

Discrete Distributions

Bernoulli, Binomial, and Poisson

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Gov 2001 · Harvard University

Spring 2026

Where We Are

From abstract machinery to named distributions

Last week: The general framework

- Random variables, PMFs, PDFs, CDFs
- Expected value, variance, Jensen's inequality
- Independence and indicator variables

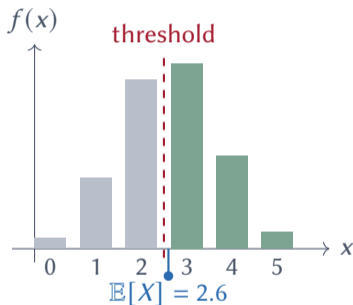
This week: Named distributions — the **vocabulary** of statistics

- **Today:** Discrete distributions (Bernoulli, Binomial, Poisson)
- **Wednesday:** Continuous distributions (Uniform, Normal, Exponential)

Reading: Aronow & Miller §1.2–1.3, Blackwell 2.2–2.3

A Puzzle from Thursday

How can you win 54% of the time but expect only 2.6 votes?



$$P(X \geq 3) = 0.54$$

Win more than half

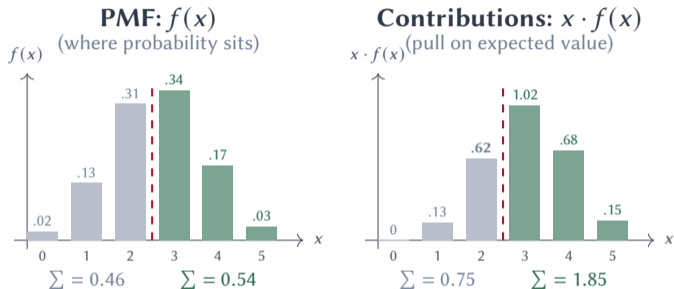
$$E[X] = 2.60$$

Below threshold

How can both be true?

PMF vs. Contributions to $E[X]$

The $x = 2$ bar looks small in the PMF, but contributes a lot to $E[X]$



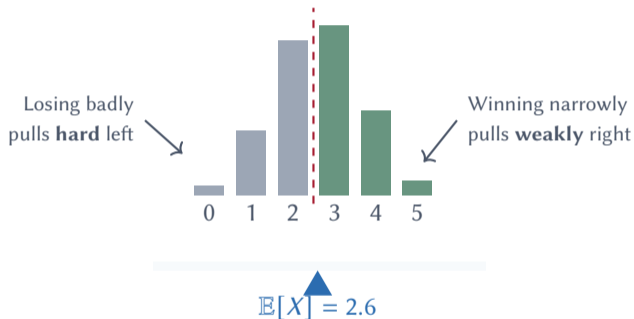
Left: PMF shows probability mass. More mass on the right (54%), so the map is *usually* struck down.

Right: Contributions to $E[X]$. The $x = 2$ bar is now substantial (0.62). That's a lot of "pull" just below threshold.

$$E[X] = 0.75 + 1.85 = 2.60 \quad (\text{sum of all contributions})$$

Expected Value is a Center of Mass

$E[X]$ is pulled by magnitude, not just frequency



Resolution: More than half the probability mass is above 3, but the *center of mass* is at 2.6. Losing badly (0, 1) pulls harder than winning narrowly (3). The asymmetry pulls $E[X]$ below threshold.

Today: Famous Discrete Distributions

Building our toolkit

The redistricting puzzle showed us why random variables matter. Now we build a toolkit of **named distributions** — probability models that appear constantly in political science.

Distribution	What it models
Bernoulli	A single yes/no outcome
Binomial	Number of successes in n trials
Poisson	Counts of rare events

For each, we'll ask: *Where did it come from? Where do we see it? What are its properties?*

Why Named Distributions?

These aren't arbitrary — they model real phenomena

Three reasons to learn these:

1. **They appear everywhere:** Elections, counts, durations, measurements
2. **They're tractable:** We can derive $E[X]$, $\text{Var}[X]$, and more
3. **They connect:** Understanding one helps you understand others

Today's cast:

- **Bernoulli** — yes/no, success/failure (the foundation)
- **Binomial** — counting successes in n trials
- **Poisson** — counting rare events

The Big Picture

Why distributions matter for inference

What we're building toward:

1. We **describe populations** with distributions (this week)
2. We **estimate parameters** (p , λ , μ) from sample data (coming soon)
3. We **quantify uncertainty** about those estimates (requires understanding distributions)

Example: A poll samples 100 voters. 58 support candidate A.

- The *population* has some true support rate p (unknown)
- Our *estimate* is $\hat{p} = 0.58$ (from sample)
- How good is this estimate? *That depends on the Binomial distribution.*

Distributions aren't just mathematical objects — they're the foundation for learning from data.

The Bernoulli Distribution

The Simplest Random Variable

Jacob Bernoulli (1655–1705)

The mathematician who formalized probability

Jacob Bernoulli was a Swiss mathematician from a family that produced eight prominent mathematicians across three generations. His posthumous work *Ars Conjectandi* (1713) was foundational to probability theory.

Key contributions:

- Proved the first version of the **Law of Large Numbers**
- Showed that with enough trials, observed frequencies converge to true probabilities
- Established probability as a rigorous mathematical field

The Bernoulli distribution — a single binary trial — is named in his honor. Simple as it is, it's the building block for much of what follows.

Where You See Bernoulli in Social Science

Any yes/no outcome is a Bernoulli trial

Political science:

- Did this citizen vote? ($p \approx 0.6$ in US presidential elections)
- Did the incumbent win this district?
- Does this respondent approve of the president?

Economics:

- Did this worker find a job this month?
- Did this firm enter the market?

Sociology:

- Did this couple divorce within 5 years?
- Did this student graduate?

Whenever your outcome is binary (0 or 1), you're in Bernoulli territory.

The Bernoulli Distribution

The simplest random variable: just 0 or 1

The model: $X \sim \text{Bernoulli}(p)$ means:

$$X = \begin{cases} 1 & \text{with probability } p \\ 0 & \text{with probability } 1 - p \end{cases}$$

PMF: $f(x) = p^x(1 - p)^{1-x}$ for $x \in \{0, 1\}$

Support: $\{0, 1\}$ — only two possible values

The Bernoulli is a single trial. What if we have many trials? That's where the Binomial comes in.

A Quick Definition: Support

What values can a random variable take?

Definition: The **support** of X is the set of values where the PMF (or PDF) is positive:

$$\text{Supp}[X] = \{x : f(x) > 0\}$$

Examples:

- Bernoulli(p): Support = $\{0, 1\}$
- Binomial(n, p): Support = $\{0, 1, 2, \dots, n\}$
- Poisson(λ): Support = $\{0, 1, 2, \dots\}$ (unbounded)

Why it matters: When computing expectations or conditioning on X , you sum/integrate over the support. Knowing what values are possible is fundamental.

For Bernoulli, $\mathbb{E}[X] = p$ **and** $\text{Var}[X] = p(1 - p)$

For $X \sim \text{Bernoulli}(p)$:

Expected value (this is key — memorize it):

$$\mathbb{E}[X] = 0 \cdot (1 - p) + 1 \cdot p = p$$

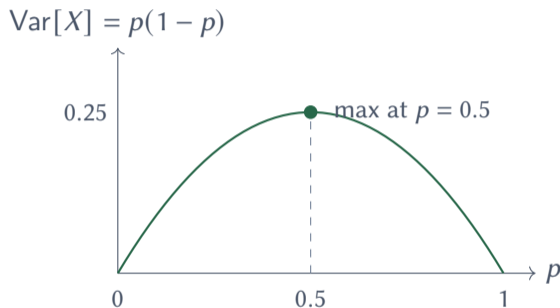
Variance:

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

Key insight: $\mathbb{E}[X] = \mathbb{P}(X = 1)$. For a 0/1 variable, the mean *is* the probability.

This is why we can estimate probabilities by computing sample means.

Bernoulli Variance is Maximized at $p = 0.5$



When outcomes are most uncertain ($p = 0.5$), variance is highest.

Certainty ($p = 0$ or $p = 1$) means zero variance — no spread if there's only one possible outcome.

The Binomial Distribution

Counting Successes

Pascal, Fermat, and the Gamblers

Probability theory was invented to solve gambling problems

In 1654, a French gambler named **Chevalier de Méré** had a problem: how should you fairly divide the pot when a dice game is interrupted mid-play?

He asked **Blaise Pascal**, who wrote to **Pierre de Fermat**. Their letters that summer are often called *the birth of probability theory*.

The “problem of points”: Each player has some probability of eventually winning the remaining rounds. Pascal and Fermat realized you need to count the *ways* each could win — the binomial coefficient:

$$\binom{n}{k} = \frac{n!}{k!(n-k)!}$$

Weirdly, gamblers drove these early innovations. And they still do: modern finance and speculation run on probability theory that traces back to these 1654 letters about dice.

The math has far exceeded gambling — but gambling remains where it started, and where a lot of the money still is.

Where You See Binomial in Social Science

Counting successes in a fixed number of trials

Political science:

- Out of 10 voters polled, how many support candidate A?
- Out of 50 precincts, how many have wait times over 1 hour?
- Out of 9 Supreme Court justices, how many vote to strike down?

Economics:

- Out of 100 loan applicants, how many default?
- Out of 20 firms, how many survive their first year?

Public health:

- Out of 500 vaccinated people, how many get infected?
- Out of 30 patients, how many respond to treatment?

Whenever you're counting successes in n independent trials, you're in Binomial territory.

From Bernoulli to Binomial

Sum of independent trials

Setup: Run n independent Bernoulli trials, each with success probability p .

Question: What's the distribution of the **total number of successes**?

If $X_1, X_2, \dots, X_n \stackrel{\text{iid}}{\sim} \text{Bernoulli}(p)$, then:

$$Y = \sum_{i=1}^n X_i \sim \text{Binomial}(n, p)$$

You saw this logic last week with the redistricting court — same idea, but now p is the same for all trials.

The Binomial PMF Counts Ways to Achieve k Successes

Three ingredients: successes, failures, arrangements

For $Y \sim \text{Binomial}(n, p)$:

$$f(k) = \mathbb{P}(Y = k) = \binom{n}{k} p^k (1 - p)^{n-k}$$

for $k \in \{0, 1, 2, \dots, n\}$

Decomposing the formula:

- p^k : probability that the k successes happen
- $(1 - p)^{n-k}$: probability that the $n - k$ failures happen
- $\binom{n}{k} = \frac{n!}{k!(n-k)!}$: number of ways to choose *which* k trials are successes

You saw this logic last week with the redistricting court — same idea, but now p is the same for all trials.

$\mathbb{E}[Y] = np$ **Because It's a Sum of Bernoullis**

Linearity of expectation does the heavy lifting

For $Y \sim \text{Binomial}(n, p)$:

Expected value: Since $Y = \sum_{i=1}^n X_i$ where $X_i \sim \text{Bernoulli}(p)$:

$$\mathbb{E}[Y] = \sum_{i=1}^n \mathbb{E}[X_i] = np$$

Variance: Since the X_i are **independent**:

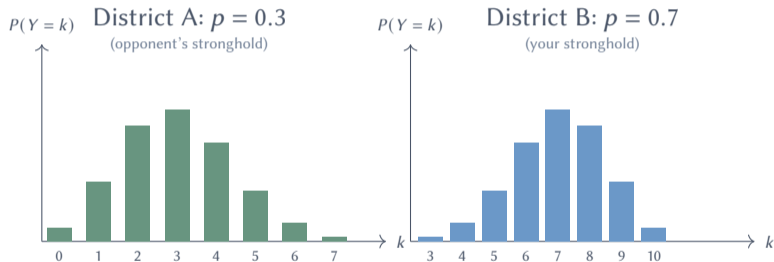
$$\text{Var}[Y] = \sum_{i=1}^n \text{Var}[X_i] = np(1 - p)$$

Linearity of expectation **always** works. Additivity of variance requires **independence**.

How Likely Is Your Candidate's Support Level?

Visualizing the Binomial: same sample size, different support rates

Poll 10 voters in two different districts:



Same sample size $n = 10$, different p . The distribution shifts with the true support rate.

Key Property: Binomials Add

If they share the same p

Theorem: If $X \sim \text{Binomial}(n, p)$ and $Y \sim \text{Binomial}(m, p)$ are **independent**, then:

$$X + Y \sim \text{Binomial}(n + m, p)$$

Intuition: X is successes in n trials, Y is successes in m trials. Together, you have $n + m$ trials.

Example: Two precincts, same underlying turnout rate $p = 0.6$.

- Precinct A: 100 voters, $X \sim \text{Bin}(100, 0.6)$
- Precinct B: 150 voters, $Y \sim \text{Bin}(150, 0.6)$
- Combined: $X + Y \sim \text{Bin}(250, 0.6)$

This only works when p is the same across both. Different p 's? No nice closed form.

Your Turn: Binomial Practice

Try these before we move on

A poll samples **200 voters**. Suppose the true approval rate is $p = 0.45$.

Let X = number who approve. Then $X \sim \text{Binomial}(200, 0.45)$.

Questions:

1. What is $\mathbb{E}[X]$?
2. What is $\text{Var}[X]$? What is the standard deviation?
3. What is $\mathbb{P}(X = 90)$? (Just set up the formula)

Answers:

1. $\mathbb{E}[X] = np = 200 \times 0.45 = 90$
2. $\text{Var}[X] = np(1 - p) = 200 \times 0.45 \times 0.55 = 49.5$, so $\sigma = \sqrt{49.5} \approx 7.04$
3. $\mathbb{P}(X = 90) = \binom{200}{90} (0.45)^{90} (0.55)^{110}$ (use software to compute)

The Poisson Distribution

Counting Rare Events

Siméon Denis Poisson (1781–1840)

From artillery to actuarial science

Poisson was a French mathematician who studied under Laplace and Lagrange. He introduced his distribution in 1837 in a work on criminal justice — studying the number of wrongful convictions in court cases.

But the distribution became famous through a morbid application: **Ladislaus Bortkiewicz** (1898) used it to model *deaths by horse kicks in the Prussian army*. He showed that these rare, random events followed the Poisson beautifully.

Why it works: When you have many opportunities for something rare to happen (many soldiers, many days), and each event is independent, the Poisson emerges naturally. The “law of rare events” — Poisson appears whenever you’re counting unlikely things in large populations.

Where You See Poisson in Social Science

Counting rare events in large populations or time windows

Political science:

- Supreme Court vacancies per presidential term (average ≈ 1.5)
- Coups in a region per decade
- Mass protests in a country per year
- Terrorist attacks per month

Economics:

- Number of bankruptcies in a sector per quarter
- Patent applications per firm per year

Criminology / Public health:

- Homicides per city per year
- Disease outbreaks per region per decade

Whenever you're counting events that happen rarely and independently, you're in Poisson territory.

The Poisson Distribution

Counting events that occur at a constant rate

The model: $X \sim \text{Poisson}(\lambda)$ counts events occurring at rate λ :

$$f(k) = \mathbb{P}(X = k) = \frac{\lambda^k e^{-\lambda}}{k!} \quad \text{for } k \in \{0, 1, 2, \dots\}$$

Support: $\{0, 1, 2, 3, \dots\}$ — can be any non-negative integer (no upper bound!)

The parameter λ is the *average rate* of events.

This formula tells us $\mathbb{P}(X = k)$ given λ . Later, we'll flip it: given observed counts, which λ makes the data most probable? That's **maximum likelihood** thinking.

Poisson Has $\mathbb{E}[X] = \text{Var}[X] = \lambda$

For $X \sim \text{Poisson}(\lambda)$:

Expected value: $\mathbb{E}[X] = \lambda$

Variance: $\text{Var}[X] = \lambda$

The mean equals the variance. This is the defining characteristic.

Why this matters: If you see count data where variance \approx mean, Poisson might be a good model. If variance \gg mean (“overdispersion”), you need something else.

Poisson Emerges When n Is Large and p Is Small

The “law of rare events”

The Poisson approximation:

If n is large and p is small (with $np = \lambda$ moderate):

$$\text{Binomial}(n, p) \approx \text{Poisson}(\lambda = np)$$

Example: Rare disease in a large population

- $n = 1,000,000$ people
- $p = 0.00001$ (1 in 100,000 chance)
- $\lambda = np = 10$

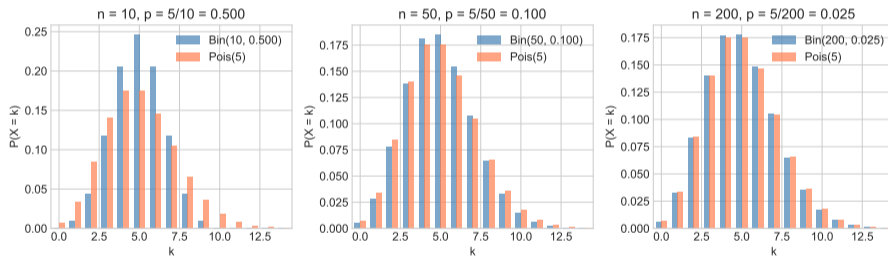
Number of cases $\approx \text{Poisson}(10)$, much easier to work with than $\text{Binomial}(1\text{M}, 0.00001)$.

This is the “law of rare events” — Poisson emerges naturally when counting unlikely things in large populations.

As n Grows and p Shrinks, Binomial \rightarrow Poisson

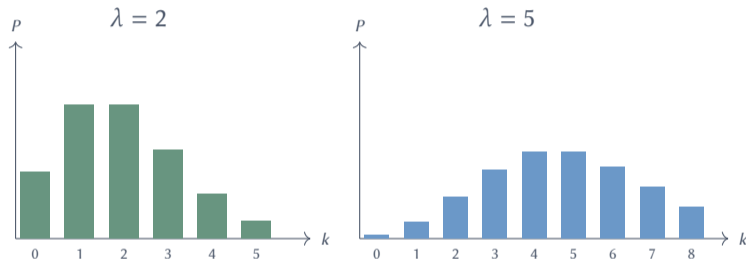
Visualization: Kaixiao Liu

Binomial \rightarrow Poisson: As $n \rightarrow \infty$, $p \rightarrow 0$, $np = \lambda$ fixed



Rule of thumb: Use Poisson approximation when $n \geq 20$ and $p \leq 0.05$.

Visualizing the Poisson



As λ increases, the distribution shifts right and becomes more symmetric.
For large λ , Poisson looks increasingly normal (another CLT application).

Key Property: Poissons Add

Theorem: If $X \sim \text{Poisson}(\lambda_1)$ and $Y \sim \text{Poisson}(\lambda_2)$ are **independent**, then:

$$X + Y \sim \text{Poisson}(\lambda_1 + \lambda_2)$$

Intuition: If events arrive at rate λ_1 from one source and λ_2 from another, the combined rate is $\lambda_1 + \lambda_2$.

Example: Counting legislative hearings

- House committees: $X \sim \text{Poisson}(12)$ per month
- Senate committees: $Y \sim \text{Poisson}(8)$ per month
- Total: $X + Y \sim \text{Poisson}(20)$

Unlike Binomial, Poisson addition works even when the rates differ.

How These Distributions Connect



- **Bernoulli** \rightarrow **Binomial**: Sum of independent 0/1 trials
- **Binomial** \rightarrow **Poisson**: Many trials, small probability (law of rare events)

Wednesday: Continuous distributions (Uniform, Normal, Exponential) and the Poisson–Exponential connection.

Summary: Three Discrete Distributions

Distribution	Support	$\mathbb{E}[X]$	$\text{Var}[X]$	Use case
Bernoulli(p)	$\{0, 1\}$	p	$p(1 - p)$	Binary outcomes
Binomial(n, p)	$\{0, \dots, n\}$	np	$np(1 - p)$	Count successes
Poisson(λ)	$\{0, 1, 2, \dots\}$	λ	λ	Rare event counts

Sum properties:

- $\text{Binomial}(n, p) + \text{Binomial}(m, p) = \text{Binomial}(n + m, p)$ (same p !)
- $\text{Poisson}(\lambda_1) + \text{Poisson}(\lambda_2) = \text{Poisson}(\lambda_1 + \lambda_2)$

These distributions will reappear constantly. Know their moments by heart.

Looking Ahead

Wednesday: Continuous distributions

- Uniform — and the “universality of uniform”
- Normal — the star of the show
- Exponential — waiting times and memorylessness
- The Poisson–Exponential connection

Reading:

- Aronow & Miller, §1.2 continued (pp. 25–50)
- Blackwell, Chapter 2.3