

## Topic 9

### Examples of Mass Functions and Densities

#### Continuous Random Variables

# Outline

Uniform

Exponential

Gamma

Beta

Normal

Test Statistics

R Commands

# Introduction

We will characterize a **family** of continuous random variables depending on the **parameter**  $\theta$ , with their density

$$f_X(x|\theta) \approx \frac{1}{\Delta x} P_\theta\{x < X \leq x + \Delta x\}.$$

We will

- use the expression  $\text{Family}(\theta)$  as shorthand for this family
- followed by the R command `family` and
- the **state space**  $S$ . The density is 0 outside of  $S$ .

# Uniform Random Variables

$U(a, b)$  (R command `unif`) on  $S = [a, b]$ ,  
 $a < b$

$$f_X(x|a, b) = \frac{1}{b-a}.$$

Independent  $U(0, 1)$  are the most common choice for generating random numbers. Use the R command `runif(n)` to simulate  $n$  independent random numbers.

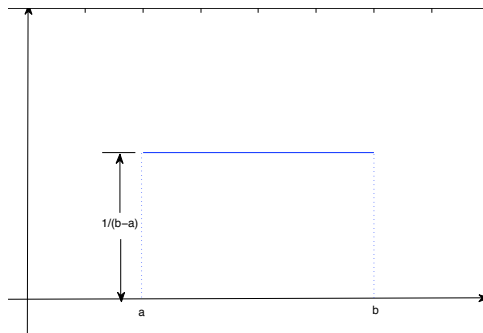


Figure: Uniform density on the interval  $[a, b]$

## Exponential Random Variables

$Exp(\lambda)$  (R command `exp`) on  $S = [0, \infty)$

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

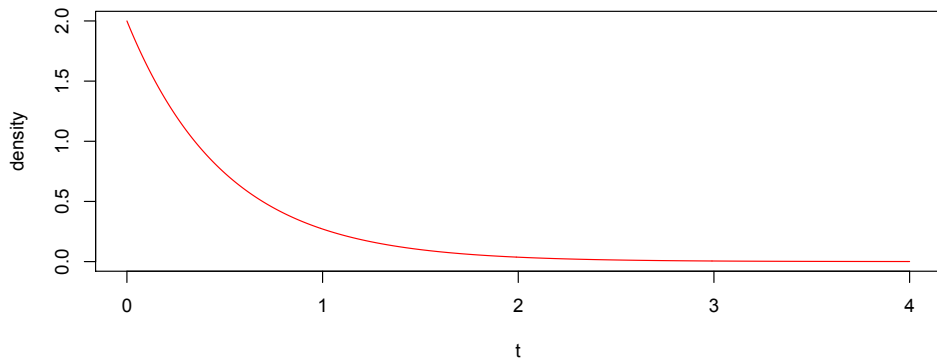


Figure: Exponential density with parameter  $\lambda = 2$

## Exponential Random Variables

Consider **Bernoulli trials** arriving at a rate of  $n$  trials per time unit.

- Let the **probability of success**  $p$  be small,
- $nt$  the number of trials up to a given time  $t$  be large, and
- $\lambda = np$  be moderate in size.

Let  $T$  be the **time of the first success**. This random time exceeds a given time  $t$  if we begin with  $nt$  consecutive failures. The survival function

$$\bar{F}_T(t) = P\{T > t\} = (1 - p)^{nt} = \left(1 - \frac{\lambda}{n}\right)^{nt} \approx e^{-\lambda t}.$$

The cumulative distribution function

$$F_T(t) = P\{T \leq t\} = 1 - P\{T > t\} \approx 1 - e^{-\lambda t}.$$

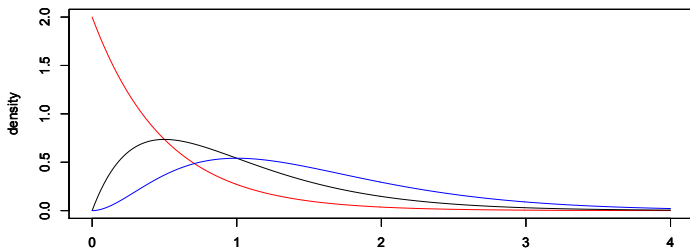
The density can be found by taking a derivative of  $F_T(t)$ .

## Gamma Random Variables

$\Gamma(\alpha, \beta)$  (R command `gamma`) on  $S = [0, \infty)$ ,

$$f_X(x|\alpha, \beta) = \frac{\beta^\alpha}{\Gamma(\alpha)} x^{\alpha-1} e^{-\beta x}$$

The **gamma function**  $\Gamma(s) = \int_0^\infty x^s e^{-x} \frac{dx}{x}$ , `gamma(s)` in R.



The **gamma density** with parameters  $\beta = 2$  and  $\alpha = 1, 2, 3$ , `Gamma( $\beta, 1$ )` is `Exp( $\beta$ )`

# Gamma Random Variables

Let  $n$  be a positive integer.

- a  $\Gamma(n, \lambda)$  random variable can be seen as an approximation to the **negative binomial random variable** using the ideas that leads from the geometric random variable to the exponential.
- Alternatively,  $\Gamma(n, \lambda)$  is the sum of  $n$  independent  $\text{Exp}(\lambda)$  random variables.
  - This special case of the gamma distribution is sometimes called the **Erlang distribution** and was originally used in models for telephone traffic.



# Beta Random Variables

$Beta(\alpha, \beta)$  (R command `beta`) on  $S = [0, 1]$

$$f_X(x|\alpha, \beta) = \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)\Gamma(\beta)} x^{\alpha-1} (1-x)^{\beta-1}.$$

Beta random variables appear in a variety of circumstances. One example is the **order statistics**. Beginning with  $n$  independent  $U(0, 1)$  random variables and rank them

$$X_{(1)}, X_{(2)}, \dots, X_{(n)}$$

from smallest to largest. Then, the  $k$ -th order statistic  $X_{(k)}$  is  $Beta(k, n - k + 1)$ .

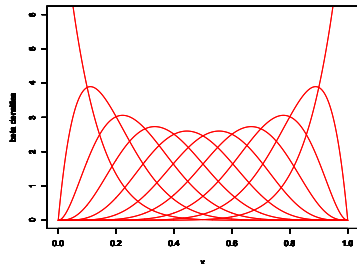


Figure: Densities of **order statistics**,  $n = 10$

# Normal Random Variables

$N(\mu, \sigma)$  (R command `norm`) on  $S = \mathbb{R}$

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

Thus, a **standard normal random variable** is  $N(0, 1)$ .

Other normal random variables are **linear transformations** of  $Z$ , the standard normal. In particular,  $X = \sigma Z + \mu$  has a  $N(\mu, \sigma)$  distribution.

The final examples, each of them derived from normal random variables, will be used in **hypothesis testing**. In practice, probabilities are generally computed using software rather than working with the densities explicitly

## Student's $t$ Random Variables

$t_\nu(\mu, \sigma)$  (R command `t`) on  $S = \mathbb{R}$

$$f_X(x|\nu, \mu, \sigma) = \frac{\Gamma((\nu+1)/2)}{\sqrt{\nu\pi}\Gamma(\nu/2)\sigma} \left(1 + \frac{(x-\mu)^2}{\nu\sigma^2}\right)^{-(\nu+1)/2}.$$

The value  $\nu$  is also called the number of **degrees of freedom**. If  $\bar{Z}$  is the sample mean of  $n$  **standard normal random variables** and

$$S^2 = \frac{1}{n-1} \sum_{i=1}^n (Z_i - \bar{Z})^2 \quad \text{is the **sample variance**}$$

$$\text{then, } T = \frac{\bar{Z}}{S/\sqrt{n}}.$$

has a  $t_{n-1}(0, 1)$  distribution.

## $\chi^2$ and $F$ Random Variables

$\chi^2_\nu$  (R command `chisq`) on  $S = [0, \infty)$

$$f_X(x|\nu) = \frac{x^{\nu/2-1}}{2^{\nu/2}\Gamma(\nu/2)} e^{-x/2}.$$

The value  $\nu$  is called the number of **degrees of freedom**. For  $\nu$  a **positive integer**,  $\chi^2_\nu$  is the **sum of the the squares** of  $\nu$  **standard normal random variables**.

$F_{\nu_1, \nu_2}$  (R command `f`) on  $S = [0, \infty)$

$$f_X(x|\nu_1, \nu_2) = \frac{\Gamma((\nu_1 + \nu_2)/2) \nu_1^{\nu_1/2} \nu_2^{\nu_2/2}}{\Gamma(\nu_1/2)\Gamma(\nu_2/2)} x^{\nu_1/2-1} (\nu_2 + \nu_1 x)^{-(\nu_1+\nu_2)/2}.$$

The  $F$  distribution is used in **analysis of variance** tests.  $F$  is the **ratio** of independent  $\chi^2_{\nu_1}$  and  $\chi^2_{\nu_2}$  random variables.

# R Commands

R can compute a variety of values for many families of distributions.

- `dfamily(x, parameters)` is the **mass function** (for discrete random variables) or **probability density** (for continuous random variables) of **family** evaluated at **x**.
- `qfamily(p, parameters)` returns **x** satisfying  $P\{X \leq x\} = p$ , the **p-th quantile** where **X** has the given distribution,
- `pfamily(x, parameters)` returns  $P\{X \leq x\}$  where **X** has the given distribution.
- `rfamily(n, parameters)` generates **n** random variables having the given distribution.

# R Commands

## Exercise.

1. Find  $P\{X = x\}$  for  $x = 0, 1, 2, 3, 4, 5$  for a  $\text{Bin}(5, 3/7)$  random variable.
2. Find the first and third quartiles as well as the median for a  $\text{Beta}(3, 3)$  random variables.
3. Find  $P\{X \leq x\}$  for  $x = 0, 1, 2, 3$  for a  $\chi^2_2$  random variable.
4. Simulate 80  $\text{Pois}(5)$  random variable. Find the mean and variance of these simulated values.