# Section 4.2 (con't.) <br> 01/17/2019 

## 1 Large sample confidence interval for $p$

Example 4.2.3
Suppose $n=40$ graduating students are asked if they plan to go to graduate school. If 8 out of 40 said yes, then $\hat{p}=8 / 40=.20$, or $20 \%$.

Question: What is the expected size of the error of estimation? ( $\mathrm{SE}=$ ?, $95 \% \mathrm{CI}=$ ?)
Math trick: If we can represent $\hat{p}$ as a sample mean, then all results already known about the sample mean apply.

Ex. Consider the binary sample: $S, F, F, S, F$

$$
\begin{array}{ccc}
\mathrm{S} & \rightarrow & 1 \\
\mathrm{~F} & \rightarrow & 0 \\
\mathrm{~F} & \rightarrow & 0 \\
\mathrm{~S} & \rightarrow & 1 \\
\mathrm{~F} & \rightarrow & 0 \\
\hline \hat{p}=2 / 5=.40 & & \bar{X}=2 / 5=.40
\end{array}
$$

"The sample proportion $\hat{p}$ is a sample mean of 0 s and 1 s "
i.e. $\hat{p}=\frac{\sum X_{i}}{n}$ or $\sum X_{i}=n \hat{p}$.

Furthermore, the sample variance is

$$
\begin{aligned}
S^{2} & =\frac{\sum\left(X_{i}-\bar{X}\right)^{2}}{n-1}=\frac{\sum\left(X_{i}^{2}-2 X_{i} \bar{X}+\bar{X}^{2}\right)}{n-1}=\frac{\sum X_{i}^{2}-2 \bar{X} \sum X_{i}+n \bar{X}^{2}}{n-1} \\
& =\frac{\sum X_{i}-2 n \bar{X}^{2}+n \bar{X}^{2}}{n-1}=\frac{\sum X_{i}-n \bar{X}^{2}}{n-1} \\
& =\frac{n \hat{p}-n \hat{p}^{2}}{n-1}=\frac{n}{n-1} \hat{p}(1-\hat{p}) \\
& =\hat{p}(1-\hat{p})
\end{aligned}
$$

From Example 4.2.2, a large sample confidence interval for $\mu$ is

$$
\left(\bar{X}-z_{\alpha / 2} \frac{S}{\sqrt{n}}, \bar{X}+z_{\alpha / 2} \frac{S}{\sqrt{n}}\right)
$$

so equivalently, a large sample confidence interval for the population proportion $p$ is

$$
\left(\hat{p}-z_{\alpha / 2} \frac{\sqrt{\hat{p}(1-\hat{p})}}{\sqrt{n}}, \hat{p}+z_{\alpha / 2} \frac{\sqrt{\hat{p}(1-\hat{p})}}{\sqrt{n}}\right)
$$

In particular, a $95 \%$ confidence interval for $p$ is

$$
\left(\hat{p}-1.96 \frac{\sqrt{\hat{p}(1-\hat{p})}}{\sqrt{n}}, \hat{p}+1.96 \frac{\sqrt{\hat{p}(1-\hat{p})}}{\sqrt{n}}\right)
$$

The term $\frac{\sqrt{\hat{p}(1-\hat{p})}}{\sqrt{n}}$ is called the standard error of $\hat{p}$.
Example 4.2.3 (con't): Recall that $\hat{p}=8 / 40=.20$. A $95 \%$ confidence interval for $p$ is

$$
\begin{gather*}
.20 \pm 1.96 \sqrt{\frac{(.20)(.80)}{40}} \\
.20 \pm 1.96(.06) \tag{.08,32}
\end{gather*}
$$

### 4.2.1 Confidence Intervals for Difference in Means

Let $X_{1}, \ldots, X_{n_{1}}$ be a random sample from $f_{1}(\cdot)$ with mean $\mu_{1}$ and variance $\sigma_{1}^{2}$ and $Y_{1}, \ldots, Y_{n_{2}}$ be a random sample from $f_{2}(\cdot)$ with mean $\mu_{2}$ and variance $\sigma_{2}^{2}$. In addition, assume that the $X$ sample and $Y$ sample are independent.

Let the difference between means $\Delta=\mu_{1}-\mu_{2}$ be estimated by

$$
\hat{\Delta}=\bar{X}-\bar{Y}
$$

It can be shown that

$$
\begin{aligned}
\operatorname{Var}(\hat{\Delta}) & =\operatorname{Var}(\bar{X}-\bar{Y})=\operatorname{Var}(\bar{X})+\operatorname{Var}(\bar{Y}) \\
& =\frac{\sigma_{1}^{2}}{n_{1}}+\frac{\sigma_{2}^{2}}{n_{2}} \doteq \frac{S_{1}^{2}}{n_{1}}+\frac{S_{2}^{2}}{n_{2}}
\end{aligned}
$$

so that

$$
\mathrm{SE} \text { of } \hat{\Delta}=\sqrt{\frac{S_{1}^{2}}{n_{1}}+\frac{S_{2}^{2}}{n_{2}}}
$$

Using the pivot method

$$
\begin{aligned}
.95 & \doteq P\left[-1.96 \leq \frac{\hat{\Delta}-\Delta}{\mathrm{SE}} \leq 1.96\right] \\
& : \\
& : \\
& =P[\hat{\Delta}-1.96(\mathrm{SE}) \leq \Delta \leq \hat{\Delta}+1.96(\mathrm{SE})] \\
& \equiv P[L \leq \Delta \leq U]
\end{aligned}
$$

so that $\hat{\Delta} \pm 1.96(\mathrm{SE})$ is an approximate $95 \%$ confidence interval.

In general, $\mathrm{a}(1-\alpha) 100 \%$ confidence interval for $\Delta=\mu_{1}-\mu_{2}$ is given by

$$
\left((\bar{X}-\bar{Y})-z_{\alpha / 2} \sqrt{\frac{S_{1}^{2}}{n_{1}}+\frac{S_{2}^{2}}{n_{2}}},(\bar{X}-\bar{Y})+z_{\alpha / 2} \sqrt{\frac{S_{1}^{2}}{n_{1}}+\frac{S_{2}^{2}}{n_{2}}}\right)
$$

Comment: The confidence interval works reasonably well when either one of the following assumptions hold

1. Both distributions $f_{1}(\cdot)$ and $f_{2}(\cdot)$ are normal
2. Both sample sizes $n_{1}$ and $n_{2}$ are reasonably large so that $\bar{X}$ and $\bar{Y}$ are approximately normal by CLT effect

An exact confidence interval for $\mu_{1}-\mu_{2}$
Suppose that the following assumptions hold

1. $X_{1}, \ldots, X_{n_{1}} \sim N\left(\mu_{1}, \sigma_{1}^{2}\right)$ and $Y_{1}, \ldots, Y_{n_{2}} \sim N\left(\mu_{2}, \sigma_{2}^{2}\right)$
2. $\sigma_{1}^{2}=\sigma_{2}^{2} \equiv \sigma^{2}$
3. The $X$ sample and $Y$ sample are independent

Then

$$
\frac{(\bar{X}-\bar{Y})-\left(\mu_{1}-\mu_{2}\right)}{\sqrt{\frac{\sigma_{1}^{2}}{n_{1}}+\frac{\sigma_{2}^{2}}{n_{2}}}}=\frac{(\bar{X}-\bar{Y})-\left(\mu_{1}-\mu_{2}\right)}{\sigma \sqrt{\frac{1}{n_{1}}+\frac{1}{n_{2}}}}
$$

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

$$
S_{p}^{2}=\frac{\sum_{i=1}^{n_{1}}\left(X_{i}-\bar{X}\right)^{2}+\sum_{j=1}^{n_{2}}\left(Y_{j}-\bar{Y}\right)^{2}}{n_{1}+n_{2}-2}=\frac{\left(n_{1}-1\right) S_{1}^{2}+\left(n_{2}-1\right) S_{2}^{2}}{n_{1}+n_{2}-2}
$$

be a pooled estimator of the common variance $\sigma^{2}$. It can be shown that

$$
\frac{\left(n_{1}+n_{2}-2\right) S_{p}^{2}}{\sigma^{2}} \sim \chi_{n_{1}+n_{2}-2}^{2}
$$

Then

$$
\begin{aligned}
\frac{(\bar{X}-\bar{Y})-\left(\mu_{1}-\mu_{2}\right)}{S_{p} \sqrt{\frac{1}{n_{1}}+\frac{1}{n_{2}}}} & =\frac{\frac{(\bar{X}-\bar{Y})-\left(\mu_{1}-\mu_{2}\right)}{\sigma \sqrt{\frac{1}{n_{1}}+\frac{1}{n_{2}}}}}{\sqrt{\frac{\left(n_{1}+n_{2}-2\right) S_{p}^{2}}{\sigma^{2}} /\left(n_{1}+n_{2}-2\right)}} \\
& \stackrel{\mathcal{D}}{=} \frac{N(0,1)}{\sqrt{\chi_{n_{1}+n_{2}-2}^{2} /\left(n_{1}+n_{2}-2\right)}} \\
& \sim t_{n_{1}+n_{2}-2 \mathrm{df}}
\end{aligned}
$$

Using the pivot method

$$
\begin{aligned}
.95 & =P\left[-t_{.025, n_{1}+n_{2}-2} \leq \frac{(\bar{X}-\bar{Y})-\left(\mu_{1}-\mu_{2}\right)}{S_{p} \sqrt{\frac{1}{n_{1}}+\frac{1}{n_{2}}}} \leq t_{.025, n_{1}+n_{2}-2}\right] \\
& : \\
& : \\
& \equiv P\left[(\bar{X}-\bar{Y})-t_{.025, n_{1}+n_{2}-2} S_{p} \sqrt{\frac{1}{n_{1}}+\frac{1}{n_{2}}} \leq \mu_{1}-\mu_{2} \leq(\bar{X}-\bar{Y})+t_{.025, n_{1}+n_{2}-2} S_{p} \sqrt{\frac{1}{n_{1}}+\frac{1}{n_{2}}}\right] \\
& \equiv P\left[L \leq \mu_{1}-\mu_{2} \leq U\right]
\end{aligned}
$$

so that $\left(\bar{X}-\bar{Y} \pm t_{.025, n_{1}+n_{2}-2} S_{p} \sqrt{\frac{1}{n_{1}}+\frac{1}{n_{2}}}\right.$ is an exact $95 \%$ confidence interval for $\mu_{1}-\mu_{2}$.
In general, a $(1-\alpha) 100 \%$ exact confidence interval for $\mu_{1}-\mu_{2}$ is given by

$$
\bar{X}-\bar{Y} \pm t_{\alpha / 2, n_{1}+n_{2}-2} S_{p} \sqrt{\frac{1}{n_{1}}+\frac{1}{n_{2}}}
$$

Example in R
> trt <- c $(91,101,110,103,93,99,104)$
> ctl <- c(87,99,77,88,91)
> mean(trt)
[1] 100.1429
> mean(ctl)
[1] 88.4
> sd(trt)
[1] 6.542899
> sd(ctl)
[1] 7.924645
> n1<-length (trt)
$>\mathrm{n} 1$
[1] 7
> n2<-length(ctl)
$>\mathrm{n} 2$
[1] 5
$>\mathrm{df}<-\mathrm{n} 1+\mathrm{n} 2-2$
$>\mathrm{df}$
[1] 10
> qt(.975,df)
[1] 2.228139
$>$ sp<-sqrt $(((n 1-1) * s d(\operatorname{trt}) \wedge 2+(n 2-1) * s d(c t 1) \wedge 2) /(n 1+n 2-2))$
$>\mathrm{sp}$
[1] 7.127813
> SE<-sp*sqrt( $1 / \mathrm{n} 1+1 / \mathrm{n} 2$ )
> SE
[1] 4.17362
> lcl<-mean(trt)-mean(ctl)-qt(.975,df)*SE
> lcl
[1] 2.443453
$>\mathrm{ucl}<-$ mean (trt)-mean (ctl) $\mathrm{tqt}(.975, \mathrm{df}) * \mathrm{SE}$
$>\mathrm{ucl}$
[1] 21.04226
> t.test(trt, ctl, var.equal=TRUE, conf.level=.95)

Two Sample t-test
data: trt and ctl
$\mathrm{t}=2.8136$, $\mathrm{df}=10, \mathrm{p}$-value $=0.01836$
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
2.44345321 .042262
sample estimates:
mean of $x$ mean of $y$
100.142988 .4000

