

# Basic Statistics Review

Last Edited: February 14, 2022

## 📌 A Note

This review covers some of the basics of statistics in the frequentist formulation of the field.

For coverage from a Bayesian perspective see [Statistical Rethinking](#) by Richard McElreath.

## ○ Basic Definitions: Population

The *population* of interest is a group about which you want to know something.

Some examples include:

- All people on Earth,
- Registered Republican voters in Iowa,
- GE Brand 30 Watt LED light bulbs,
- All evergreen trees in a given forest and
- All iris flowers.

## 🕒 Basic Definitions: Sample

A *sample* is the collection of data from a subset of the population in which you are interested.

If we have a sample size of  $n$  observations, we can think of the sample as a collection of  $n$  random variables,  $X_i$  for  $i = 1, \dots, n$ .

However, it is standard to denote samples with lowercase letters,  $x_i$ .

## 6 Basic Definitions: Random Sample

We say that a sample is *random* if its constituent observations have been selected at random.

## 6 Basic Definitions: Sample Statistics

A *sample statistic* is an estimate of a parameter intrinsic to the population of interest calculated using the data collected from a sample.

Note: When the sample is randomly selected, a sample statistic is thus an example of a random variable.

# Common Sample Statistics

## Sample Mean

Let  $x_i$  denote the data from the  $i^{\text{th}}$  observation. The *sample mean* is found by taking the arithmetic mean of the sample. Formally,

$$\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i$$

# Common Sample Statistics

## Sample Variance

Let  $x_i$  denote the data from the  $i^{\text{th}}$  observation. The sample variance is defined to be:

$$s^2 = \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2$$

## Sample Standard Deviation

The square root of the sample variance.



# Common Sample Statistics

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# Common Sample Statistics

## Sample Covariance

Let  $x_i, y_i$  denote the data from the  $i^{\text{th}}$  observation. The sample covariance between  $x$  and  $y$  is defined to be:

$$s_{x,y} = \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})$$

## Sample Pearson Correlation

$$r = \frac{s_{x,y}}{s_x s_y}$$

This measures the strength of the linear relationship between  $x$  and  $y$ .

# 📊 Hypothesis Testing

In statistics, you often want to know something about a population parameter in comparison to some baseline.

The formal procedure to do this is known as a *hypothesis test*.

## Examples

- Is the average parts per billion of POFA is below a safe consumable level?
- Is the proportion of people in support of bond measure 4 greater than .5?
- Do students at high school A have higher SAT scores than those high school B?

# How to Conduct a Hypothesis Test

There is a population parameter you are interested in,  $\theta$ .

Take a random sample, and estimate the parameter,  $\hat{\theta}$ , this is a draw of random variable.

Assume a value for the parameter, this is called the *null hypothesis*,  $H_0: \theta = \theta_0$ .

Under the null hypothesis, and other reasonable assumptions, we can derive the probability distribution that  $\hat{\theta}$  follows.

We then present an alternative hypothesis,  $H_1$  or  $H_A$  (depending on the text), which is something like the following:  $H_A: \theta \neq \theta_0$  or  $H_A: \theta > \theta_0$  or  $H_A: \theta < \theta_0$ .

Then using the probability distribution under the null hypothesis, calculate the probability that  $\hat{\theta}$  is as extreme as what you observed. If it is small, you reject  $H_0$  in favor of  $H_A$ .

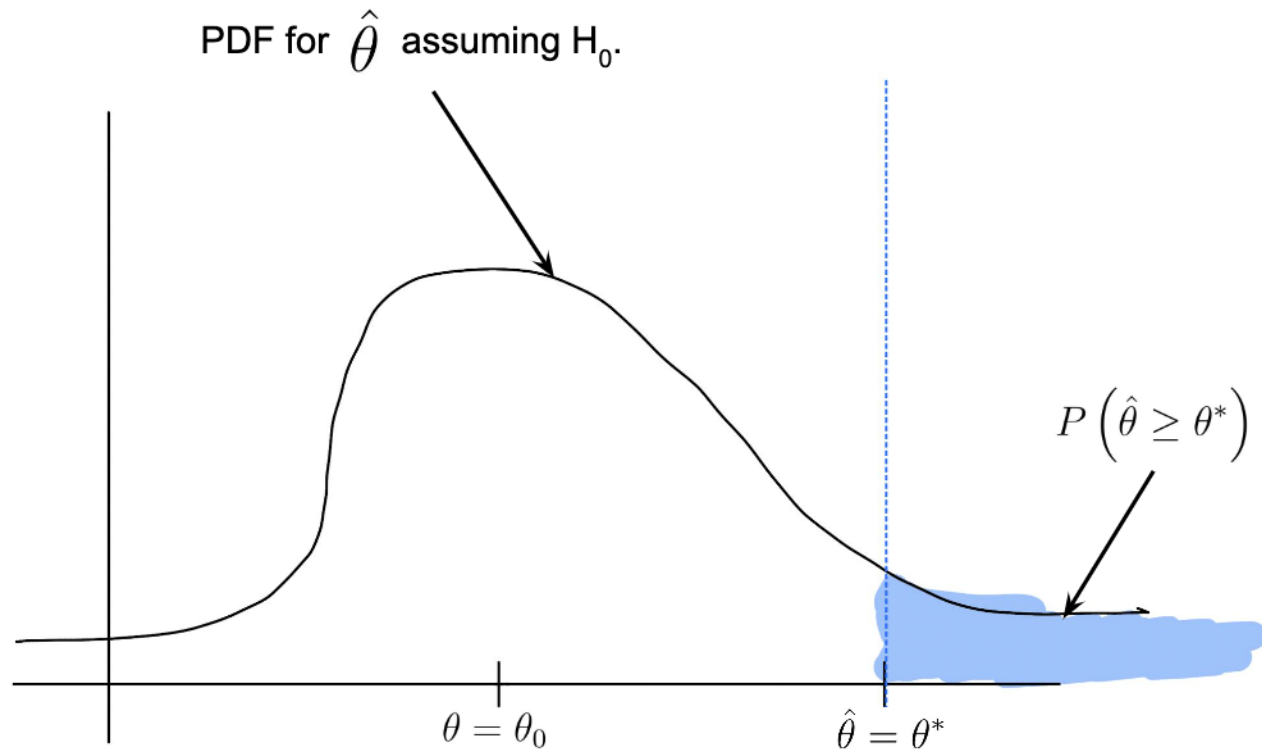
# How to Conduct a Hypothesis Test: Illustrated

$$H_0: \theta = \theta_0$$

$$H_A: \theta > \theta_0$$

Estimate  
from sample:  $\hat{\theta} = \theta^*$

If the blue highlighted  
region is sufficiently small,  
we would reject the null  
hypothesis in favor of  $H_A$ .



## 6 How to Conduct a Hypothesis Test: Example

Problem: You want to know if a coin is fair, meaning that the probability of heads is 0.5. In particular, is the coin more likely to land heads than tails?

$$H_0: p = 0.5$$

$$H_A: p > 0.5$$

Random Sample: The coin was flipped 10 times, resulting in 8 heads and 2 tails

Under the null hypothesis, the probability of getting at least 8 heads is:

$$\binom{10}{8} \cdot 5^{10} + \binom{10}{9} \cdot 5^{10} + \binom{10}{10} \cdot 5^{10} = 0.0546875,$$

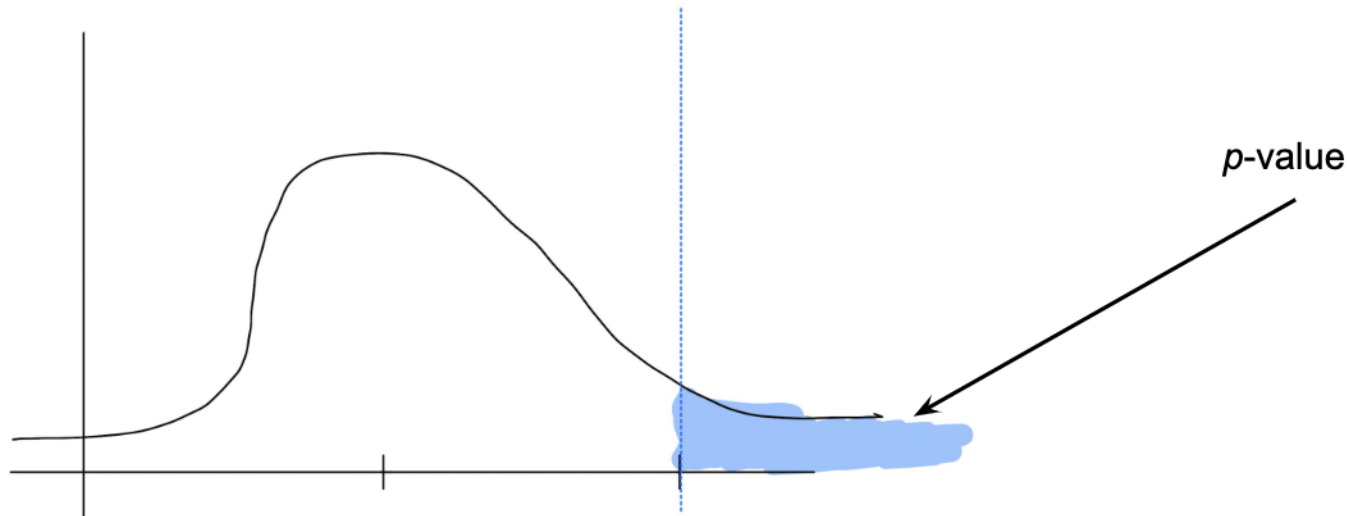
which is pretty small, but larger than the 0.05 standard. In the present problem we wouldn't reject  $H_0$ , but we should probably be a bit wary that this coin might not be fair.

# 📊 Hypothesis Testing: $p$ -values

When conducting a hypothesis test, the  $p$ -value is the probability, under the null hypothesis, that your sample statistic is at least as extreme as what you observed.

In the example on slide 14,  $p = 0.0546875$ .

In the illustration on slide 13, the  $p$ -value is represented by the blue shaded area.



# 6 Hypothesis Testing: Error Types

When conducting a hypothesis test, there are four possible outcomes as diagrammed on the right.

*Type I Error:* We reject  $H_0$  when it is in fact true,  $P(\text{Type I Error}) = p\text{-value of the test}$ .

*Type II Error:* We fail to reject  $H_0$  when it is not True. We typically take  $P(\text{Type II Error}) = \beta$ .

		Hypothesis Test Outcome	
		Fail to Reject $H_0$	Reject $H_0$
Truth	$H_0$ is True		Type I Error
	$H_0$ is False	Type II Error	



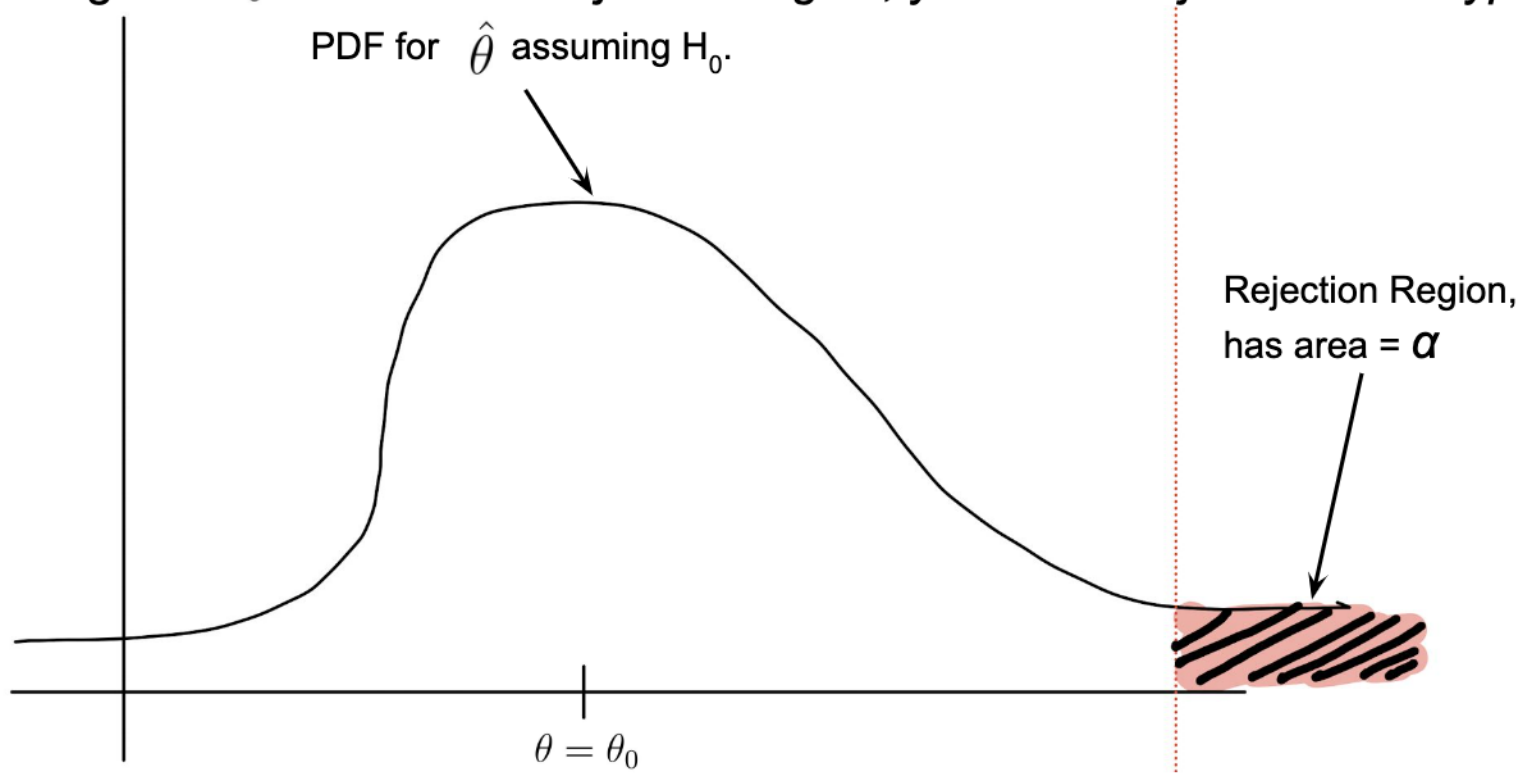
## 6 Hypothesis Testing: Significance Level

The *significance level* of a hypothesis test is the maximum allowable value of a Type I Error for which we would reject the null hypothesis.

This is denoted with an  $\alpha$ , if you produce a  $p$ -value less than  $\alpha$  you would reject the null hypothesis. A standard value for  $\alpha = 0.05$ .

# 🔍 Hypothesis Testing: Rejection Region

The *rejection region* of a hypothesis test is a region for your test statistic,  $\hat{\theta}$ , in which you would reject the null hypothesis. In the illustration this is the highlighted red hatched region. *If  $\hat{\theta}$  lands in the rejection region, you would reject the null hypothesis.*



## Constructing a Confidence Interval

Here is a typical process for constructing a  $100(1 - \alpha)$  confidence interval for  $\theta$ .

- Take a random sample, calculate  $\hat{\theta}$
- Calculate the standard error of  $\hat{\theta}$ , denoted as  $se(\hat{\theta})$
- Based on the probability distribution for  $\hat{\theta}$ , find the probability modifier,  $p_{\hat{\theta},(1-\alpha)}$ , that is the value such that  $P(\hat{\theta} \geq p_{\hat{\theta},(1-\alpha)}) = (1 - \alpha)$
- The interval is then typically of the form:

$$\hat{\theta} \pm p_{\hat{\theta},(1-\alpha)} se(\hat{\theta})$$

# 🗨️ Interpreting a Confidence Interval

Confidence intervals have been notoriously misinterpreted since their introduction.

If you are interested in learning more about how we should think about confidence intervals, I encourage you to read this paper,

<https://link.springer.com/article/10.3758/s13423-015-0947-8#Fn1>.