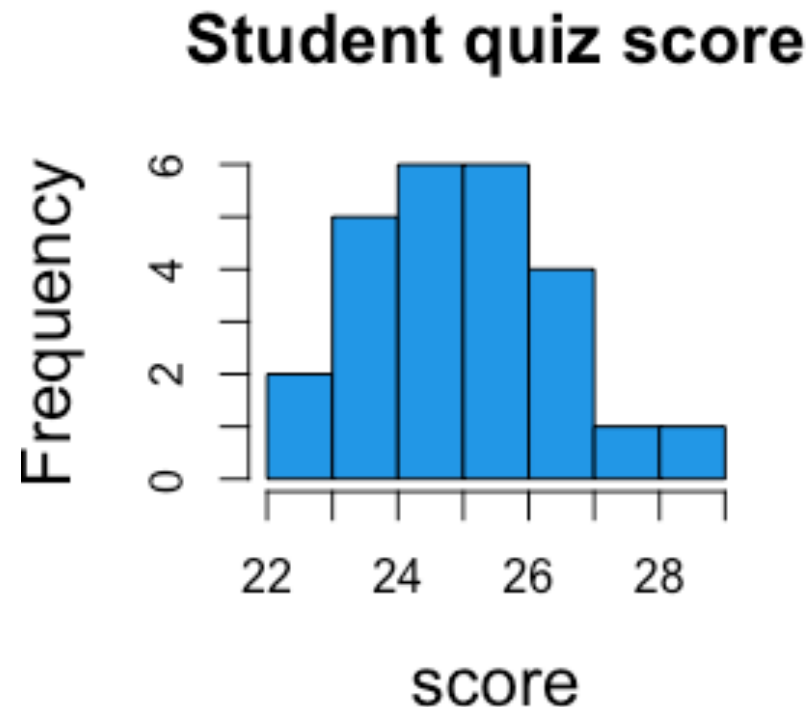
- Average quiz score of 25 students:

25.8, 24.6, 26.1, 22.9, 25.1, 27.3, 24.0, 24.5, 23.9,
26.2, 24.3, 24.6, 23.3, 25.5, 28.1, 24.8, 23.5, 26.3,
25.4, 25.5, 23.9, 27.0, 24.8, 22.9, 25.4.

- **Questions:** Based on this SRS, is the current mean different from that in 2022 (24.5)? (**Testing**)

Look at the data first...

```
> quizscore<-c(25.8, 24.6, 26.1, 22.9, 25.1, 27.3, 24.0, 24.5, 23.9, 26.2,
24.3, 24.6, 23.3, 25.5, 28.1, 24.8, 23.5, 26.3, 25.4, 25.5, 23.9, 27.0, 2
4.8, 22.9, 25.4)
> hist(quizscore,col=4,main="Student quiz score",xlab="score",cex.lab=1.5,
cex.main=1.5)
```



Do these data look like they were sampled from a normal distribution?

25 might not be "large enough" to approximate the sampling distribution of $\frac{\bar{X}_n - \mu}{S/\sqrt{n}}$ by $N(0,1)$

Test: $H_0: \mu = 24.5$ vs. $H_a: \mu \neq 24.5$

t.test() reports all output available for the test specified by the user

```
> t.test(quizscore, alternative="two.sided", mu=24.5)
```

One Sample t-test

```
data: quizscore
```

```
t = 1.9675, df = 24, p-value = 0.06079
```

```
alternative hypothesis: true mean is not equal to 24.5
```

```
95 percent confidence interval:
```

```
24.47413 25.58187
```

```
sample estimates:
```

```
mean of x
```

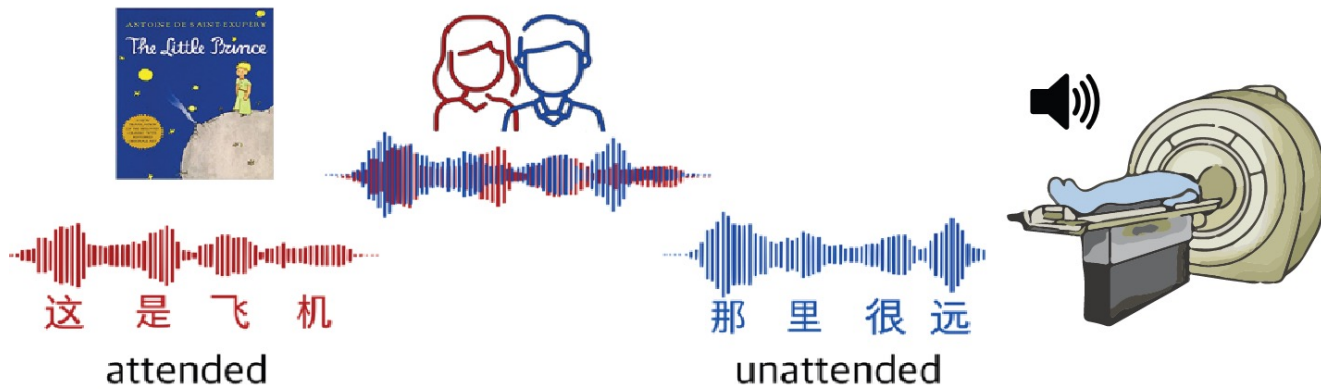
```
25.028
```

```
> 2*(1-pt(1.9675,24))
```

```
[1] 0.06078647
```

Inference for two samples

Difference in analysis: Form of the test statistic depends on whether the samples are **independent** or **paired**



two participant groups:
hearing-impaired
normal hearing

- Paired \rightarrow inference for the mean difference is identical to inference for μ
- Independent \rightarrow can we assume $\sigma_1 = \sigma_2$?
 - Equal variance assumption
 - Unequal variance assumption

Example: Cocktail party experiment

- Both hearing-impaired (N=49) and normal hearing participants (N=45) listened to mixed speech and single-talker speech in the fMRI scanner.
- Participants reported self-rated intelligibility score (on a 1-7 Likert scale) for each speech after the experiment
- **Question 1:** Is mixed speech more difficult to understand than single-talker speech for hearing-impaired and normal hearing listeners?
- **Question 2:** Are hearing-impaired listeners have more difficulty understanding mixed and single-talker speech than normal hearing listeners?

Sampling distributions for sums and differences of independent normal means

- Let \bar{X} be the sample mean from a SRS of size n_x from a $N(\mu_x, \sigma_x^2)$ population.
- Let \bar{Y} be the sample mean from a SRS of size n_y from a $N(\mu_y, \sigma_y^2)$ population.
- Assume that the two populations and the samples from them are independent. Then:

$$\bar{X} \pm \bar{Y} \sim N\left(\mu_x \pm \mu_y, \frac{\sigma_x^2}{n_x} + \frac{\sigma_y^2}{n_y}\right)$$

$H_0: \mu_1 - \mu_2 \leq D_0$ vs. $H_a: \mu_1 - \mu_2 > D_0$, reject H_0 if $t^* > t_{\alpha, df}$

$H_0: \mu_1 - \mu_2 \geq D_0$ vs. $H_a: \mu_1 - \mu_2 < D_0$, reject H_0 if $t^* < -t_{\alpha, df}$

$H_0: \mu_1 - \mu_2 = D_0$ vs. $H_a: \mu_1 - \mu_2 \neq D_0$, reject H_0 if $|t^*| > t_{\alpha/2, df}$

$$\text{where: } T^* = \frac{(\bar{X}_1 - \bar{X}_2) - D_0}{\sqrt{\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2}}}$$

$$df = \frac{(n_1 - 1)(n_2 - 1)}{(1 - c)^2(n_1 - 1) + c^2(n_2 - 1)} \quad \text{for } c = \frac{s_1^2/n_1}{s_1^2/n_1 + s_2^2/n_2}$$