

Statistics and Probability

Bas Machielsen

2025-06-11

Agenda

This presentation provides a refresher on the fundamental statistical concepts that form the bedrock of econometrics.

1. Basic Probability Theory
2. Conditional Probability
3. Random Variables
4. Discrete Probability Distributions
5. Continuous Probability Distributions
6. The Normal Distribution
7. Covariance and Correlation
8. Sampling
9. Sampling Distributions
10. The Central Limit Theorem
11. Estimation
12. Hypothesis Testing

1. Basic Probability Theory

Experiments, Outcomes, and Sample Spaces

- ▶ Experiment: A process or action whose result is uncertain.
 - ▶ *Example:* Rolling a six-sided die.
 - ▶ *Example:* Surveying a household to ask about their income.
 - ▶ *Example:* Observing next year's GDP growth rate.
- ▶ Outcome: A single possible result of an experiment.
 - ▶ *Example:* The die shows a 4.
 - ▶ *Example:* The household's income is 52,000.
 - ▶ *Example:* GDP growth is 2.3.
- ▶ Sample Space (S): The set of *all possible* outcomes of an experiment.
 - ▶ *Example (Die Roll):* $S = 1, 2, 3, 4, 5, 6$
 - ▶ *Example (Household Income):* $S \in [0, \infty]$

Events

- ▶ Event: A subset of the sample space; a collection of one or more outcomes. We can calculate probabilities for events.

Using the die roll example where $S = 1, 2, 3, 4, 5, 6$:

- ▶ **Event A:** The outcome is an even number.
 - ▶ $A = 2, 4, 6$
 - ▶ The probability of Event A is $P(A) = 3/6 = 0.5$
- ▶ **Event B:** The outcome is greater than 4.
 - ▶ $B = 5, 6$
 - ▶ The probability of Event B is $P(B) = 2/6 \approx 0.33$
- ▶ **The intersection of A and B ($A \cap B$):** The outcome is even AND greater than 4.
 - ▶ $A \cap B = 6$
 - ▶ $P(A \cap B) = 1/6$

2. Conditional Probability

The Probability of A, Given B

Conditional Probability is the probability of an event occurring, given that another event has already occurred.

The probability of event A occurring given that event B has occurred is written as $P(A|B)$.

Definition:

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

Intuition: We are restricting our sample space. We know B happened, so the “universe” of possible outcomes is now just B . Within that new universe, we want to know the chance that A also happens.

Conditional Probability: Example

Let's use our die roll example again: $S = 1, 2, 3, 4, 5, 6$,

$A = \{\text{Outcome is an even number}\} = \{2, 4, 6\}$,

$B = \{\text{Outcome is greater than 4}\} = \{5, 6\}$

Question: What is the probability that the number is even, *given* that we know it is greater than 4? We want to find $P(A|B)$.

1. **Find $P(B)$:** The probability of rolling a number greater than 4 is $P(B) = 2/6$.
2. **Find $P(A \cap B)$:** The probability of rolling a number that is even AND greater than 4 is $P(6) = 1/6$.
3. **Apply the formula:**

$$P(A|B) = \frac{P(A \cap B)}{P(B)} = \frac{1/6}{2/6} = \frac{1}{2} = 0.5$$

Intuition Check: If we know the outcome is in $B = 5, 6$, there are only two possibilities. Of these, only one (6) is even. So the probability is $1/2$. It matches!

3. Random Variables

Definition and Types

Random Variable (RV): A variable whose value is a numerical outcome of a random phenomenon. We use capital letters (e.g., X , Y) to denote a random variable. There are two main types of random variables:

Discrete Random Variable: A variable that can only take on a finite or countably infinite number of distinct values.

- ▶ *Example:* The number of heads in three coin flips (X can be 0, 1, 2, 3).
- ▶ *Example:* The number of defaults in a portfolio of 100 loans (X can be 0, 1, ..., 100).

Continuous Random Variable: A variable that can take on any value within a given range.

- ▶ *Example:* The exact price of a stock tomorrow.
- ▶ *Example:* The annual percentage growth in GDP (Y could be 2.1%, 2.11%, 2.113%...).

4. Distributions for Discrete RVs

Probability Mass Function (PMF)

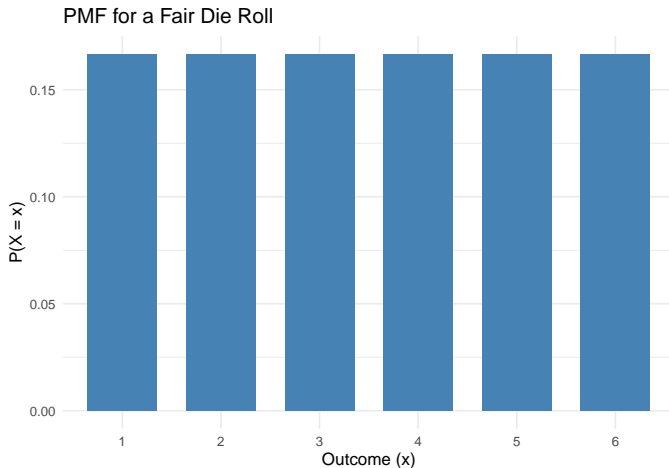
For a discrete random variable X , the **Probability Mass Function (PMF)** gives the probability that X is exactly equal to some value x .

$$f(x) = P(X = x)$$

A PMF has two key properties: 1. $0 \leq f(x) \leq 1$ for all x . 2. $\sum f(x) = 1$ (The sum of probabilities over all possible values is 1).

PMF Example

Example: Let X be the outcome of a fair die roll. The PMF is: $f(1) = 1/6$, $f(2) = 1/6$, ..., $f(6) = 1/6$.



Expected Value

The **Expected Value** of a discrete random variable X , denoted $E[X]$ or μ , is the long-run average value of the variable. It's a weighted average of the possible outcomes, where the weights are the probabilities.

Definition:

$$E[X] = \mu = \sum_x x \cdot P(X = x)$$

Example: Expected value of a fair die roll.

$$E[X] = (1 \times 1/6) + (2 \times 1/6) + (3 \times 1/6) + (4 \times 1/6) + (5 \times 1/6) + (6 \times 1/6)$$

$$E[X] = (1 + 2 + 3 + 4 + 5 + 6)/6 = 21/6 = 3.5$$

Note: The expected value doesn't have to be a possible outcome!

Variance and Standard Deviation

Variance, denoted $Var(X)$ or σ^2 , measures the spread or dispersion of a random variable around its mean. A larger variance means the outcomes are more spread out.

Definition:

$$Var(X) = \sigma^2 = E[(X - \mu)^2] = \sum_x (x - \mu)^2 \cdot P(X = x)$$

Standard Deviation, $SD(X)$ or σ , is the square root of the variance. It's often easier to interpret because it's in the same units as the random variable itself.

$$SD(X) = \sigma = \sqrt{Var(X)}$$

Example: The Bernoulli Distribution

The **Bernoulli distribution** is a fundamental discrete distribution for any experiment with two outcomes, typically labeled “success” (1) and “failure” (0).

Let X be a Bernoulli random variable where $P(X = 1) = p$ and $P(X = 0) = 1 - p$.

- ▶ **Econometric relevance:** Models binary outcomes like employed/unemployed, default/no-default, buy/don't-buy.
- ▶ **Expected Value:** $E[X] = (1 \times p) + (0 \times (1 - p)) = p$
- ▶ **Variance:**

$$\begin{aligned} \text{Var}(X) &= (1 - p)^2 \times p + (0 - p)^2 \times (1 - p) \\ &= (1 - p)^2 \times p + p^2 \times (1 - p) \\ &= p(1 - p) \times [(1 - p) + p] = p(1 - p) \end{aligned}$$

5. Distributions for Continuous RVs

Probability Density Function (PDF)

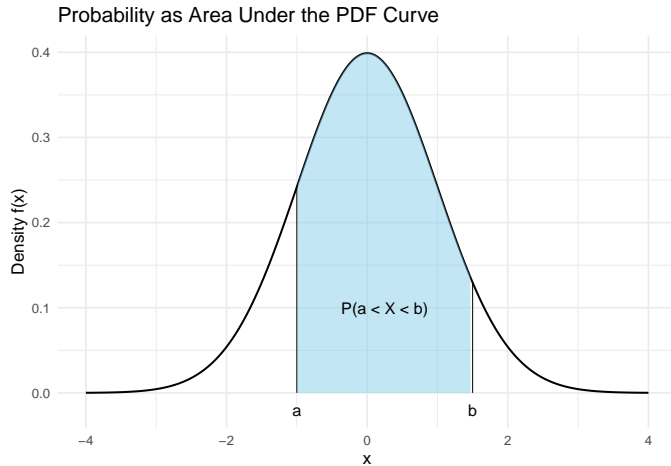
For a **continuous** random variable, the probability of it taking on any *single* specific value is zero! $P(X = x) = 0$. Why? Because there are infinitely many possible values.

Instead, we use a **Probability Density Function (PDF)**, $f(x)$.

Key Idea: Probability is represented by the **area under the curve** of the PDF.

$P(a \leq X \leq b) = \text{Area under } f(x) \text{ between } a \text{ and } b.$

Example PDF



Cumulative Distribution Function (CDF)

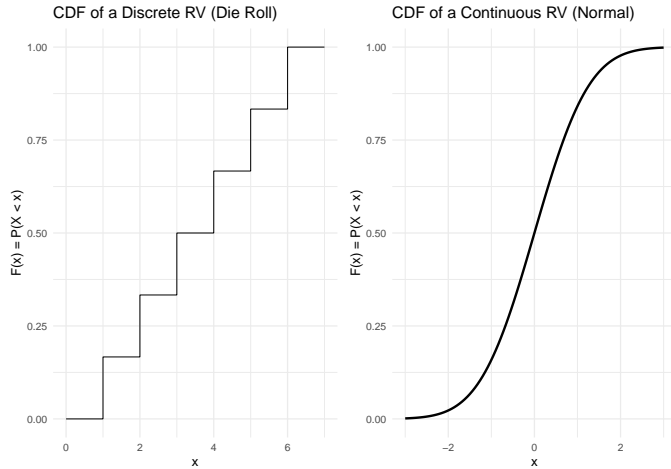
The **Cumulative Distribution Function (CDF)**, $F(x)$, gives the probability that a random variable X is *less than or equal to* a certain value x . It's a unifying concept for both discrete and continuous variables.

$$F(x) = P(X \leq x)$$

Properties:

- ▶ $F(x)$ is non-decreasing.
- ▶ $F(x)$ ranges from 0 to 1.
- ▶ For continuous RVs, $P(a \leq X \leq b) = F(b) - F(a)$.

Example CDF



6. The Normal Distribution

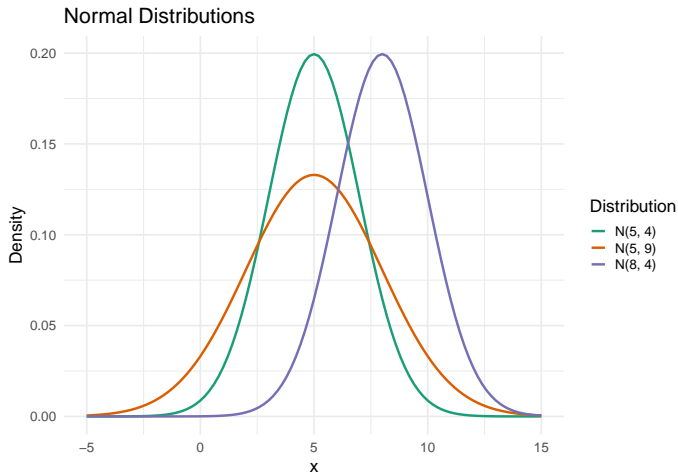
Properties of the Normal Distribution

The **Normal Distribution** is the most important probability distribution in statistics and econometrics. It is defined by its mean μ and its variance σ^2 . We write $X \sim N(\mu, \sigma^2)$.

Properties:

- ▶ **Bell-shaped** and symmetric around its mean μ .
- ▶ Mean = Median = Mode.
- ▶ The curve is completely determined by μ (center) and σ (spread).

Example Normal Distribution



The Standard Normal Distribution (Z)

The **Standard Normal Distribution** is a special case of the normal distribution with a mean of 0 and a variance of 1. $Z \sim N(0, 1)$.

Standardization (creating a Z-score): We can convert any normally distributed random variable $X \sim N(\mu, \sigma^2)$ into a standard normal variable Z using the formula:

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

Why is this useful? It allows us to use a single table (or software function) to find probabilities for *any* normal distribution. The Z-score tells us how many standard deviations an observation X is away from its mean μ .

Finding Probabilities

Historically, probabilities for the standard normal distribution were found using **Z-tables**, which provide $P(Z \leq z)$.

Today, we use software like R, Stata, or Python.

Example: Suppose annual returns on a mutual fund are normally distributed with a mean of 8% and a standard deviation of 10%. $X \sim N(0.08, 0.01)$. What's the probability of a negative return, $P(X < 0)$?

1. **Standardize the value:** $Z = (0 - 0.08)/0.10 = -0.8$

2. **Find the probability:** We need to find

$$P(X < 0) = P\left(\frac{X - 0.08}{0.01} < \frac{0 - 0.08}{0.01}\right) = P(Z < -0.8).$$

Finding Probabilities (Cont.)

3. **Using R, Python or Stata:** The *pnorm()* and *norm.cdf* functions give the area to the left (the CDF).

```
pnorm(-0.8, mean = 0, sd = 1)
```

```
## [1] 0.2118554
```

```
from scipy.stats import norm  
norm.cdf(-0.8)
```

```
## np.float64(0.2118553985833967)
```

So, there is about a **21.2%** chance of experiencing a negative return.

7. Covariance and Correlation

Covariance

Covariance measures the joint variability of two random variables. It tells us the *direction* of the linear relationship.

Definition:

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

- ▶ $\text{Cov}(X, Y) > 0$: X and Y tend to move in the same direction. When X is above its mean, Y tends to be above its mean.
- ▶ $\text{Cov}(X, Y) < 0$: X and Y tend to move in opposite directions.
- ▶ $\text{Cov}(X, Y) = 0$: No linear relationship between X and Y .

Drawback: The magnitude of covariance is hard to interpret because it depends on the units of X and Y . (e.g., $\text{Cov}(\text{GDP}, \text{Consumption})$ will be a huge number).

Correlation

The **Correlation Coefficient** (ρ or r) is a standardized version of covariance that measures both the *strength* and *direction* of the linear relationship between two variables.

Definition:

$$\rho_{XY} = \frac{\text{Cov}(X, Y)}{\sigma_X \sigma_Y}$$

Properties:

- ▶ Ranges from **-1 to +1**.
- ▶ $\rho = +1$: Perfect positive linear relationship.
- ▶ $\rho = -1$: Perfect negative linear relationship.
- ▶ $\rho = 0$: No linear relationship.
- ▶ It is unitless, making it easy to interpret and compare.

Correlation \neq Causation

This is the most important lesson in all of econometrics.

A strong correlation between two variables does not mean that one *causes* the other.
There could be:

1. **Reverse Causality:** Y causes X .
2. **Omitted Variable Bias (Lurking Variable):** A third variable Z causes both X and Y .

Classic Example: * Ice cream sales (X) and drowning deaths (Y) are highly positively correlated. * Does eating ice cream cause drowning? No. * The omitted variable is **hot weather** (Z), which causes people to both buy more ice cream and swim more (leading to more drownings).

8. Introduction to Sampling

Population vs. Sample

Population The entire group of individuals, objects, or data points that we are interested in studying. * *Example:* All households in the United States. * *Example:* All firms listed on the New York Stock Exchange.

Sample A subset of the population from which we actually collect data. * *Example:* A survey of 2,000 U.S. households. * *Example:* The stock prices of 50 firms from the NYSE.

Why sample? It's often impossible or too expensive to collect data on the entire population. We use samples to make inferences about the population.

Parameters vs. Statistics

Parameter A numerical characteristic of a **population**. These are typically unknown and what we want to estimate. They are considered fixed values. *

Examples: Population mean (μ), population variance (σ^2), population correlation (ρ).

Statistic A numerical characteristic of a **sample**. We calculate statistics from our data. A statistic is a random variable, as its value depends on the particular sample drawn. * **Examples:** Sample mean (\bar{x}), sample variance (s^2), sample correlation (r).

The core idea of inference is to use a **sample statistic** to learn about a **population parameter**.

Simple Random Sampling

Simple Random Sampling (SRS) is the most basic sampling method.

Definition: A sample of size n where every possible sample of that size has an equal chance of being selected, and every individual in the population has an equal chance of being included.

Importance: SRS is the ideal. Statistical methods (like the ones we're learning) are built on the assumption of random sampling. If a sample is not drawn randomly, our inferences may be biased and incorrect.

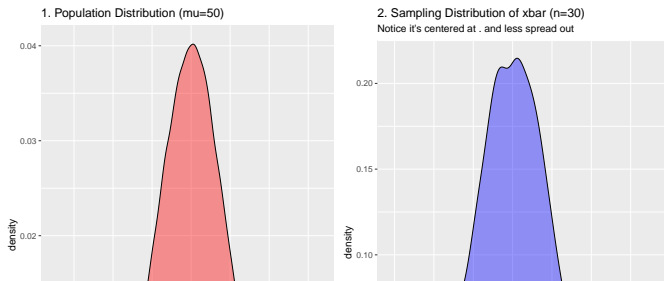
9. The Concept of a Sampling Distribution

The Distribution of a Statistic

This is a crucial, but sometimes tricky, concept.

Imagine this thought experiment: 1. There is a population with an unknown mean μ .
2. We take a random sample of size n (e.g., $n=100$) and calculate its sample mean, \bar{x}_1 .
3. We take a *different* random sample of size n and get a different sample mean, \bar{x}_2 . 4. We repeat this process 10,000 times, getting $\bar{x}_1, \bar{x}_2, \dots, \bar{x}_{10000}$.

The **Sampling Distribution** of the sample mean is the probability distribution of all these possible \bar{x} values. It's the distribution of a statistic, not of the original data.



10. The Central Limit Theorem (CLT)

The Most Important Theorem in Statistics

The **Central Limit Theorem (CLT)** states:

If you take a sufficiently large random sample ($n \geq 30$ is a common rule of thumb) from a population with mean μ and standard deviation σ , the sampling distribution of the sample mean \bar{x} will be approximately normally distributed, *regardless of the original population's distribution*.

Furthermore, the mean of this sampling distribution will be the population mean μ , and its standard deviation (called the **standard error**) will be σ/\sqrt{n} .

$$\bar{X} \approx N\left(\mu, \frac{\sigma^2}{n}\right)$$

Why the CLT is a “Miracle”

The implications of the CLT are profound:

1. **We can use the normal distribution for inference on the mean even if the underlying data is not normal.** Many economic variables (like income) are highly skewed, but the CLT lets us work with their sample means.
2. **It provides a precise formula for the variance of the sample mean (σ^2/n).**
This shows that as our sample size n increases, the sample mean \bar{x} becomes a more precise estimator of the population mean μ (its sampling distribution gets narrower).

The CLT is the foundation that allows us to build confidence intervals and conduct hypothesis tests for the mean.

11. Introduction to Estimation

Point Estimators

An **estimator** is a rule (a formula) for calculating an estimate of a population parameter based on sample data. The value it produces is called an **estimate**.

A **Point Estimator** is a formula that produces a single value as the estimate.

Common Point Estimators:

- * The sample mean \bar{x} is a point estimator for the population mean μ .
- * The sample proportion \hat{p} is a point estimator for the population proportion p .
- * The sample variance s^2 is a point estimator for the population variance σ^2 .

Desirable Properties of Estimators

How do we know if an estimator is “good”? We look for three properties (conceptually):

1. Unbiasedness

- ▶ An estimator is unbiased if its expected value is equal to the true population parameter. $E[\theta] = \theta$.
- ▶ *Analogy:* On average, the shots hit the center of the target. There's no systematic over- or under-estimation.

2. Efficiency

- ▶ Among all unbiased estimators, the most efficient one is the one with the smallest variance.
- ▶ *Analogy:* The shots are tightly clustered around the center. It's a precise estimator.

3. Consistency

- ▶ An estimator is consistent if, as the sample size n approaches infinity, the value of the estimator converges to the true parameter value.
- ▶ *Analogy:* The more information you get, the closer you get to the truth.

12. Introduction to Hypothesis Testing

The Logic of a Statistical Test

Hypothesis Testing is a formal procedure for checking whether our sample data provides convincing evidence against a preconceived claim about the population.

The Logic: Proof by Contradiction

1. We start by assuming something is true about the population (the **Null Hypothesis**).
2. We then look at our sample data.
3. We ask: "If the null hypothesis were true, how likely is it that we would get sample data like this?"
4. If our sample data is very unlikely under the null hypothesis, we reject our initial assumption in favor of an alternative.

Null and Alternative Hypotheses

Every hypothesis test has two competing hypotheses:

Null Hypothesis (H_0) The claim being tested. It's the "status quo" or "no effect" hypothesis. It always contains an equality sign ($=$, \leq , or \geq). * *Example:* The new drug has no effect on blood pressure ($\mu_{change} = 0$). * *Example:* The mean income in a region is 50,000 ($\mu = 50000$).

Alternative Hypothesis (H_A or H_1) The claim we are trying to find evidence *for*. It's what we conclude if we reject the null hypothesis. It never contains an equality sign (\neq , $<$, or $>$). * *Example:* The new drug does have an effect ($\mu_{change} \neq 0$). * *Example:* The mean income is not 50,000 ($\mu \neq 50000$).

Test Statistics and P-Values (Conceptual)

How do we decide whether our data is “unlikely”?

Test Statistic A value calculated from sample data that measures how far our sample statistic (e.g., \bar{x}) is from the parameter value claimed by the null hypothesis (μ_0). It's often standardized, like a Z-score.

$$\text{Test Statistic} = \frac{\text{Sample Statistic} - \text{Null Hypothesis Value}}{\text{Standard Error}}$$

P-Value The probability of observing a test statistic as extreme (or more extreme) than the one calculated, *assuming the null hypothesis is true*. * **Small P-Value (e.g., < 0.05)**: The observed data is very unlikely if H_0 were true. We **reject** H_0 . The evidence supports H_A . * **Large P-Value (e.g., > 0.05)**: The observed data is plausible if H_0 were true. We **fail to reject** H_0 . There is not enough evidence to support H_A .

Questions?