STAT 2593

Lecture 034 - Z tests and Confidence Intervals for a Difference of Two Population Means

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Z tests and Confidence Intervals for a Difference of Two Population Means

Learning Objectives

1. Understand the mean and variance for the estimator of a difference of means, under normality assumptions.

2. Understand the Z hypothesis test for a difference of means, under normality assumptions.

3. Form confidence intervals for the estimated difference between two different means, under normality assumptions.



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We can consider the typical standardization, forming

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 - The hypothesis test runs exactly as expected.

Confidence Intervals for the Mean Difference

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If we want an α level confidence interval for μ₁ – μ₂, we can take

$$\overline{X} - \overline{Y} \pm Z_{\alpha/2} \sqrt{\frac{\sigma_1^2}{n} + \frac{\sigma_2^2}{m}}.$$

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 - If the sample sizes are large enough, these results will hold approximately.
 - If not, we will need to rely on alternative distributions to conduct the test.



Two populations can be compared under the assumption of normality by estimating the mean difference by the difference of sample means.

Under normality assumptions, or approximate normality assumptions, the difference will follow a normal distribution and normal procedures apply.