

# Math Review

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# Summation Operator

## Definition 1: Summation Operator

The **summation** operator

$$\sum_{i=1}^n$$

is a convenient way of expressing summations.

- The  $i = 1$  means we start from index  $i = 1$ .
- The  $n$  means we sum until  $i = n$ .
- $\sum_{i \in A}$  means we only sum over the indices contained in  $A$ .

# Properties of the Summation Operator

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$$5. \sum_{i=1}^n \frac{x_i}{y_i} \neq \frac{\sum_{i=1}^n x_i}{\sum_{i=1}^n y_i}.$$

# Linear Functions

## Definition 2: Linear Function

A variable  $y$  is a **linear function** of a single variable  $x$  if

$$y = \beta_0 + \beta_1 x.$$

- $\beta_0$  is the intercept.
- $\beta_1$  is the slope.



# Non-Linear Functions

## Definition 3: Non-Linear Function

A variable  $y$  is a **non-linear function** of a single variable  $x$  if

$$y = f(x).$$

- $f(x)$  could be  $x^2$ ,  $\sqrt{x}$ ,  $e^x$ , etc.

# The Natural Logarithm Function

## Definition 4: The Natural Logarithm Function

The **natural logarithm** is a function defined as  $y = \ln(x)$ .

# The Natural Logarithm

## Property 2: Natural Logarithm

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6.  $\ln\left(\frac{x_1}{x_2}\right) = \ln(x_1) - \ln(x_2)$ , for  $x_1, x_2 > 0$ .



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6.  $\ln\left(\frac{x_1}{x_2}\right) = \ln(x_1) - \ln(x_2)$ , for  $x_1, x_2 > 0$ .
7.  $\ln(x^c) = c \ln(x)$ , for  $x > 0$  and for any number  $c$ .

# The Natural Logarithm

## Example 1: Example of Property 2.5

Consider three variables  $x_1$ ,  $x_2$ , and  $x_3$  all greater than zero. Then,

$$\begin{aligned}\ln\left(\prod_{i=1}^3 x_i\right) &= \ln(x_1 * x_2 * x_3) \\ &= \ln(x_1) + \ln(x_2) + \ln(x_3) \\ &= \sum_{i=1}^3 \ln(x_i).\end{aligned}$$

# Differential Calculus

## Definition 5: Derivative

The **derivative** represents how a function changes as its inputs change. Formally, it represents the rate of change or the slope of a function at a particular point.

- We denote the **derivative** of the function  $f$  with respect to  $x$  as  $\frac{df(x)}{dx}$ .

# Differential Calculus

## Property 3: Differential Calculus

Suppose  $f$  is a function and  $x$  is a variable.

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4. If  $f(x) = \ln(x)$ , then  $\frac{df(x)}{dx} = \frac{1}{x}$ .
5. If  $f(x) = c + x$  for any constant  $c$ , then  $\frac{df(x)}{dx} = 1$ .



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5. If  $f(x) = c + x$  for any constant  $c$ , then  $\frac{df(x)}{dx} = 1$ .
6. If  $f(x) = cx$  for any constant  $c$ , then  $\frac{df(x)}{dx} = c$ .

# Partial Differentiation

## Definition 6: Partial Derivative

The **partial derivative** is a derivative taken with respect to one variable while holding the other variables constant. It measures the rate of change of a function with respect to one of its variables in a multivariable function.

- We denote the **partial derivative** of the multivariable function  $f$  with respect to one of its arguments  $x_1$  as  $\frac{\partial f(x_1, \dots, x_n)}{\partial x_1}$ .

# Partial Differentiation

## Question 1: Partial Differentiation

Suppose  $y = \beta_0 + \beta_1x_1 + \beta_2x_2 + \beta_3x_1x_2$ .

$$\frac{\partial y}{\partial x_2} = ?$$

# Partial Differentiation

## Question 1: Partial Differentiation

Suppose  $y = \beta_0 + \beta_1x_1 + \beta_2x_2 + \beta_3x_1x_2$ .

$$\frac{\partial y}{\partial x_2} = ?$$

## Answer to Question 1

$$\frac{\partial y}{\partial x_2} = \beta_2 + \beta_3x_1.$$

# First Order Condition

## Definition 7: First Order Condition

The **first order condition** for maximizing or minimizing a function is that the partial derivatives of the function with respect to all variables must be equal to zero. Mathematically, for a function  $f(x_1, x_2, \dots, x_n)$ , this means:

$$\frac{\partial f}{\partial x_1} = 0, \frac{\partial f}{\partial x_2} = 0, \dots, \frac{\partial f}{\partial x_n} = 0.$$

- This condition is necessary for finding local maximum/minimum points of the function.
- Upon setting these derivatives equal to zero, we then solve for the variable in question to determine its function maximizing/minimizing value.

# Why Do We Need Statistics in Econometrics?

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What purpose does statistics serve in econometric analysis?

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What purpose does statistics serve in econometric analysis?

## Answer to Question 3

We want to obtain a **point estimate of a parameter and statistics provides estimation methods**. After obtaining a point estimate, we can obtain confidence intervals that allow us to conduct hypothesis tests to determine the significance of that parameter.

# Sample

## Definition 8: Sample

A **sample**  $x_1, \dots, x_n = \{x_i\}_{i=1}^n$  of  $n$  observations is a subset of a population used to represent the entire group as a whole.

- A **sample** is used to make inferences about the population.
- A well-chosen **sample** should accurately reflect the characteristics of the population (the entire pool of observations we can select a **sample** from).
- A **sample** is said to be random if each observation has an equal probability of being selected.



# Descriptive Statistics

## Definition 9: Descriptive Statistics

**Descriptive statistics** involve summarizing and organizing our sample data so it can be easily understood.

- Common **descriptive statistics** include mean, median, variance, and standard deviation.

# Sample Mean

## Definition 10: Sample Mean

The **sample mean** (average) of a sample  $\{x_i\}_{i=1}^n$  is

$$\bar{X} = \frac{1}{n} \sum_{i=1}^n x_i = n^{-1} \sum_{i=1}^n x_i.$$

- The **mean** is a measure of central tendency.
- $\bar{X}$  attempts to estimate the population **mean**  $\mu$ .
- The **mean** is sensitive to outliers, which can skew the result.

# Sample Variance

## Definition 11: Sample Variance

The **sample variance**  $\hat{\sigma}^2$  of a sample  $\{x_i\}_{i=1}^n$  is defined as

$$\hat{\sigma}^2 = \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{X})^2$$

and represents how dispersed our data is.

- $\hat{\sigma}^2$  attempts to estimate the population **variance**  $\sigma^2$ .

# Sample Standard Deviation

## Definition 12: Standard Deviation

The **sample standard deviation**  $\hat{\sigma}$  of a sample  $\{x_i\}_{i=1}^n$  is defined as

$$\hat{\sigma} = \sqrt{\hat{\sigma}^2} = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{X})^2}$$

and is a standardized version of how dispersed our data is.

- $\hat{\sigma}$  attempts to estimate the population **standard deviation**  $\sigma$ .

# Sample Covariance

## Definition 13: Sample Covariance

The **sample covariance** of a sample  $\{(x_i, y_i)\}_{i=1}^n$  is

$$\hat{\sigma}_{xy} = \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{X})(y_i - \bar{Y}).$$

# Sample Correlation

## Definition 14: Sample Correlation

The **sample correlation** of a sample  $\{(x_i, y_i)\}_{i=1}^n$  is

$$\begin{aligned}\hat{\rho}_{xy} &= \frac{\frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{X})(y_i - \bar{Y})}{\sqrt{\frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{X})^2} \sqrt{\frac{1}{n-1} \sum_{i=1}^n (y_i - \bar{Y})^2}} \\ &= \frac{\hat{\sigma}_{xy}}{\hat{\sigma}_x \hat{\sigma}_y}.\end{aligned}$$

- This number is bounded between  $-1$  and  $1$  so we can determine how strong a relationship is, unlike the covariance.

# Experiments

## Definition 15: Experiment

An **experiment** is a process by which an observation is made.

## Example 2: Six Sided Dice Experiment

Rolling a six sided dice is an **experiment** and the observation made is the number the dice lands on.

# Samples Spaces

## Definition 16: Sample Space

The **sample space**  $S$  associated with an experiment is the set consisting of all possible sample points.

## Example 3: Six Sided Dice Sample Space

The **sample space** of a six sided dice consists of the outcomes 1, 2, 3, 4, 5, and 6.



# Events

## Definition 17: Event

An **event**  $A$  in a sample space is a collection of sample points - that is, any subset of the sample space.

## Example 4: Six Sided Dice Events

Some events of the six sided dice rolling experiment include:

1. The dice landing on the number 5 ( $A = \{5\}$ ).
2. The dice landing on an odd number ( $A = \{1, 3, 5\}$ ).
3. The dice landing on 1 or 6 ( $A = \{1, 6\}$ ).

# Probability

## Definition 18: Probability

The term **probability** of an event  $A$ , denoted by  $\mathbb{P}(A)$ , is a measure of one's belief in the occurrence of a future event.

# Probability

## Property 4: Probability

If  $S$  is our sample space consisting of pairwise mutually exclusive events (no two events can happen at the same time)  $A_1, A_2, \dots, A_n$  in  $S$ , then

1.  $\mathbb{P}(A) \geq 0$ .

2.  $\mathbb{P}(S) = 1$ .

3.  $\mathbb{P}(A_1 \cup \dots \cup A_n) = \sum_{i=1}^n \mathbb{P}(A_i)$ .

# Probability

## Question 4: Probability

What is the **probability** of rolling a six sided dice and landing on an odd number?

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What is the **probability** of rolling a six sided dice and landing on an odd number?

## Answer to Question 4

The **probability** of any outcome of the six sided dice experiment is  $\frac{1}{6}$ . We are interested in the events  $A_1 = \{1\}$ ,  $A_2 = \{3\}$ , and  $A_3 = \{5\}$ . Since each of these events is pairwise mutually exclusive, we have that

$$\mathbb{P}(A_1 \cup A_2 \cup A_3) = \mathbb{P}(A_1) + \mathbb{P}(A_2) + \mathbb{P}(A_3) = \frac{1}{6} + \frac{1}{6} + \frac{1}{6} = \frac{1}{2}.$$

# Probability Theorems

## Theorem 1: Multiplicative Law of Probability

The probability of  $A$  and  $(\cap) B$  occurring is defined as

$$\mathbb{P}(A \cap B) = \mathbb{P}(A) \cdot \mathbb{P}(B|A) = \mathbb{P}(B) \cdot \mathbb{P}(A|B).$$

## Theorem 2: Complement Law of Probability

If  $A$  is an event and  $A^c$  ( $A$  complement) is the event that  $A$  does not occur, then

$$\mathbb{P}(A) = 1 - \mathbb{P}(A^c).$$

# Conditional Probability

## Definition 19: Conditional Probability

The conditional probability of an event  $A$  given an event  $B$  has occurred is defined as

$$\mathbb{P}(A|B) = \frac{\mathbb{P}(A \cap B)}{\mathbb{P}(B)}.$$

## Example 5: Conditional Probability

Denote the event  $A$  as rolling a six sided dice and landing on a 1. Denote the event  $B$  as rolling a six sided dice and landing on an odd number. Then,

$$\mathbb{P}(A|B) = \frac{\mathbb{P}(A \cap B)}{\mathbb{P}(B)} = \frac{\frac{1}{6}}{\frac{1}{2}} = \frac{2}{6} = \frac{1}{3}.$$

## Independent Events

### Definition 20: Independent Events

Two events are **independent** if the occurrence of one event does not affect the occurrence of the other. Mathematically, events  $A$  and  $B$  are independent if any of the following holds:

1.  $\mathbb{P}(A|B) = \mathbb{P}(A)$ .
2.  $\mathbb{P}(B|A) = \mathbb{P}(B)$ .
3.  $\mathbb{P}(A \cap B) = \mathbb{P}(A) \cdot \mathbb{P}(B)$ .

### Example 6: Independent Events

Denote the event  $A$  as rolling a six sided dice and landing on a 5. Denote the event  $B$  as flipping a coin and landing on tails. Then,

$$\mathbb{P}(A \cap B) = \mathbb{P}(A) \cdot \mathbb{P}(B) = \frac{1}{6} \cdot \frac{1}{2} = \frac{1}{12}.$$



# Random Variables

## Definition 21: Random Variable

A **random variable** is a variable that takes on numerical values determined by the outcome of an experiment.

- We typically denote **random variables** with capital letters such as  $X$  and  $Y$ .
- Examples of **random variables** include a person's height and a student's GPA.

# Discrete Random Variables

## Definition 22: Discrete Random Variable

A random variable  $X$  is said to be **discrete** if it can assume only a finite or countably infinite number of distinct values.

# Probability Density Function (PDF)

## Definition 23: Probability Density Function (PDF)

The **probability density function**  $f_X$  for a random variable  $X$  provides  $f_X(x) = \mathbb{P}(X = x)$  for all  $x$ .

# Probability Density Function (PDF)

## Example 7: Probability Density Function (PDF)

If we let  $X$  equal 0 when the flip of a coin lands on tails while equaling 1 when the flip of a coin lands on heads, then the PDF of  $X$  can be completely characterized as

$$f_X(1) = \mathbb{P}(X = 1) = \frac{1}{2}$$
$$f_X(0) = \mathbb{P}(X = 0) = \frac{1}{2}.$$

- $X$  is an example of a Bernoulli random variable.

# Cumulative Distribution Function (CDF)

## Definition 24: Cumulative Distribution Function (CDF)

The **cumulative distribution function (CDF)** of a random variable  $X$ , denoted by  $F_X$ , is such that  $F_X(x) = \mathbb{P}(X \leq x)$  for all  $x$ .

- If  $X$  has the **CDF**  $F_X$ , then

$$\mathbb{P}(X > x) = 1 - \mathbb{P}(X \leq x) = 1 - F_X(x).$$

# Cumulative Distribution Function (CDF)

## Question 5: Cumulative Distribution Function (CDF)

If  $X$  is the random variable denoting the outcome of a dice roll, what is  $\mathbb{P}(X \leq 5)$ ?

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## Answer to Question 5

$$\begin{aligned}F_X(5) &= \mathbb{P}(X \leq 5) \\&= 1 - \mathbb{P}(X > 5) \\&= 1 - \mathbb{P}(X = 6) \\&= 1 - \frac{1}{6} \\&= \frac{5}{6}.\end{aligned}$$

# Continuous Random Variables

## Definition 25: Continuous Random Variable

A random variable  $X$  is said to be **continuous** if it can assume an infinite number of values.

- A good example of this is a person's weight.



# Expected Value

## Definition 26: Expected Value

If  $X$  is a discrete random variable with outcomes  $x_1, \dots, x_n$  and PDF  $f_X$ , then the **expected value** of  $X$  is

$$\mathbb{E}[X] = \sum_{i=1}^n x_i f_X(x_i).$$

If  $X$  is a continuous random variable with PDF  $f_X$  and can take on any real number, then the **expected value** of  $X$  is

$$\mathbb{E}[X] = \int_{-\infty}^{\infty} x f_X(x) dx.$$

- We often denote the **expected value** of a random variable by  $\mu$ .

# Expected Value

## Example 8: Expected Value

If  $X$  is a random variable denoting the outcome of a dice roll, then

$$\begin{aligned}\mathbb{E}[X] &= \sum_{i=1}^n x_i f_X(x_i) \\ &= \sum_{i=1}^6 x_i f_X(x_i) \\ &= 1 \cdot \frac{1}{6} + 2 \cdot \frac{1}{6} + 3 \cdot \frac{1}{6} + 4 \cdot \frac{1}{6} + 5 \cdot \frac{1}{6} + 6 \cdot \frac{1}{6} \\ &= \frac{1}{6}(1 + 2 + 3 + 4 + 5 + 6) \\ &= \frac{1}{6} \cdot 21 \\ &= 3.5.\end{aligned}$$

# Expected Value

## Property 5: Expected Value

If  $X$  and  $Y$  are any random variables and  $a$  and  $b$  are constants,

1.  $\mathbb{E}[a] = a.$

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1.  $\mathbb{E}[a] = a$ .
2.  $\mathbb{E}[aX] = a\mathbb{E}[X]$ .
3.  $\mathbb{E}[aX + bY] = a\mathbb{E}[X] + b\mathbb{E}[Y]$ .

# Expected Value

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3.  $\mathbb{E}[aX + bY] = a\mathbb{E}[X] + b\mathbb{E}[Y]$ .
4.  $\mathbb{E}[XY] = \mathbb{E}[X]\mathbb{E}[Y]$  when  $X$  and  $Y$  are independent.

# Conditional Expectation

## Definition 27: Conditional Expectation

If  $X$  and  $Y$  are random variables, then the **conditional expectation** of  $Y$  given  $X$  is  $\mathbb{E}[Y|X]$ .

- Given we have information on  $X$ , what can we say about  $Y$ .

# Conditional Expectation Properties

## Property 6: Conditional Expectation

If  $X$  and  $Y$  are any random variables and  $g_1$  and  $g_2$  are functions of  $X$ ,

1.  $\mathbb{E}[g(X)|X] = g(X)$ .



# Conditional Expectation Properties

## Property 6: Conditional Expectation

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1.  $\mathbb{E}[g(X)|X] = g(X)$ .
2.  $\mathbb{E}[g_1(X)Y + g_2(X)|X] = g_1(X)\mathbb{E}[Y|X] + g_2(X)$ .

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2.  $\mathbb{E}[g_1(X)Y + g_2(X)|X] = g_1(X)\mathbb{E}[Y|X] + g_2(X)$ .
3.  $\mathbb{E}[Y|X] = \mathbb{E}[Y]$  when  $X$  and  $Y$  are independent.

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2.  $\mathbb{E}[g_1(X)Y + g_2(X)|X] = g_1(X)\mathbb{E}[Y|X] + g_2(X)$ .
3.  $\mathbb{E}[Y|X] = \mathbb{E}[Y]$  when  $X$  and  $Y$  are independent.
4.  $\mathbb{E}[Y] = \mathbb{E}[\mathbb{E}[Y|X]]$ .

## Co-Variability of Random Variables

### Definition 28: Covariance

The **covariance** of two random variables  $X$  and  $Y$  is given by

$$\text{Cov}[X, Y] = \mathbb{E}[(X - \mu_X)(Y - \mu_Y)] = \mathbb{E}[XY] - \mathbb{E}[X]\mathbb{E}[Y].$$

- **Covariance** is a measure of how two variables are related or vary with one another.
- If  $\text{Cov}[X, Y] > 0$ , we say  $X$  and  $Y$  are positively related.
- If  $\text{Cov}[X, Y] < 0$ , we say  $X$  and  $Y$  are negatively related.

# Independence of Random Variables

## Definition 29: Independence of Random Variables

If  $X$  and  $Y$  are independent, then  $\text{Cov}[X, Y] = 0$ .

## Variability of Random Variables

### Definition 30: Variance of a Random Variable

The **variance** of a random variable  $X$  is given by

$$\begin{aligned}\mathbb{V}[X] &= \mathbb{E} [(X - \mu)^2] \\ &= \mathbb{E} [X^2] - \mu^2 \\ &= \sigma^2.\end{aligned}$$

### Definition 31: Standard Deviation of a Random Variable

The **standard deviation** of a random variable  $X$  is given by

$$\sigma = \sqrt{\mathbb{V}[X]}.$$

# Variability of Random Variables

## Property 7: Variance

If  $X$  and  $Y$  are random variables and  $a$  and  $b$  are constants, then

1.  $\mathbb{V}[a] = \mathbb{V}[b] = 0$  .

# Variability of Random Variables

## Property 7: Variance

If  $X$  and  $Y$  are random variables and  $a$  and  $b$  are constants, then

1.  $\mathbb{V}[a] = \mathbb{V}[b] = 0$  .
2.  $\mathbb{V}[aX + b] = \mathbb{V}[aX] + \mathbb{V}[b] = a^2\mathbb{V}[X]$ .



# Variability of Random Variables

## Property 7: Variance

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2.  $\mathbb{V}[aX + b] = \mathbb{V}[aX] + \mathbb{V}[b] = a^2\mathbb{V}[X]$ .
3. If  $X$  and  $Y$  are not independent, then  
 $\mathbb{V}[X + Y] = \mathbb{V}[X] + \mathbb{V}[Y] + 2\text{Cov}[X, Y]$ .

# Variability of Random Variables

## Property 7: Variance

If  $X$  and  $Y$  are random variables and  $a$  and  $b$  are constants, then

1.  $\mathbb{V}[a] = \mathbb{V}[b] = 0$  .
2.  $\mathbb{V}[aX + b] = \mathbb{V}[aX] + \mathbb{V}[b] = a^2\mathbb{V}[X]$ .
3. If  $X$  and  $Y$  are not independent, then  
 $\mathbb{V}[X + Y] = \mathbb{V}[X] + \mathbb{V}[Y] + 2\text{Cov}[X, Y]$ .
4.  $\mathbb{V}[Y] = \mathbb{E}[\mathbb{V}[Y|X]] + \mathbb{V}[\mathbb{E}[Y|X]]$ .

# Correlation

## Definition 32: Correlation Between Random Variables

If  $X$  and  $Y$  are two random variables, then the **correlation** between  $X$  and  $Y$  is defined as

$$\text{Corr}[X, Y] = \frac{\text{Cov}[X, Y]}{\sigma_X \sigma_Y}.$$

- The **correlation** between any two random variables is bounded between  $-1$  and  $1$ .

# Correlation Versus Covariance

## Question 6: Correlation Versus Covariance

What is the difference between **correlation** and **covariance**?

# Correlation Versus Covariance

## Question 6: Correlation Versus Covariance

What is the difference between **correlation** and **covariance**?

## Answer to Question 6

The **correlation** is bounded between  $-1$  and  $1$  so by using it we can obtain both the magnitude (small or large) and direction (positive or negative) of a relationship between two variables while the **covariance** only gives a direction.

# Distributions

## Definition 33: Distribution

A **distribution** describes how the values of a random variable are spread or distributed. It provides the probabilities of occurrence of different possible outcomes in an experiment. Distributions can be represented using probability density functions.

# Normal Distribution

## Definition 34: Normal Distribution

A **normal distribution**, also known as a Gaussian distribution, is a continuous probability distribution characterized by its bell-shaped curve. The probability density function (PDF) of a normally distributed random variable  $X$  with mean  $\mu$  and variance  $\sigma^2$  is given by:

$$f_X(x) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(x - \mu)^2}{2\sigma^2}\right).$$

- The normal distribution is symmetric around its mean.
- If  $X$  is a normally distributed random variable with mean  $\mu$  and variance  $\sigma^2$ , we write  $X \sim \mathbb{N}(\mu, \sigma^2)$ .

# Normal Distribution

## Property 8: Normal Distribution

If  $X$  and  $Y$  are independent normal random variables with mean  $\mu_X$  and  $\mu_Y$ , respectively, and variance  $\sigma_X^2$  and  $\sigma_Y^2$ , then

1.  $X + Y \sim \mathbb{N}(\mu_X + \mu_Y, \sigma_X^2 + \sigma_Y^2)$ .
2.  $cX + b \sim \mathbb{N}(c\mu_X + b, c^2\sigma_X^2)$  for any constants  $c$  and  $b$ .



## Standardizing a Random Variable

### Definition 35: Standardizing a Random Variable

If  $X$  is a random variable with mean  $\mu$  and variance  $\sigma^2$ , then its **standardized** version is

$$Z = \frac{X - \mu}{\sigma}$$

with mean  $\mathbb{E}[Z] = 0$  and variance  $\mathbb{V}[Z] = 1$ .

- If  $X$  is normally distributed, then  $Z$  follows the **standard normal distribution** (i.e.,  $Z \sim \mathbb{N}(0, 1)$ ).

# Independent and Identically Distributed (i.i.d.)

## Definition 36: Independent and Identically Distributed (i.i.d.)

A sample  $\{x_i\}_{i=1}^n$  is said to be **independent and identically distributed (i.i.d.)** if each random variable in the sample:

1. Is **independent**: The occurrence of any one variable does not affect the others.
2. Is **identically distributed**: All variables follow the same probability distribution.

# Central Limit Theorem

## Theorem 3: Central Limit Theorem

If  $X_1, X_2, \dots, X_n$  are i.i.d. random variables with mean  $\mu$  and variance  $\sigma^2$ , then as  $n$  approaches infinity,

$$\frac{\bar{X} - \mu}{\sigma/\sqrt{n}} \xrightarrow{d} \mathbb{N}(0, 1).$$

- This means that  $\bar{X}$  converges toward a normal distribution with mean  $\mu$  and variance  $\frac{\sigma^2}{n}$  for large  $n$ .

# Statistical Inference

## Definition 37: Terms in Statistical Inference

1. A **parameter** is the true value of what we are estimating.
2. An **estimator** is a random variable that attempts to estimate the parameter.
3. An **estimate** is the value produced by the estimator.
4. A **sampling distribution** is the distribution of our estimator.

# Statistical Inference

## Example 9: Example of Terms in Statistical Inference

- The mean of a sample  $\{x_i\}_{i=1}^n$  given by  $\bar{X} = n^{-1} \sum_{i=1}^n x_i$  is an **estimator**.
- The number given by this sample is an **estimate** of the **parameter**  $\mu$ .
- If we were to repeatedly draw samples and compute  $\bar{X}$  for each sample, we would form the **sampling distribution** for  $\bar{X}$ .

# Unbiased Estimators

## Definition 38: Unbiased Estimator

An estimator  $\hat{\beta}$  of the parameter  $\beta$  is **unbiased** if

$$\mathbb{E} \left[ \hat{\beta} \right] = \beta.$$

- On average, our estimator gives us the correct answer.

# Consistency

## Definition 39: Consistency

An estimator  $\hat{\beta}$  of the parameter  $\beta$  is **consistent** if

$$\mathbb{P}\left(\left|\hat{\beta} - \beta\right| > \epsilon\right) \rightarrow 0$$

as  $n \rightarrow \infty$  for any  $\epsilon > 0$ .

- As we get a larger sample, our estimator converges toward the truth.
- We often write  $\hat{\beta} \xrightarrow{P} \beta$ .

# Efficient

## Definition 40: Efficient

An unbiased estimator  $\hat{\beta}$  of the parameter  $\beta$  is **efficient** in the class of unbiased estimators if

$$\mathbb{V}[\hat{\beta}] \leq \mathbb{V}[\tilde{\beta}]$$

for any other unbiased estimator  $\tilde{\beta}$  of  $\beta$ .

- If we were to gather multiple samples, estimate  $\hat{\beta}$  for each sample, form a sampling distribution, and compute the variance of the sampling distribution,  $\hat{\beta}$  would have the smallest such variance.



# Thank You!