An Introduction to Statistics & Programming

Welcome!

First off, breathe! We will all make it through this together!

My quick teaching philosophy:

1. I love talking not lecturing—ask me questions!
2. We are all here because we enjoy learning, which is the goal of my course: learning. DO NOT WORRY ABOUT YOUR GRADES—take that stress off of yourself.

Schedule for Today

In addition to a **15 minute break at 2:30 PM**, we will take two 5-ish minute breaks at:

- **5 min break @ 1:45 PM**
- **5 min break @ 4:00 PM**

Feel free to ask me even more questions during this time!

Overview

- Introduction to Statistical Science
  - Descriptive Statistics
  - Quick look at Probability Theory
  - Inferential Statistics
- Introduction to Programming with R
  - Base R
  - Tidyverse

Goals for Today

- Refresh yourself on statistics!
- Learn about statistical estimation and tests
- Data importing and transformation with R

A Reassuring Reminder

> Statistics is hard, especially when effects are small and variable and measurements are noisy.
> — McShane et al. (2019)

Introduction to Statistical Science

What is Statistical Science?

> Statistical science is the science of developing and applying methods for collecting, analyzing, and interpreting data.
> — Agresti & Kateri, 2022

Three Aspects of Statistical Science

- Design: Planning on how to gather relevant data.
- Description: Summarizing the data.
- Inference: Making evaluations (generalizations) based on the data.

Design of Studies

The design of a study focuses on planning a study so that it produces useful data. This involves:

- Deciding how to sample and who to sample
- Constructing surveys for **observational studies**
- Constructing treatments for **experimental studies**

Description

Description focuses on how to summarize the raw data without losing too much information. Descriptive statistics are statistics calculated from the raw data that summarize all (or most) of the information contained in the data:

- Mean, median, and mode
- Variance and standard deviation
- Cumulative distribution of the data

Inference

Inference focuses on how to make evaluations (generalizations) from the data that take into consideration the uncertainty present in the data. These data-based evaluations take the form of:

- Predictions
- Interval and point estimates
- Probability (P) values

Populations & Samples

The purpose of most analyses is to learn something about the **population** from the collected data or **sample**.

- A **population** is the collection of every unit or subject (e.g. person) that one wishes to generalize to from the results of their study.
- A **sample** is the actual collected data one is using to make these generalizations.

Actual vs Conceptual Populations

Depending on the research question, the population may be **real** or it may be **conceptual**. **Conceptual** populations are often future populations we want to generalize to, but which we have to use data collected on current populations.

Variables

Variables are characteristics of the sample or population that vary across subjects.
Data consists of a set of variables:

```r
data_employees <- peopleanalytics::employees
data_employees_tbl <- tibble::as_tibble(data_employees)

set.seed(3)
data_employees_tbl |>
  dplyr::sample_n(5) |>
  dplyr::select(
    employee_id,
    trainings,
    ed_field,
    dept
  )
```

```
# A tibble: 5 × 4
  employee_id trainings ed_field         dept
        <int>     <int> <chr>            <chr>
1        1773         4 Medical          Research & Development
2        1652         2 Marketing        Sales
3        1999         2 Medical          Research & Development
4        1548         2 Medical          Research & Development
5        1698         5 Technical Degree Sales
```

Types of Variables by Measurement Scale

We can classify variables into two broad categories based on their measurement scale–the types of values the variable can take on:

- Quantitative: Values are numbers
- Categorical: Values are categories

Types of Variables by Measurement Scale

```r
set.seed(4)
data_employees_tbl |>
  dplyr::sample_n(5) |>
  dplyr::select(
    job_tenure,
    dept
  )
```

```
# A tibble: 5 × 2
  job_tenure dept
       <int> <chr>
1          0 Research & Development
2          2 Sales
3          3 Sales
4          0 Sales
5          0 Sales
```

Types of Quantitative Variables

Quantitative variables can be further classified into two groups:

- Discrete: Values are distinct, separable numbers (e.g. integers)
- Continuous: Values are on an infinite continuum (e.g. real numbers)

Types of Quantitative Variables

```r
set.seed(4)
data_employees_tbl |>
  dplyr::sample_n(5) |>
  dplyr::select(
    trainings,
    commute_dist
  )
```

```
# A tibble: 5 × 2
  trainings commute_dist
      <int>        <int>
1         4            9
2         4           20
3         2            1
4         2           19
5         0           12
```

Types of Categorical Variables

Similar to quantitative variables, categorical variables can also be classified into two groups:

- Dichotomous / Binary: Two categories
- Multicategorical: Three or more categories

Types of Categorical Variables

```r
set.seed(4)
data_employees_tbl |>
  dplyr::sample_n(5) |>
  dplyr::select(
    overtime,
    ed_field
  )
```

```
# A tibble: 5 × 2
  overtime ed_field
  <chr>    <chr>
1 No       Life Sciences
2 No       Life Sciences
3 No       Life Sciences
4 Yes      Marketing
5 No       Life Sciences
```

Roles of Variables

Variables can not only be categorized by the kinds and ranges of values they take on, but also by the **role they take on in the analysis**:

- Response, Outcome, Dependent Variable, Criterion Variable
- Predictor, Independent Variable, Feature, Covariate

Data Collection

The strength of the inferences you can make depends on the quality of your data. The quality of your data is very dependent on the method used to collect it:

- Experiments
- Observational Studies

Experiments

In experiments—also known as randomized control trials (RCTs)—data are collected by **randomly** assigning subjects to an experimental trial or condition, then collecting the subsequent outcome data.

By randomly assigning subjects to conditions, you are effectively ensuring that any differences in the outcome variable by condition is due solely to the condition not to any other **lurking** variable.

Observational Studies

In observational studies, the researchers **observe** collect a sample of subjects and **observe** their outcomes across the variables of interest. One type of observational study design is a **survey study**.

The important difference between observational studies and experiments is that subjects are **not randomly assigned** to treatments.

Describing your Data

Thinking in Disributions

The distribution of a given variable gives the frequency of each value of the variable. This frequency can be in either:

- Absolute terms: Count of observations
- Relative terms: Proportion or percent of observations

A variable's distribution completely describes the variable.

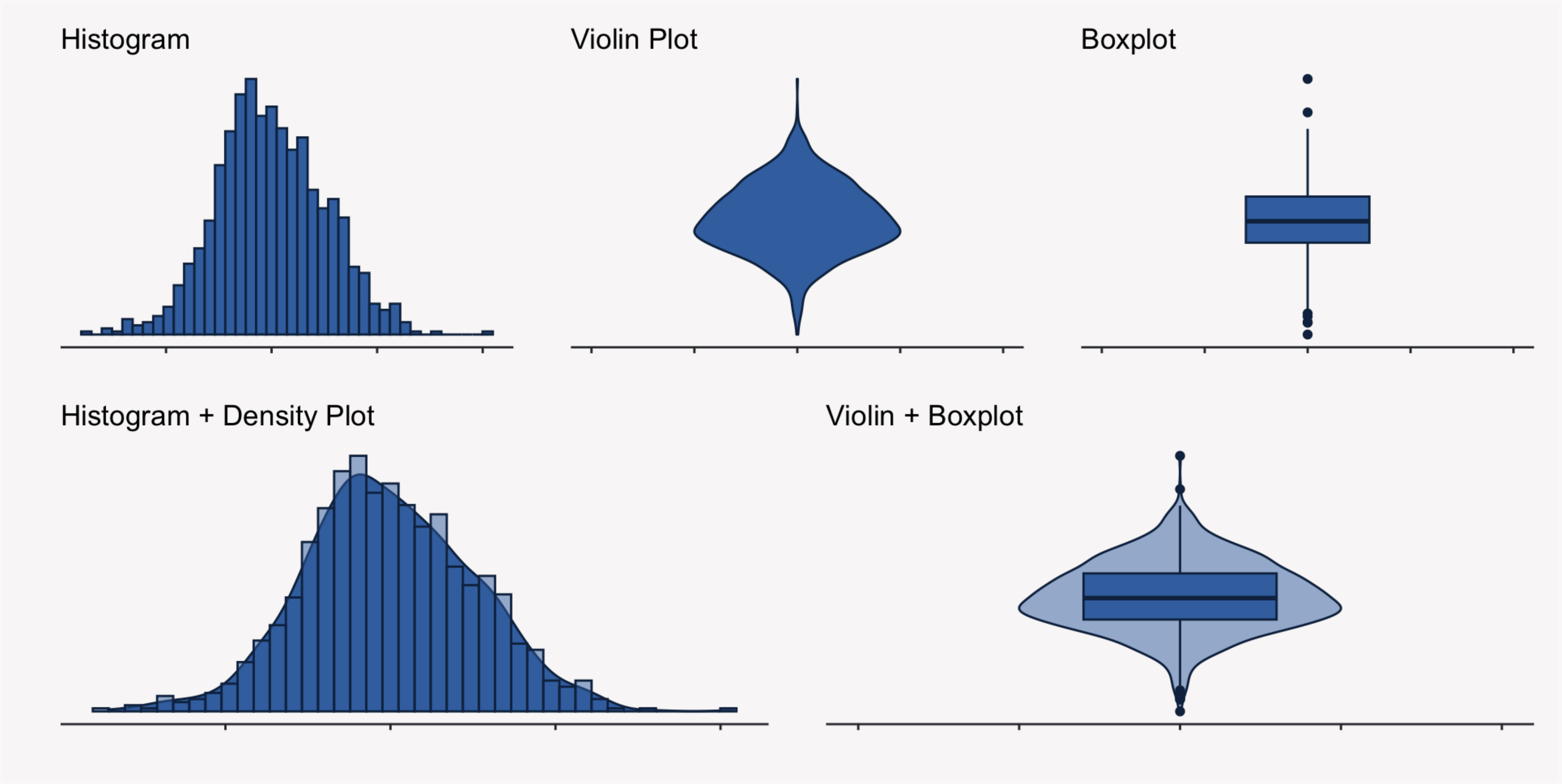
Importance of Plots

Plotting your data immediately gives you more information than looking at the raw numbers:

- Visual information about the **center, spread, and shape** of your data.
- Alert you to **outlier values**.

Examples of Plots

```r
set.seed(2311)
x <- rnorm(1000)
data <- tibble::tibble(x = x)
```



What is a Statistic?

Statistics are numbers computed from your data that provide useful **numerical** information about the characteristics of a variable's distribution such as its center (mean) or spread (standard deviation).

```r
mean(data_employees_tbl$commute_dist) |> round(2) # Mean
```

```
[1] 9.19
```

```r
median(data_employees_tbl$commute_dist) # Median
```

```
[1] 7
```

```r
sd(data_employees_tbl$commute_dist) |> round(2) # SD
```

```
[1] 8.11
```

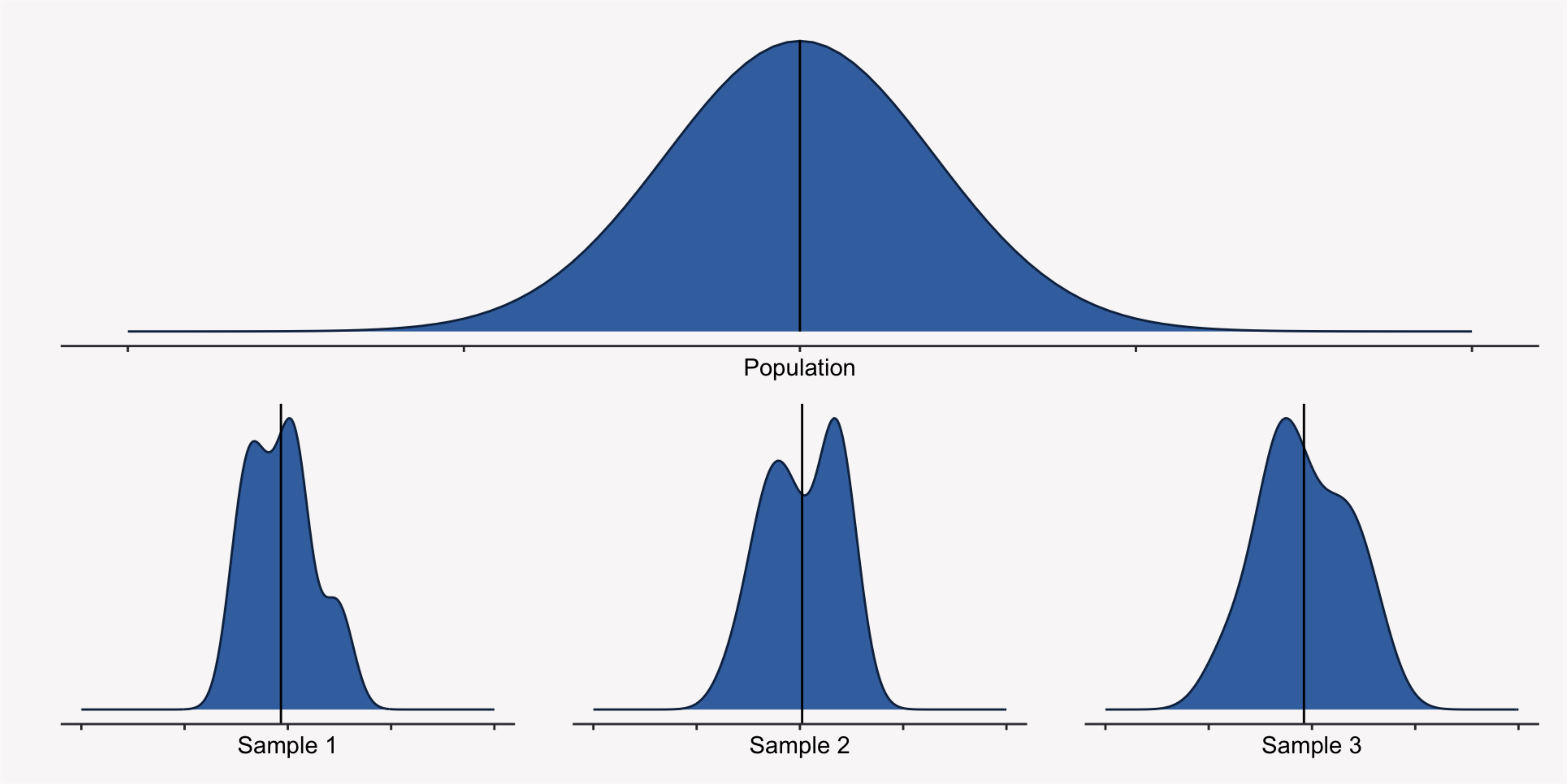
Statistic vs Population Parameter

Population parameters (or parameters) are numerical summaries of our population.

Statistics are estimates of these parameters calculated from data sampled from this population.

Usually, we do not have access to our full population of interest, so we sample our data from it and learn about its characteristics (parameters) through the statistics we compute from our sampled data.

Statistic vs Population Parameter

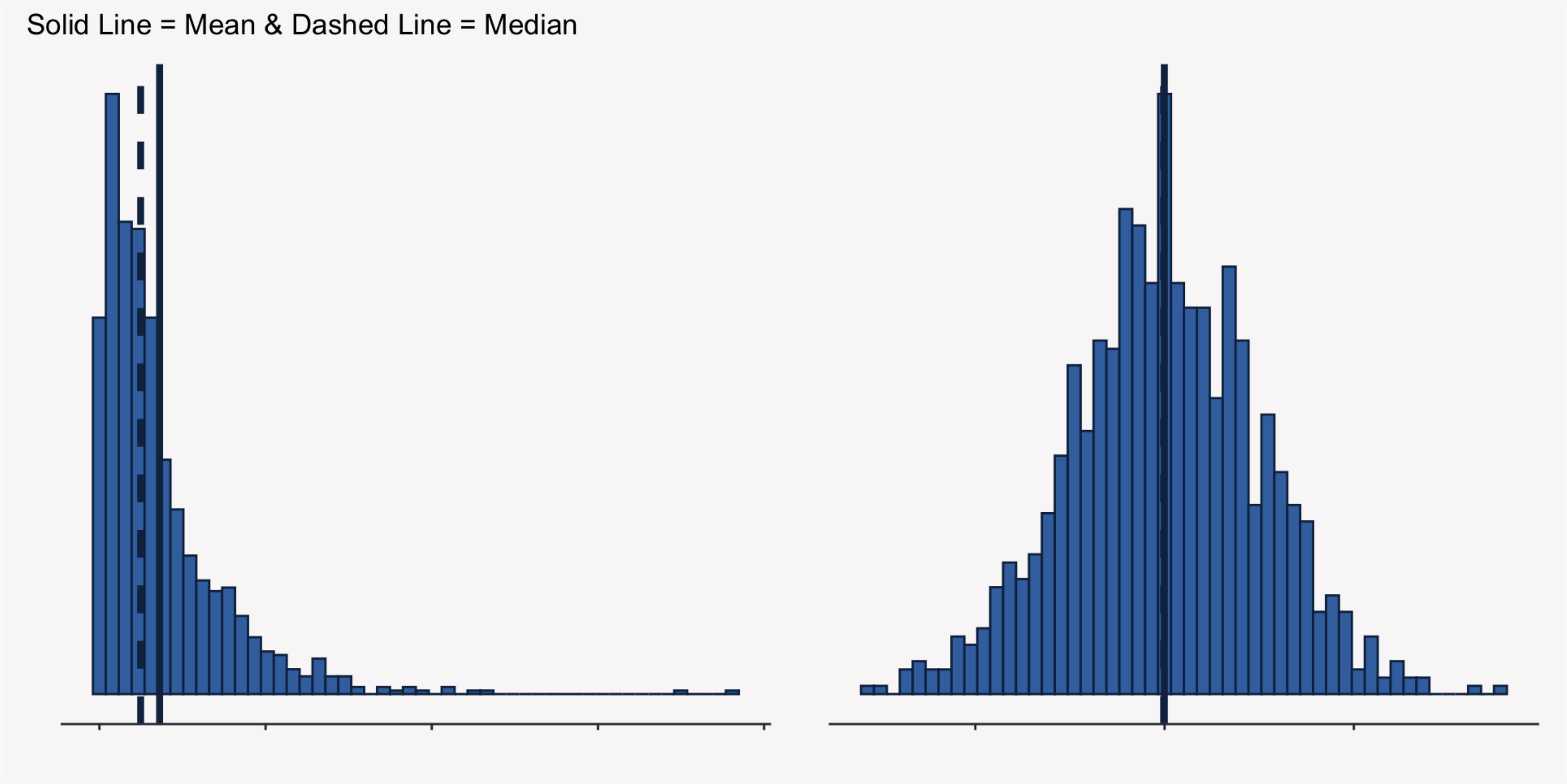


Describing the Center of your Data

One common way to describe your data is to compute a statistic that tells you where the center of your data is—the average or expected value of your data. There are three statistics you can compute:

- **Mean**: The average value.
- **Median**: The value at which 50% of your data lies below it.
- **Mode**: The most common value.

Describing the Center of your Data

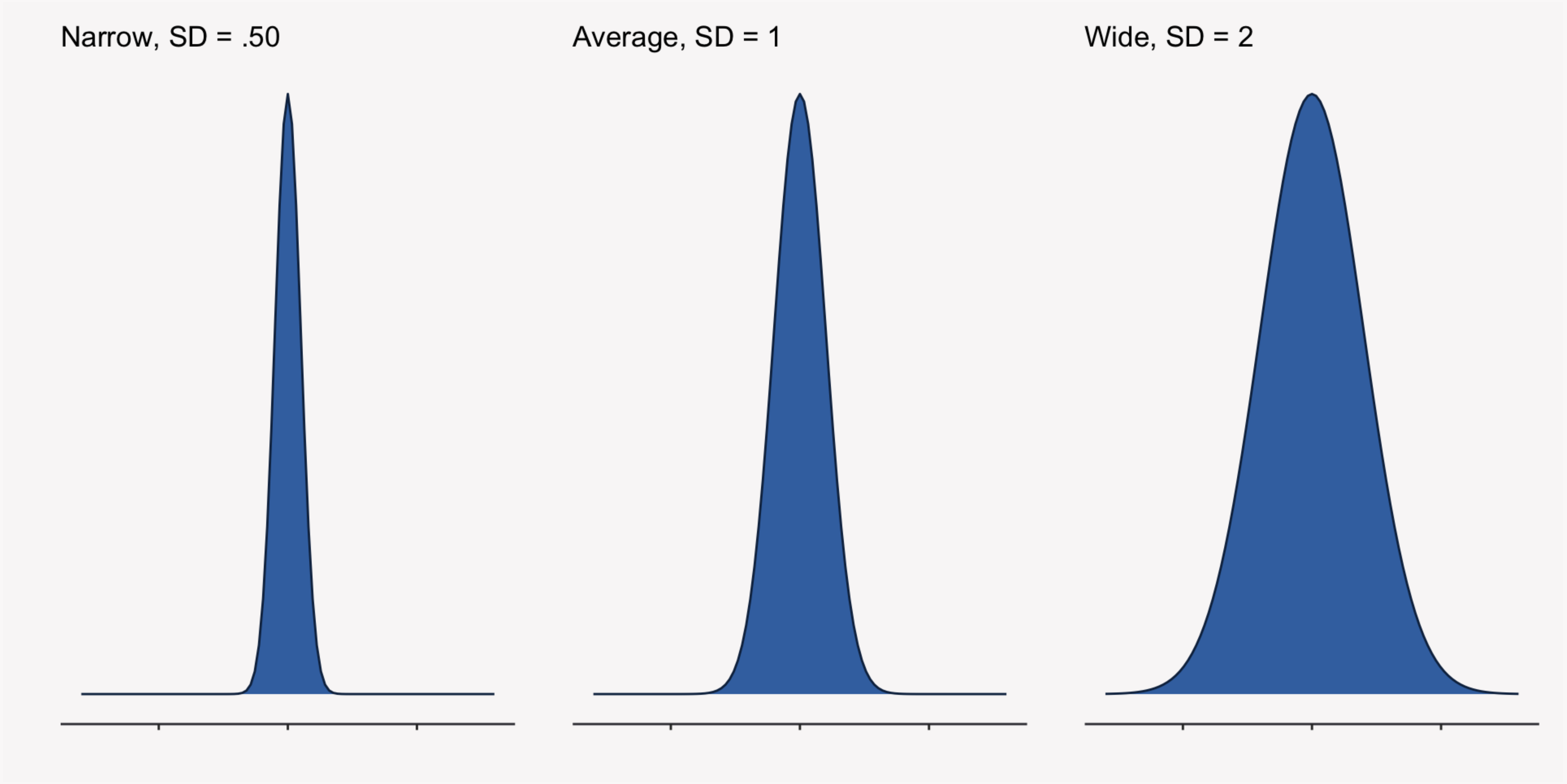


Describing the Spread of your Data

You can describe the **spread** of your data by computing statistics that tells you generally how far the observations are from the mean of your data. There are three statistics you can compute:

- **Variance**: The average squared distance your data falls from the mean.
- **Standard Deviation**: The average distance your data falls from the mean (square root of variance).
- **Range**: Maximum value minus the minimum value of your data.

Describing the Spread of your Data

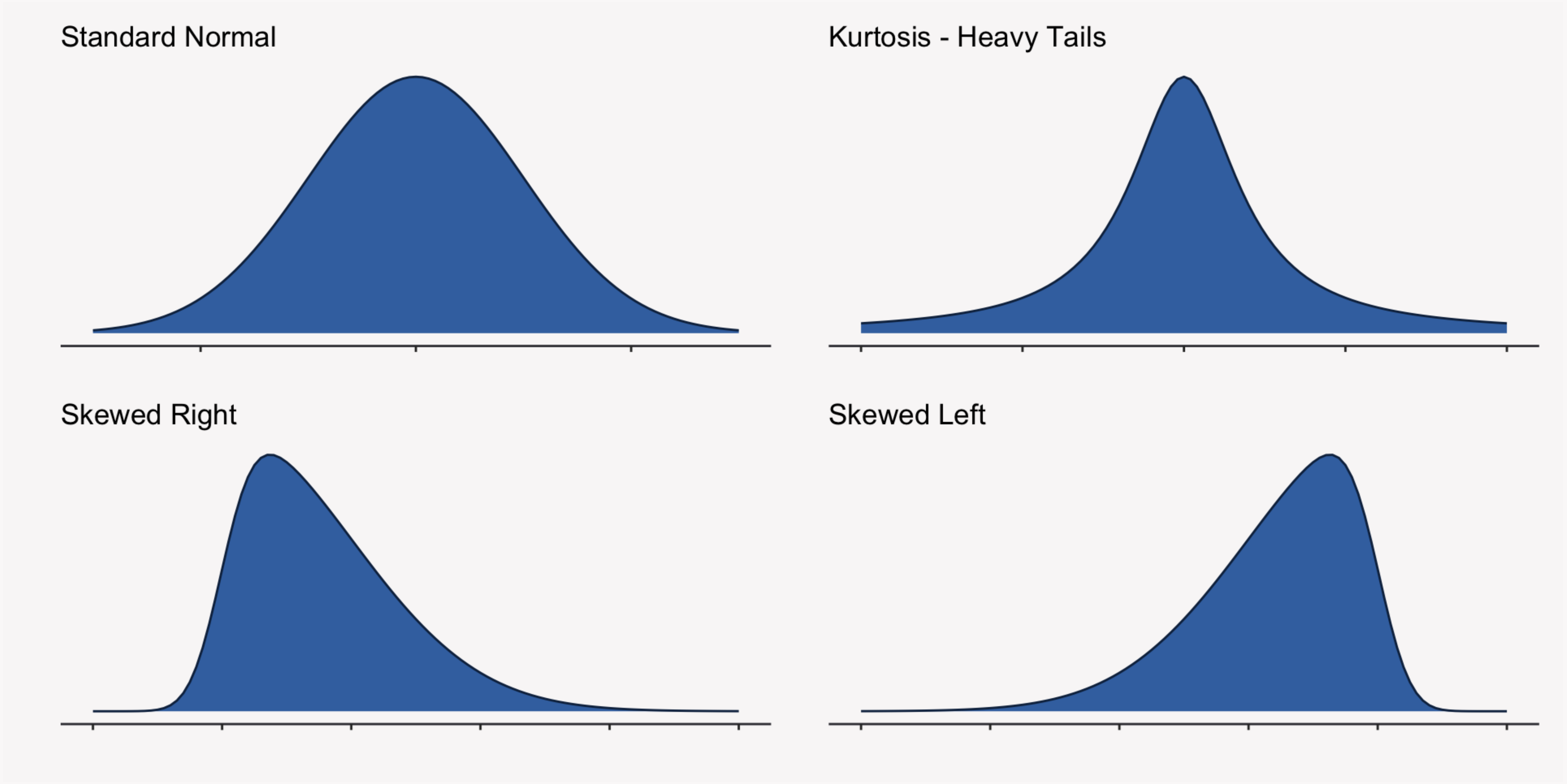


Describing the Shape of your Data

Oftentimes, you will also want to talk about the **shape** of your data. Typically, this is about how **skewed** or asymmetric your data is in one direction or how heavy the **tails** of your distribution are:

- **Skewness**: How long the tails of your distribution are in a given direction.
- **Kurtosis**: How heavy the tails of your distribution are.

Describing the Shape of your Data



Describing the Relationship between two Variables

We can also describe the linear relationship between two variables by computing either the **covariation** or **correlation** between two variables. Both of these metrics tell us the extent to which two variables are **linearly related** to one another.

Correlation Coefficient

The correlation coefficient is just a standardized version of the covariance statistic with values that range from -1 to 1.

- Positive Correlation: **High (low)** values of one variable, X, are frequently seen with **high (low)** values of another variable.
- Negative Correlation: **High (low)** values of one variable, X, are frequently seen with **low (high)** values of another variable.

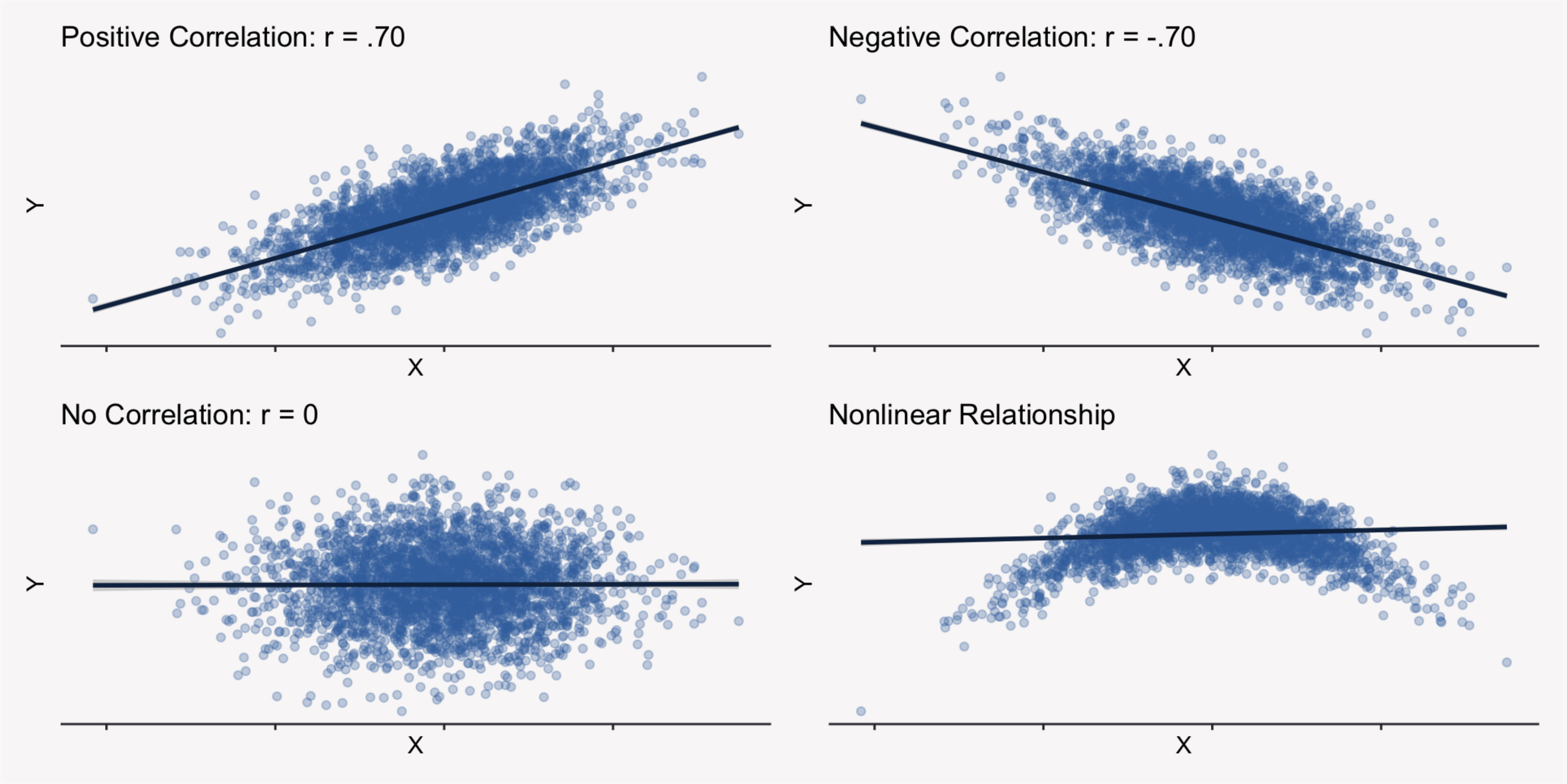
```r
set.seed(324)
x <- rnorm(100, sd = 50)
y <- 1 * x + rnorm(100, sd = 100)

cov(x, y) |> round(2)
```

```
[1] 2522.9
```

```r
cor(x, y) |> round(2)
```

```
[1] 0.45
```

Plotting the Relationship Between two Variables



An Introduction to Probability Theory

What is Probability?

Probability is the language of uncertainty.

Anytime we are dealing with random events such as the outcome of a coin toss or the response to a survey question, we rely on probability to talk about these events.

Probability as a Long-Run Frequency

> For an observation of a random phenomen, the probability of a particular outcome is the proportion of times that outcome would occur in an indefinitely long sequence of like observations, under the same conditions.
> — Agresti & Kateri, 2022

The Three Rules of Probability

All of probability theory rests on three rules:

1.
2.
3. If two events are mutually exclusive, then the probability of event one **or** event two happening is equal to

A Concrete Example

You’re a Human Capital Analytics researcher at a large, multinational organization and you have access to all of the firm’s HR data over the past fiscal year, which includes three key variables: `voluntary_turnover`, `job_satisfacation`, and `office_region`.

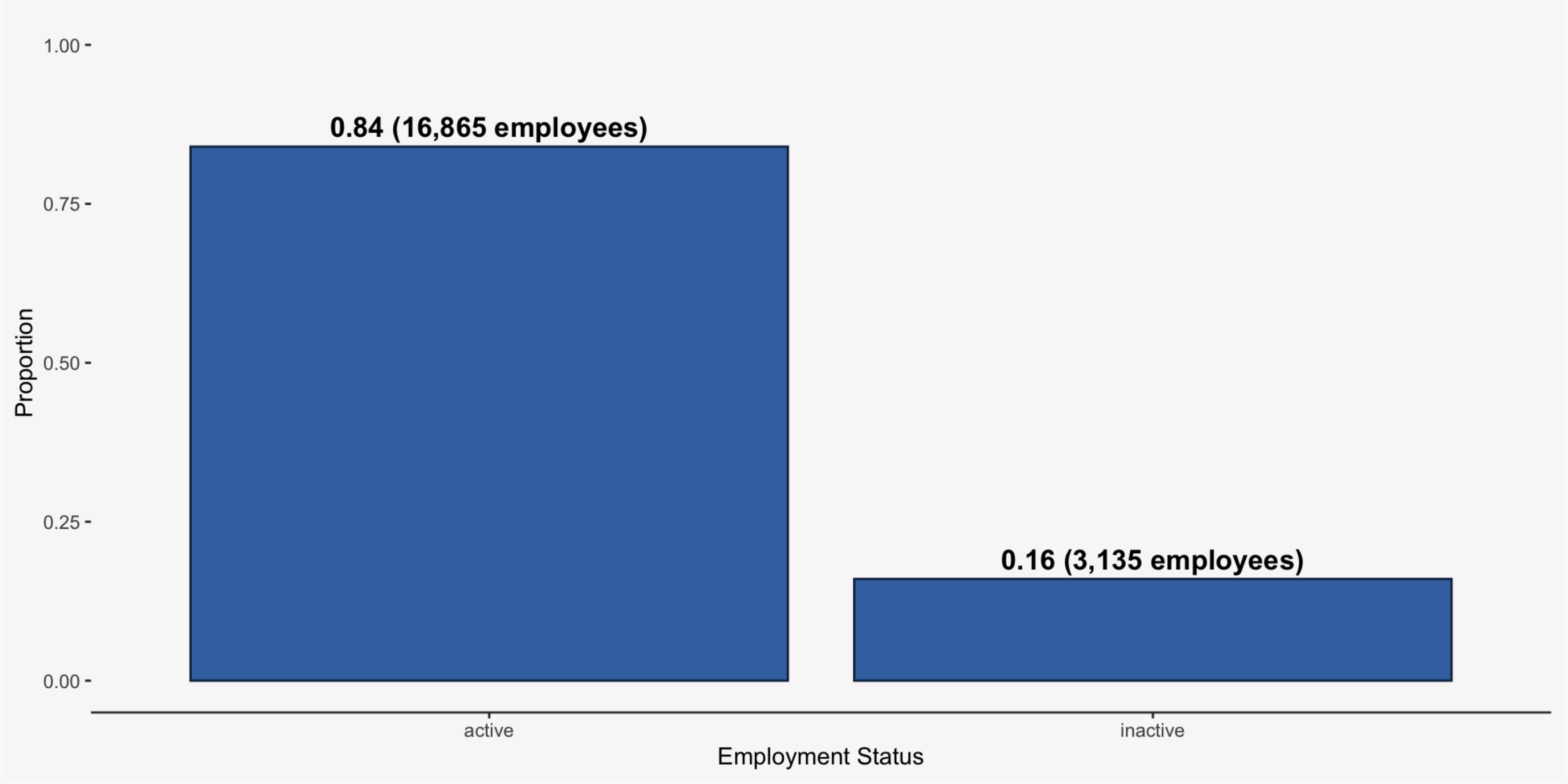
Your manager asks you to determine the likelihood that an employee leaves the firm. How do you approach this project?

A Concrete Example

```
# A tibble: 20,000 × 3
   voluntary_turnover job_satisfaction office_region
   <chr>              <fct>            <fct>        
 1 active             Neutral          China        
 2 active             Satisfied        Latin Am.    
 3 active             Satisfied        North America
 4 inactive           Neutral          North America
 5 active             Neutral          China        
 6 active             Neutral          China        
 7 inactive           Neutral          Latin Am.    
 8 active             Dissatisfied     Europe       
 9 active             Neutral          Europe       
10 active             Dissatisfied     Europe       
# ℹ 19,990 more rows
```

Probability of Voluntary Turnover

A quick way to determine the probability of voluntary turnover is to look at the proportion of employees who left the firm in the last year. This proportion is .16, so the .



Joint Probability

Joint probability is the probability of some event happening for two or more random variables.

For example, what is the probability of `employment_status == inactive & job_satisfaction == satisfied`?

Employment Status & Job Satisfaction: Joint Probability

	active	inactive
Dissatisfied	0.06	0.04
Neutral	0.50	0.10
Satisfied	0.28	0.02

Conditional Probability

Conditional probability is the probability of one event occurring given the occurrence of another event. This is written mathematically as:

which is read as the **probability of Event 1 conditional on (or given) Event 2**.

Employment Status Given Job Satisfaction: Conditional Probability

What is the probability that an employee's status is inactive given that they had responded they were dissatisfied with their job on an an earlier attitude survey? What happens to this probability as job satisfaction moves from dissatisfied to satisfied?

	active	**inactive**
Dissatisfied	0.63	0.37
Neutral	0.84	0.16
Satisfied	0.93	0.07

Independent Events

Two events are said to be independent if the probability of one event occurring **does not** change given the occurrence of the other event:

Office Region & Job Satisfaction: Independent Events

How does the probability of an employee's job satisfaction response change depending on the region they're working in? Or does it change?

	Dissatisfied	Neutral	Satisfied
North America	0.10	0.59	0.31
Asia	0.11	0.62	0.27
China	0.11	0.59	0.30
EEMEA	0.10	0.59	0.31
Europe	0.09	0.61	0.29
Latin Am.	0.10	0.60	0.29

Random Variables

Whether you realize it or not, we have been talking about `voluntary_turnover` as a **random variable**.

A **random variable** is a function of a random phenomenon that maps an outcome of that phenomenon to a real number.

In our example, `voluntary_turnover` is a random variable that maps the outcome of an employee's decision to leave or remain with their organization to a real number: 1 or 0.

Types of Random Variables: Discrete & Continuous

Random variables, like quantitative variables, can be classified into two broad categories:

- Discrete: Separate, distinct outcome values like integers
- Continuous: Infinite continuum of possible outcomes

Voluntary Turnover as a Random Variable

As a random variable, `voluntary_turnover` maps `inactive` to 1 and `active` to 0:

Because the random variable is a function of a random phenomenon, we can still calculate probabilities for the outcome:

Connecting Probability to Statistics with Random Variables

The big gain from introducing **random variables** is that we can now apply mathematical and statistical models to the numerical values, and we can use more general probability distributions to describe the distributions of these random variables.

For instance, we can say `voluntary_turnover` can be modeled using a binomial distribution.

Probability Distributions

Probability distributions are mathematical models that can be used to summarize the random variation in the random variables by specifying the probabilities of all possible outcomes of the random variable.

Modeling Voluntary Turnover with a Binomial Distribution

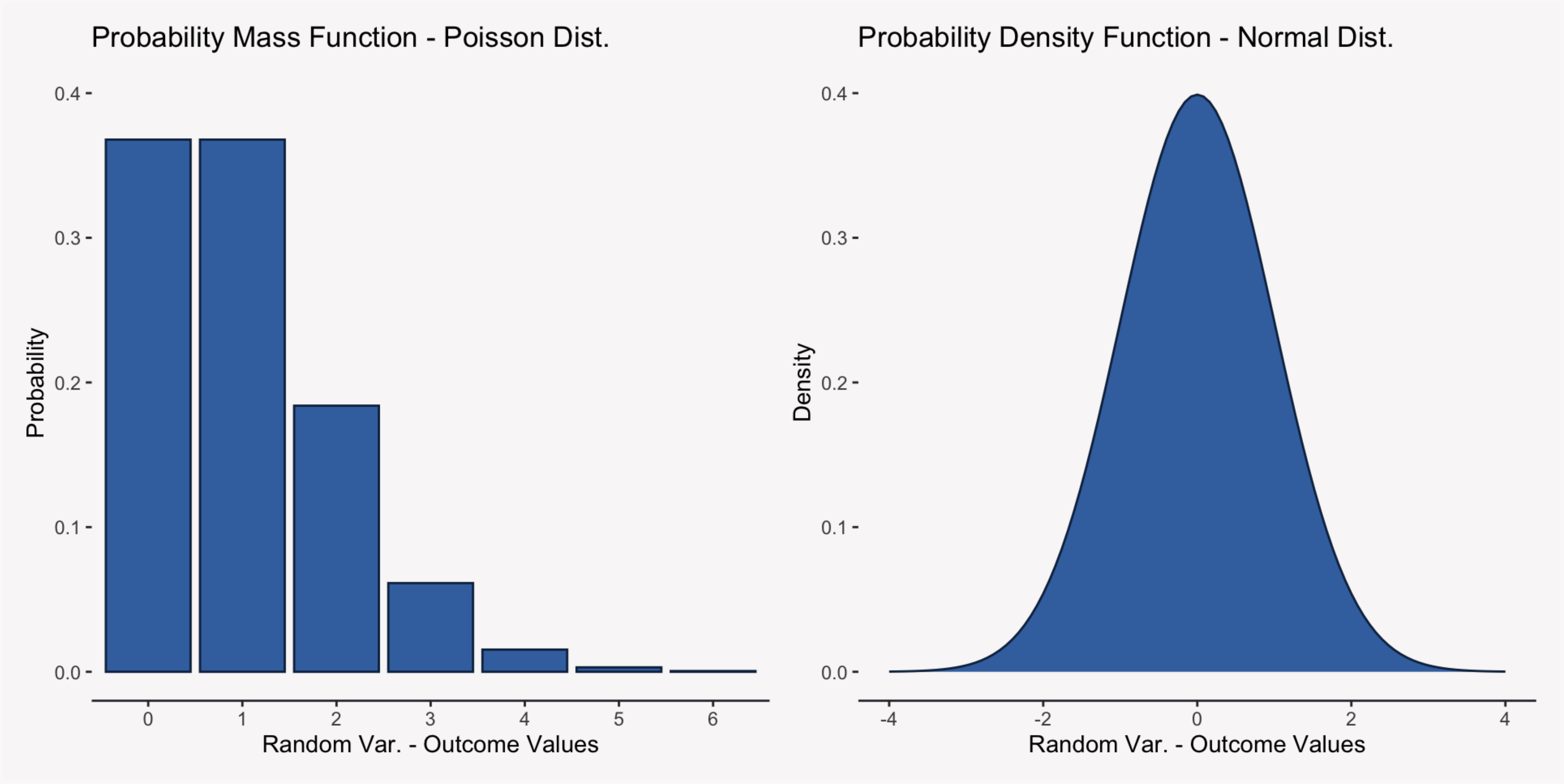
The Bernoulli distribution is a probability distribution that can be used to model a random variable that has two outcomes. It specifies the probability of the first outcome, 1, as **p** and the second outcome, as **1 - p**:

Probability Mass & Density Functions

Probability Mass and Density Functions (PMF & PDF, respectively) are mathematical functions that take the **value of a random variable as an input** and return the **probability of that value occurring as an output**. Every statistical model we will use will assume a certain PMF or PDF.

- **PMF** is a probability distribution function for **discrete random variables**
- **PDF** is a probability distribution function for **continuous random variables**

Plotting PMFs and PDFs

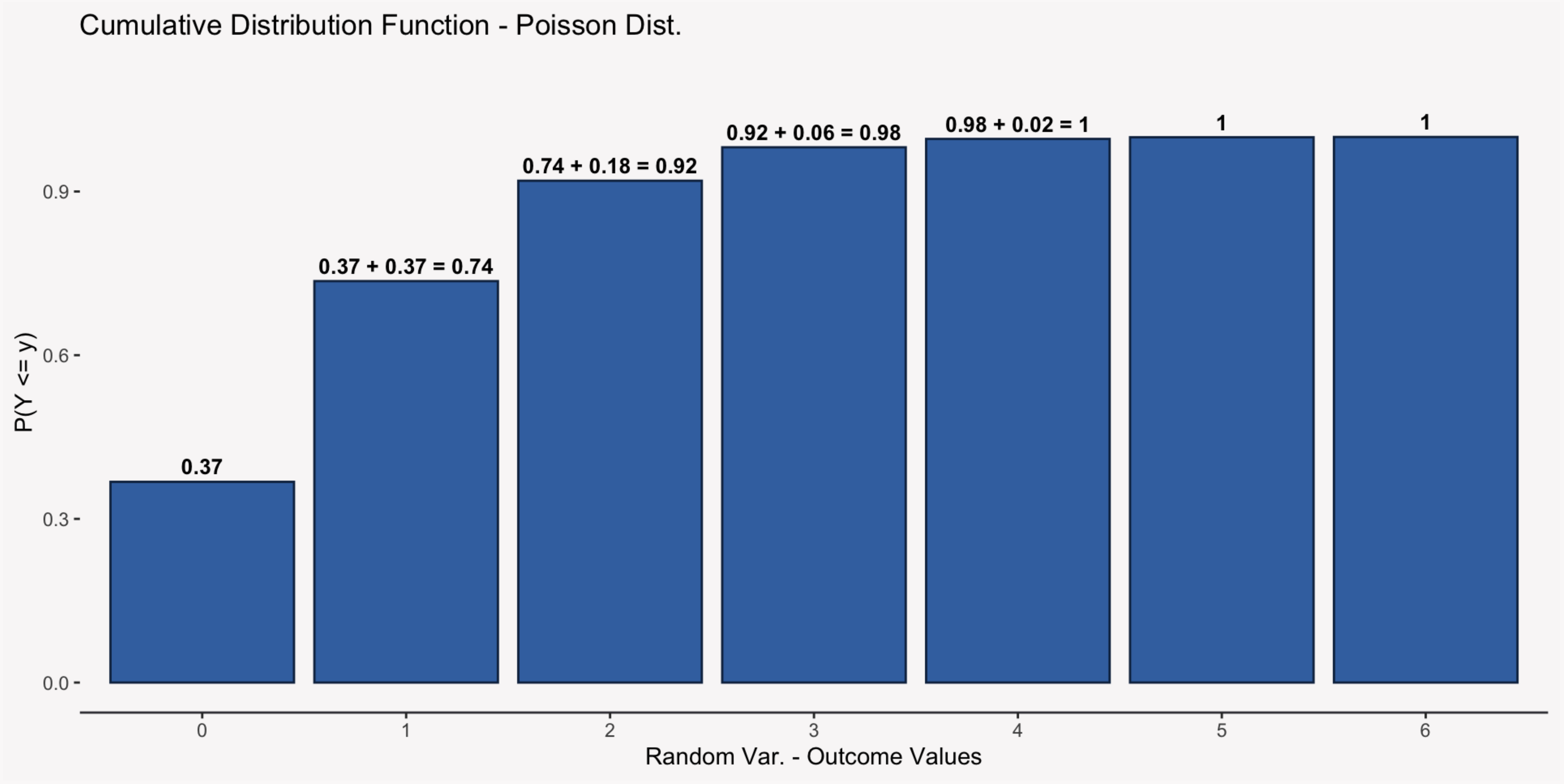


Cumulative Distribution Function

Closely related to the PMF/PDF, the Cumulative Distribution Function (CDF) specifies the **cumulative probability** that a random variable takes a value, Y, or any value less than Y:

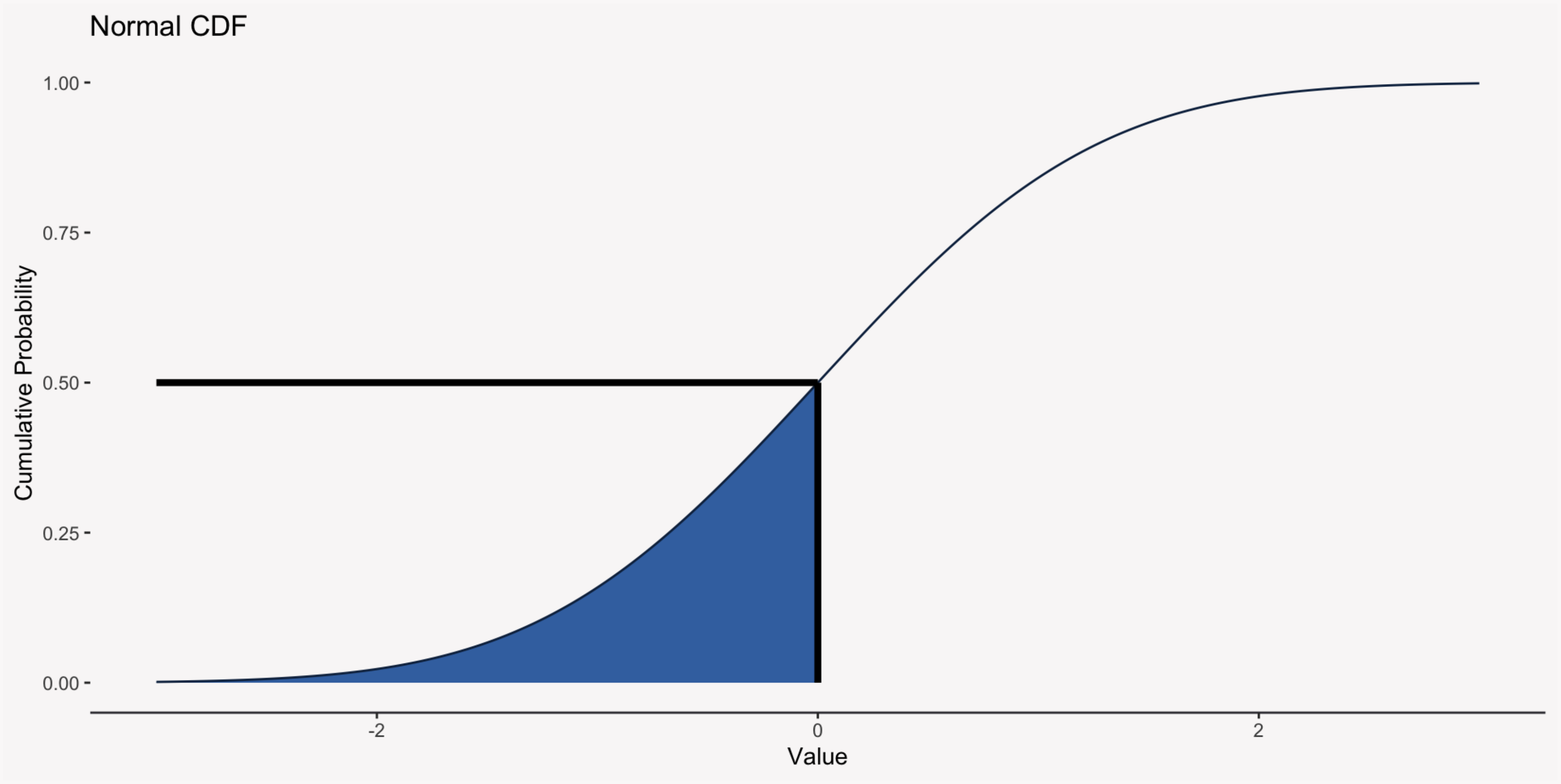
In our example, what is the probability that `involuntary_turnover` takes a value of 0? What is the probability `involuntary_turnover` takes a value less than or equal to 1?

Cumulative Distribution Function



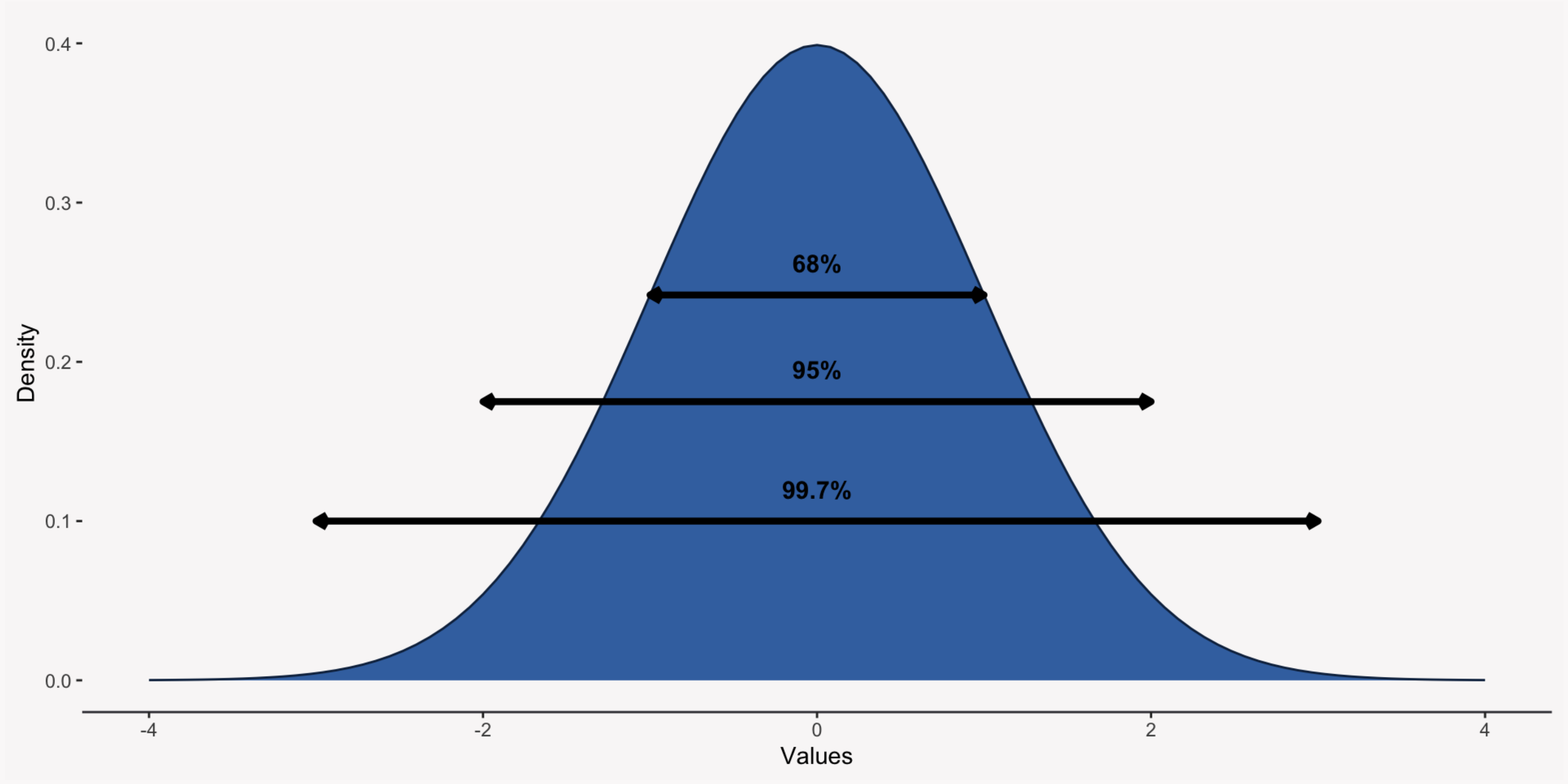
The CDF of the Normal Distribution

Think about the CDF as a way to compute the percentiles of a distribution. What is the 50th percentile—the value where 50% or less of the observations fall—for the Normal CDF below?



Getting to Know the Normal Distribution Better

- It has two parameters: Mean & Variance.
- 68% of its mass is between SDs from its mean, 95% of its mass is between SDs from its mean, and 99.7% of its mass is between SDs from its mean.



Generalizing from your Data

Inferential Statistics

Usually, when you analyze your data you want to generalize the results from your specific dataset to a broader population or more general phenomenon. This is called **statistical inference**. We infer something from our data about a more general phenomenon.

Example: Recruiters' trust in AI

Your organization is considering adopting an AI automated resume scraper program to lessen the burden on the recruiters. Before committing to the tool, however, your manager has asked you to determine if the recruiters would trust the outcomes provided by the AI system.

To assess this, you administer a single survey question to **three random samples of 50 recruiters**:

I trust the outcome provided by an artificially intelligent system.

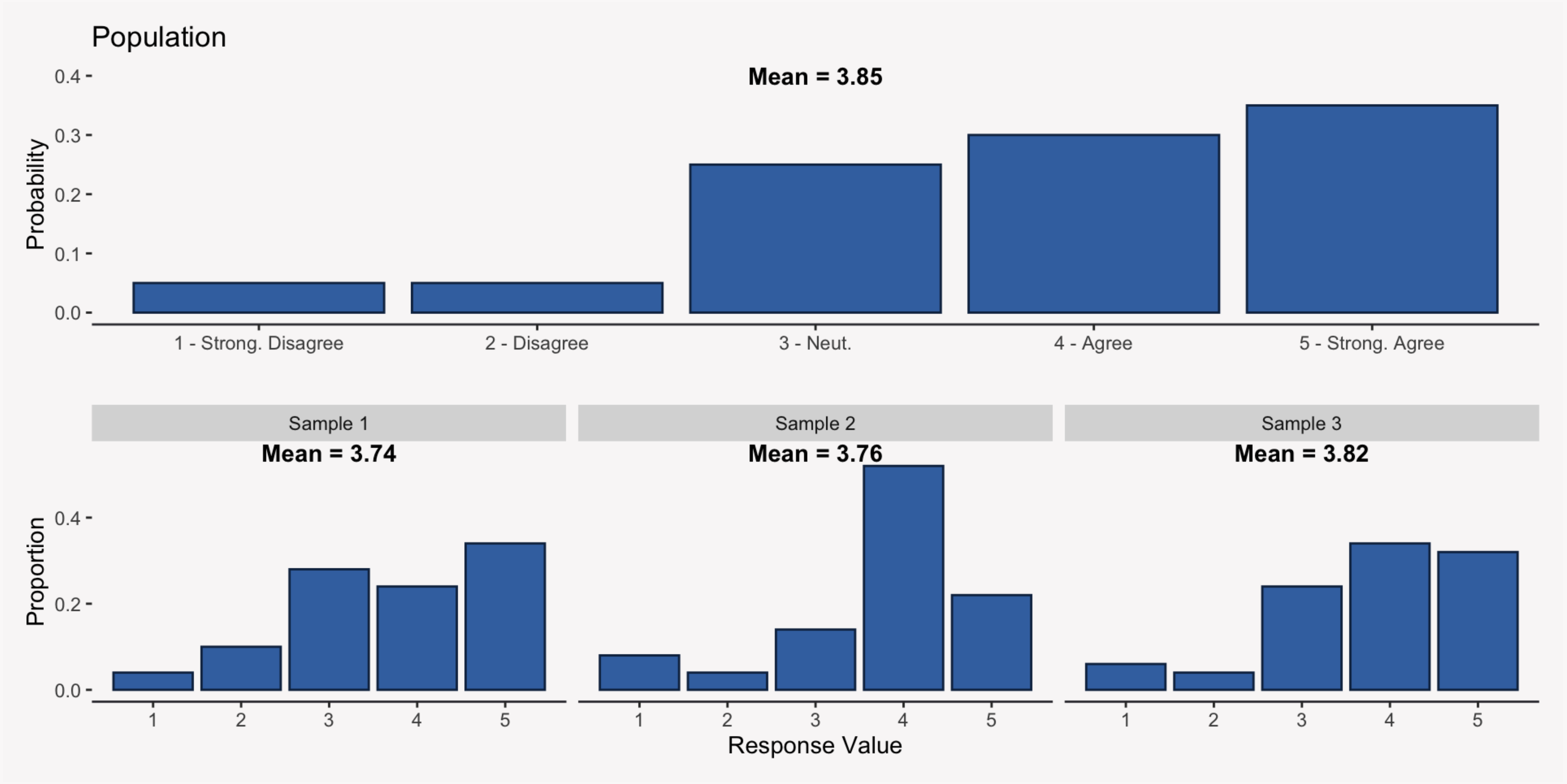
Example: Do Recruiters' trust AI?

To determine how recruiters feel about AI, on average, you compute the mean of each sample and find the following:

sample_1	sample_2	sample_3
3.74	3.76	3.82

The average response is different across the three different samples. Is this expected? What should you do?

Populations & Sample Variation



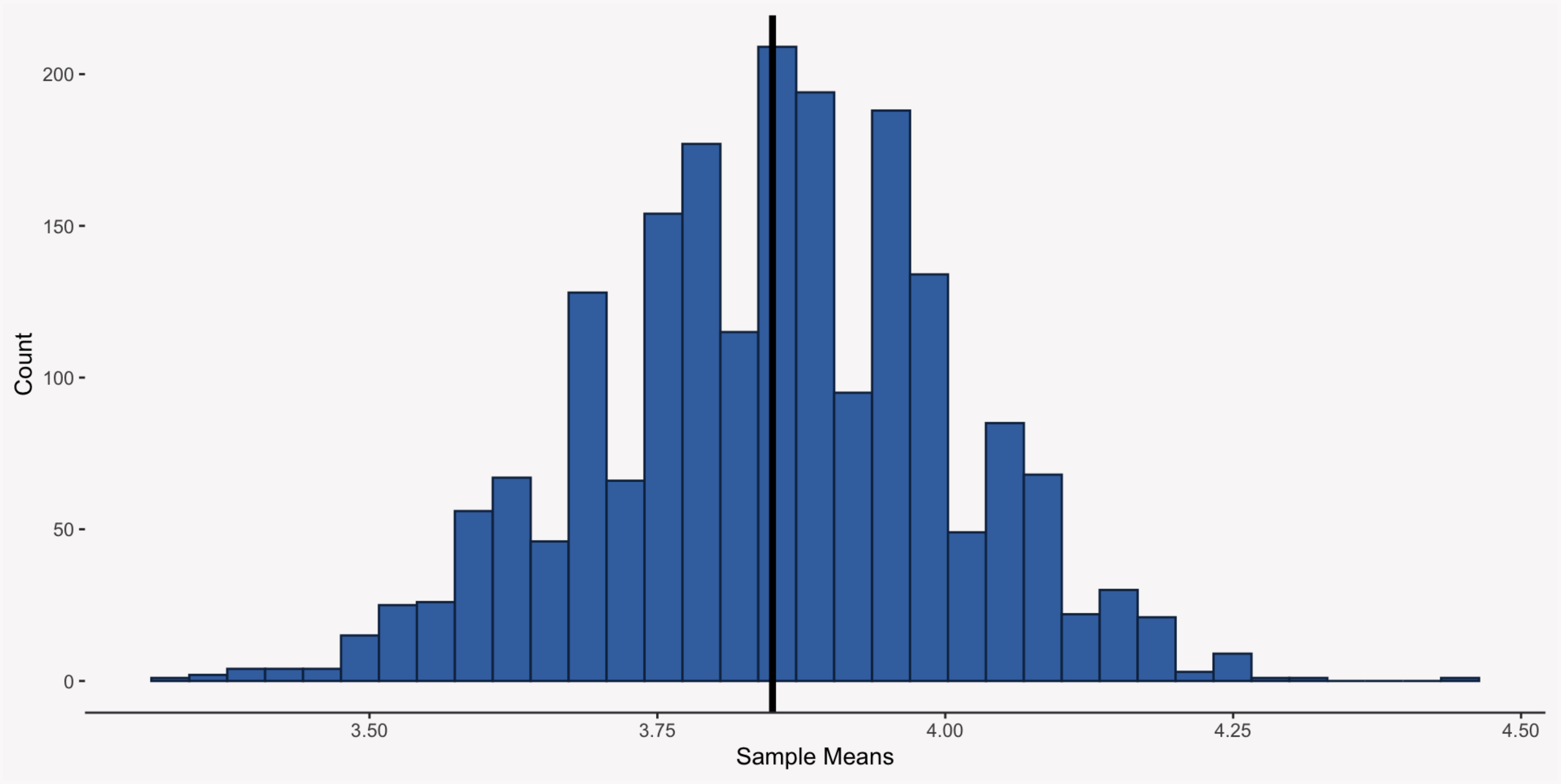
Statistics as Random Variables

Because statistics like the sample mean are computed from a sample that contains random variation, we **expect** our statistics to behave like **random variables**.

Like a random variable, we can specify a probability distribution for our statistic called a **sampling distribution**.

Sampling Distributions

Imagine you can draw an infinite number of random samples from a population and then for each sample you compute the sample mean. The distribution of these sample means is referred to as the **sampling distribution of the mean**.



The Mean & Standard Deviation of a Sampling Distribution

Like all distributions, we can compute the mean and standard deviation of a sampling distribution and obtain useful information:

- **Mean of a sampling distribution** = Population Parameter
- **Standard deviation of a sampling distribution** = Uncertainty in our statistic

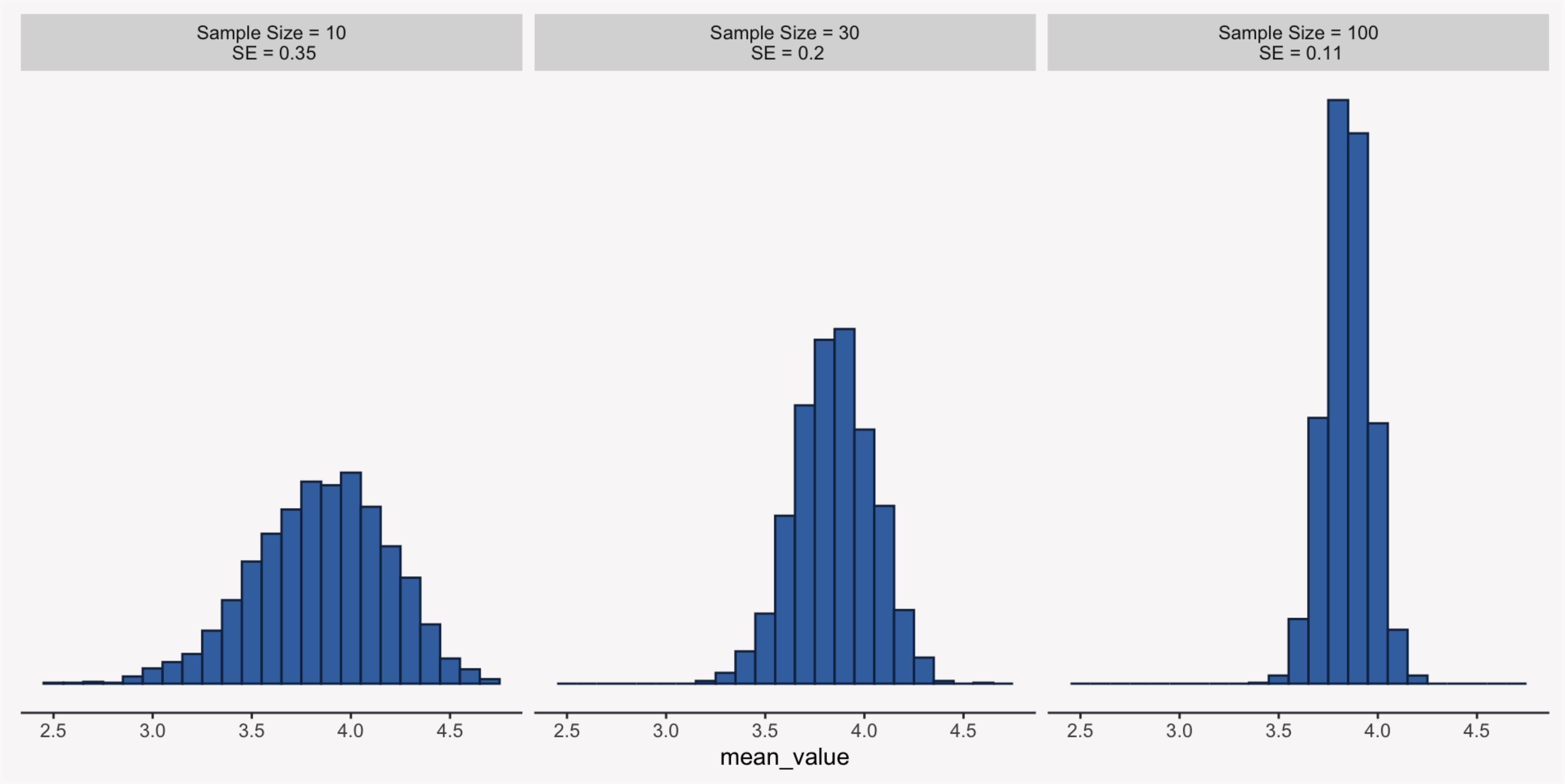
The Standard Error

The standard deviation of a sampling distribution is known by another name: **the standard error**. The standard error quantifies our uncertainty in a given statistic and is fundamental to inferential statistics.

For the mean, the standard error can be calculated as:

The Standard Error

We can reduce the standard error, thereby reducing our uncertainty, by increasing our sample size:

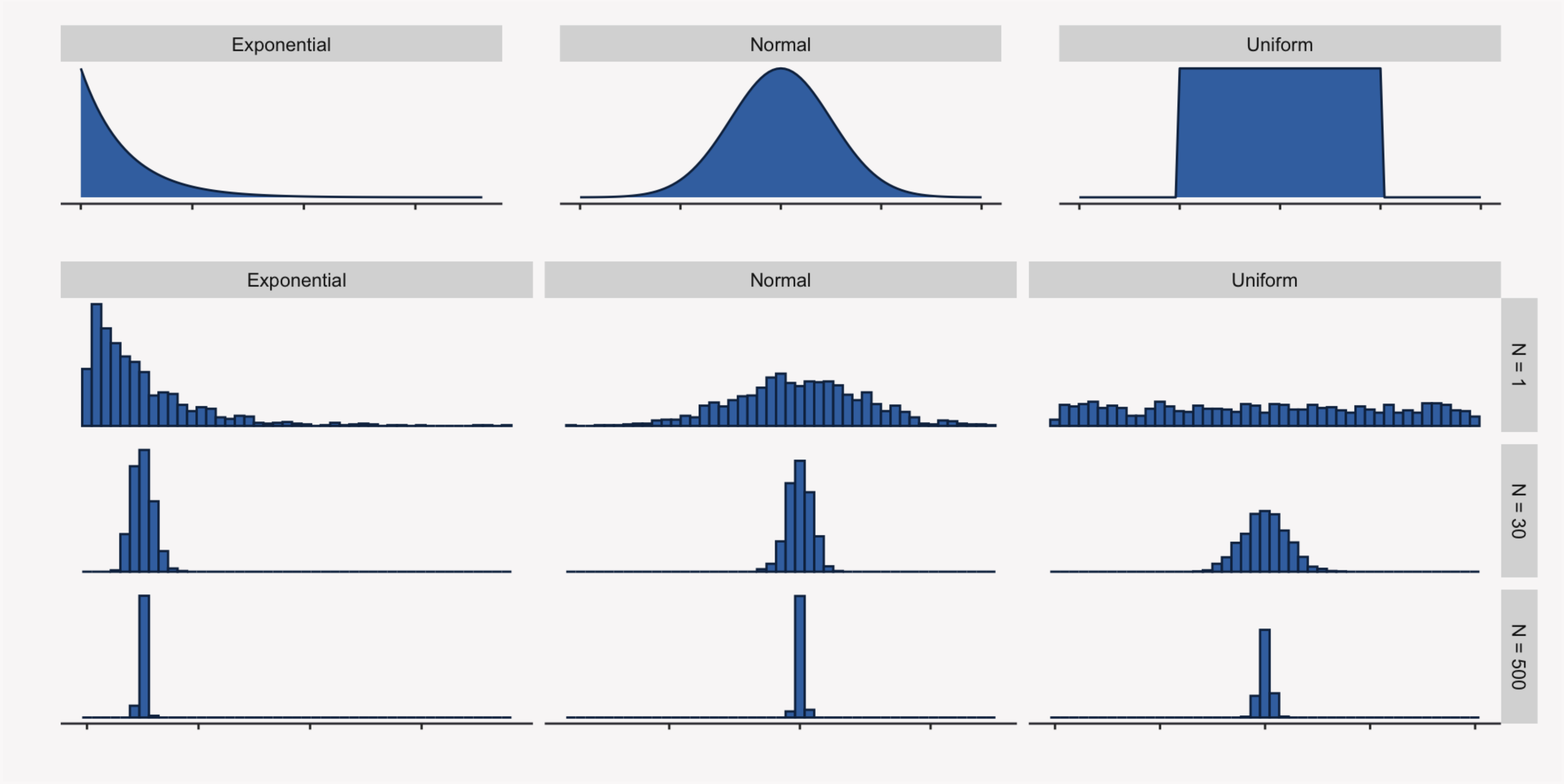


The Norm of Normality: The Central Limit Theorem

The Central Limit Theorem (CLT) is a mathematical finding that tells us that the sampling distribution of a statistic like the mean starts to **closely resemble a normal distribution as the sample size increases** regardless of the distribution of the sample data itself!

The CLT plays a very important role in all of our statistical inference!

Central Limit Theorem



Statistical Estimation & Tests

What is Statistical Estimation?

The goal of every data analytic project is to **estimate** some population parameter by computing some statistic or **point estimate**. This is statistical estimation.

Point Estimates & Interval Estimates

Statistical estimates can either come as point estimates or interval estimates:

- Point Estimate: A single value that estimates the population parameter.
- Interval Estimate: An interval of values centered around the point estimate.

Differences in Recruiters’ trust in AI by Job Experience

Your manager asks you to administer the survey one more time to a larger sample of 300 recruiters, **but this time they would like you to measure the amount of years the employee has been in the recruiting industry as a proxy for job experience `job_exp`**.

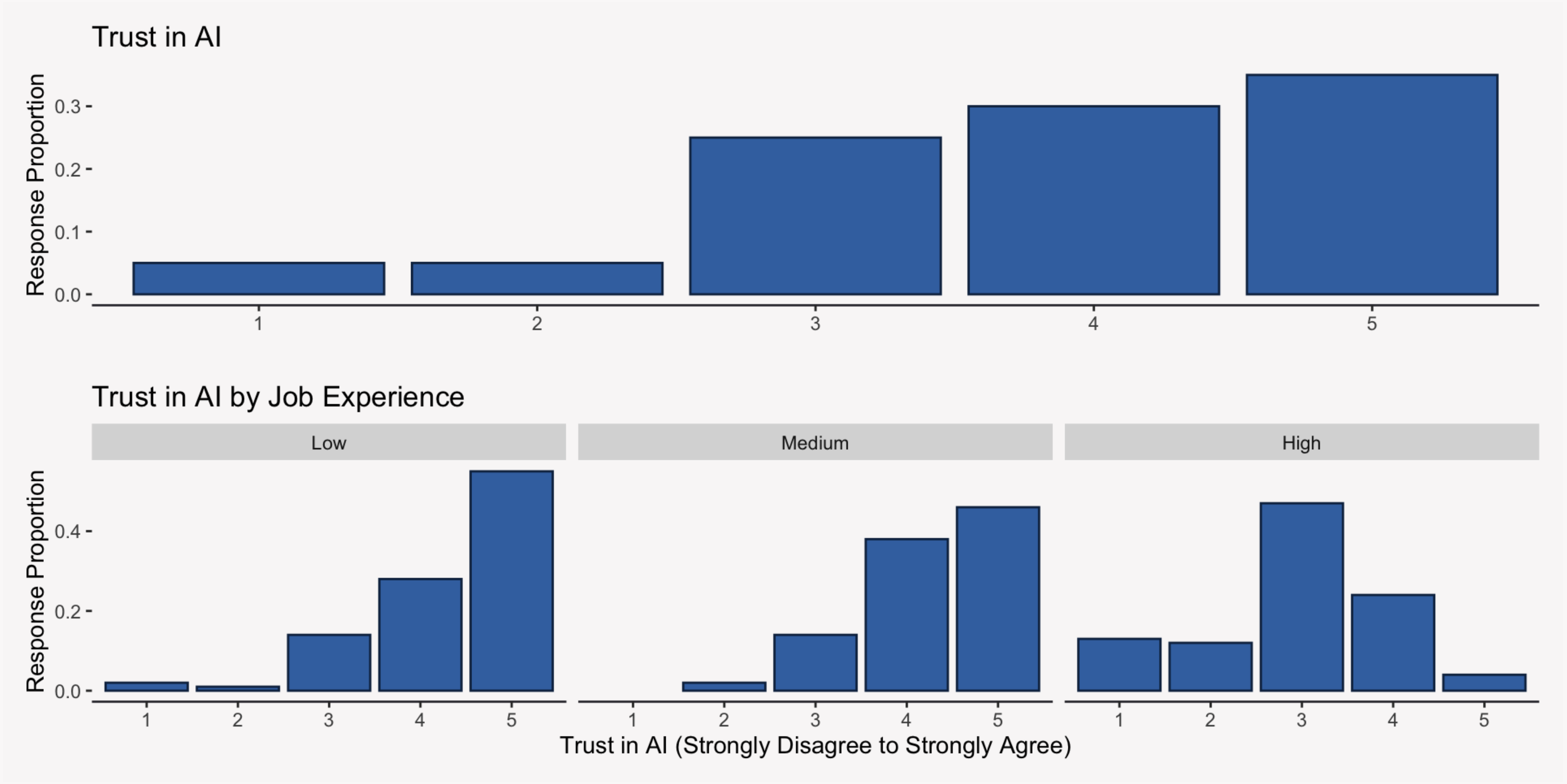
Your manager would like to know if employees’ trust differs based on their level of job experience. How should you approach this project?

A Glimpse of your Data

```r
set.seed(435)
data |>
  dplyr::slice_sample(n = 10) |>
  dplyr::select(
    job_exp,
    trust_in_ai
  ) |>
  dplyr::arrange(
    job_exp
  )
```

```
# A tibble: 10 × 2
   job_exp trust_in_ai
   <fct>         <dbl>
 1 Low               5
 2 Low               3
 3 Low               5
 4 Low               5
 5 High              1
 6 High              3
 7 High              3
 8 High              3
 9 Medium            5
10 Medium            5
```

Plotting your Data



Estimating the Mean & Variance by Job Experience

For each job experience group, we can **estimate the population means** by computing the sample mean and standard deviation of their responses to the trust in AI question:

Job Exp.	Mean Trust	SD Trust	N
Low	4.33	0.90	100
Medium	4.28	0.78	100
High	2.94	1.02	100

A Confidence (Interval) Estimate for the Mean

Because there is uncertainty in our data, we would like to move away from providing a single estimate of trust in AI for each group and provide an interval of estimates that adequately quantifies the uncertainty we have in our estimate:

Job Exp.	Mean Trust	95% Conf. Int.	SE	SD Trust	N
Low	4.33	4.15 - 4.51	0.090	0.90	100
Medium	4.28	4.13 - 4.43	0.078	0.78	100
High	2.94	2.74 - 3.14	0.102	1.02	100

Interpreting a Confidence Interval

Confidence intervals have a very strict (and kind of odd) interpretation:

If you were to randomly sample a large number of samples from a population and create a 95% confidence interval around the sample mean, then 95% of those intervals would contain the population mean.

Building a Confidence Interval

Generally, to build a confidence interval, you need three pieces of information:

- Point estimate to build the interval around
- The probability distribution that best approximates the estimate's sampling distribution (almost always the normal distribution)
- The Standard Error of the estimate (the standard deviation of the sampling distribution)
- The level of "confidence" (i.e. how confident you are that the population parameter is contained in the interval)

Building a Confidence Interval

- : Point estimate (sample mean)
- is the value at which 95% of the mass of the standard normal distribution falls
- SE: The standard error of the estimate

Are the Differences in Recruiters’ trust in AI by Job Experience Real?

We saw that the sample means of trust in AI differed by job experience level, but are those differences real or are they a result of random noise (sample variation)?

We can use a statistical test to determine if the difference we see in the sample means is indicative of true population-level differences.

Stating a Statistical Hypothesis

In statistics, a hypothesis is a statement about the population distribution. Researchers typically formulate two kinds of hypotheses: **null hypothesis ()** and **alternative (researcher's) hypothesis ()**.

- is a statement that the population parameter takes on some value—usually 0.
- is a statement that the population parameters takes on an alternative **set** of values that fit with the researcher's theory.

The Direction of a Statistical Hypothesis

Hypotheses can be directional or non-directional.

A **directional hypothesis** is a hypothesis that makes an explicit statement about whether one group will have a larger (or smaller) mean than another group.

A **non-directional hypothesis** is a hypothesis that states that the means of the two groups differ, but does not specify which group has a larger (or smaller) mean.

Trust in AI Hypotheses

: In this organization, there are **no differences** between mean-level trust in AI for employees with low job experience and mean-level trust in AI for employees with either medium or high job experience.

: In this organization, the mean-level trust in AI for employees with low job experience **is higher than** the mean-level trust in AI for employees with medium job experience and high experience.

What is a Statistical Significance Test?

A **statistical significance test**, or just test, uses data to summarize the evidence about a hypothesis, usually the null, by comparing a point estimate of the parameter of interest (e.g. sample mean) to the value predicted by the hypothesis (e.g. 0 in the case of the null hypothesis).

The Four Elements of a Statistical Test

- **Assumptions**: Background assumptions that need to hold for our test to be valid.
- **Hypotheses**: The and hypotheses, which need to be formulated before analyses happen.
- **Test Statistic**: Summary of how far away a statistical estimate is from the population value predicted by .
- **P-value & Conclusion**: A decision on whether to reject or not reject if the probability of our data coming from the null population distribution is sufficiently low as measured by a **P-value**.

A Significance Test for Trust in AI

To determine if trust in AI differs by job experience, we are going to use a **z-test** to test our two null hypotheses, which can be framed as hypotheses about **the mean differences** between trust in AI by job experience:

: :

Understanding a Z-Test

A Z-test is a test that compares the mean of one variable to a specific population parameter specified by the null hypothesis (usually 0) or to the mean of a different variable. To conduct a Z-test you can follow these steps:

1. Ensure the Z-test assumptions are met.
2. Set the the probability threshold you need to surpass for an effect to be considered significant—**your alpha level**.
3. Compute your test statistic and determine if it is significant at your specified alpha-level.

Z-Test Assumptions

1. The populations from which the samples were taken from must be normal.
2. The population SDs must be known or the sample sizes for each group must be large (~30 or more observations per group).

Determing your Alpha-Level

The -level, also called the significance level, is a number between 0 and 1 such that we reject if the P-value of the test statistic is less than or equal to .

Generally, we set to .05 or .01. To reject the , the P-value needs to be less than or equal to .05 or .01, respectively.

Z-Test Test Statistic

When you are comparing two groups to one another, like we are, the test statistic, , is defined as:

Difference in Trust in AI Means by Job Experience

Comp.	Low Exp. Mean	Mean Trust	Mean Diff.	Low Exp. Var.	Var. Trust	n
Low - Medium	4.33	4.28	0.05	0.81	0.61	100
Low - High	4.33	2.94	1.39	0.81	1.04	100

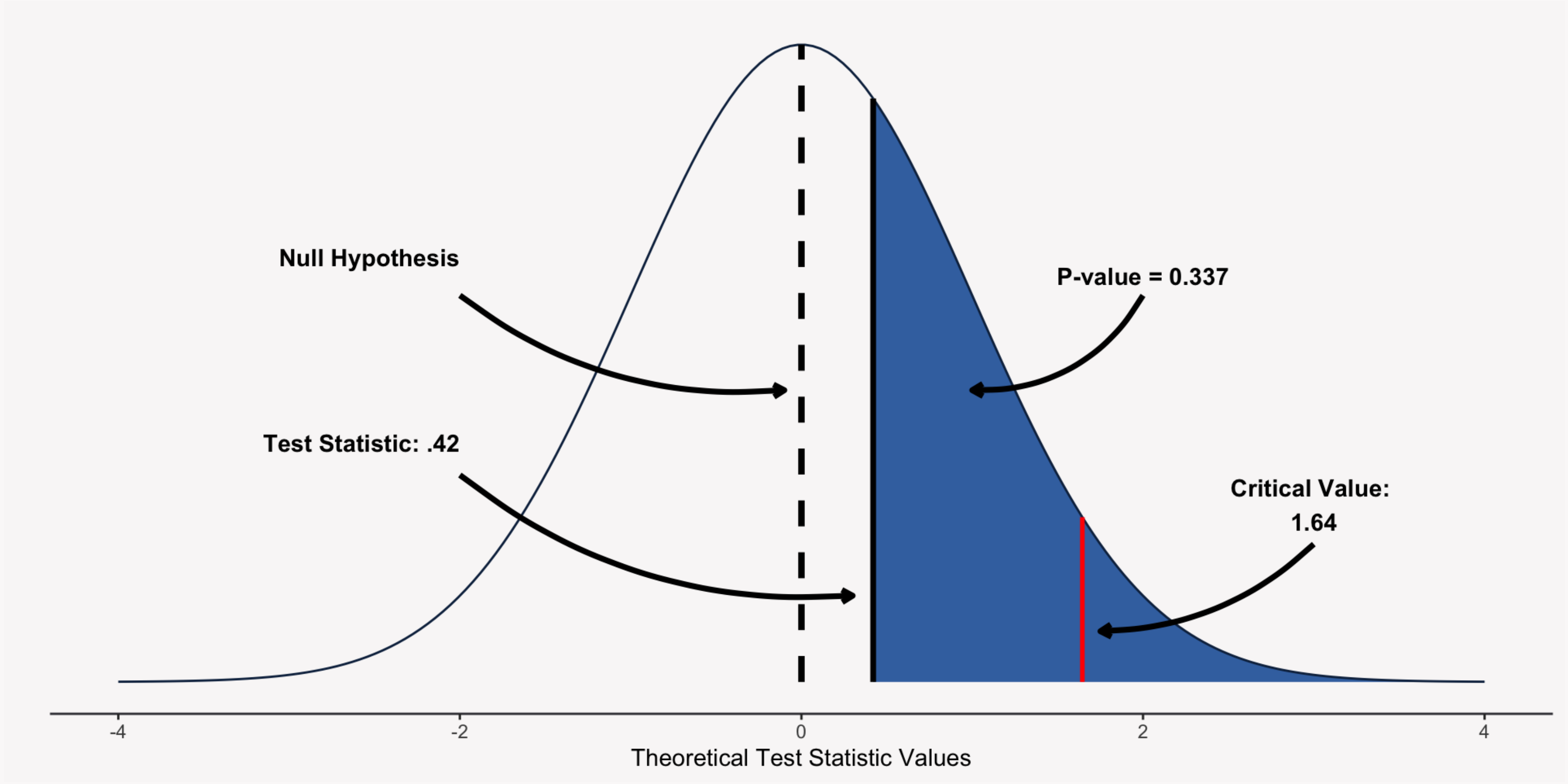
Determining the P-Value

A P-value is a tricky thing to think about, it is the probability of seeing a value greater than or equal to your test value **given that the sampling distribution specified by the null hypothesis is true**.

If your P-value is small (usually less than .05), then you can conclude that your test statistic is very unlikely to have come from the null distribution and thus you can **reject the null hypothesis**.

Visualizing the P-Value

We assume (somewhat safely thanks to the CLT), the our estimate has a **normal sampling distribution** and according to our **null hypothesis of no effect** the mean of the normal distribution should be 0 and the SD should be 1. We can use the **CDF of the standard normal distribution** to compute the P-value.



Using R to Conduct a Z-test: Medium Job Experience

```r
low_group <- data$trust_in_ai[data$job_exp == "Low"]
medium_group <- data$trust_in_ai[data$job_exp == "Medium"]

z_low_medium <- BSDA::z.test(
  x = low_group, y = medium_group, alternative = "greater",
  sigma.x = sd(low_group), sigma.y = sd(medium_group)
)

z_low_medium
```

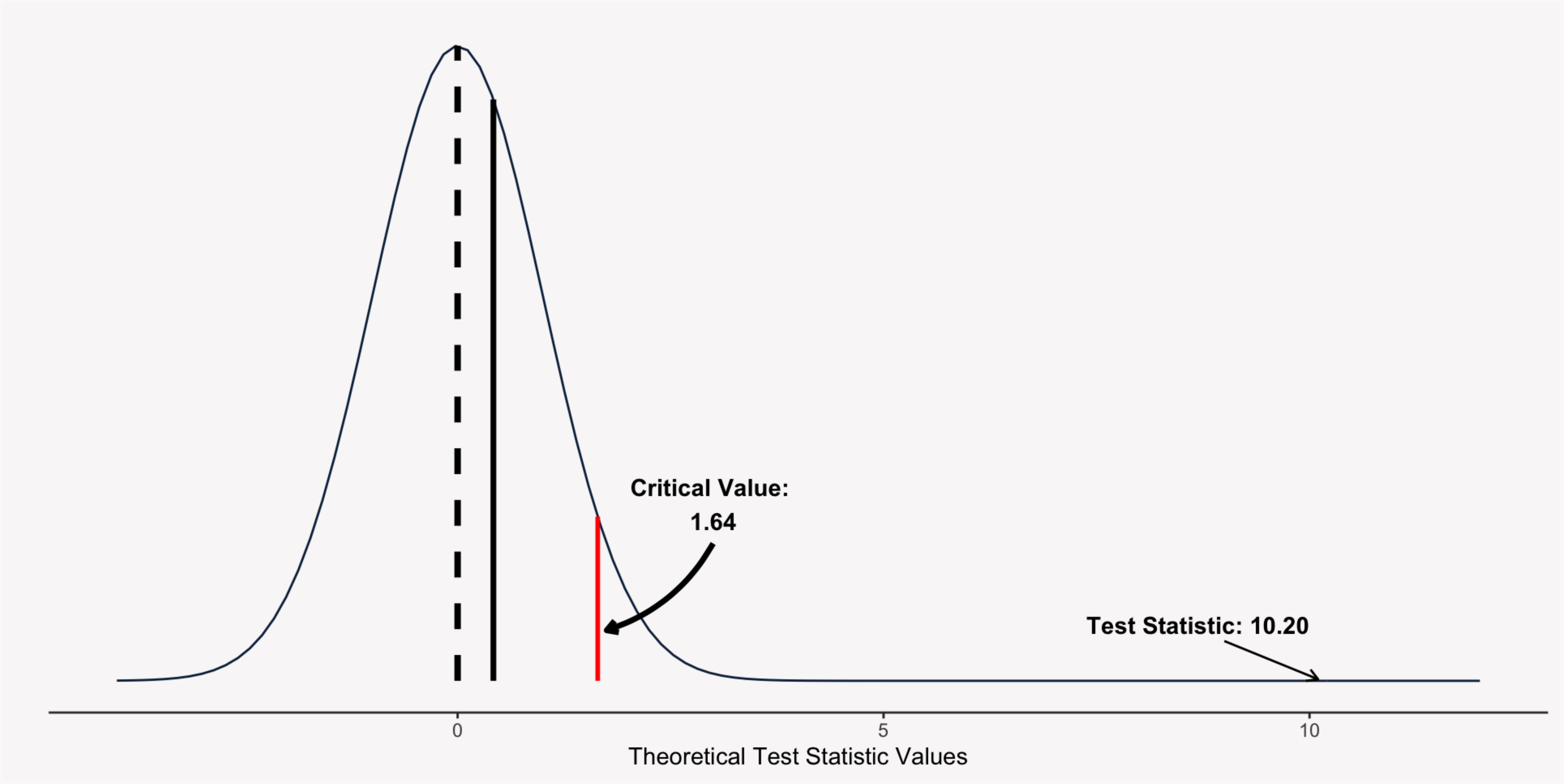
```

	Two-sample z-Test

data:  low_group and medium_group
z = 0.42005, p-value = 0.3372
alternative hypothesis: true difference in means is greater than 0
95 percent confidence interval:
 -0.1457907         NA
sample estimates:
mean of x mean of y 
     4.33      4.28 
```

Using R to Conduct a Z-test: High Job Experience

```r
low_group <- data$trust_in_ai[data$job_exp == "Low"]
high_group <- data$trust_in_ai[data$job_exp == "High"]

z_low_high <- BSDA::z.test(
  x = low_group, y = high_group, alternative = "greater",
  sigma.x = sd(low_group), sigma.y = sd(high_group)
)

z_low_high
```

```
    Two-sample z-Test

data:  low_group and high_group
z = 10.203, p-value < 2.2e-16
alternative hypothesis: true difference in means is greater than 0
95 percent confidence interval:
 1.16591      NA
sample estimates:
mean of x mean of y 
     4.33      2.94 
```

Visualizing a Very Small P-Value



Types of Decision Errors

The conclusion you come to thanks to a statistical test is not guaranteed to be the right one. There is always a risk of making a decision error:

	Reject	**Do Not Reject**
is true	Type 1 Error	Correct Decision
is false	Correct Decision	Type 2 Error

Protecting Against Errors

To protect against a **Type 1 Error**, we can make our -level very small, which will make it very difficult to reject , but this increases **Type 2 Error**.

One way to guard against **Type 2 Error** is by using an appropriate statistical test on a **large** sample of data.

An Introduction to R

First Steps

- Download R if you haven’t already
- Download RStudio

What is R?

R is a programming language that is generally used for statistical computing.

Why Learn R?

To analyze the data you collect, you will need to be familiar with some kind of general programming language (R, Python, etc.) or a more specific statistical program (SPSS, SAS). I recommend and use R because it is:

- Open-source (free to download, use, and improve)
- Highly flexible language
- Can estimate A LOT of different statistical models

Integrated Development Environment & RStudio

An integrated development environment (IDE) is an application that makes programming a little easier and organized. It includes all of the tools one needs to program effectively and efficiently.

RStudio is an IDE initially developed for R, but it can be used for other programming languages too.

If you have not already, please go ahead and download RStudio from here.

Writing Scripts in R

Just because you can write R code in just about any kind of digital document (Word, Notes, Notepad) does not mean you should!

It is best practice to write your code in an R Script (.R) in RStudio (in my opinion at least).

Using Comments in Your Code

You can write comments in your own code by beginning a line with #. R will not evaluate any text on a line that begins with #.

```r
# This is a comment. Use comments to leave yourself notes in your script.
```

Programming with Base R

Objects in R

Everything you do in R will involve some kind of **object** that you have created. Think of an **object** like a box that you can place data in, so that R can later access and manipulate the data. An important of the code below is the assignment operator `<-` which is how R knows to assign `value` to `object_name`.

```r
object_name <- value
```

Atomic Vectors

- An atomic vector is just a simple vector of data.
- R recognizes six types of atomic vectors:
  - Integers
  - Doubles (Numeric)
  - Characters
  - Logicals
  - Complex
  - Raw

Integer & Numeric Vectors

Integer vectors contain only integers. Add `L` after each number so R recognizes it as an integer. **Numeric (doubles) vectors** contain real numbers. These are the default vectors for numbers.

```r
integer_vec <- c(1L, 2L, 50L)
numeric_vec <- c(1, 2, 50, 45.23)
```

Character Vector

Character vectors contain only text data also referred to as string data. Basically anything surrounded by `""` or `' '` is considered string data.

```r
character_vec <- c("1", "abc", "$#2")
```

Logical Vector

Logical vectors are vectors that can only contain `TRUE` or `FALSE` values also referred to as boolean values.

```r
logical_vec <- c(TRUE, FALSE)
```

Adding Attributes

You can think of attributes as metadata for R objects. As a user you will not need to worry too much about attributes directly, but attributes tell R how to interact with the specific object and allow the user to store information that is secondary to the analyses they are conducting.

names Attribute

```r
days_of_week <- 1:7
names(days_of_week) <- c("mon", "tues", "wed", "thurs", "fri", "sat", "sun")
names(days_of_week)
```

```
[1] "mon"   "tues"  "wed"   "thurs" "fri"   "sat"   "sun"
```

```r
attributes(days_of_week)
```

```
$names
[1] "mon"   "tues"  "wed"   "thurs" "fri"   "sat"   "sun"
```

`dim` Attribute

```r
days_of_week <- 1:14
dim(days_of_week) <- c(2, 7) # 2 Rows, 7 Columns
attributes(days_of_week)
```

```
$dim
[1] 2 7
```

```r
class(days_of_week)
```

```
[1] "matrix" "array"
```

Creating Factors

R stores categorical data using factors, which are integer vectors with two attributes: `class` and `levels`.

```r
days_of_week <- factor(c("mon", "tues", "wed", "thurs", "fri", "sat", "sun"))
typeof(days_of_week)
```

```
[1] "integer"
```

```r
attributes(days_of_week)
```

```
$levels
[1] "fri"    "mon"    "sat"    "sun"    "thurs" "tues"   "wed"

$class
[1] "factor"
```

Data Frames: Best way to Represent Data

Data frames are the best way to structure and store data in R. Data frames are sort of the R equivalent of an excel spreadsheet.

Each column in a data frame is a vector, so a data frame can combine a numeric vector as one column with a character vector as another column.

```r
data_frame_1 <- data.frame(NUMERIC = c(1, 3), CHARACTER = c("a", "b"),
                           LOGICAL = c(TRUE, FALSE))
data_frame_1
```

```
  NUMERIC CHARACTER LOGICAL
1       1         a    TRUE
2       3         b   FALSE
```

Viewing Your Data

You can use `View()` to open up a spreadsheet-like view of your data.

```r
View(data_frame_1)
```

Selecting Data from Data Frames

You will mainly select data from data frames using one of the two following methods:

```r
data_frame_1[1, 1] # Index the row and/or column
```

```
[1] 1
```

```r
data_frame_1[, 1] # Leaving the column or row index blank selects the whole vector
```

```
[1] 1 3
```

```r
data_frame_1$NUMERIC # Use a $ operator to reference the column name
```

```
[1] 1 3
```

Functions in R

Functions are objects in R that take user inputs, apply some predefined set of operations, and return an expected output.

```r
sum(c(1, 3))
```

```
[1] 4
```

The Elements of a Function

R comes with a variety of predefined functions and they all follow the same structure:

- A **name** for the function.
- The **arguments** that change across different function calls.
- The **body** which contains the code that is repeated across different calls.

The Elements of a Function

```r
name <- function(argument) {
  body
}
```

Example Base Function

```r
x <- c(1, 4, 6)
sum(x)
```

```
[1] 11
```

```r
mean(x)
```

```
[1] 3.666667
```

```r
min(x)
```

```
[1] 1
```

Linking Functions Together

R lets you link any number of functions together by nesting them. R will start with the innermost function and then work its way outward.

```r
sum(abs(c(-1, -1, 1, 1)))
```

```
[1] 4
```

Using the pipe `|>`

The `|>` operator allows you to take the output of one function and feed it directly into the first argument of the next function. Using the `|>` makes it easier to read your code, which is a good thing.

```r
c(-1, -1, 1, 1) |>
  abs() |>
  sum()
```

```
[1] 4
```

Packages: The Lifeblood of R

A lot of what makes R such an effective programming language (especially for statistics) is the sheer number of available R packages. An R package is a collection of functions that complement one another for a given task. New packages are always being developed and anyone can author one!

Installing & Loading Packages

You can use `install.packages` to install a package once and then `library` to load that package and gain access to all of its functions.

```r
install.packages("package_name")
library(package_name)
```

Reading and Writing Data

There are a number of different methods to read and write data into R. The two most common functions are:

```r
data <- read.csv("filepath/file-name.csv")

write.csv(data, "filepath/file-name.csv")
```

Importing Data from an R Package

Oftentimes, R packages will come with their own datasets that we can load into R. The `peopleanalytics` package has many such datasets that we will use today:

```r
data_employees <- peopleanalytics::employees
```

Getting Help with R

There are two ways to get help in R:

- Add `?` in front of your function, which will result in RStudio displaying the help page for that function.
- Google what you are trying to do. More often than not, someone else has run into your problem, found a solution, and posted it. Stand on their shoulders!

```r
?sum()
```

Introduction to the Tidyverse

What is the Tidyverse?

The tidyverse is a collection of R packages that “share a common philosophy of data and R programming and are designed to work together.”

Installing Packages from the Tidyverse

```r
install.packages("tidyverse")
```

tibble: Data frame of Tidyverse

Tibbles are the tidyverse’s version of a `data.frame`. They can be loaded from the tidyverse package: `tibble`.

```r
data_employees_tbl <- tibble::as_tibble(data_employees)
data_employees_tbl
```

```
# A tibble: 1,470 × 36
   employee_id active stock_opt_lvl trainings   age commute_dist ed_lvl ed_field
         <int> <chr>          <int>     <int> <int>        <int>  <int> <chr>   
 1        1001 No                 0         0    41            1      2 Life Sc…
 2        1002 Yes                1         3    49            8      1 Life Sc…
 3        1003 No                 0         3    37            2      2 Other   
 4        1004 Yes                0         3    33            3      4 Life Sc…
 5        1005 Yes                1         3    27            2      1 Medical 
 6        1006 Yes                0         2    32            2      2 Life Sc…
 7        1007 Yes                3         3    59            3      3 Medical 
 8        1008 Yes                1         2    30           24      1 Life Sc…
 9        1009 Yes                0         2    38           23      3 Life Sc…
10        1010 Yes                2         3    36           27      3 Medical 
# ℹ 1,460 more rows
# ℹ 28 more variables: gender <chr>, marital_sts <chr>, dept <chr>,
#   engagement <int>, job_lvl <int>, job_title <chr>, overtime <chr>,
#   business_travel <chr>, hourly_rate <int>, daily_comp <int>,
#   monthly_comp <int>, annual_comp <int>, ytd_leads <int>, ytd_sales <int>,
```

`dplyr`: Your Data Multitool

The package `dplyr` should become your go-to data manipulation and structuring tool! It contains many useful functions that make it surprisingly easy to manipulate and structure your data.

The Philosophy of `dplyr` Functions

Every function in `dplyr` follows this philosophy:

- First argument is always a data frame.
- Remaining arguments are usually names of columns on which to operate.
- The output is always a new data frame (tibble).

`dplyr` functions are also further grouped by whether they operate on **rows**, **columns**, **groups**, or **tables**.

Using `dplyr` to Operate on Rows

The following `dplyr` functions can **filter**, **reduce**, or **reorder** the rows of a data frame:

```r
dplyr::filter(data_employees_tbl, job_level %in% c(4, 5))

dplyr::distinct(data_employees_tbl, ed_lvl, ed_field)

dplyr::arrange(data_employees_tbl, work_exp)
```

Using dplyr to Operate on Columns

The following dplyr functions can **select**, **rename**, **add/change**, or **relocate** the columns of a data frame:

```r
dplyr::select(data_employees_tbl, dept)

dplyr::rename(data_employees_tbl, job_level = job_lvl)

dplyr::mutate(data_employees_tbl, salary = monthly_comp * 12)

dplyr::relocate(data_employees_tbl, job_lvl, .before = employee_id)
```

Using `dplyr` to Operate on Groups

The following `dplyr` functions can **group** and **summarize** your data by a predefined group indicator:

```r
data_employees_tbl |>
  dplyr::group_by(
    job_lvl
  ) |>
  dplyr::summarize(
    annual_comp_mean = mean(annual_comp),
    annual_comp_median = median(annual_comp)
  )
```

In this code chunk, we have grouped by an employee's job level and summarized their annual salary by job level.

Using `dplyr` to Operate on Tables

The following`dplyr` functions can be used to **join different tables (data frames)** together by a unique identifier:

```r
data_job <- peopleanalytics::job |> tibble::as_tibble()

data_payroll <- peopleanalytics::payroll |> tibble::as_tibble()

data_job_payroll <-
  data_job |>
  dplyr::left_join(
    data_payroll,
    by = "employee_id"
  )
```

R Resources

https://r4ds.hadley.nz/

More to come this semester...