## CH. 10 Statistical Inference for Two Samples

- Inference on the difference in means of two normal distributions, variances known
- Inference on the difference in means of two normal distributions, variances unknown
- Paired t-test
- Inference on the variances of two normal distributions
- Inference on two population proportions


## 10-1 Introduction



Two independent populations.

## 10-1 Inference for a Difference in Means of Two Normal Distributions, Variances Known

## Assumptions

1. $X_{11}, X_{12}, \ldots, X_{1 n_{1}}$ is a random sample from population 1 .
2. $X_{21}, X_{22}, \ldots, X_{2 n_{2}}$ is a random sample from population 2.
3. The two populations represented by $X_{1}$ and $X_{2}$ are independent.
4. Both populations are normal.

$$
\begin{aligned}
& E\left(\bar{X}_{1}-\bar{X}_{2}\right)=E\left(\bar{X}_{1}\right)-E\left(\bar{X}_{2}\right)=\mu_{1}-\mu_{2} \\
& V\left(\bar{X}_{1}-\bar{X}_{2}\right)=V\left(\bar{X}_{1}\right)+V\left(\bar{X}_{2}\right)=\frac{\sigma_{1}^{2}}{n_{1}}+\frac{\sigma_{2}^{2}}{n_{2}}
\end{aligned}
$$

## 10-1 Inference for a Difference in Means of Two Normal Distributions, Variances Known

The quantity

$$
\begin{equation*}
Z=\frac{\bar{X}_{1}-\bar{X}_{2}-\left(\mu_{1}-\mu_{2}\right)}{\sqrt{\frac{\sigma_{1}^{2}}{n_{1}}+\frac{\sigma_{2}^{2}}{n_{2}}}} \tag{10-1}
\end{equation*}
$$

has a $N(0,1)$ distribution.

## 10-1 Inference for a Difference in Means of Two Normal Distributions, Variances Known

10-1.1 Hypothesis Tests for a Difference in Means, Variances Known

Null hypothesis: $\quad H_{0}: \mu_{1}-\mu_{2}=\Delta_{0}$
Test statistic: $\quad Z_{0}=\frac{\overline{X_{1}}-\overline{X_{2}}-\Delta_{0}}{\sqrt{\frac{\sigma_{1}^{2}}{n_{1}}+\frac{\sigma_{2}^{2}}{n_{2}}}}$

$$
\begin{gathered}
\text { Alternative Hypotheses } \\
\hline H_{1}: \mu_{1}-\mu_{2} \neq \Delta_{0} \\
H_{4}: \mu_{1}-\mu_{2}>\Delta_{0} \\
H_{1}: \mu_{1}-\mu_{2}<\Delta_{0}
\end{gathered}
$$

Rejection Criterion

$$
\begin{gathered}
z_{0}>z_{\alpha / 2} \text { or } z_{0}<-z_{\alpha / 2} \\
z_{0}>z_{\alpha} \\
z_{0}<-z_{\alpha}
\end{gathered}
$$

## 10-1 Inference for a Difference in Means of Two Normal Distributions, Variances Known

## Example 10-1

A product developer is interested in reducing the drying time of a primer paint. Two formulations of the paint are tested; formulation 1 is the standard chemistry, and formulation 2 has a new drying ingredient that should reduce the drying time. From experience, it is known that the standard deviation of drying time is 8 minutes, and this inherent variability should be unaffected by the addition of the new ingredient. Ten specimens are painted with formulation 1 , and another 10 specimens are painted with formulation 2 ; the 20 specimens are painted in random order. The two sample average drying times are $\bar{x}_{1}=121$ minutes and $\bar{x}_{2}=112$ minutes, respectively. What conclusions can the product developer draw about the effectiveness of the new ingredient, using $\alpha=0.05$ ?

We apply the eight-step procedure to this problem as follows:

1. The quantity of interest is the difference in mean drying times, $\mu_{1}-\mu_{2}$, and $\Delta_{0}=0$.
2. $H_{0}: \mu_{1}-\mu_{2}=0$ or $H_{0}: \mu_{1}=\mu_{2}$.
3. $H_{1}: \mu_{1}>\mu_{2}$. We want to reject $H_{0}$ if the new ingredient reduces mean drying time.
4. $\alpha=0.05$

## 10-1 Inference for a Difference in Means of Two Normal Distributions, Variances Known

Example 10-1
5. The test statistic is

$$
z_{0}=\frac{\bar{x}_{1}-\bar{x}_{2}-0}{\sqrt{\frac{\sigma_{1}^{2}}{n_{1}}+\frac{\sigma_{2}^{2}}{n_{2}}}}
$$

where $\sigma_{1}^{2}=\sigma_{2}^{2}=(8)^{2}=64$ and $n_{1}=n_{2}=10$.
6. Reject $H_{0}: \mu_{1}=\mu_{2}$ if $z_{0}>1.645=z_{0.05}$.
7. Computations: Since $\bar{x}_{1}=121$ minutes and $\bar{x}_{2}=112$ minutes, the test statistic is

$$
z_{0}=\frac{121-112}{\sqrt{\frac{(8)^{2}}{10}+\frac{(8)^{2}}{10}}}=2.52
$$

## 10-1 Inference for a Difference in Means of Two Normal Distributions, Variances Known

Example 10-1
8. Conclusion: Since $z_{0}=2.52>1.645$, we reject $H_{0}: \mu_{1}=\mu_{2}$ at the $\alpha=0.05$ level and conclude that adding the new ingredient to the paint significantly reduces the drying time. Alternatively, we can find the $P$-value for this test as

$$
P \text {-value }=1-\Phi(2.52)=0.0059
$$

Therefore, $H_{0}: \mu_{1}=\mu_{2}$ would be rejected at any significance level $\alpha \geq 0.0059$.

## 10-1 Inference for a Difference in Means of Two Normal Distributions, Variances Known

10-1.2 Type II Error and Choice of Sample Size Use of Operating Characteristic Curves

Two-sided or one-sided alternative: $\quad d=\frac{\sqrt{\sigma_{1}^{2}+\sigma_{2}^{2}}}{\text { ( }}=\frac{\sqrt{\sigma_{1}^{2}+\sigma_{2}^{2}}}{\sqrt{2}}$

Choose equal sample sizes, $\mathrm{n}=\mathrm{n}_{1}=\mathrm{n}_{2}$
If not possible: $n_{1} \neq n_{2}$, compute equivalent value of $n$ as follows

$$
n=\frac{\sigma_{1}^{2}+\sigma_{2}^{2}}{\sigma_{1}^{2} / n_{1}+\sigma_{2}^{2} / n_{2}}
$$

make adjustment to $\mathrm{n}_{1}$ and $\mathrm{n}_{2}$ until the specified $\beta$ is reached.

## 10-1 Inference for a Difference in Means of Two Normal Distributions, Variances Known

10-1.2 Type II Error and Choice of Sample Size
Sample Size Formulas
Two-sided alternative:

For the two-sided alternative hypothesis with significance level $\alpha$, the sample size $n_{1}=n_{2}=n$ required to detect a true difference in means of $\Delta$ with power at least 1- $\beta$ is

$$
\begin{equation*}
n \simeq \frac{\left(z_{\alpha / 2}+z_{\beta}\right)^{2}\left(\sigma_{1}^{2}+\sigma_{2}^{2}\right)}{\left(\Delta-\Delta_{0}\right)^{2}} \tag{10-5}
\end{equation*}
$$

## 10-1 Inference for a Difference in Means of Two Normal Distributions, Variances Known

10-1.2 Type II Error and Choice of Sample Size Sample Size Formulas

## One-sided alternative:

For a one-sided alternative hypothesis with significance level $\alpha$, the sample size $n_{1}=n_{2}=n$ required to detect a true difference in means of $\Delta\left(\neq \Delta_{0}\right)$ with power at least $1-\beta$ is

$$
\begin{equation*}
n=\frac{\left(z_{\alpha}+z_{\beta}\right)^{2}\left(\sigma_{1}^{2}+\sigma_{2}^{2}\right)}{\left(\Delta-\Delta_{0}\right)^{2}} \tag{10-6}
\end{equation*}
$$

## 10-1 Inference for a Difference in Means of Two Normal Distributions, Variances Known

## Example 10-3

To illustrate the use of these sample size equations, consider the situation described in Example 10-1, and suppose that if the true difference in drying times is as much as 10 minutes, we want to detect this with probability at least 0.90 . Under the null hypothesis, $\Delta_{0}=0$. We have a one-sided alternative hypothesis with $\Delta=10, \alpha=0.05$ (so $z_{\mathrm{a}}=z_{0.05}=1.645$ ), and since the power is $0.9, \beta=0.10$ (so $z_{\beta}=z_{0.10}=1.28$ ). Therefore we may find the required sample size from Equation $10-6$ as follows:

$$
n=\frac{\left(z_{\alpha}+z_{\beta}\right)^{2}\left(\sigma_{1}^{2}+\sigma_{2}^{2}\right)}{\left(\Delta-\Delta_{0}\right)^{2}}=\frac{(1.645+1.28)^{2}\left[(8)^{2}+(8)^{2}\right]}{(10-0)^{2}}=11
$$

This is exactly the same as the result obtained from using the O.C. curves.

$$
d=\frac{\left|\mu_{1}-\mu_{2}-0\right|}{\sqrt{\sigma_{1}^{2}+\sigma_{2}^{2}}}=\frac{10}{\sqrt{8^{2}+8^{2}}}=0.88
$$

ALSO, with $\beta=0.1, \mathrm{~d}=0.88, \alpha=0.05$ from Appendix Chart VIIc $\mathrm{n}=\mathrm{n}_{1}=\mathrm{n}_{2} \approx 11$

## 10-1 Inference for a Difference in Means of Two Normal Distributions, Variances Known

10-1.3 Confidence Interval on a Difference in Means, Variances Known

## Definition

If $\bar{x}_{1}$ and $\bar{x}_{2}$ are the means of independent random samples of sizes $n_{1}$ and $n_{2}$ from two independent normal populations with known variances $\sigma_{1}^{2}$ and $\sigma_{2}^{2}$, respectively, a $100(1-\alpha) \%$ confidence interval for $\mu_{1}-\mu_{2}$ is

$$
\begin{equation*}
\bar{x}_{1}-\bar{x}_{2}-z_{\alpha / 2} \sqrt{\frac{\sigma_{1}^{2}}{n_{1}}+\frac{\sigma_{2}^{2}}{n_{2}}} \leq \mu_{1}-\mu_{2} \leq \bar{x}_{1}-\bar{x}_{2}+z_{\alpha / 2} \sqrt{\frac{\sigma_{1}^{2}}{n_{1}}+\frac{\sigma_{2}^{2}}{n_{2}}} \tag{10-7}
\end{equation*}
$$

where $z_{\alpha / 2}$ is the upper $\alpha / 2$ percentage point of the standard normal distribution.

## 10-1 Inference for a Difference in Means of Two Normal Distributions, Variances Known

## Example 10-4

Tensile strength tests were performed on two different grades of aluminum spars used in manufacturing the wing of a commercial transport aircraft. From past experience with the spar manufacturing process and the testing procedure, the standard deviations of tensile strengths are assumed to be known. The data obtained are as follows: $n_{1}=10, \bar{x}_{1}=87.6, \sigma_{1}=1$, $n_{2}=12, \bar{x}_{2}=74.5$, and $\sigma_{2}=1.5$. If $\mu_{1}$ and $\mu_{2}$ denote the true mean tensile strengths for the two grades of spars, we may find a $90 \%$ confidence interval on the difference in mean strength $\mu_{1}-\mu_{2}$ as follows:

$$
\bar{x}_{1}-\bar{x}_{2}-z_{\alpha / 2} \sqrt{\frac{\sigma_{1}^{2}}{n_{1}}+\frac{\sigma_{2}^{2}}{n_{2}}} \leq \mu_{1}-\mu_{2} \leq \bar{x}_{1}-\bar{x}_{2}+z_{\alpha / 2} \sqrt{\frac{\sigma_{1}^{2}}{n_{1}}+\frac{\sigma_{2}^{2}}{n_{2}}}
$$

$87.6-74.5-1.645 \sqrt{\frac{(1)^{2}}{10}+\frac{(1.5)^{3}}{12}} \leq \mu_{1}-\mu_{2} \leq 87.6-74.5+1.645 \sqrt{\frac{\left(1^{2}\right)}{10}+\frac{(1.5)^{2}}{12}}$

## 10-1 Inference for a Difference in Means of Two Normal Distributions, Variances Known

## Example 10-4

Therefore, the 90\% confidence interval on the difference in mean tensile strength (in kilograms per square millimeter) is

$$
12.22 \leq \mu_{1}-\mu_{2} \leq 13.98 \text { (in kilograms per square millimeter) }
$$

Notice that the confidence interval does not include zero, implying that the mean strength of aluminum grade $1\left(\mu_{1}\right)$ exceeds the mean strength of aluminum grade $2\left(\mu_{2}\right)$. In fact, we can state that we are $90 \%$ confident that the mean tensile strength of aluminum grade 1 exceeds that of aluminum grade 2 by between 12.22 and 13.98 kilograms per square millimeter.

## 10-1 Inference for a Difference in Means of Two Normal Distributions, Variances Known

## Choice of Sample Size

$$
\begin{equation*}
n=\left(\frac{z_{\alpha / 2}}{E}\right)^{2}\left(\sigma_{1}^{2}+\sigma_{2}^{2}\right) \tag{10-8}
\end{equation*}
$$

The required sample size so that the error in estimating $\mu_{1}-\mu_{2}$ by $\bar{x}_{1}-\bar{x}_{2}$ will be less than $E$ at $100(1-\alpha) \%$ confidence.

## 10-1 Inference for a Difference in Means of Two Normal Distributions, Variances Known

One-Sided Confidence Bounds
Upper Confidence Bound

$$
\begin{equation*}
\mu_{1}-\mu_{2} \leq \bar{x}_{1}-\bar{x}_{2}+z_{\alpha} \sqrt{\frac{\sigma_{1}^{2}}{n_{1}}+\frac{\sigma_{2}^{2}}{n_{2}}} \tag{10-9}
\end{equation*}
$$

Lower Confidence Bound

$$
\begin{equation*}
\bar{x}_{1}-\bar{x}_{2}-z_{\alpha} \sqrt{\frac{\sigma_{1}^{2}}{n_{1}}+\frac{\sigma_{2}^{2}}{n_{2}}} \leq \mu_{1}-\mu_{2} \tag{10-10}
\end{equation*}
$$

## 10-2 Inference for a Difference in Means of Two Normal Distributions, Variances Unknown

10-2.1 Hypotheses Tests for a Difference in Means, Variances Unknown

$$
\text { Case 1: } \sigma_{1}^{2}=\sigma_{2}^{2}=\sigma^{2}
$$

We wish to test:

$$
\begin{aligned}
& H_{0}: \mu_{1}-\mu_{2}=\Delta_{0} \\
& H_{1}: \mu_{1}-\mu_{2} \neq \Delta_{0}
\end{aligned}
$$

## 10-2 Inference for a Difference in Means of Two Normal Distributions, Variances Unknown

10-2.1 Hypotheses Tests for a Difference in Means, Variances Unknown
Case 1: $\sigma_{1}^{2}=\sigma_{2}^{2}=\sigma^{2}$
combine $S_{1}^{2}$ and $S_{2}^{2}$ to form an estimator of $\sigma^{2}$
The pooled estimator of $\sigma^{2}$ :

The pooled estimator of $\sigma^{2}$, denoted by $S_{p}^{2}$, is defined by

$$
\begin{equation*}
S_{p}^{2}=\frac{\left(n_{1}-1\right) s_{1}^{2}+\left(n_{2}-1\right) s_{2}^{2}}{n_{1}+n_{2}-2} \tag{10-12}
\end{equation*}
$$

## 10-2 Inference for a Difference in Means of Two Normal Distributions, Variances Unknown

10-2.1 Hypotheses Tests for a Difference in Means, Variances Unknown

$$
\text { Case 1: } \sigma_{1}^{2}=\sigma_{2}^{2}=\sigma^{2}
$$

Given the assumptions of this section, the quantity

$$
\begin{equation*}
T=\frac{\bar{X}_{1}-\bar{X}_{2}-\left(\mu_{1}-\mu_{2}\right)}{S_{p} \sqrt{\frac{1}{n_{1}}+\frac{1}{n_{2}}}} \tag{10-13}
\end{equation*}
$$

has a $t$ distribution with $n_{1}+n_{2}-2$ degrees of freedom.

## 10-2 Inference for a Difference in Means of Two Normal Distributions, Variances Unknown

## Definition: The Two-Sample or Pooled t-Test

Null hypothesis

$$
H_{0}: \mu_{1}-\mu_{2}=\Delta_{0}
$$

Test statistic:

$$
\begin{equation*}
T_{0}=\frac{\bar{X}_{1}-\bar{X}_{2}-\Delta_{0}}{S_{p} \sqrt{\frac{1}{n_{1}}+\frac{1}{n_{2}}}} \tag{10-14}
\end{equation*}
$$

| $\frac{\text { Alternative Hypothesis }}{H_{1}: \mu_{1}-\mu_{2} \neq \Delta_{0}}$ |  | $\frac{\text { Rejection Criterion }}{}$ |
| :---: | :--- | :--- |
|  |  | $t_{0}>t_{\alpha / 2, n_{1}+n_{2}-2}$ or |
| $H_{1:}: \mu_{1}-\mu_{2}>\Delta_{0}$ |  | $t_{0}<-t_{\alpha / 2, n_{1}+n_{2}-2}$ |
| $H_{1}: \mu_{1}-\mu_{2}<\Delta_{0}$ |  | $t_{0}<-t_{\alpha, n_{1}+n_{2}-2}$ |
|  |  |  |

## 10-2 Inference for a Difference in Means of Two Normal Distributions, Variances Unknown

## Example 10-5

Two catalysts are being analyzed to determine how they affect the mean yield of a chemical process. Specifically, catalyst 1 is currently in use, but catalyst 2 is acceptable. Since catalyst 2 is cheaper, it should be adopted, providing it does not change the process yield. A test is run in the pilot plant and results in the data shown in Table 10-1. Is there any difference between the mean yields? Use $\alpha=0.05$, and assume equal variances.

## 10-2 Inference for a Difference in Means of Two Normal Distributions, Variances Unknown

Example 10-5
Table 10-1 Catalyst Yield Data, Example 10.5

| Observation <br> Number | Catalyst 1 | Catalyst 2 |
| :---: | :---: | :---: |
| 1 | 91.50 | 89.19 |
| 2 | 94.18 | 90.95 |
| 3 | 92.18 | 90.46 |
| 4 | 95.39 | 93.21 |
| 5 | 91.79 | 97.19 |
| 6 | 89.07 | 97.04 |
| 7 | 94.72 | 91.07 |
| 8 | 89.21 | 92.75 |
|  | $\bar{x}_{1}=92.255$ | $\bar{x}_{2}=92.733$ |
|  | $s_{1}=2.39$ | $s_{2}=2.98$ |

## 10-2 Inference for a Difference in Means of Two Normal Distributions, Variances Unknown

## Example 10-5

The solution using the eight-step hypothesis-testing procedure is as follows:

1. The parameters of interest are $\mu_{1}$ and $\mu_{2}$, the mean process yield using catalysts

1 and 2, respectively, and we want to know if $\mu_{1}-\mu_{2}=0$.
2. $H_{0}: \mu_{1}-\mu_{2}=0$ or $H_{0}: \mu_{1}=\mu_{2}$
3. $H_{1}: \mu_{1} \neq \mu_{2}$
4. $\alpha=0.05$
5. The test statistic is

$$
t_{0}=\frac{\bar{x}_{1}-\bar{x}_{2}-0}{s_{p} \sqrt{\frac{1}{n_{1}}+\frac{1}{n_{2}}}}
$$

6. 

$$
\text { Reject } H_{0} \text { if } t_{0}>t_{0.025,14}=2.145 \text { or if } t_{0}<-t_{0.025,14}=-2.145 .
$$

## 10-2 Inference for a Difference in Means of Two Normal Distributions, Variances Unknown

## Example 10-5

7. Computations: From Table 10-1 we have $\bar{x}_{1}=92.255, s_{1}=2.39, n_{1}=8, \bar{x}_{2}=92.733$, $s_{2}=2.98$, and $n_{2}=8$. Therefore

$$
\begin{aligned}
& s_{p}^{2}=\frac{\left(n_{1}-1\right) s_{1}^{2}+\left(n_{2}-1\right) s_{2}^{2}}{n_{1}+n_{2}-2}=\frac{(7)(2.39)^{2}+7(2.98)^{2}}{8+8-2}=7.30 \\
& s_{p}=\sqrt{7.30}=2.70
\end{aligned}
$$

and

$$
t_{0}=\frac{\bar{x}_{1}-\bar{x}_{2}}{2.70 \sqrt{\frac{1}{n_{1}}+\frac{1}{n_{2}}}}=\frac{92.255-92.733}{2.70 \sqrt{\frac{1}{8}+\frac{1}{8}}}=-0.35
$$

8. Conclusions: Since $-2.145<t_{0}=-0.35<2.145$, the null hypothesis cannot be rejected. That is, at the 0.05 level of significance, we do not have strong evidence to conclude that catalyst 2 results in a mean yield that differs from the mean yield when catalyst 1 is used.

## 10-2 Inference for a Difference in Means of Two Normal Distributions, Variances Unknown

## Minitab Output for Example 10-5

Minitab Computations
Two-Sample T-Test and CI: Cat 1, Cat 2
Two-sample T for Cat 1 vs Cat 2

| Cat 1 | 8 | 92.26 | 2.39 | 0.84 |
| :--- | :--- | :--- | :--- | :--- |
| Cat 2 | 8 | 92.73 | 2.99 | 1.1 |

Difference $=\mathrm{mu}$ Cat $1-\mathrm{muCat} 2$
Estimate for difference: -0.48
$95 \% \mathrm{CI}$ for difference: $(-3.37,2.42)$
T-Test of difference $=0($ vs not $=):$ T-Value $=-0.35 \mathrm{P}$-Value $=0.730 \mathrm{DF}=14$
Both use Pooled StDev $=2.70$

## 10-2 Inference for a Difference in Means

 of Two Normal Distributions, Variances Unknown
(a)

(b)

Normal probability plot: 1) normality assumption can be made.
2) similar slopes indicate assumption of equal variances

Comparative box plot: no obvious difference in the two catalysts. However, catalyst 2 has slightly greater sample variability.

## 10-2 Inference for a Difference in Means of Two Normal Distributions, Variances Unknown

10-2.1 Hypotheses Tests for a Difference in Means, Variances Unknown
Case 2: $\sigma_{1}^{2} \neq \sigma_{2}^{2}$

$$
\begin{equation*}
T_{0}^{*}=\frac{\bar{X}_{1}-\bar{X}_{2}-\Delta_{0}}{\sqrt{\frac{S_{1}^{2}}{n_{1}}+\frac{S_{2}^{2}}{n_{2}}}} \tag{10-15}
\end{equation*}
$$

is distributed approximately as $t$ distribution with degrees of freedom $v$ given by

## 10-2 Inference for a Difference in Means of Two Normal Distributions, Variances Unknown

10-2.1 Hypotheses Tests for a Difference in Means, Variances Unknown

Case 2: $\sigma_{1}^{2} \neq \sigma_{2}^{2}$

$$
v=\frac{\left(\frac{S_{1}^{2}}{n_{1}}+\frac{S_{2}^{2}}{n_{2}}\right)^{2}}{\frac{\left(\frac{\left.s_{1}^{2} / n_{1}\right)^{2}}{n_{1}-1}+\frac{\left(S_{2}^{2} / n_{2}\right)^{2}}{n_{2}-1}\right.}{} \text { 2 }}
$$

## 10-2 Inference for a Difference in Means of Two Normal Distributions, Variances Unknown

## Example 10-6

Arsenic concentration in public drinking water supplies is a potential health risk. An article in the Arizona Republic (Sunday, May 27, 2001) reported drinking water arsenic concentrations in parts per billion (ppb) for 10 methropolitan Phoenix communities and 10 communities in rural Arizona. The data follow:

Metro Phoenix $\left(\bar{x}_{1}=12.5, s_{1}=7.63\right)$
Phoentx, 3
Chandler, 7
Gilbert, 25
Glendale, 10
Mesa, 15
Paradise Valley, 6
Peoria, 12
Scottsdale, 25
Tempe, 15
Sun City, 7

Rural Arizona $\left(\bar{x}_{2}=27.5, s_{2}=15.3\right)$
Rimrock, 48
Goodyear, 44
New River, 40
Apachie Junction, 38
Buckeye, 33
Nogales, 21
Black Canyon City, 20
Sedona, 12
Payson, 1
Casa Grande, 18

## 10-2 Inference for a Difference in Means of Two Normal Distributions, Variances Unknown

## Example 10-6 (Continued)

Figure 10-2 Normal probability plot of the arsenic concentration data from Example 10-6.


## 10-2 Inference for a Difference in Means of Two Normal Distributions, Variances Unknown

## Example 10-6 (Continued)

We wish to determine it there is any difference in mean arsenic concentrations between metropolitan Phoenix communities and communities in rural Arizona. Figure $10-3$ shows a normal probability plot for the two samples of arsenic concentration. The assumption of normality appears quite reasonable, but since the slopes of the two straight lines are very different, it is unlikely that the population variances are the same.

Applying the eight-step procedure gives the following:

1. The parameters of interest are the mean arsenic concentrations for the two geographic regions, say $\mu_{1}$ and $\mu_{2}$, and we are interested in determining whether $\mu_{1}-\mu_{2}=0$.
2. $H_{0}: \mu_{1}-\mu_{2}=0$ or $H_{0}: \mu_{1}=\mu_{2}$
3. $H_{1:}: \mu_{1} \neq \mu_{2}$
4. $\alpha=0.05$ (say)

## 10-2 Inference for a Difference in Means of Two Normal Distributions, Variances Unknown

## Example 10-6 (Continued)

5. The test statistic is

$$
t_{0}^{*}=\frac{\bar{x}_{1}-\bar{x}_{2}-0}{\sqrt{\frac{s_{1}^{2}}{n_{1}}+\frac{s_{2}^{2}}{n_{2}}}}
$$

6. The degrees of freedom on $t_{0}^{*}$ are found from Equation 10-16 as

$$
v=\frac{\left(\frac{s_{1}^{2}}{n_{1}}+\frac{s_{2}^{2}}{n_{2}}\right)^{2}}{\frac{\left(s_{1}^{2} / n_{1}\right)^{2}}{n_{1}-1}+\frac{\left(s_{2}^{2} / n_{2}\right)^{2}}{n_{2}-1}}=\frac{\left[\frac{(7.63)^{2}}{10}+\frac{(15.3)^{2}}{10}\right]^{2}}{\frac{\left[(7.63)^{2} / 10\right]^{2}}{9}+\frac{\left[(15.3)^{2} / 10\right]^{2}}{9}}=13.2 \approx 13
$$

Therefore, using $\alpha=0.05$, we would reject $H_{0}: \mu_{1}=\mu_{2}$ if $t_{0}^{*}>t_{0.025_{11}}=2.160$ or if $t_{0}^{*}<-t_{0.025,13}=-2.160$

## 10-2 Inference for a Difference in Means of Two Normal Distributions, Variances Unknown

## Example 10-6 (Continued)

7. Computations: Using the sample data we find

$$
t_{0}^{*}=\frac{\bar{x}_{1}-\bar{x}_{2}}{\sqrt{\frac{s_{1}^{2}}{n_{1}}+\frac{s_{2}^{2}}{n_{2}}}}=\frac{12.5-27.5}{\sqrt{\frac{(7.63)^{2}}{10}+\frac{(15.3)^{2}}{10}}}=-2.77
$$

8. Conclusions: Because $t_{0}^{*}=-2.77<t_{0,025.13}=-2.160$, we reject the null hypothesis. Therefore, there is evidence to conclude that mean arsenic concentration in the drinking water in rural Arizona is different from the mean arsenic concentration in metropolitan Phoenix drinking water. Furthermore, the mean arsenic concentration is higher in rural Arizona communities. The $P$-value for this test is approximately $P=0.016$.

## 10-2 Inference for a Difference in Means of Two Normal Distributions, Variances Unknown

10-2.2 Type II Error and Choice of Sample Size
Case 1: $\sigma_{1}^{2}=\sigma_{2}^{2}=\sigma^{2}$
Use operating characteristic curves in Appendix Charts VIIe, VIIf, VIIg, VIIh.

$$
\begin{aligned}
& d=\frac{\left|\Delta-\Delta_{0}\right|}{2 \sigma} \\
& n^{*}=2 n-1
\end{aligned}
$$

Case 2: $\sigma_{1}^{2} \neq \sigma_{2}^{2}$
No operating characteristic curves are available.

## 10-2 Inference for a Difference in Means of Two Normal Distributions, Variances Unknown

## 10-2.2 Type II Error and Choice of Sample Size

## Example 10-7

Consider the catalyst experiment in Example 10-5. Suppose that, if catalyst 2 produces a mean yield that differs from the mean yield of catalyst 1 by $4.0 \%$, we would like to reject the null hypothesis with probability at least 0.85 . What sample size is required?

Using $s_{p}=2.70$ as a rough estimate of the common standard deviation $\sigma$, we have $d=|\Delta| / 2 \sigma=$ $|4.0| \overline{/[(2)(2.70)]}=0.74$. From Appendix Chart VIIe with $d=0.74$ and $\beta=0.15$, we find $n^{*}=20$, approximately. Therefore, since $n^{*}=2 n-1$,

$$
n=\frac{n^{*}+1}{2}=\frac{20+1}{2}=10.5=11(\text { say })
$$

and we would use sample sizes of $n_{1}=n_{2}=n=11$.

## 10-2 Inference for a Difference in Means of Two Normal Distributions, Variances Unknown

## Minitab Output for Example 10-7

## Minitab Computations

Power and Sample Size
2-Sample $t$ Test
Testing mean $1=$ mean 2 (versus not $=$ )
Calculating power for mean $1=$ mean $2+$ difference
Alpha $=0.05$ Sigma $=2.7$

|  | Sample | Target | Actual |
| :---: | :---: | :---: | :---: |
| Difference | Size | Power | Power |
| 4 | 10 | 0.8500 | 0.8793 |

## 10-2 Inference for a Difference in Means of Two Normal Distributions, Variances Unknown

10-2.3 Confidence Interval on the Difference in Means, Variance Unknown

$$
\text { Case 1: } \sigma_{1}^{2}=\sigma_{2}^{2}=\sigma^{2}
$$

If $\bar{x}_{1}, \bar{x}_{2}, s_{1}^{2}$ and $s_{2}^{2}$ are the sample means and variances of two random samples of sizes $n_{1}$ and $n_{2}$, respectively, from two independent normal populations with unknown but equal variances, then a $100(1-\alpha) \%$ confidence interval on the difference in means $\mu_{1}-\mu_{2}$ is

$$
\begin{align*}
& \bar{x}_{1}-\bar{x}_{2}-t_{\alpha / 2, n_{1}+n_{2}-2} s_{p} \sqrt{\frac{1}{n_{1}}+\frac{1}{n_{2}}} \\
& \quad \leq \mu_{1}-\mu_{2} \leq \bar{x}_{1}-\bar{x}_{2}+t_{\alpha / 2, n_{1}+n_{2}-2} s_{p} \sqrt{\frac{1}{n_{1}}+\frac{1}{n_{2}}} \tag{10-19}
\end{align*}
$$

where $s_{p}=\sqrt{\left[\left(n_{1}-1\right) s_{1}^{2}+\left(n_{2}-1\right) s_{2}^{2}\right] /\left(n_{1}+n_{2}-2\right)}$ is the pooled estimate of the common population standard deviation, and $t_{\alpha / 2, n_{1}+n_{2}-2}$ is the upper $\alpha / 2$ percentage point of the $t$ distribution with $n_{1}+n_{2}-2$ degrees of freedom.

## 10-2 Inference for a Difference in Means of Two Normal Distributions, Variances Unknown

Case 1: $\sigma_{1}^{2}=\sigma_{2}^{2}=\sigma^{2}$

## Example 10-8

An article in the journal Hazardous Waste and Hazardous Materials (Vol. 6, 1989) reported the results of an analysis of the weight of calcium in standard cement and cement doped with lead. Reduced levels of calcium would indicate that the hydration mechanism in the cement is blocked and would allow water to attack various locations in the cement structure. Ten samples of standard cement had an average weight percent calcium of $\bar{x}_{1}=90.0$, with a sample standard deviation of $s_{1}=5.0$, while 15 samples of the lead-doped cement had an average weight percent calcium of $\bar{x}_{2}=87.0$, with a sample standard deviation of $s_{2}=4.0$.

We will assume that weight percent calcium is normally distributed and find a $95 \%$ confidence interval on the difference in means, $\mu_{1}-\mu_{2}$, for the two types of cement. Furthermore, we will assume that both normal populations have the same standard deviation.

## 10-2 Inference for a Difference in Means of Two Normal Distributions, Variances Unknown

Case 1: $\sigma_{1}^{2}=\sigma_{2}^{2}=\sigma^{2}$

## Example 10-8 (Continued)

The pooled estimate of the common standard deviation is found using Equation 10-12 as follows:

$$
\begin{aligned}
s_{p}^{2} & =\frac{\left(n_{1}-1\right) s_{1}^{2}+\left(n_{2}-1\right) s_{2}^{2}}{n_{1}+n_{2}-2} \\
& =\frac{9(5.0)^{2}+14(4.0)^{2}}{10+15-2} \\
& =19.52
\end{aligned}
$$

## 10-2 Inference for a Difference in Means of Two Normal Distributions, Variances Unknown

$$
\text { Case 1: } \sigma_{1}^{2}=\sigma_{2}^{2}=\sigma^{2}
$$

## Example 10-8 (Continued)

Therefore, the pooled standard deviation estimate i $s_{0}=\sqrt{19.52}=4.4$ The $95 \%$ confidence interval is found using Equation 10-19:

$$
\bar{x}_{1}-\bar{x}_{2}-t_{0.005,23} s_{p} \sqrt{\frac{1}{n_{1}}+\frac{1}{n_{2}}} \leq \mu_{1}-\mu_{2} \leq \bar{x}_{1}-\bar{x}_{2}+t_{0.005,2} s_{p} \sqrt{\frac{1}{n_{1}}+\frac{1}{n_{2}}}
$$

or upon substituting the sample values and using toms,23 $=2.069$

$$
\begin{aligned}
90.0-87.0-2.069(4.4) \sqrt{\frac{1}{10}+\frac{1}{15}} & \leq \mu_{1}-\mu_{2} \\
& \leq 90.0-87.0+2.069(4.4) \sqrt{\frac{1}{10}+\frac{1}{15}}
\end{aligned}
$$

## 10-2 Inference for a Difference in Means of Two Normal Distributions, Variances Unknown

Case 1: $\sigma_{1}^{2}=\sigma_{2}^{2}=\sigma^{2}$

## Example 10-8 (Continued)

which reduces to

$$
-0.72 \leq \mu_{1}-\mu_{2} \leq 6.72
$$

Notice that the $95 \%$ confidence interval includes zero; therefore, at this level of confidence we cannot conclude that there is a difference in the means. Put another way, there is no evidence that doping the cement with lead affected the mean weight percent of calcium; therefore, we cannot claim that the presence of lead affects this aspect of the hydration mechanism at the $95 \%$ level of confidence.

## 10-2 Inference for a Difference in Means of Two Normal Distributions, Variances Unknown

## 10-2.3 Confidence Interval on the Difference in Means, Variance Unknown

Case 2: $\sigma_{1}^{2} \neq \sigma_{2}^{2}$
If $\bar{x}_{1}, \bar{x}_{2}, s_{1}^{2}$, and $s_{2}^{2}$ are the means and variances of two random samples of sizes $n_{1}$ and $n_{2}$, respectively, from two independent normal populations with unknown and unequal variances, an approximate $100(1-\alpha) \%$ confidence interval on the difference in means $\mu_{1}-\mu_{2}$ is

$$
\begin{equation*}
\bar{x}_{1}-\bar{x}_{2}-t_{\alpha / 2, v} \sqrt{\frac{s_{1}^{2}}{n_{1}}+\frac{s_{2}^{2}}{n_{2}}} \leq \mu_{1}-\mu_{2} \leq \bar{x}_{1}-\bar{x}_{2}+t_{\alpha / 2, v} \sqrt{\frac{s_{1}^{2}}{n_{1}}+\frac{s_{2}^{2}}{n_{2}}} \tag{10-20}
\end{equation*}
$$

where $v$ is given by Equation 10-16 and $t_{\alpha / 2, \nu}$ is the upper $\alpha / 2$ percentage point of the $t$ distribution with $v$ degrees of freedom.

## 10-4 Paired $\boldsymbol{t}$-Test

- A special case of the two-sample $t$-tests of Section 10-2 occurs when the observations on the two populations of interest are collected in pairs.
- Each pair of observations, say $\left(X_{1 j}, X_{2 j}\right)$, is taken under homogeneous conditions, but these conditions may change from one pair to another.
- The test procedure consists of analyzing the differences on each pair.


## 10-4 Paired t-Test

## The Paired $t$-Test

Null hypothesis: $H_{0}: \mu_{D}=\Delta_{0}$
Test statistic: $\quad T_{0}=\frac{\bar{D}-\Delta_{0}}{S_{D} / \sqrt{n}}$

$$
\begin{align*}
& D_{j}=X_{1 j}-X_{2 j} \\
& \bar{D}=\text { sample average of } \mathrm{D}_{\mathrm{j}} \\
& S_{D}=\text { sample standard dev. of } \mathrm{D}_{\mathrm{j}}
\end{align*}
$$

Alternative Hypothesis

$$
\begin{aligned}
& H_{1}: \mu_{D} \neq \Delta_{0} \\
& H_{1}: \mu_{D}>\Delta_{0} \\
& H_{1}: \mu_{D}<\Delta_{0}
\end{aligned}
$$

Rejection Region

$$
\begin{aligned}
& t_{0}>t_{\alpha / 2, n-1} \quad \text { or } \quad t_{0}<-t_{\alpha / 2, n-1} \\
& t_{0}>t_{\alpha, n-1} \\
& t_{0}<-t_{\alpha, n-1}
\end{aligned}
$$

## 10-4 Paired t-Test

## Example 10-9

An article in the Joumal of Strain Analysis (1983, Vol. 18, No. 2) compares several methods for predicting the shear strength for steel plate girders. Data for two of these methods, the Karlsruhe and Lehigh procedures, when applied to nine specific girders, are shown in Table 10-2. We wish to determine whether there is any difference (on the average) between the two methods.

Table 10-2 Strength Predictions for Nine Steel Plate Girders

| (Predicted Load/Observed Load) |  |  |  |
| :---: | :---: | :---: | :---: |
| Girder | Karlsruhe Method | Lehigh Method | Difference $d_{j}$ |
| $\mathrm{~S} 1 / 1$ | 1.186 | 1.061 | 0.119 |
| $\mathrm{~S} 2 / 1$ | 1.151 | 0.992 | 0.159 |
| $\mathrm{~S} 3 / 1$ | 1.322 | 1.063 | 0.259 |
| $\mathrm{~S} 4 / 1$ | 1.339 | 1.062 | 0.277 |
| $\mathrm{~S} 5 / 1$ | 1.200 | 1.065 | 0.138 |
| $\mathrm{~S} 2 / 1$ | 1.402 | 1.178 | 0.224 |
| $\mathrm{~S} 2 / 2$ | 1.365 | 1.037 | 0.328 |
| $\mathrm{~S} 2 / 3$ | 1.537 | 1.086 | 0.451 |
| $\mathrm{~S} 2 / 4$ | 1.559 | 1.052 | 0.507 |

## 10-4 Paired t-Test

## Example 10-9

The eight-step procedure is applied as follows:

1. The parameter of interest is the difference in mean shear strength between the two methods, say, $\mu_{D}=\mu_{1}-\mu_{2}=0$.
2. $H_{0}: \mu_{D}=0$
3. $H_{1}: \mu_{D} \neq 0$
4. $\alpha=0.05$
5. The test statistic is

$$
t_{0}=\frac{\bar{d}}{s_{D} / \sqrt{n}}
$$

6. 

Reject $H_{0}$ if $t_{0}>t_{0.025,8}=2.306$ or if $t_{0}<-t_{0.025,8}=-2.306$.

## 10-4 Paired t-Test

## Example 10-9

7. Computations: The sample average and standard deviation of the differences $d_{j}$ are $\bar{d}=0.2736$ and $s_{D}=0.1356$. so the test statistic is

$$
t_{0}=\frac{\bar{d}}{s_{D} / \sqrt{n}}=\frac{0.2736}{0.1356 / \sqrt{9}}=6.05
$$

8. Conclusions: Since $t_{0}=6.05>2.306$, we conclude that the strength prediction methods yield different results. Specifically, the data indicate that the Karlsruhe method produces, on the average, higher strength predictions than does the Lehigh method. The $P$-value for $t_{0}=6.05$ is $P=0.0002$, so the test statistic is well into the critical region.

## 10-4 Paired t-Test

## Paired Versus Unpaired Comparisons

So how do we decide to conduct the experiment? Should we pair the observations or not? Although there is no general answer to this question, we can give some guidelines based on the above discussion.

1. If the experimental units are relatively homogeneous (small $\sigma$ ) and the correlation within pairs is small, the gain in precision attributable to pairing will be offset by the loss of degrees of freedom, so an independent-sample experiment should be used.
2. If the experimental units are relatively heterogeneous (large $\sigma$ ) and there is large positive correlation within pairs, the paired experiment should be used. Typically, this case occurs when the experimental units are the same for both treatments; as in Example 10-9, the same girders were used to test the two methods.

## 10-4 Paired t-Test

## A Confidence Interval for $\mu_{\mathrm{D}}$

## Definition

If $\bar{d}$ and $s_{D}$ are the sample mean and standard deviation of the difference of $n$ random pairs of normally distributed measurements, a $100(1-\alpha) \%$ confidence interval on the difference in means $\mu_{D}=\mu_{1}-\mu_{2}$ is

$$
\begin{equation*}
\bar{d}-t_{\alpha / 2, n-1} s_{D} / \sqrt{n} \leq \mu_{D} \leq \bar{d}+t_{\alpha / 2, n-1} s_{D} / \sqrt{n} \tag{10-23}
\end{equation*}
$$

where $t_{\alpha / 2, n-1}$ is the upper $\alpha / 2 \%$ point of the $t$-distribution with $n-1$ degrees of freedom.

## 10-4 Paired t-Test

## Example 10-10

Table 10.3 Time in Seconds to Parallel Park Two Automobiles

| Subject | Automobiles |  |  |
| :---: | :---: | :---: | :---: |
|  | $1\left(x_{1 j}\right)$ | $2\left(x_{2 j}\right)$ | $\frac{\text { Difference }}{\left(d_{j}\right)}$ |
| 1 | 37.0 | 17.8 | 19.2 |
| 2 | 25.8 | 20.2 | 5.6 |
| 3 | 16.2 | 16.8 | -0.6 |
| 4 | 24.2 | 41.4 | -17.2 |
| 5 | 22.0 | 21.4 | 0.6 |
| 6 | 33.4 | 38.4 | -5.0 |
| 7 | 23.8 | 16.8 | 7.0 |
| 8 | 58.2 | 32.2 | 26.0 |
| 9 | 33.6 | 27.8 | 5.8 |
| 10 | 24.4 | 23.2 | 1.2 |
| 11 | 23.4 | 29.6 | -6.2 |
| 12 | 21.2 | 20.6 | 0.6 |
| 13 | 36.2 | 32.2 | 4.0 |
| 14 | 29.8 | 53.8 | -24.0 |

## 10-4 Paired t-Test

## Example 10-10

The journal Human Factors (1962, pp. 375-380) reports a study in which $n=14$ subjects were asked to parallel park two cars having very different wheel bases and turning radii. The time in seconds for each subject was recorded and is given in Table 10-3. From the column of observed differences we calculate $\bar{d}=1.21$ and $s_{D}=12.68$. The $90 \%$ confidence interval for $\mu_{D}=\mu_{1}-\mu_{2}$ is found from Equation 9-24 as follows:

$$
\begin{aligned}
\bar{d}-t_{0.05,13} s_{D} / \sqrt{n} & \leq \mu_{D} \leq \bar{d}+t_{0.05,13} s_{D} / \sqrt{n} \\
1.21-1.771(12.68) / \sqrt{14} & \leq \mu_{D} \leq 1.21+1.771(12.68) / \sqrt{14} \\
-4.79 & \leq \mu_{D} \leq 7.21
\end{aligned}
$$

Notice that the confidence interval on $\mu_{D}$ includes zero. This implies that, at the $90 \%$ level of confidence, the data do not support the claim that the two cars have different mean parking times $\mu_{1}$ and $\mu_{2}$. That is, the value $\mu_{D}=\mu_{1}-\mu_{2}=0$ is not inconsistent with the observed data.

## 10-5 Inferences on the Variances of Two Normal Populations

## 10-5.1 The F Distribution

We wish to test the hypotheses:

$$
\begin{aligned}
& H_{0}: \sigma_{1}^{2}=\sigma_{2}^{2} \\
& H_{1}: \sigma_{1}^{2} \neq \sigma_{2}^{2}
\end{aligned}
$$

- The development of a test procedure for these hypotheses requires a new probability distribution, the
F distribution.


## 10-5 Inferences on the Variances of Two Normal Populations

## 10-5.1 The F Distribution

Let $W$ and $Y$ be independent chi-square random variables with $u$ and $v$ degrees of freedom, respectively. Then the ratio

$$
\begin{equation*}
F=\frac{W / u}{Y / v} \tag{10-26}
\end{equation*}
$$

has the probability density function

$$
\begin{equation*}
f(x)=\frac{\Gamma\left(\frac{u+v}{2}\right)\left(\frac{u}{v}\right)^{u / 2} x^{(u / 2)-1}}{\Gamma\left(\frac{u}{2}\right) \Gamma\left(\frac{v}{2}\right)\left[\left(\frac{u}{v}\right) x+1\right]^{(u+v / 2},} \quad 0<x<\infty \tag{10-27}
\end{equation*}
$$

and is said to follow the $F$ distribution with $u$ degrees of freedom in the numerator and $v$ degrees of freedom in the denominator. It is usually abbreviated as $F_{u, v}$

## 10-5 Inferences on the Variances of Two Normal Populations

## 10-5.1 The F Distribution




Figure 10-4 Probability density functions of two $F$ distributions.

Figure 10.5 Upper and lower percentage points of the $F$ distribution.

## 10-5 Inferences on the Variances of Two Normal Populations

## 10-5.1 The $F$ Distribution

The lower-tail percentage points $f_{1-\alpha, u, \nu}$ can be found as follows.

$$
\begin{equation*}
f_{1-\alpha, \mu, v}=\frac{1}{f_{\alpha, v, u}} \tag{10-28}
\end{equation*}
$$

## 10-5 Inferences on the Variances of Two Normal Populations

## 10-5.2 Hypothesis Tests on the Ratio of Two Variances

Let $X_{11}, X_{12}, \ldots, X_{1 n_{1}}$ be a random sample from a normal population with mean $\mu_{1}$ and variance $\sigma_{1}^{2}$, and let $X_{21}, X_{22}, \ldots, X_{2 n_{2}}$ be a random sample from a second normal population with mean $\mu_{2}$ and variance $\sigma_{2}^{2}$. Assume that both normal populations are independent. Let $S_{1}^{2}$ and $S_{2}^{2}$ be the sample variances. Then the ratio
$F=\frac{\left(n_{1}-1\right) S_{1}^{2} / \sigma_{1}^{2}\left(n_{1}-1\right)}{\left(n_{2}-1\right) S_{2}^{2} / \sigma_{2}^{2}\left(n_{2}-1\right)} \quad F=\frac{S_{1}^{2} / \sigma_{1}^{2}}{S_{2}^{2} / \sigma_{2}^{2}}$
has an $F$ distribution with $n_{1}-1$ numerator degrees of freedom and $n_{2}-1$ denominator degrees of freedom.

## 10-5 Inferences on the Variances of Two Normal Populations

10-5.2 Hypothesis Tests on the Ratio of Two Variances

Null hypothesis:
Test statistic:

$$
\begin{align*}
& H_{0}: \sigma_{1}^{2}=\sigma_{2}^{2} \\
& F_{0}=\frac{S_{1}^{2}}{S_{2}^{2}} \tag{10-29}
\end{align*}
$$

Alternative Hypotheses

$$
\begin{aligned}
& H_{1}: \sigma_{1}^{2} \neq \sigma_{2}^{2} \\
& H_{1}: \sigma_{1}^{2}>\sigma_{2}^{2} \\
& H_{1}: \sigma_{1}^{2}<\sigma_{2}^{2}
\end{aligned}
$$

Rejection Criterion

$$
f_{0}>f_{\alpha / 2, n_{1}-1, n_{2}-1} \text { or } f_{0}<f_{1-\alpha / 2, n_{1}-1, n_{2}-1}
$$

$$
f_{0}>f_{\alpha, n_{1}-1, n_{2}-1}
$$

$$
f_{0}<f_{1-\mathrm{a}, n_{1}-1, n_{2}-1}
$$

# 10-5 Inferences on the Variances of Two Normal Populations 

## Example 10-11

Oxide layers on semiconductor wafers are etched in a mixture of gases to achieve the proper thickness. The variability in the thickness of these oxide layers is a critical characteristic of the wafer, and low variability is desirable for subsequent processing steps. Two different mixtures of gases are being studied to determine whether one is superior in reducing the variability of the oxide thickness. Twenty wafers are etched in each gas. The sample standard deviations of oxide thickness are $s_{1}=1.96$ angstroms and $s_{2}=2.13$ angstroms, respectively. Is there any evidence to indicate that either gas is preferable? Use $\alpha=0.05$.

## 10-5 Inferences on the Variances of Two Normal Populations

## Example 10-11

The eight-step hypothesis-testing procedure may be applied to this problem as follows:

1. The parameters of interest are the variances of oxide thickness $\sigma_{1}^{2}$ and $\sigma_{2}^{2}$. We will assume that oxide thickness is a normal random variable for both gas mixtures.
2. $H_{0}: \sigma_{1}^{2}=\sigma_{2}^{2}$
3. $H_{1}: \sigma_{1}^{2} \neq \sigma_{2}^{2}$
4. $\alpha=0.05$
5. The test statistic is given by Equation 10-29:

$$
f_{0}=\frac{s_{1}^{2}}{s_{2}^{2}}
$$

## 10-5 Inferences on the Variances of Two Normal Populations

## Example 10-11

6. Since $n_{1}=n_{2}=20$, we will reject $H_{0}: \sigma_{1}^{2}=\sigma_{2}^{2}$ if $f_{0}>f_{0.025,19,19}=2.53$ or if $f_{0}<f_{0.975,19,19}=1 / f_{0.025,19,19}=1 / 2.53=0.40$.
7. Computations: Since $s_{1}^{2}=(1.96)^{2}=3.84$ and $s_{2}^{2}=(2.13)^{2}=4.54$, the test statistic is

$$
f_{0}=\frac{s_{1}^{2}}{s_{2}^{2}}=\frac{3.84}{4.54}=0.85
$$

8. Conclusions: Since $f_{0.975,19,19}=0.40<f_{0}=0.85<f_{0.025,19,19}=2.53$, we cannot reject the null hypothesis $H_{0}: \sigma_{1}^{2}=\sigma_{2}^{2}$ at the 0.05 level of significance. Therefore, there is no strong evidence to indicate that either gas results in a smaller variance of oxide thickness.

## 10-5 Inferences on the Variances of Two Normal Populations

## 10-5.3 Type II Error and Choice of Sample Size

Appendix Charts $\Psi 1 \%$, VII $p$, VII $q$, and VIImprovide operating characteristic curves for the $F$-test given in Section 10-5.1 for $\alpha=0.05$ and $\alpha=0.01$, assuming that $n_{1}=n_{2}=n$. Charts VIIo and VII $p$ are used with the two-sided alternate hypothesis. They plot $\beta$ against the abscissa parameter

$$
\begin{equation*}
\lambda=\frac{\sigma_{1}}{\sigma_{2}} \tag{10-30}
\end{equation*}
$$

for various $n_{1}=n_{2}=n$. Charts VII $q$ and VIIr are used for the one-sided alternative hypotheses.

## 10-5 Inferences on the Variances of Two Normal Populations

## Example 10-12

For the semiconductor wafer oxide etching problem in Example 10-11, suppose that one gas resulted in a standard deviation of oxide thickness that is half the standard deviation of oxide thickness of the other gas. If we wish to detect such a situation with probability at least 0.80 , is the sample size $n_{1}=n_{2}=20$ adequate?

Note that if one standard deviation is half the other,

$$
\lambda=\frac{\sigma_{1}}{\sigma_{2}}=2
$$

By referring to Appendix Chart VII $o$ with $n_{1}=n_{2}=n=20$ and $\lambda=2$, we find that $\beta=0.20$. Therefore, if $\beta=0.20$, the power of the test (which is the probability that the difference in standard deviations will be detected by the test) is 0.80 , and we conclude that the sample sizes $n_{1}=n_{2}=20$ are adequate.

## 10-5 Inferences on the Variances of Two Normal Populations

## 10-5.4 Confidence Interval on the Ratio of Two Variances

If $s_{1}^{2}$ and $s_{2}^{2}$ are the sample variances of random samples of sizes $n_{1}$ and $n_{2}$, respectively, from two independent normal populations with unknown variances $\sigma_{1}^{2}$ and $\sigma_{2}^{2}$, then a $100(1-\alpha) \%$ confidence interval on the ratio $\sigma_{1}^{2} / \sigma_{2}^{2}$ is

$$
\begin{equation*}
\frac{s_{1}^{2}}{s_{2}^{2}} f_{1-\alpha / 2, n_{2}-1, n_{1}-1} \leq \frac{\sigma_{1}^{2}}{\sigma_{2}^{2}} \leq \frac{s_{1}^{2}}{s_{2}^{2}} f_{\alpha / 2, n_{2}-1, n_{1}-1} \tag{10-31}
\end{equation*}
$$

where $f_{\alpha / 2, n_{2}-1, n_{1}-1}$ and $f_{1-\alpha / 2 n_{2}-1, n_{1}-1}$ are the upper and lower $\alpha / 2$ percentage points of the $F$ distribution with $n_{2}-1$ numerator and $n_{1}-1$ denominator degrees of freedom, respectively. A confidence interval on the ratio of the standard deviations can be obtained by taking square roots in Equation 10-31.

# 10-5 Inferences on the Variances of Two Normal Populations 

## Example 10-13

A company manufactures impellers for use in jet-turbine engines. One of the operations involves grinding a particular surface finish on a titanium alloy component. Two different grinding processes can be used, and both processes can produce parts at identical mean surface roughness. The manufacturing engineer would like to select the process having the least variability in surface roughness. A random sample of $n_{1}=11$ parts from the first process results in a sample standard deviation $s_{1}=5.1$ microinches, and a random sample of $n_{2}=16$ parts from the second process results in a sample standard deviation of $s_{2}=4.7$ microinches. We will find a $90 \%$ confidence interval on the ratio of the two standard deviations, $\sigma_{1} / \sigma_{2}$.

## 10-5 Inferences on the Variances of Two Normal Populations

## Example 10-13

Assuming that the two processes are independent and that surface roughness is normally distributed, we can use Equation 10-31 as follows:

$$
\begin{aligned}
& \frac{s_{1}^{2}}{s_{2}^{2}} f_{0.95,15,10} \leq \frac{\sigma_{1}^{2}}{\sigma_{2}^{2}} \leq \frac{s_{1}^{2}}{s_{2}^{2}} f_{0.05,15,10} \\
& \frac{(5.1)^{2}}{(4.7)^{2}} 0.39 \leq \frac{\sigma_{1}^{2}}{\sigma_{2}^{2}} \leq \frac{(5.1)^{2}}{(4.7)^{2}} 2.85 \\
& 0.678 \leq \frac{\sigma_{1}}{\sigma_{2}} \leq 1.832 \quad \\
& \quad \begin{array}{l}
\text { [it includes } 1, \text { so cannot claim } \\
\text { that the two standard deviations }
\end{array} \\
& \\
& \text { are different at } 90 \% \text { confidence.] }
\end{aligned}
$$

where $f_{0.95,15,10}=1 / f_{0.05,10,15}=1 / 2.54=0.39$

## 10-6 Inference on Two Population Proportions

10-6.1 Large-Sample Test on the Difference in Population Proportions

We wish to test the hypotheses:

$$
\begin{aligned}
& H_{0}: p_{1}=p_{2} \\
& H_{1}: p_{1} \neq p_{2}
\end{aligned}
$$

## 10-6 Inference on Two Population Proportions

10-6.1 Large-Sample Test on the Difference in Population Proportions

The following test statistic is distributed approximately as standard normal and is the basis of the test:

$$
\begin{equation*}
Z=\frac{\hat{P}_{1}-\hat{P}_{2}-\left(p_{1}-p_{2}\right)}{\sqrt{\frac{p_{1}\left(1-p_{1}\right)}{n_{1}}+\frac{p_{2}\left(1-p_{2}\right)}{n_{2}}}} \tag{10-32}
\end{equation*}
$$

## 10-6 Inference on Two Population Proportions

## 10-6.1 Large-Sample Test on the Difference in

 Population ProportionsNull hypothesis: $\quad H_{0}: p_{1}=p_{2}$
Test statistic:

$$
\begin{equation*}
Z_{0}=\frac{\hat{P}_{1}-\hat{P}_{2}}{\sqrt{\hat{P}(1-\hat{P})\left(\frac{1}{n_{1}}+\frac{1}{n_{2}}\right)}} \tag{10-33}
\end{equation*}
$$

where $\hat{P}=\frac{X_{1}+X_{2}}{n_{1}+n_{2}}$

Alternative Hypotheses
Rejection Criterion

$$
\begin{aligned}
& H_{1}: p_{1} \neq p_{2} \\
& H_{1}: p_{1}>p_{2} \\
& H_{1}: p_{1}<p_{2}
\end{aligned}
$$

$$
z_{0}>z_{\mathrm{a} / 2} \text { or } z_{0}<-z_{\mathrm{a} / 2}
$$

$$
z_{0}>z_{\alpha}
$$

$$
z_{0}<-z_{\alpha}
$$

## 10-6 Inference on Two Population Proportions

## Example 10-14

Extracts of St. John's Wort are widely used to treat depression. An article in the April 18, 2001 issue of the Journal of the American Medical Association ("Effectiveness of St. John's Wort on Major Depression: A Randomized Controlled Trial") compared the efficacy of a standard extract of St. John's Wort with a placebo in 200 outpatients diagnosed with major depression. Patients were randomly assigned to two groups; one group received the St. John's Wort, and the other received the placebo. After eight weeks, 19 of the placebo-treated patients showed improvement, whereas 27 of those treated with St. John's Wort improved. Is there any reason to believe that St. John's Wort is effective in treating major depression? Use $\alpha=0.05$. The eight-step hypothesis testing procedure leads to the following results:

Placebo: yalancı ilaç
St. John's wort: sarı kantaron

## 10-6 Inference on Two Population Proportions

## Example 10-14

1. The parameters of interest are $p_{1}$ and $p_{2}$, the proportion of patients who improve following treatment with St. John's Wort $\left(p_{1}\right)$ or the placebo $\left(p_{2}\right)$.
2. $H_{0}: p_{1}=p_{2}$
3. $H_{1}: p_{1} \neq p_{2}$
4. $\alpha=0.05$
5. The test statistic is

$$
z_{0}=\frac{\hat{p}_{1}-\hat{p}_{2}}{\sqrt{\hat{p}(1-\hat{p})\left(\frac{1}{n_{1}}+\frac{1}{n_{2}}\right)}}
$$

where $\hat{p}_{1}=27 / 100=0.27, \hat{p}_{2}=19 / 100=0.19, n_{1}=n_{2}=100$, and

$$
\hat{p}=\frac{x_{1}+x_{2}}{n_{1}+n_{2}}=\frac{19+27}{100+100}=0.23
$$

## 10-6 Inference on Two Population Proportions

## Example 10-14

6. Reject $H_{0}: p_{1}=p_{2}$ if $z_{0}>z_{0.025}=1.96$ or if $z_{0}<-z_{0.025}=-1.96$.
7. Computations: The value of the test statistic is

$$
z_{0}=\frac{0.27-0.19}{\sqrt{0.23(0.77)\left(\frac{1}{100}+\frac{1}{100}\right)}}=1.35
$$

8. Conclusions: Since $z_{0}=1.35$ does not exceed $z_{0.025}$, we cannot reject the null hypothesis. Note that the $P$-value is $P \simeq 0.177$. There is insufficient evidence to support the claim that St. John's Wort is effective in treating major depression.

## 10-6 Inference on Two Population Proportions

## Minitab Output for Example 10-14

Minitab Computations
Test and CI for Two Proportions

| Sample | X | N | Sample p |
| :---: | :---: | :---: | :---: |
| 1 | 27 | 100 | 0.270000 |
| 2 | 19 | 100 | 0.190000 |

Estimate for $\mathrm{p}(1)-\mathrm{p}(2): 0.08$
$95 \% \mathrm{Cl}$ for $\mathrm{p}(1)-\mathrm{p}(2):(-0.0361186,0.196119)$
Test for $p(1)-p(2)=0(v s$ not $=0): Z=1.35 P$-Value $=0.177$

## 10-6 Inference on Two Population Proportions

## 10-6.2 Type II Error and Choice of Sample Size

If the alternative hypothesis is two sided, the $\beta$-error is

$$
\begin{align*}
\beta= & \Phi\left[\frac{z_{\alpha / 2} \sqrt{\overline{p q}\left(1 / n_{1}+1 / n_{2}\right)}-\left(p_{1}-p_{2}\right)}{\sigma_{P_{1}-\hat{P}_{2}}}\right] \\
& -\Phi\left[\frac{-z_{\alpha / 2} \sqrt{\overline{p q}\left(1 / n_{1}+1 / n_{2}\right)}-\left(p_{1}-p_{2}\right)}{\sigma_{\hat{P}_{1}-\hat{P}_{2}}}\right] \tag{10-35}
\end{align*}
$$

$$
\begin{aligned}
& \sigma_{\hat{P}_{1}-\hat{P}_{2}}=\sqrt{\frac{p_{1}\left(1-p_{1}\right)}{n_{1}}+\frac{p_{2}\left(1-p_{2}\right)}{n_{2}}} \\
& \bar{p}=\frac{n_{1} p_{1}+n_{2} p_{2}}{n_{1}+n_{2}} \quad \text { and } \quad \bar{q}=\frac{n_{1}\left(1-p_{1}\right)+n_{2}\left(1-p_{2}\right)}{n_{1}+n_{2}}
\end{aligned}
$$

## 10-6 Inference on Two Population Proportions

## 10-6.2 Type II Error and Choice of Sample Size

If the alternative hypothesis is $H_{1}: p_{1}>p_{2}$,

$$
\begin{equation*}
\beta=\Phi\left[\frac{z_{\alpha} \sqrt{\overline{p q}\left(1 / n_{1}+1 / n_{2}\right)}-\left(p_{1}-p_{2}\right)}{\sigma_{\hat{P}_{1}-\hat{p}_{2}}}\right] \tag{10-36}
\end{equation*}
$$

and if the alternative hypothesis is $H_{1}: p_{1}<p_{2}$,

$$
\begin{equation*}
\beta=1-\Phi\left[\frac{-z_{\alpha} \sqrt{\overline{p q}\left(1 / n_{1}+1 / n_{2}\right)}-\left(p_{1}-p_{2}\right)}{\sigma_{\hat{P}_{1}-p_{2}}}\right] \tag{10-37}
\end{equation*}
$$

## 10-6 Inference on Two Population Proportions

## 10-6.2 Type II Error and Choice of Sample Size

For the two-sided alternative, the common sample size is $\quad n_{1}=n_{2}=n$

$$
\begin{equation*}
n=\frac{\left[z_{\alpha / 2} \sqrt{\left(p_{1}+p_{2}\right)\left(q_{1}+q_{2}\right) / 2}+z_{\beta} \sqrt{p_{1} q_{1}+p_{2} q_{2}}\right]^{2}}{\left(p_{1}-p_{2}\right)^{2}} \tag{10-38}
\end{equation*}
$$

where $q_{1}=1-p_{1}$ and $q_{2}=1-p_{2}$.

## 10-6 Inference on Two Population Proportions

## 10-6.3 Confidence Interval on the Difference in the Population Proportions

If $\hat{p}_{1}$ and $\hat{p}_{2}$ are the sample proportions of observation in two independent random samples of sizes $n_{1}$ and $n_{2}$ that belong to a class of interest, an approximate twosided $100(1-\alpha) \%$ confidence interval on the difference in the true proportions $p_{1}-p_{2}$ is

$$
\begin{align*}
\hat{p}_{1}-\hat{p}_{2}- & z_{\alpha / 2} \sqrt{\frac{\hat{p}_{1}\left(1-\hat{p}_{1}\right)}{n_{1}}+\frac{\hat{p}_{2}\left(1-\hat{p}_{2}\right)}{n_{2}}} \\
& \leq p_{1}-p_{2} \leq \hat{p}_{1}-\hat{p}_{2}+z_{\alpha / 2} \sqrt{\frac{\hat{p}_{1}\left(1-\hat{p}_{1}\right)}{n_{1}}+\frac{\hat{p}_{2}\left(1-\hat{p}_{2}\right)}{n_{2}}} \tag{10-39}
\end{align*}
$$

where $z_{\alpha / 2}$ is the upper $\alpha / 2$ percentage point of the standard normal distribution.

## 10-6 Inference on Two Population Proportions

## Example 10-15

Consider the process manufacturing crankshaft bearings described in Example 8-6. Suppose that a modification is made in the surface finishing process and that, subsequently, a second random sample of 85 axle shafts is obtained. The number of defective shafts in this second sample is 8 . Therefore, since $n_{1}=85, \hat{p}_{1}=0.12, n_{2}=85$, and $\hat{p}_{2}=8 / 85=0.09$, we can obtain an approximate $95 \%$ confidence interval on the difference in the proportion of defective bearings produced under the two processes from Equation 10-39 as follows:

$$
\begin{aligned}
& \hat{p}_{1}-\hat{p}_{2}-z_{0.025} \sqrt{\frac{\hat{p}_{1}\left(1-\hat{p}_{1}\right)}{n_{1}}+\frac{\hat{p}_{2}\left(1-\hat{p}_{2}\right)}{n_{2}}} \\
& \leq p_{1}-p_{2} \leq \hat{p}_{1}-\hat{p}_{2}+z_{0.025} \sqrt{\frac{\hat{p}_{1}\left(1-\hat{p}_{1}\right)}{n_{1}}+\frac{\hat{p}_{2}\left(1-\hat{p}_{2}\right)}{n_{2}}}
\end{aligned}
$$

## 10-6 Inference on Two Population Proportions

## Example 10-15

or

$$
\begin{aligned}
& 0.12-0.09-1.96 \sqrt{\frac{0.12(0.88)}{85}+\frac{0.09(0.91)}{85}} \\
& \leq p_{1}-p_{2} \leq 0.12-0.09+1.96 \sqrt{\frac{0.12(0.88)}{85}+\frac{0.09(0.91)}{85}}
\end{aligned}
$$

This simplifies to

$$
-0.06 \leq p_{1}-p_{2} \leq 0.12
$$

This confidence interval includes zero, so, based on the sample data, it seems unlikely that the changes made in the surface finish process have reduced the proportion of defective crankshaft bearings being produced.

