(§5.1-5.3 Large-Sample Confidence Interval for Mean; Proportion; Small-Sample Interval for Mean)

§5.4 (Large-Sample) Confidence Inferences for the Difference of Two Means

§5.5 Confidence Inferences for the Difference of Two Proportions

(§5.6 Small-Sample Confidence Inferences for the Difference of Two Means)

# 5.4 Confidence Intervals for the Difference of Two Means

We compare two population means,  $\mu_X$  and  $\mu_Y$ , by studying their difference,  $\mu_X - \mu_Y$ . Notation:

	Population 1	Population 2
Variable	X	Y
Mean	$\mu_X$	
Standard deviation		$\sigma_Y$
Sample size	$n_X$	
Sample mean	$\bar{X}$	
Sample standard deviation		$s_Y$

For inference about  $\mu_X - \mu_Y$ , use the statistic \_\_\_\_\_.

To find a confidence interval for  $\mu_X - \mu_Y$ , we need the distribution of \_\_\_\_\_. Recall for independent X and Y:

- (§2.5)  $\mu_{X-Y} =$
- (§2.5)  $\sigma_{X-Y}^2 =$
- (§2.5)  $\sigma_{\bar{X}}^2 =$
- (§4.5) If  $X \sim N(\mu_X, \sigma_X^2)$  and  $Y \sim N(\mu_Y, \sigma_Y^2)$ , then  $X Y \sim$
- (§4.11) For large n, the CLT says  $\bar{X} \sim$

It follows that, for large  $n_X$  and  $n_Y$ ,  $\bar{X} - \bar{Y} \sim$  \_\_\_\_\_\_

## Confidence Intervals on the Difference of Two Means

Recall that many confidence intervals have the form

 $\begin{array}{l} (\text{point estimate}) \pm (\text{margin of error}) \\ = (\text{point estimate}) \pm (\underline{\qquad} \text{value for confidence}) \times [(\text{estimated or true}) \underline{\qquad} \text{of point estimate}] \\ = \hat{\theta} \pm (\text{table value for confidence}) \times \sigma_{\hat{\theta}} \end{array}$ 

 $(\approx)$ 

#### **Derive a Confidence Interval**

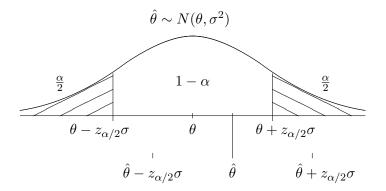
Here's our previous derivation of a confidence interval for a normally distributed statistic:

• Consider a statistic  $\hat{\theta}$  as an estimator for a parameter  $\theta$ , where  $\hat{\theta} \sim N(\theta, \sigma^2)$ 

(Generalize because it's \_\_\_\_\_\_ to write  $\theta$  than \_\_\_\_\_\_,  $\hat{\theta}$  than \_\_\_\_\_\_, and \_\_\_\_\_ than  $\sqrt{\frac{\sigma_X^2}{n_X} + \frac{\sigma_Y^2}{n_Y}}$ .)

- Let  $z_{\alpha/2}$  = the z-score cutting off a right tail area \_\_\_\_\_ from N(0,1) (as before), so  $P(-z_{\alpha/2} < Z < z_{\alpha/2}) = \underline{\qquad} (draw)$
- Unstandardize using Z = to get  $P(-z_{\alpha/2} < \frac{\hat{\theta} \theta}{\sigma} < z_{\alpha/2}) = 1 \alpha$ ; solve in two ways:
  - for  $\hat{\theta}$  in the middle:  $P(\theta z_{\alpha/2}\sigma < \hat{\theta} < \theta + z_{\alpha/2}\sigma) = 1 \alpha$  (pictured \_\_\_\_\_)
  - for  $\theta$  in the middle:  $P(\hat{\theta} z_{\alpha/2}\sigma < \theta < \hat{\theta} + z_{\alpha/2}\sigma) = 1 \alpha$  (draw)

That is,  $\hat{\theta} \pm z_{\alpha/2}\sigma$  contains \_\_\_\_\_ for a proportion \_\_\_\_\_ of random samples (see picture, below). It's the  $100\%(1-\alpha)$  confidence interval for  $\theta$ .



#### The Case of a Difference of Two Means

Letting  $\theta =$ \_\_\_\_\_ and  $\hat{\theta} =$ \_\_\_\_\_, gives the confidence interval we need:

Let  $X_1, \dots, X_{n_X}$  and  $Y_1, \dots, Y_{n_Y}$  be independent large random samples from populations with means  $\mu_X$  and  $\mu_Y$  and standard deviations  $\sigma_X$  and  $\sigma_Y$ . A 100%  $(1 - \alpha)$  confidence interval for  $\mu_X - \mu_Y$  is (.

$$(\bar{X} - \bar{Y}) \pm z_{\alpha/2} \sqrt{\frac{\sigma_X^2}{n_X} + \frac{\sigma_Y^2}{n_Y}}$$

(We usually need to use  $\sigma_X \approx \_\_$  and  $\sigma_Y \approx \_$ .)

e.g. A crayon maker is comparing the effects of two yellow dyes on crayon brittleness. Dye B is more expensive than dye A, but might produce a stronger crayon. 40 crayons are tested with each dye, and the impact strength (in joules) is measured for each. The A strength averaged 2.6, with standard deviation 1.4. The B strength averaged 3.8, with standard deviation 1.2. Find a 99% confidence interval for the difference, B - A, in population strengths.

# 5.5 Confidence Intervals for the Difference of Two Proportions

We compare two population proportions,  $p_X$  and  $p_Y$ , by studying their difference,  $p_X - p_Y$ . Notation:

	Population 1	Population 2	
Success probability	$p_X$	$p_Y$	
#Trials	$n_X$	$n_Y$	
#Successes	X	Y	
Sample proportion of successes	$\hat{p}_X = \frac{X}{n_X}$	$\hat{p}_Y = \frac{Y}{n_Y}$	
For informer about a second the statistic			

For inference about  $p_X - p_Y$ , use the statistic \_\_\_\_\_

To find a confidence interval for  $p_X - p_Y$ , we need the distribution of  $\hat{p}_X - \hat{p}_Y$ . Recall for independent X and Y:

• If 
$$X \sim N(\mu_X, \sigma_X^2)$$
 and  $Y \sim N(\mu_Y, \sigma_Y^2)$ , then  $X - Y \sim$  (§4.5)

• If  $X \sim Bin(n, p)$ , and np > 10 and n(1-p) > 10, then  $X \sim N(\_,\_]$ , \_\_\_\_\_) ( $\approx$ ; because CLT applies to  $X = \sum_{i=1}^{n} B_i$ , where  $B_i \sim Bernoulli(p)$ ) (§4.11)

$$\implies \hat{p} = \frac{X}{n} \sim$$

It follows that, for  $n_X p_X > 10$ ,  $n_X (1 - p_X) > 10$ ,  $n_Y p_Y > 10$ , and  $n_Y (1 - p_Y) > 10$ ,

$$\hat{p}_X - \hat{p}_Y \sim$$

We need the standard deviation for inference about the unknown  $p_X - p_Y$ , but we don't know \_\_\_\_\_\_ or \_\_\_\_\_. If the #successes and #failures are more than \_\_\_\_\_\_ in each sample, we can approximate them with \_\_\_\_\_\_ and \_\_\_\_\_.

## Confidence Intervals on the Difference of Two Proportions

Recall, again, that many confidence intervals have the form

(point estimate)  $\pm$  (margin of error) =(point estimate)  $\pm$  (table value for confidence)  $\times$  [(estimated or true) standard deviation of point estimate] = $\hat{\theta} \pm$  (table value for confidence)  $\times \sigma_{\hat{\theta}}$ 

### The Old Confidence Interval

If the #successes and #failures are more than 10 in each sample, then the old  $100\%(1-\alpha)$  confidence interval for  $p_X - p_Y$  is

$$(\hat{p}_X - \hat{p}_Y) \pm z_{\alpha/2} \sqrt{\frac{\hat{p}_X(1 - \hat{p}_X)}{n_X} + \frac{\hat{p}_Y(1 - \hat{p}_Y)}{n_Y}}$$

For small samples, this interval  $p_X - p_Y$  for a proportion  $1 - \alpha$  of samples.

### The New Plus-Four Confidence Interval

Recent research (2000) describes an improvement: add four fake observations, two successes and two failures, \_\_\_\_\_\_\_ to each sample. (The §5.2 plus-four interval for a single proportion added \_\_\_\_\_\_ successes and \_\_\_\_\_\_ failures to the single sample.)

Let independent  $X \sim Bin(n_X, p_X)$  and  $Y \sim Bin(n_Y, p_Y)$ . Define

$$\tilde{n}_X =$$
\_\_\_\_\_,  $\tilde{n}_Y =$ \_\_\_\_\_,  $\tilde{p}_X =$ \_\_\_\_\_, and  $\tilde{p}_Y =$ \_\_\_\_\_\_

Then the  $(100\%)(1-\alpha)$  plus-four confidence interval for  $p_X - p_Y$  is

$$(\tilde{p}_X - \tilde{p}_Y) \pm z_{\alpha/2} \sqrt{\frac{\tilde{p}_X(1 - \tilde{p}_X)}{\tilde{n}_X} + \frac{\tilde{p}_Y(1 - \tilde{p}_Y)}{\tilde{n}_Y}}$$

This interval can be used if  $n_X > 4$  and  $n_Y > 4$ , without regard for the #successes and #failures. (Since  $(p_X - p_Y) \in [\_\_\_]$ , trim the interval if it extends outside  $[\_\_\_]$ .)

e.g. A randomized double-blind experiment assigned 244 smokers who wanted to quit to receive nicotine patches and another 245 to receive patches and an antidepressant. After a year, 40 in the first group and 87 in the second had quit. Give a 99% plus-four confidence interval for the difference (treatment - control) in proportions of smokers who quit.