Government 10: Quantitative Political Analysis

Sean Westwood

Statistical Significance

How to make sense of results?

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- Focus on findings and computing differences.

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Today:

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Today:

- Systematic approach for understanding which differences are meaningful and which are not.

What is Statistical Significance?

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It helps researchers decide if their findings are reliable and can be generalized to a larger population.

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2. Large differences are not always (or even often) significant
3. Larger samples provide more reliable results
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5. Significance does not imply causation

Hypothesis Testing

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Here it would be:

-"Artillery attacks have no effect on rebel activity"

Hypothesis Testing

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$$H_a(\text{Alternative Hypothesis})$$

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If we find significant evidence for a relationship and we are predicting a relationship, then we can reject the null hypothesis of no relationship.

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We can never say:

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Instead, we can say:

1. There is (is not) significant evidence to support our hypothesis.
2. We can reject (fail to reject) the null hypothesis

What do we do with a null hypothesis?

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What do we do with a null hypothesis?

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OR

- Fail to reject the null and do not find evidence supporting the alternative hypothesis

The next step: standard of evidence

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A p-value (or probability value) is a statistical metric used to evaluate the strength of evidence against a null hypothesis in hypothesis testing.

Specifically, the p-value represents the probability of obtaining test results at least as extreme as the observed results, assuming that the null hypothesis is true.

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Where does this threshold come from?

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Created the p-value

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We use a higher threshold because of sample size limitations and cost concerns.

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What do they mean?

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Significant: If the t-statistic is large (positive or negative), it means the difference between the groups is unlikely to have happened by random chance.

Not significant: If the t-statistic is small, it means the difference could easily be due to random variation.

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Significant: A low p-value ($<=$ .05) indicates we should reject the null hypothesis—there might be a real effect or difference.

Not significant: A high p-value ($>$.05) suggests that there's not enough evidence to reject the null hypothesis, and any observed difference might be due to random chance.

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- With a sample we can be wrong!
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A 95% confidence interval gives a range of values that, if we were to repeat the sampling process many times, would contain the true value of the parameter we are estimating in 95% of those intervals.

How to think about a confidence interval

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- Assume we can repeat a survey 100 times.
- Assume we compute a confidence interval for each survey
- 95% of those intervals would contain the true population mean.

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$$\text{Upper CI} = 50 + 1.96 * 5 = 59.8$$

$$\text{Lower CI} = 50 - 1.96 * 5 = 40.2$$

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$$\text{Upper CI} = 50 + 1.96 * 5 = 59.8$$

$$\text{Lower CI} = 50 - 1.96 * 5 = 40.2$$

We would write this as "95% CI [40.2, 59.8]"

Interpretation:

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A 95% confidence interval is a way to estimate the true value of a population parameter (what we are trying to estiamte from a sample).

It provides a range that likely includes the true value based on sample data.

Example 1

Testing the impact of a college degree on voting behavior.

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H_a: Holding a college degree increase voter turnout.

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Difference: 20% increase in voter turnout.

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Results:

Difference: 20% increase in voter turnout. p-value: 0.04; t-statistic: 5.23; 95% Confidence Interval: [17.23, 22.14]

Conclusion:

A college degree increases voting by 20% (95% CI [17.23, 22.14]). This is a statistically significant effect.

Example 2

Testing the relationship between anger and support for violence

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- Control Group Support: 15%.
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- Difference: 57%

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- Control Group Support: 15%.
- Angry Group Support: 72%.
- Difference: 57%

P-Value $<$ 0.001; t-statistic: 19.23; 95% Confidence Interval: [53.7, 60.3]

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H_a: Anger decreases support for violence.

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- Control Group Support: 15%.
- Angry Group Support: 72%.
- Difference: 57%

P-Value < 0.001; t-statistic: 19.23; 95% Confidence Interval: [53.7, 60.3]

Conclusion: Anger increases support for violence 57% (95% CI [53.7, 60.3]). This is a statistically significant effect.

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- LOW SAT Group: 70%
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- LOW SAT Group: 70%
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- Difference: 3%

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- LOW SAT Group: 70%
- High SAT Group: 73%
- Difference: 3%

p-value: 0.08; t-statistic: 1.45; 95% Confidence Interval: [-1.2, 7.2]

Example 3

Testing the relationship between SAT scores and college graduation rates.

Hypotheses:

H_a: SAT scores increase college graduation rates.

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- LOW SAT Group: 70%
- High SAT Group: 73%
- Difference: 3%

p-value: 0.08; t-statistic: 1.45; 95% Confidence Interval: [-1.2, 7.2]

Conclusion: SAT scores are not significantly related to college graduation rates, with a difference in graduation rates of 3% (95% CI [-1.2, 7.2]). This is a statistically significant effect.

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- Differences in proportions (not covered in this class)

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Differences in means

What is a t-test?

- A statistical test used to determine if there is a significant difference between the means of two groups.
- Often used when sample sizes are small, and the population standard deviation is unknown.

Origins of the t-test

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- Worked as a chemist and statistician at the Guinness Brewery in Dublin, Ireland.
- Published under the pseudonym "Student," hence the name "Student's t-test."

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Limitations and Assumptions

Assumptions:

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