Gov 50: 20. Hypothesis testing: One-sample Tests

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- 1. Today's agenda
- 2. Statistical thought experiments
- 3. Hypothesis tests
- 4. p-values
- 5. Small samples

1/ Today's agenda

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 - Midterm 2: definitely harder, but remember the curve!
 - You all are learning a ton in this class and it shows.

2/ Statistical thought experiments

Your friend asks you to grab a tea with milk for her before meeting up and she says that she prefers tea poured before the milk. You stop by Tealuxe and ask for a tea with milk. When you bring it to her, she complains that it was prepared milk-first.

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 - Ask friend to pick which 4 of the 8 were milk-first.

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- Chances of guessing all 4 correct is $\frac{1}{70} \approx 0.014$ or 1.4%.
- \rightsquigarrow the guessing hypothesis might be implausible.

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 - A recent poll of 1600 registered voters found that 43% of the public approves of Donald Trump.
 - Has support for Trump changed or could this poll be just due to random chance?

3/ Hypothesis tests

Hypothesis testing procedure

Conducted with several steps:

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- This procedure is general, but we'll focus on tests of a single population mean today.

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- Probabilistic proof by contradiction: try to disprove the null.

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How many SEs away from the null guess is the sample mean?

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- This poll: $\overline{X} = 0.43$ with sample size n = 1600
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- Estimate the test statistic:

$$Z_{\text{obs}} = \frac{\overline{X} - p}{\sqrt{p(1-p)/n}} = \frac{0.43 - 0.46}{\sqrt{0.46(1 - 0.46)/1600}}$$
$$\approx -2.4$$

4/ p-values

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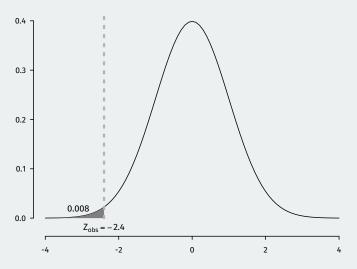
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 - \triangleright We know Z is distributed standard normal \rightsquigarrow use R!

Standard normal probabilities in R

 The pnorm(x) function will give the probability of being less x in a standard normal:

```
pnorm(-2.4)
```

```
## [1] 0.0082
```



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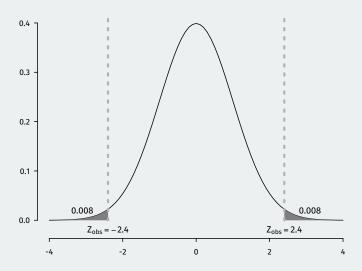
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 - ightharpoonup Because of the symmetry of the normal: $2 \times \mathbb{P}(Z > |Z_{\text{obs}}|)$



• two-sided p-value: 0.016

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 - ► Smaller p-values ~ more evidence against the null.

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 - p < 0.01 "highly significant"

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- Type II error less serious (missed out on an awesome finding)

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 - ~> can't determine p-values
 - ► ~ can't get z values for confidence intervals
- Very difficult to get around this problem without more information.

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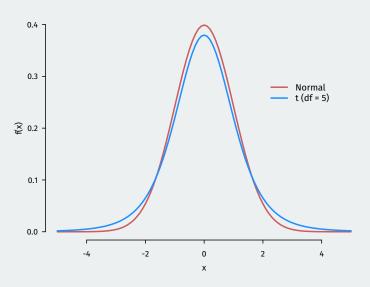
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 - ► Similar to normal with fatter tails ~ higher likelihood of extreme events.

Who was Student?

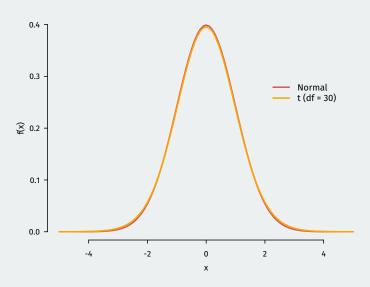




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- R will almost always calculate p-values for you, so details of t-distribution aren't massively important.

Next time

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- Next week: inference for regression.