

Common Distributions

Background

Bernoulli

Binomial

Examples of Binomial Distribution

- Number of hexamine pallets in a batch of $n = 50$ total pallets made from a palletizing machine that conform to some standard.
- Number of runs of the same chemical process with percent yield above 80 given that you run the process 1000 times.
- Number of winning lottery tickets when you buy 10 tickets of the same kind.

Recall the shape of distributions.

Common
Distributions

Background

Bernoulli

Binomial

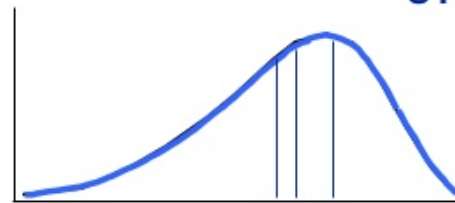
Skewness



Bell-shaped

Mode = Mean = Median

SYMMETRIC



Mean — | — | — | — Mode
 ↑ ↑ ↑
 Median

SKEWED LEFT
(negatively)



Mode — | — | — | — Mean
 ↑ ↑ ↑
 Median

SKEWED RIGHT
(positively)

Common Distributions

Background

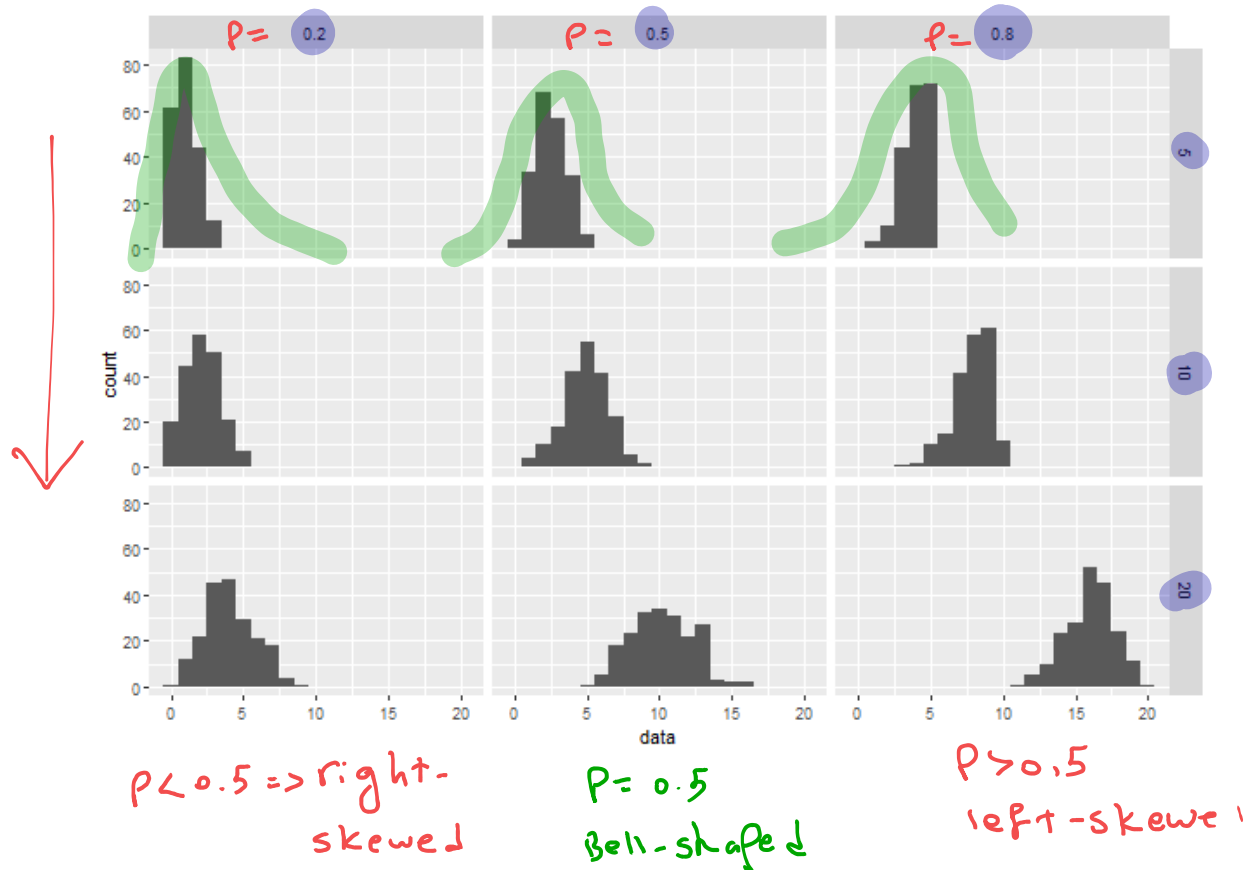
Bernoulli

Binomial
as $n \uparrow$,
skewness
decreases

for different values of n, p , binomial distribution has different shapes.

The Binomial Distribution

Plots of Binomial distribution based on different success probabilities and sample sizes.



Common Distributions

The Binomial Distribution

Background

Example [10 component machine]

Bernoulli

Suppose you have a machine with 10 independent components **in series**. The machine only works if all the components work. Each component succeeds with probability $p = 0.95$ and fails with probability $1 - p = 0.05$.

Binomial

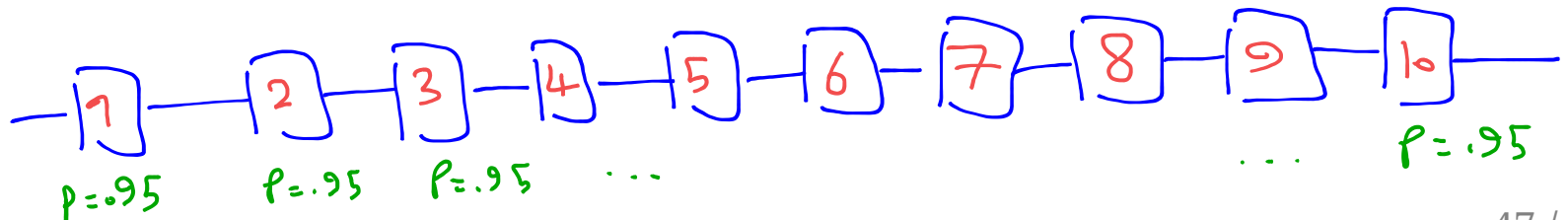
Let Y be the number of components that succeed in a given run of the machine. Then

fully specified distribution

→ $Y \sim \text{Binomial}(n = 10, p = 0.95)$

Question: what is the probability of the machine working properly?

series component system:



Each part works with probability $P = .95$.

a series system works properly if all components work.

So,

$$P(\text{"machine working"}) = P(\text{"all components work"})$$

$$= P(Y = 10)$$

$$= P(10)$$

$$\text{Recall: } P(j) = \frac{n!}{j!(n-j)!} p^j (1-p)^{n-j}$$

$(n=10, p=.95)$

$$= \frac{10!}{\underbrace{10!(10-10)!}_{0! = 1}} (0.95)^{10} (1-0.95)^{10-10}$$

$$= (0.95)^{10} = \underline{\underline{0.5987}}$$

not a very reliable system

Common Distributions

The Binomial Distribution

Background

Example [10 component machine]

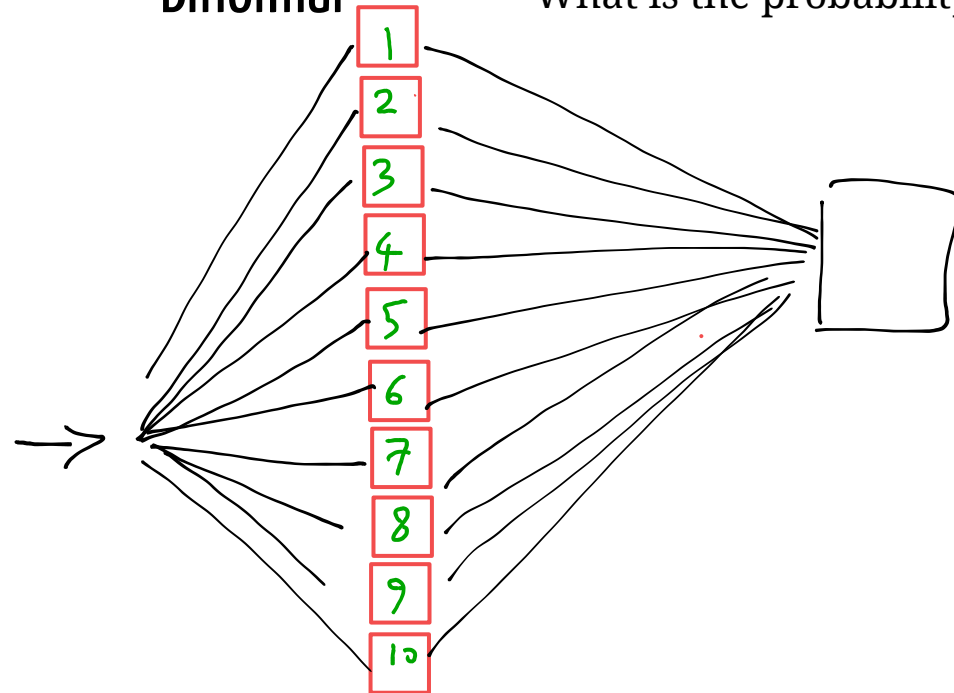
$$Y \sim \text{Binomial}(n = 10, p = 0.95)$$

Bernoulli

What if I arrange these 10 components **in parallel?** This machine succeeds if at least 1 of the components succeeds.

Binomial

What is the probability that the new machine succeeds?



$$P(\text{"machine works"}) = P(\text{"at least one component works"})$$

$$= P(Y \geq 1)$$

(complement)

$$= 1 - P(Y < 1)$$

$$= 1 - P(Y = 0)$$

$$= 1 - P(0)$$

$$= 1 - \frac{10!}{0!(10-0)!} (0.95)^0 (1-0.95)^{10-0}$$

$$= 1 - (0.05)^{10}$$

$$\approx 1 \quad (\text{a very reliable system})$$

Binomial Distribution

Expected Value and Variance

Common Distributions

The Binomial Distribution

Background

Expected value:

$$E(X) = n \cdot p$$

Bernoulli

Binomial

Variance:

$$\text{Var}(X) = n \cdot (1 - p) \cdot p$$

Recall: Bernoulli distribution \equiv Bernoulli (p)

$E(X) = p \rightarrow$ Binomial is " n " independent Bernoulli trials
So, $E(\text{Binomial}) = n \cdot p$

$\text{Var}(X) = p(1-p) \rightarrow$ similarly, $\text{Var}(\text{Binomial}) = n p(1-p)$

Common Distributions

The Binomial Distribution

Background

Example [10 component machine]

Bernoulli

Calculate the expected number of components to succeed and the variance.

Binomial

$$Y \sim \text{Binomial}(n=10, p=0.95)$$

$$E(Y) = n \cdot p = 10(0.95) = 9.5$$

(we expect 9.5 components to succeed working in the machine)

$$\text{Var}(Y) = np(1-p) = 10(0.95)(1-0.95) = 0.475$$

$$\text{SD}(Y) = \sqrt{\text{Var}(Y)} = \sqrt{0.475} = 0.689$$

Standard Deviation

Common Distributions

Background

Bernoulli

Binomial

The Binomial Distribution

A few useful notes:

- In order to say that " X has a binomial distribution with n trials and success probability p " we write

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

- If X_1, X_2, \dots, X_n are n independent Bernoulli random variables with the same p then $X = X_1 + X_2 + \dots + X_n$ is a binomial random variable with n trials and success probability p .
- Again, n and p are referred to as "parameters" for the Binomial distribution. Both are considered fixed.
- Don't focus on the actual way we got the expected value - focus on the trick of trying to get part of your complicated summation to "go away" by turning it into the sum of a probability function.

Note: There is no close form for CDF of Binomial.

The Geometric Distribution

another generic discrete r.v.

Common
Distributions

The Geometric Distribution

Background

Origin: A series of independent random experiments, or trials, are performed. Each trial results in one of two possible outcomes: successful or failure. The probability of a successful outcome, p , is the same across all trials. The trials are performed until a successful outcome is observed.

Bernoulli

Binomial

Definition: X is the trial upon which the first successful outcome is observed. X can take values $1, 2, \dots$

Geometric

probability function:

With $0 < p < 1$,

$$f(x) = \begin{cases} p(1-p)^{x-1} & x = 1, 2, \dots, \\ 0 & \text{o.w.} \end{cases}$$

There's only one parameter.

at least one trial
to observe the first
success.

Common Distributions

Background

Bernoulli

Binomial

Geometric

Examples of Geometric Distribution

- Number of rolls of a fair die until you land a 5
- Number of shipments of raw materials you get until you get a defective one (**success** does not need to have positive meaning)
- Number of car engine starts until the battery dies.

Common Distributions

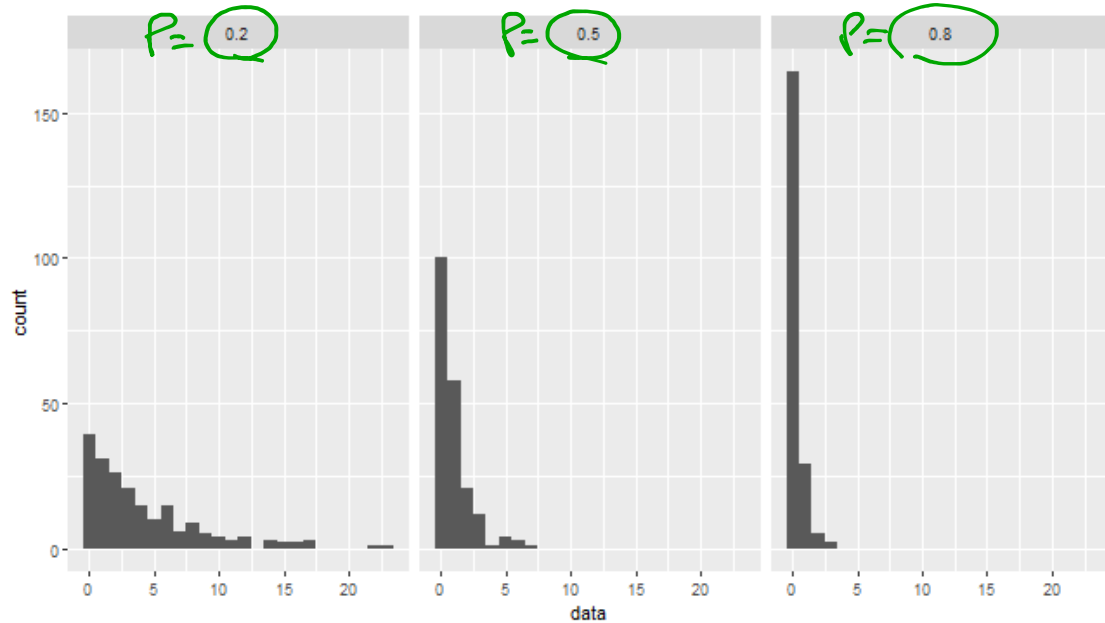
Background

Bernoulli

Binomial

Geometric

Shape of Geometric Distribution



The probability of observing the first success decreases as the number of trials increases (even at a faster rate as p increases)

Common Distributions

The Geometric Distribution

close form CDF

Background

Cumulative probability function: $F(x) = 1 - (1 - p)^x$

Here's how we get that cumulative probability function:

Bernoulli

Binomial

Geometric

optional reading

- The probability of a failed trial is $1 - p$.
- The probability the first trial fails is also just $1 - p$.
- The probability that the first two trials both fail is $(1 - p) \cdot (1 - p) = (1 - p)^2$.
- The probability that the first x trials all fail is $(1 - p)^x$.
- This gets us to this math:

$$\begin{aligned} F(x) &= P(X \leq x) \\ &= 1 - P(X > x) \\ &= 1 - (1 - p)^x \end{aligned}$$

CDF of Geometric distribution

Mean
and
Variance
of Geometric Distribution

Common Distributions

Background

Bernoulli

Binomial

Geometric

The Geometric Distribution

$$X \sim \text{Geom}(p)$$

Expected value:

$$E(X) = \frac{1}{p}$$

Variance:

$$\text{Var}(X) = \frac{1-p}{p^2}$$

Common Distributions

Example

Background

NiCad batteries: An experimental program was successful in reducing the percentage of manufactured NiCad cells with internal shorts to around 1%. Let T be the test number at which the first short is discovered. Then,

Bernoulli

$T \sim \text{Geom}(p)$.

$$\rightarrow f(t) = P(T=t) = (1-p)^{t-1}, \quad t=1,2,\dots$$

Binomial

Calculate

- $P(\text{1st or 2nd cell tested has the 1st short})$

$$P(T=1 \text{ or } T=2) = P(T=1) + P(T=2) = f(1) + f(2)$$

$$f(t) = (0.01)(0.99)^{t-1} = (0.01)(0.99)^{1-1} + (0.01)(0.99)^{2-1} = 0.0199$$

Geometric

- $P(\text{at least 50 cells tested without finding a short})$

$$P(T > 50) = 1 - P(T \leq 50) = 1 - F(50)$$

(Geometric dist. has closed form CDF)

$$= 1 - [1 - (1-p)^{50}]$$

$$= 1 - [1 - (1-0.01)^{50}] = (0.99)^{50} = 0.61$$

So, with 61% probability, the first 50

Common
Distributions

Example

NiCad have no short.

Background

NiCad batteries:

Calculate the expected test number at which the first short is discovered and the variance in test numbers at which the first short is discovered.

Bernoulli

Binomial

$$T \sim \text{Geom}(p) \Rightarrow E(T) = \frac{1}{p}$$

$$\text{Var}(T) = \frac{1-p}{p^2}$$

Geometric

$$\Rightarrow E(T) = \frac{1}{0.01} = 100$$

(on average, we need to test 100 NiCad batteries until we observe the first short)

$$\text{Var}(T) = \frac{1-0.01}{(0.01)^2} = \frac{0.99}{(0.01)^2} = 9900$$

Common Distributions

Example

Background

A shipment of 200 widgets arrives from a new widget distributor. The distributor has claimed that the widgets there is only a 10% defective rate on the widgets. Let X be the random variable associated with the number of trials until finding the first defective widgets.

$p=0.1$

Bernoulli

(success here is finding defective widget)

Binomial

- What is the probability distribution associated with this random variable X ? Precisely specify the parameter(s).

Geometric

$$X \sim \text{Geom}(p=0.1), x=1, 2, 3, \dots$$

- How many widgets would you expect to test before finding the first defective widget?

$$E(X) = \frac{1}{p} = \frac{1}{0.1} = 10$$

i.e. we need to test on avg. 10 widgets to see the first defective one.

Common Distributions

Example

Background

You find your first defective widget while testing the third widget.

Bernoulli

- What is the probability that a the first defective widget would be found **on** the third test if there are only 10% defective widgets from in the shipment?

Binomial

$$P(x = 3) = p(1 - p)^{x-1}$$

$$= 0.1(1 - 0.1)^{3-1}$$

$$= 0.1(0.9)^2 = 0.081$$

Geometric

Common Distributions

Example

Background

- What is the probability that a the first defective widget would be found **by** the third test if there are only 10% defective widgets from in the shipment?

Bernoulli

$$P(X \leq 3) = F_X(3) = 1 - (1 - p)^3$$

Binomial

$$= 1 - (1 - .1)^3$$

$$= 1 - (0.9)^3 = 0.271$$

Geometric

Recall: in Geometric distribution:

$$\text{CDF} : F(x) = 1 - (1-p)^x$$

$$\text{pmf} : f(x) = p(1-p)^{x-1}, \quad x = 1, 2, 3, \dots$$

The Poisson Distribution

Common Distributions

The Poisson Distribution

Background

Origin: A rare occurrence is watched for over a specified interval of time or space.

Bernoulli

It's often important to keep track of the total number of occurrences of some relatively rare phenomenon.

Binomial

Definition

Consider a variable

Geometric

X : the count of occurrences of a phenomenon across a specified interval of time or space

Poisson

or

X : the number of times the rare occurrence is observed

This count/number of times the rare occurrence is observed can be associated to a well-known pmf.

Common
Distributions

The Poisson Distribution

another generic
pmf.

Background

probability function:

The **Poisson** (λ) distribution is a discrete probability distribution with pmf

Bernoulli

$$f(x) = \begin{cases} \frac{e^{-\lambda} \lambda^x}{x!} & x = 0, 1, \dots \\ 0 & o.w. \end{cases}$$

Binomial

Geometric

For $\lambda > 0$

Poisson

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

parameter of
Poisson dist.

Common
Distributions

The Poisson Distribution

Background

These occurrences must:

- be independent
- be sequential in time (no two occurrences at once)
- occur at the same constant rate λ

Bernoulli

Binomial

λ the *rate parameter*, is the expected number of occurrences in **the specified interval of time or space** (i.e $E(X) = \lambda$)

Geometric

Poisson

Common Distributions

Background

Bernoulli

Binomial

Geometric

Poisson

The Poisson Distribution

Examples that could follow a Poisson(λ) distribution :

Y is the number of shark attacks off the coast of CA next year, $\lambda = 100$ attacks per year

Z is the number of shark attacks off the coast of CA next month, $\lambda = 100/12$ attacks per month

N is the number of α -particles emitted from a small bar of polonium, registered by a counter in a minute, $\lambda = 459.21$ particles per minute

J is the number of particles per hour,
 $\lambda = 459.21 * 60 = 27,552.6$ particles per hour.

Common Distributions

Background

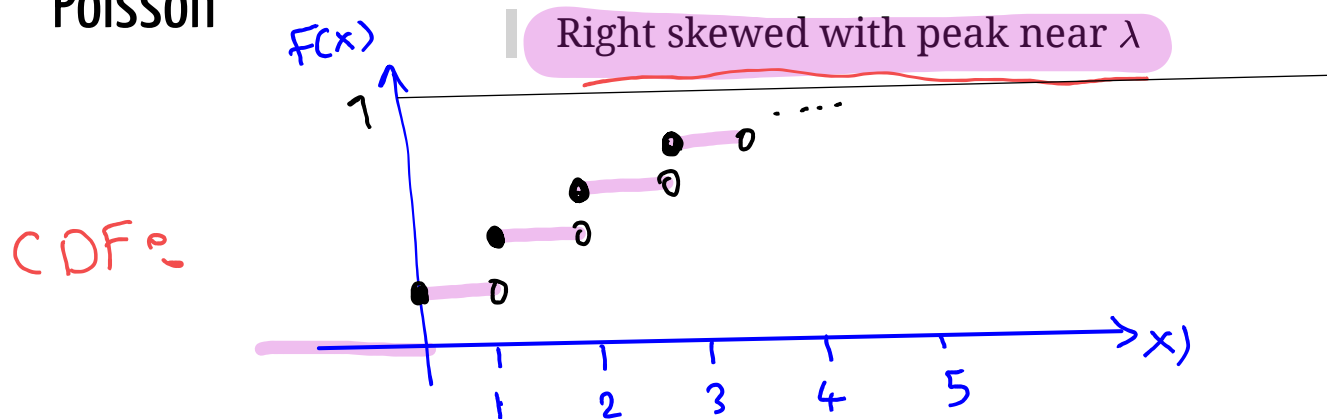
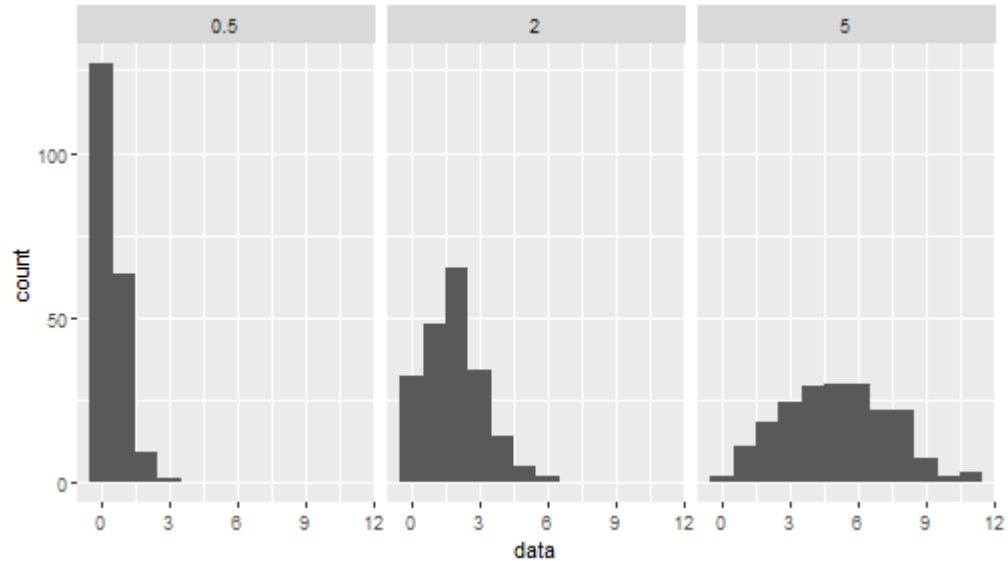
Bernoulli

Binomial

Geometric

Poisson

The Poisson Distribution



Common
Distributions

The Poisson Distribution

Background

For X a Poisson (λ) random variable,

$$\mu = \mathbb{E}X = \sum_{x=0}^{\infty} x \frac{e^{-\lambda} \lambda^x}{x!} = \lambda$$

$$\sigma^2 = \text{Var}X = \sum_{x=0}^{\infty} (x - \lambda)^2 \frac{e^{-\lambda} \lambda^x}{x!} = \lambda$$

Bernoulli

Binomial

Geometric

Poisson

Common Distributions

Example

Background

Arrivals at the library

Bernoulli

Some students' data indicate that between 12:00 and 12:10pm on Monday through Wednesday, an average of around 125 students entered Parks Library at ISU. Consider modeling

Binomial

M : the number of students entering the ISU library between 12:00 and 12:01pm next Tuesday

Geometric

Model $M \sim \text{Poisson}(\lambda)$. What would a reasonable choice of λ be?

Poisson

$$\left. \begin{array}{l} 125 \text{ students in } 10' \\ \lambda \text{ in } 1' \end{array} \right\} \Rightarrow \lambda = \frac{125}{10}$$

Common Distributions

Example

Background

Arrivals at the library

Bernoulli

Under this model, the probability that between 10 and 15 students arrive at the library between 12:00 and 12:01 PM is:

Binomial

$$M \sim \text{Poisson}(\lambda = \frac{125}{10})$$

Geometric

$$P(m) = \frac{e^{-\lambda} \lambda^m}{m!}, m = 0, 1, 2, \dots$$

Poisson

$$\begin{aligned} P(10 \leq M \leq 15) &= P(10) + P(11) + P(12) + P(13) + P(14) + P(15) \\ &= \frac{e^{-12.5} (12.5)^{10}}{10!} + \frac{e^{-12.5} (12.5)^{11}}{11!} + \dots + \frac{e^{-12.5} (12.5)^{15}}{15!} \\ &= 0.6 \end{aligned}$$

Common Distributions

Shark attacks

Background

Let X be the number of unprovoked shark attacks that will occur off the coast of Florida next year. Model

$$X \sim \text{Poisson}(\lambda).$$

Bernoulli

From the shark data at

<http://www.flmnh.ufl.edu/fish/sharks/statistics/FLactivity.htm>,
246 unprovoked shark attacks occurred from 2000 to 2009.

Binomial

What would a reasonable choice of λ be?

Geometric

Poisson

246 attacks in 10 years
 λ attacks in next year.
(only a year)

$$\Rightarrow \lambda = \frac{246}{10} = 24.6$$

Common Distributions

Shark attacks

Background

Under this model, calculate the following:

- $P(\text{no attacks next year})$

Bernoulli

$$P(X=0) = P(0) = \frac{e^{-24.6} (24.6)^0}{0!} = e^{-24.6} = 2.07 \times 10^{-11}$$

Binomial

(so unlikely to have no attacks ☺)

Geometric

- $P(\text{at least 5 attacks})$

Poisson

$$P(X \geq 5) = 1 - P(X < 5) = 1 - P(X \leq 4)$$
$$= 1 - [P(0) + P(1) + P(2) + P(3) + P(4)]$$

$$= \dots = 0.999249 \quad (\text{so probable to have at least 5 attacks})$$

- $P(\text{more than 10 attacks})$

$$P(X > 10) = 1 - P(X \leq 10) = \dots$$

wrap up

- Binomial distribution

of experiments \leftarrow
Probability of success \rightarrow
 $X \sim \text{binomial}(n, p)$

$X :=$ The number of successes out of " n " Bernoulli trials. $X = 0, 1, 2, \dots, n$

- each trial is independent of the other trials

- The probability of success, p , is the same over all n trials.

- No closed form CDF. (e.g. $P(X \leq 4) = P(X=0 \text{ or } X=1 \text{ or } X=2 \text{ or } X=3 \text{ or } X=4)$)

- $E X = n \cdot p$

- $\text{var} X = n p (1-p)$

- $\text{SD}(X) = \sqrt{\text{var} X} = \sqrt{n p (1-p)}$

- Geometric distribution: $X \sim \text{Geom}(p)$

X := The number of trials until observing the first success. $X = 1, 2, 3, \dots$

- Each trial is independent of others.

- The prob. of success, p , is the same for all trials.

(e.g. $P(X \leq 20) = 1 - (1-p)^{20}$)

← - Closed Form CDF: $F_X(x) = 1 - (1-p)^x$

$$- E X = \frac{1}{p}$$

$$- \text{Var } X = \frac{1-p}{p^2}$$

$$- \text{SD}(X) = \sqrt{\text{Var } X} = \sqrt{\frac{1-p}{p^2}}$$

Poisson distribution;

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

X = The count of occurrences over a specific period of time or space.

$$X = 0, 1, 2, \dots$$

- independent occurrences
- no two occurrences at the same time
- occur at the same constant rate λ .

λ is the rate parameter & is the expected number of occurrences in the specific interval of time or space

