

## Topic 9

# Examples of Mass Functions and Densities

## Discrete Random Variables

# Outline

Bernoulli

Binomial

Negative Binomial

Poisson

Hypergeometric

# Introduction

Write

$$f_X(x|\theta) = P_\theta\{X = x\}$$

for the **mass function** of the given **family** of discrete random variables depending on the **parameter**  $\theta$ . We will

- use the expression  $Family(\theta)$  as shorthand for this family
- followed by the R command `family` and
- the **state space**  $S$ .

# Bernoulli Random Variables

$Ber(p)$  on  $S = \{0, 1\}$

$$f_X(x|p) = \left\{ \begin{array}{ll} 0 & \text{with probability } (1 - p), \\ 1 & \text{with probability } p, \end{array} \right\} = p^x(1 - p)^{1-x}.$$

This is the simplest random variable, taking on only two values, namely, 0 and 1.

Think of it as the outcome of a **Bernoulli trial**, i.e., a single toss of an unfair coin that turns up heads with probability  $p$ .

## Binomial Random Variables

$Bin(n, p)$  (R command `binom`) on  $S = \{0, 1, \dots, n\}$

$$f_X(x|p) = \binom{n}{x} p^x (1-p)^{n-x}.$$

The binomial distribution arises from computing the probability of  $x$  **successes** in  $n$  **Bernoulli trials**.

Considered in this way, the family  $Ber(p)$  is also  $Bin(1, p)$ .

**Exercise.** Enter in R `plot(c(0:12), dbinom(c(0:12), 12, p, ), type="h")` for  $p=0.25, 0.5, 0.75$ . Describe what you see.

## Negative Binomial Random Variables

$Negbin(n, p)$  (R command `nbinom`) on  $S = \mathbb{N}$

$$f_X(x|p) = \binom{n+x-1}{x} p^n (1-p)^x.$$

This random variable is the number of *failed* Bernoulli trials before the *n-th success*.

To find the mass function,

- For the outcome  $\{X = x\}$ , the *n-th success* must occur on the  $n + x$ -th trial. So,
- we must have  $n - 1$  successes and  $x$  failures in first  $n + x - 1$  Bernoulli trials
- followed by success on the last trial.

## Negative Binomial Random Variables

The first  $n + x - 1$  trials and the last trial are **independent** and so the **probabilities multiply**.

$$\begin{aligned}
 P_p\{X = x\} &= P_p\{n - 1 \text{ successes in } n + x - 1 \text{ trials, success in the } n - x\text{-th trial}\} \\
 &= P_p\{n - 1 \text{ successes in } n + x - 1 \text{ trials}\} P_p\{\text{success in the } n - x\text{-th trial}\} \\
 &= \binom{n + x - 1}{n - 1} p^{n-1} (1 - p)^x \cdot p = \binom{n + x - 1}{x} p^n (1 - p)^x
 \end{aligned}$$

The first factor is computed from the **binomial distribution**, the second from the **Bernoulli distribution**. Note the use of the identity

$$\binom{m}{k} = \binom{m}{m - k}$$

in giving the final formula.

## Poisson Random Variables

$Pois(\lambda)$  (R command `pois`) on  $S = \mathbb{N}$

$$f_X(x|\lambda) = \frac{\lambda^x}{x!} e^{-\lambda}.$$

The Poisson distribution approximates of the binomial distribution for  $n$  large,  $p$  small, but the product  $\lambda = np$  is moderate.

Examples.

- **bacterial colonies**
  - $n$  is the number of bacteria and  $p$  is the probability of a mutation,
- **recombination events during meiosis**
  - $n$  is the number of nucleotides on a chromosome and  $p$  is the probability of a recombination event occurring at a particular nucleotide.

The product  $\lambda$  is the **mean** number of events.



## Poisson Random Variables

The approximation is based on the limit

$$\lim_{n \rightarrow \infty} \left(1 - \frac{\lambda}{n}\right)^n = e^{-\lambda}.$$

We compute binomial probabilities, replace  $p$  by  $\lambda/n$  and take a limit as  $n \rightarrow \infty$ .

In this computation, we use the fact that for a fixed value of  $x$ ,

$$\frac{(n)_x}{n^x} \rightarrow 1 \quad \text{and} \quad \left(1 - \frac{\lambda}{n}\right)^{-x} \rightarrow 1 \quad \text{as } n \rightarrow \infty$$

## Poisson Random Variables

$$P\{X = 0\} = \binom{n}{0} p^0 (1-p)^n = \left(1 - \frac{\lambda}{n}\right)^n \approx e^{-\lambda}$$

$$P\{X = 1\} = \binom{n}{1} p^1 (1-p)^{n-1} = n \frac{\lambda}{n} \left(1 - \frac{\lambda}{n}\right)^{n-1} \approx \lambda e^{-\lambda}$$

$$P\{X = 2\} = \binom{n}{2} p^2 (1-p)^{n-2} = \frac{n(n-1)}{2} \left(\frac{\lambda}{n}\right)^2 \left(1 - \frac{\lambda}{n}\right)^{n-2} = \frac{n(n-1)}{n^2} \frac{\lambda^2}{2} \left(1 - \frac{\lambda}{n}\right)^{n-2} \approx \frac{\lambda^2}{2} e^{-\lambda}$$

$$\vdots$$

$$\vdots$$

$$\vdots$$

$$P\{X = x\} = \binom{n}{x} p^x (1-p)^{n-x} = \frac{(n)_x}{x!} \left(\frac{\lambda}{n}\right)^x \left(1 - \frac{\lambda}{n}\right)^{n-x} = \frac{(n)_x}{n^x} \frac{\lambda^x}{x!} \left(1 - \frac{\lambda}{n}\right)^{n-x} \approx \frac{\lambda^x}{x!} e^{-\lambda}.$$

Exercise. Explain why

$$\sum_{x=0}^{\infty} f_X(x) = \sum_{x=0}^{\infty} \frac{\lambda^x}{x!} e^{-\lambda} = 1.$$

# Hypergeometric Random Variables

$\text{Hyper}(m, n, k)$  (R command `hyper`) on  $S = \{\max\{0, k - n\}, \dots, \min\{m, k\}\}$

$$f_X(x|m, n, k) = \frac{\binom{m}{x} \binom{n}{k-x}}{\binom{m+n}{k}}$$

- Begin with an urn holding  $m$  white balls and  $n$  black balls.
- Remove  $k$  at random and
- let the random variable  $X$  denote the number of white balls.

## Hypergeometric Random Variables

We consider equally likely outcomes to determine  $f_X(x|m, n, k) = P_{m,n,k}\{X = x\}$ .

- The total number of possible outcomes,  $\#(\Omega)$ , namely, the number of ways to choose  $k$  balls out of an urn containing  $m + n$  balls.

$$\binom{m+n}{k}.$$

This will be the **denominator** for the probability.

- For the **numerator**, the outcomes that result in  $x$  white balls from the total of  $m$ , we must also choose  $k - x$  black balls from the total of  $n$ . By the multiplication property, the number of ways  $\#(A_x)$  to accomplish this is product.

$$\binom{m}{x} \binom{n}{k-x}.$$

Finally,  $f_X(x|m, n, k) = \#(A_x)/\#(\Omega)$ .