

Hypothesis Testing 3

More on Null Distributions and P-values, Test-stats

Grinnell College

Review

Hypothesis Testing: formal technique for answering a question with two competing possibilities

Null Hypothesis: represents a skeptical view or a perspective of no difference

- ▶ H_0 : 'parameter' = (some value)

Alternate Hypothesis: what the researchers actually want to show with the study

- ▶ H_A : 'parameter' [$<$ / $>$ / \neq] (some value)

Review

This is the general outline we will follow for Hypothesis Testing

1. Define hypotheses
2. Create a null distribution (represents H_0)
3. See how our statistic compares to this
4. Compute a p-value
 - ▶ do the results look unlikely if H_0 is true?
5. Interpretations / Conclusions

Note: We will see alternatives to simulation for step 2 today

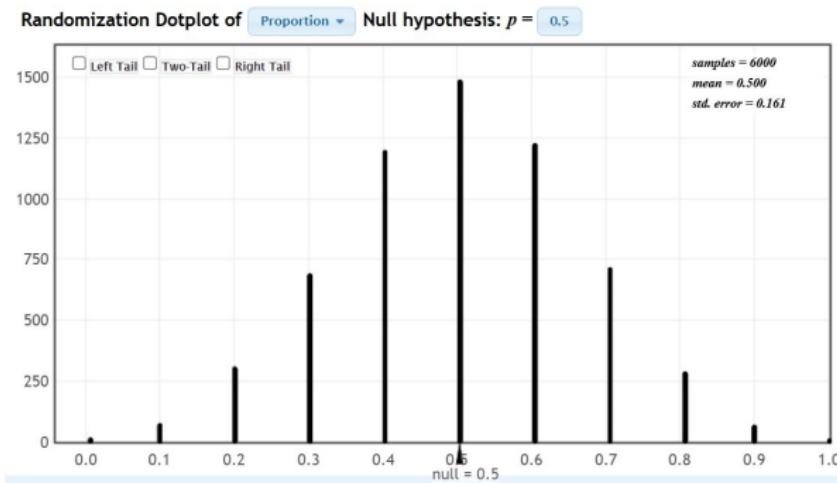
Review – Null Distribution

Null Distribution

The distribution of the statistics if the null hypothesis is true

- ▶ simulates what the null hypothesis looks like

We looked at the coin-flip scenario. Null distribution of fair coin, 10 flips



- ▶ Notice the shape of this (Normal). We could use Normal distribution methods to compute a p-value instead.

Null Distribution – Proportion

Conditions

- ▶ Representative Sample
- ▶ $np_0 \geq 10$ (Success condition)
- ▶ $n(1 - p_0) \geq 10$ (Failure condition)

With the conditions met, the null distribution for \hat{p} looks like this:

$$\hat{p} \sim N(p_0, \sqrt{\frac{p_0(1 - p_0)}{n}})$$

- ▶ distribution of \hat{p} 's is Normal
- ▶ mean = p_0 , $sd = \sqrt{\frac{p_0(1 - p_0)}{n}}$

Note: We are going to do something so we can use Standard Normal distribution instead.

Test Statistics

$$\hat{p} \sim N(p_0, \sqrt{\frac{p_0(1-p_0)}{n}})$$

The test-statistic saves us from having to plot this Normal distribution every time. We will *standardize* \hat{p} to make the distribution simpler.

$$\frac{\hat{p} - p_0}{\underbrace{\sqrt{\frac{p_0(1-p_0)}{n}}}_{\text{Test Statistic}}} \sim N(0, 1)$$

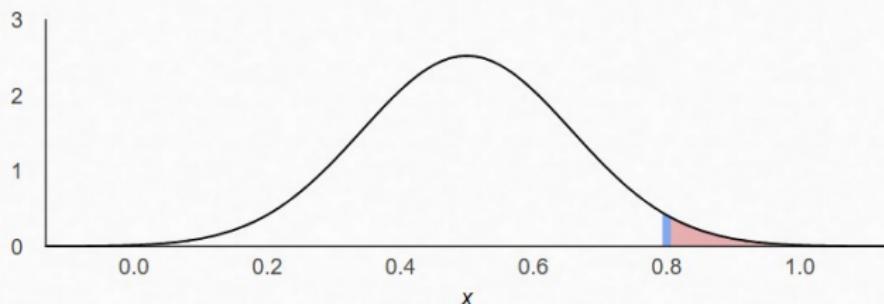
- ▶ the whole term on the left is the Test-statistic
- ▶ we can compute this value and we know it follows $N(0,1)$

Coin Flip Example

For our scenario of 10 flips...

- ▶ $\hat{p} = 8/10 = 0.8$
- ▶ $p_0 = 0.5$
- ▶ $\sqrt{\frac{p_0(1-p_0)}{n}} = \sqrt{\frac{0.5(1-0.5)}{10}} = 0.158$

$\mu =$	0.5	$\sigma =$	0.158
$x =$.8	$P(X > x) =$	0.0288

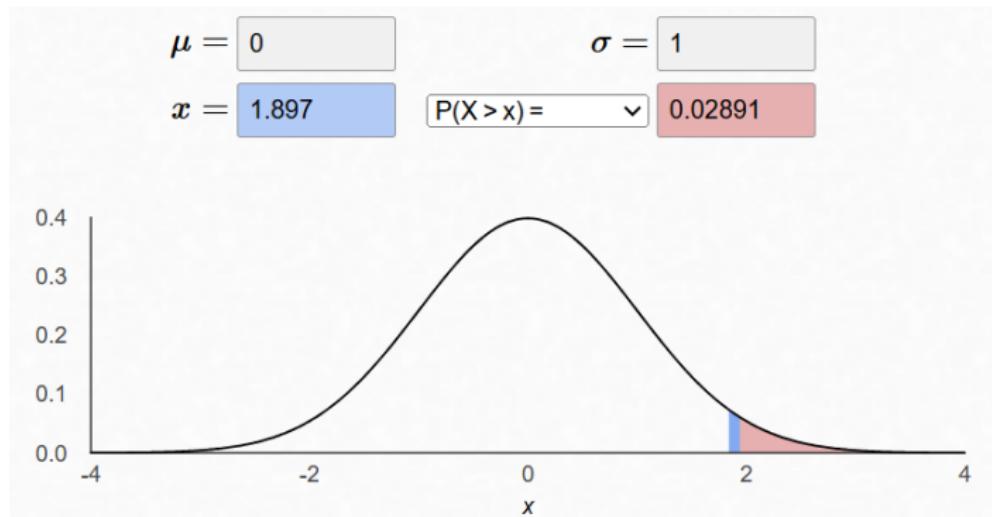


- ▶ can use Null distr. and \hat{p} to get p-value (pnorm in R)

Coin Flip Example

For our scenario of 10 flips...

- ▶ $\hat{p} = 8/10 = 0.8, p_0 = 0.5$
- ▶ $Z = \frac{\hat{p} - p_0}{\sqrt{\frac{p_0(1-p_0)}{n}}} = \frac{0.8 - 0.5}{\sqrt{\frac{0.5(1-0.5)}{10}}} = 1.897$



- ▶ std. Normal distribution and Z value to get p-value ('pnorm()')
- ▶ Z-values are comparable across different studies

Test-statistics

From here on out, we will place almost all of our emphasis on Test-statistics instead of elaborately detailing what the null distribution should look like.

More on P-values

Forms of the Alternate Hypothesis

- ▶ H_A : parameter > 'hypothesized value' (right-tailed test) **OR**
- ▶ H_A : parameter < 'hypothesized value' (left-tailed test) **OR**
- ▶ H_A : parameter \neq 'hypothesized value' (two-tailed test)

Up until now we have only seen how to calculate p-values Alternate Hypotheses that use the $>$ symbol.

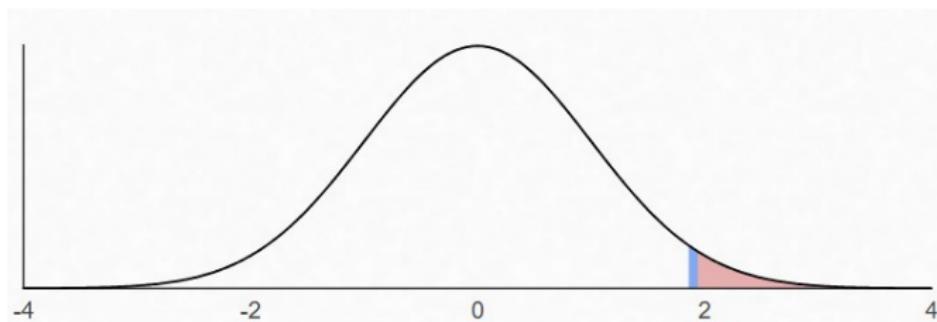
- ▶ coin flip biased in favor of heads ($H_A : p > 0.5$)
- ▶ Monday breakups ($H_A : p > \frac{1}{7}$)

More on P-values

H_A : parameter > 'hypothesized value' (right-tailed test)

- ▶ to find a p-value, you find where the Test-statistic is on a $N(0,1)$ distribution, then find the area to the right of it under the curve

Suppose test-stat $Z = 1.9$



```
> pnorm(1.9, lower.tail=F)
[1] 0.02871656
```

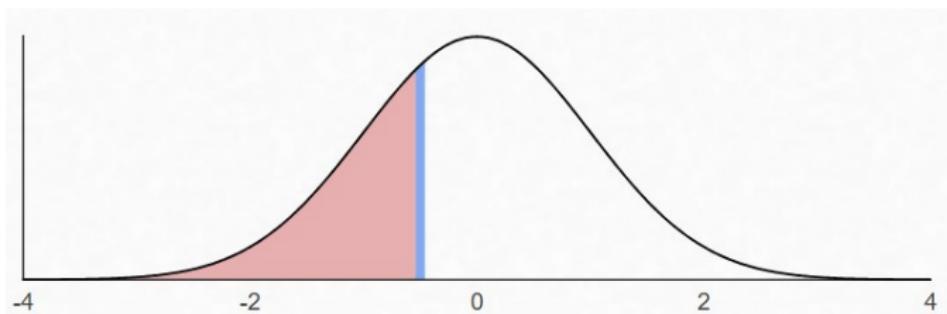
- ▶ This is how we would get p-value for coinflip example

More on P-values

H_A : parameter < 'hypothesized value' (left-tailed test)

- ▶ to find a p-value, you find where the Test-statistic is on a $N(0,1)$ distribution, then find the area to the left of it under the curve

Suppose test-stat $Z = -.5$



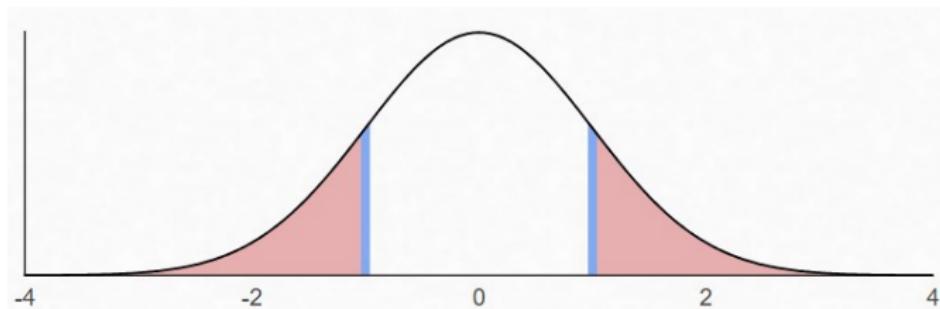
```
> pnorm(-.5)
[1] 0.3085375
```

More on P-values

H_A : parameter \neq 'hypothesized value' (two-tailed test)

- ▶ to find a p-value, you find where the Test-statistic is on a $N(0,1)$ distribution
- ▶ area to the right ($\text{Test-stat} > 0$) or area to the left ($\text{Test-stat} < 0$)
- ▶ multiply this area by 2

Suppose test-stat $Z = 1$



```
> 2*pnorm(1, lower.tail=F)
[1] 0.3173105
> 2*pnorm(-1)
[1] 0.3173105
```

Example: Iowa Smoking Rates

A public health researcher wants to know if adult rate of smoking cigarettes in Iowa is lower than the national rate of 11%. A random sample of 500 Iowans adults is surveyed and finds a sample rate of 10%. Do these data provide convincing evidence that the smoking rate in Iowa is lower than the national average?

$$H_0: p = 0.11 \quad H_A: p < 0.11$$

$$Z = \frac{\hat{p} - p_0}{\sqrt{\frac{p_0(1-p_0)}{n}}} = \frac{0.10 - 0.11}{\sqrt{\frac{.11 \times .89}{500}}} = \frac{-0.01}{\sqrt{0.0001958}} = -0.71$$

```
> pnorm(-0.71, lower.tail=T)
[1] 0.2388521
```

Conclusion According to this study there is little to no evidence the adult rate of smoking in Iowa is less than the national rate.

Note: the real rate of smoking in Iowa is MUCH higher. Study from 2019: <https://hhs.iowa.gov/media/11502/download?inline>

Summary

We can use Normal distribution stuff we've seen previously to get p-values.

- ▶ Check conditions to make sure it works!
- ▶ Compute Z-score then use `pnorm` to get p-value

Which method to use?

- ▶ Conditions met → Normal distribution
- ▶ Conditions not-met → Simulation (Statkey)

Bonus: My plug for probability theory

Note: You will not be tested on this slide.

Where does the null distribution come from?

Suppose we have a sample of n observations from a population with a binary outcome (1 or 0) and $p = P(\text{success}) = P(1)$. We can treat these as Bernoulli events, then using the Bernoulli random variable stuff from the RV lecture slides. Bernoulli: $E(X) = p$, $\text{var}(X) = p(1-p)$

n independent Bernoulli events, look at the average of them all as $\hat{p} = \bar{X}$

- ▶ $E(\hat{p}) = E\left(\frac{1}{n} \sum X_i\right) = \frac{1}{n}(np) = p$
- ▶ $V(\hat{p}) = V\left(\frac{1}{n} \sum X_i\right) = \frac{1}{n^2} np(1-p) = \frac{p(1-p)}{n}$
- ▶ large $n \rightarrow \hat{p}$ will be approx. Normal (CLT)

And so $\hat{p} \sim N(p, \sqrt{\frac{p(1-p)}{n}})$