STAT 2593

Lecture 026 - Large Sample Confidence Intervals for a Population Mean and Proportion

Dylan Spicker

Large Sample Confidence Intervals for a Population Mean and Proportion

1. Construct confidence intervals for normal population means in large samples with unknown variance.

2. Construct confidence intervals for the sample proportion in large samples.

A quick disclaimer on introductory statistics education.

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Note, if n is not large enough, this argument will not hold.

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 - ▶ Use an estimated *s*, or a conservative one if a range is known.

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• If an estimate of p is not known, taking p = 0.5 remains conservative.

Summary

When variance is unknown, but the population is still assumed to be normal, we can use the central limit theorem and large sample sizes to justify the same procedure for constructing confidence intervals.

When a population proportion is estimated, if the normal approximation to the binomial applies, the same procedure can be applied.