Supplemental Note to Section 7.1

1. When X_i are **normal** and σ^2 is **known**: (CI)

   $$Z = \frac{\bar{X} - \mu}{\sigma/\sqrt{n}} \sim N(0,1) \text{ exactly}$$

   See: Example 7.1-1 and Example 7.1-2.
   Note: exactly normal. Thus, n can be small or large.
   Theory: exact normal distribution.

2. When X_i are **normal** and σ^2 is **unknown**: (CI)

   $$T = \frac{\bar{X} - \mu}{S/\sqrt{n}} \sim t(\text{df} = n-1) \text{ exactly}$$

   See: Example 7.1-5.
   Note: exact t-distribution. Thus, n can be small or large.
   Theory: exact t-distribution.

3. When X_i are **not necessarily normal** ($n \geq 30$) and σ^2 is **known**: (approximate CI)

   $$Z = \frac{\bar{X} - \mu}{\sigma/\sqrt{n}} \overset{\bullet}{\sim} N(0,1)$$

   See: Example 7.1-3.
   Theory: CLT.

4. When X_i are **not necessarily normal** ($n \geq 30$) and σ^2 is **unknown**: (approximate CI)

   $$Z = \frac{\bar{X} - \mu}{S/\sqrt{n}} \overset{\bullet\bullet}{\sim} N(0,1)$$

   See: Example 7.1-4.
   Theory: CLT + Slutzky.

- When X_i are **not necessarily normal** ($n < 30$) and σ^2 is **unknown**: (approximate CI)

  $$T = \frac{\bar{X} - \mu}{S/\sqrt{n}} \overset{\bullet\bullet\bullet}{\sim} t(\text{df} = n-1)$$

  Note: if $n \geq 30$, then use 4.
  Theory: CLT + Slutzky + Rule of thumb.

Supplemental Note to Section 7.2

1. When $X_i \sim N(\mu_x, \sigma_x^2)$ for $i = 1, 2, \ldots, n$ and $Y_j \sim N(\mu_y, \sigma_y^2)$ for $j = 1, 2, \ldots, m$ (σ_x^2 and σ_y^2 are **known**):
$$Z = \frac{(\bar{X} - \bar{Y}) - (\mu_x - \mu_y)}{\sqrt{\sigma_x^2/n + \sigma_y^2/m}} \sim N(0,1) \text{ exactly}$$
See: Example 7.2-1.
Note: exactly normal. Thus, n and m can be small or large.
Theory: exact normal distribution.

2. When $X_i \sim N(\mu_x, \sigma_x^2)$ for $i = 1, 2, \ldots, n$ and $Y_j \sim N(\mu_y, \sigma_y^2)$ for $j = 1, 2, \ldots, m$ ($\sigma_x^2 = \sigma_y^2 = \sigma^2$ but σ^2 is **unknown**):
$$T = \frac{(\bar{X} - \bar{Y}) - (\mu_x - \mu_y)}{\sqrt{S_p^2 \, (1/n + 1/m)}} \sim t(\text{df}) \text{ exactly}$$
where $\text{df} = (n-1) + (m-1)$ and
$$S_p^2 = \frac{(n-1)S_x^2 + (m-1)S_y^2}{(n-1)+(m-1)}.$$
See: Example 7.2-2.
Note: exact t-distribution. Thus, n and m can be small or large.
Theory: exact t-distribution.

3. When X_i are **not necessarily normal** for $i = 1, 2, \ldots, n$ ($n \geq 30$) and Y_j are **not necessarily normal** for $j = 1, 2, \ldots, m$ ($m \geq 30$).
$$Z = \frac{(\bar{X} - \bar{Y}) - (\mu_x - \mu_y)}{\sqrt{S_x^2/n + S_y^2/m}} \overset{\bullet\bullet}{\sim} N(0,1)$$
Theory: CLT + Slutzky.

4. When X_i are **not necessarily normal** for $i = 1, 2, \ldots, n$ ($n < 30$) and Y_j are **not necessarily normal** for $j = 1, 2, \ldots, m$ ($m < 30$).
$$T = \frac{(\bar{X} - \bar{Y}) - (\mu_x - \mu_y)}{\sqrt{S_x^2/n + S_y^2/m}} \overset{\bullet}{\sim} t(\text{df} = r),$$
where
$$r = \left\lfloor \frac{\left(\frac{S_x^2}{n} + \frac{S_y^2}{m}\right)^2}{\frac{1}{n-1}\left(\frac{S_x^2}{n}\right)^2 + \frac{1}{m-1}\left(\frac{S_y^2}{m}\right)^2} \right\rfloor$$
Theory: Welch.

