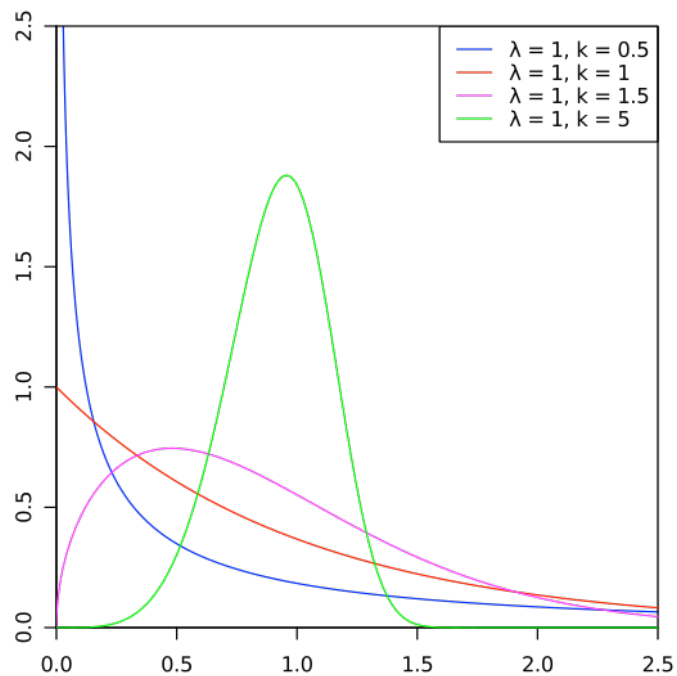
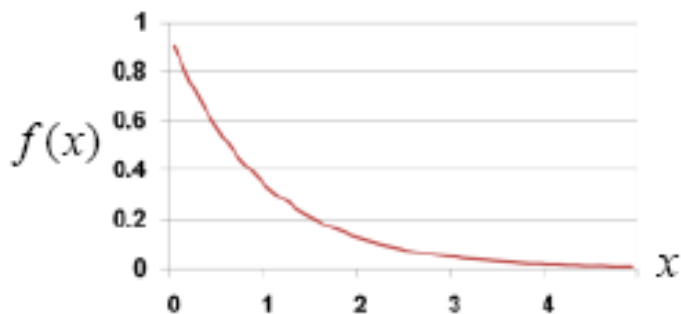


continuous random variables



Discrete random variable: takes values in a finite or countable set, e.g.

$X \in \{1, 2, \dots, 6\}$ with equal probability

X is positive integer i with probability 2^{-i}

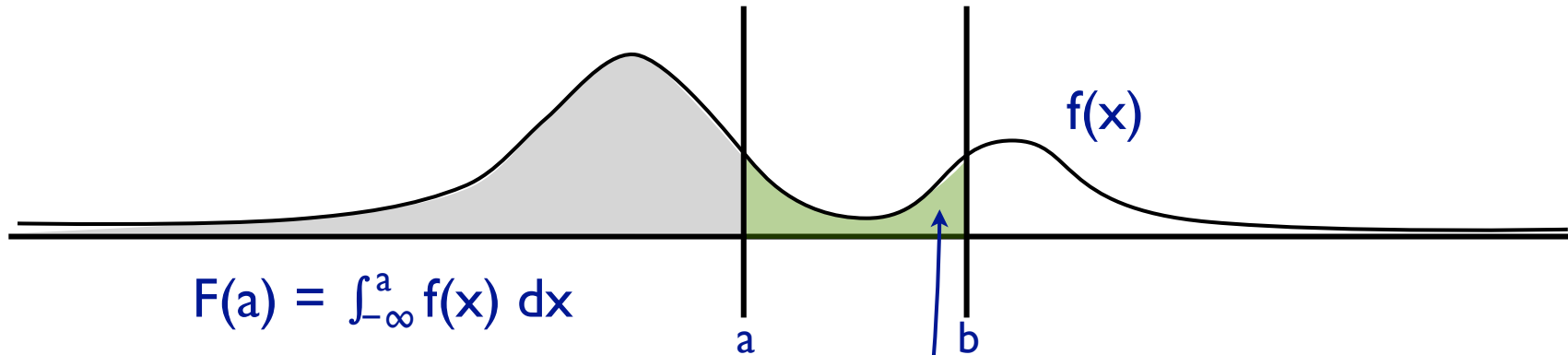
Continuous random variable: takes values in an uncountable set, e.g.

X is the weight of a random person (a real number)

X is a randomly selected point inside a unit square

X is the waiting time until the next packet arrives at the server

$f(x)$: the *probability density function* (or simply “density”)



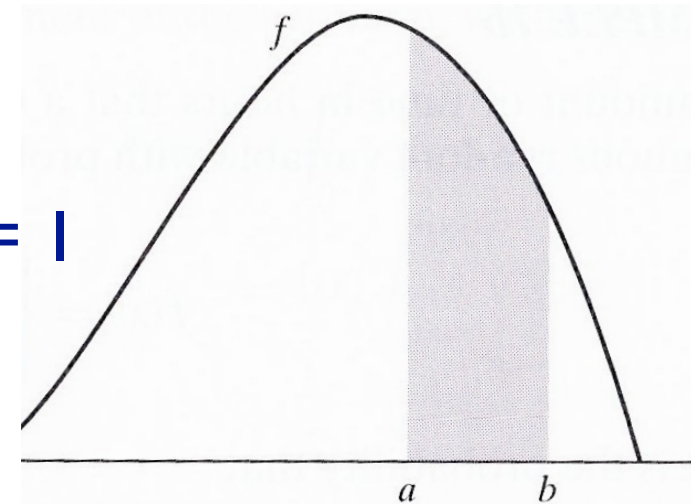
$P(X \leq a) = F(x)$: the *cumulative distribution function* (or simply “distribution”)

$$P(a < X \leq b) = F(b) - F(a)$$

Need $f(x) \geq 0$, & $\int_{-\infty}^{+\infty} f(x) dx (= F(+\infty)) = 1$

A key relationship:

$$f(x) = \frac{d}{dx} F(x), \text{ since } F(a) = \int_{-\infty}^a f(x) dx,$$



Densities are *not* probabilities

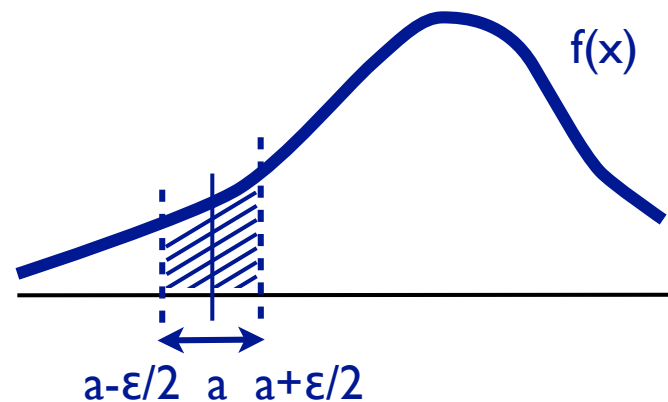
$$P(X = a) = P(a \leq X \leq a) = F(a) - F(a) = 0$$

I.e., the probability that a continuous random variable falls *at* a specified point is *zero*

$$P(a - \varepsilon/2 \leq X \leq a + \varepsilon/2) =$$

$$F(a + \varepsilon/2) - F(a - \varepsilon/2)$$

$$\approx \varepsilon \cdot f(a)$$



I.e., The probability that it falls *near* that point is proportional to the density; in a large random sample, expect more samples where density is higher (hence the name “density”).

Much of what we did with discrete r.v.s carries over almost unchanged, with $\sum_{x\dots}$ replaced by $\int \dots dx$

E.g.

For discrete r.v. X , $E[X] = \sum_x xp(x)$

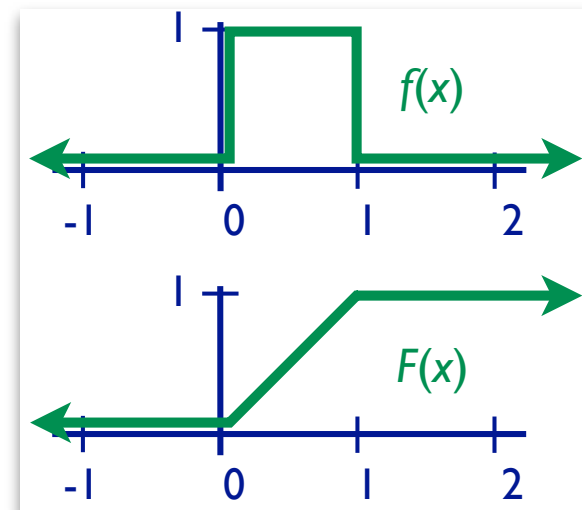
For continuous r.v. X , $E[X] = \int_{-\infty}^{\infty} x \cdot f(x) dx$

Why?

(a) We define it that way

(b) The probability that X falls “near” x , say within $x \pm dx/2$, is $\approx f(x)dx$, so the “average” X should be $\approx \sum xf(x)dx$ (summed over grid points spaced dx apart on the real line) and the limit of that as $dx \rightarrow 0$ is $\int xf(x)dx$

$$\text{Let } f(x) = \begin{cases} 1 & \text{for } 0 < x < 1 \\ 0 & \text{elsewhere} \end{cases}$$



$$F(a) = \int_{-\infty}^a f(x) dx$$

$$= \begin{cases} 0 & \text{if } a \leq 0 \\ a & \text{if } 0 < a \leq 1 \text{ (since } a = \int_0^a 1 dx \text{)} \\ 1 & \text{if } 1 < a \end{cases}$$

$$E[X] = \int_{-\infty}^{\infty} x f(x) dx = \int_0^1 x dx = \left. \frac{x^2}{2} \right|_0^1 = \frac{1}{2}$$

$$E[X^2] = \int_{-\infty}^{\infty} x^2 f(x) dx = \int_0^1 x^2 dx = \left. \frac{x^3}{3} \right|_0^1 = \frac{1}{3}$$

$$\text{Var}[X] = E[X^2] - (E[X])^2 = \frac{1}{3} - \frac{1}{4} = \frac{1}{12} \quad (\sigma \approx 0.29)$$

Linearity

$$E[aX+b] = aE[X]+b$$

$$E[X+Y] = E[X]+E[Y]$$

still true, just as
for discrete

Functions of a random variable

$$E[g(X)] = \int g(x)f(x)dx$$

just as for discrete,
but w/integral

Definition is same as in the discrete case

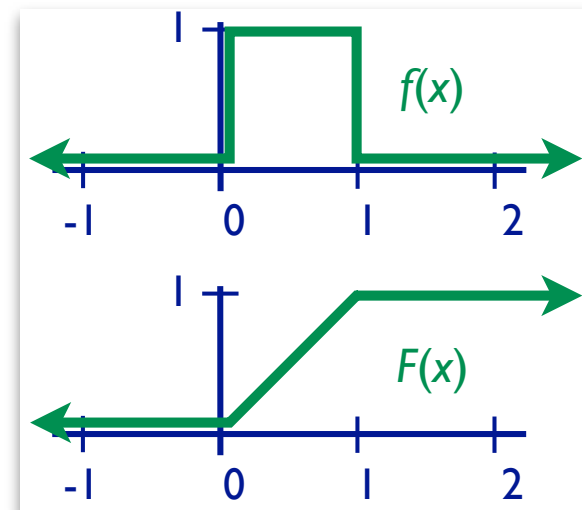
$$\text{Var}[X] = E[(X-\mu)^2] \quad \text{where } \mu = E[X]$$

Identity still holds:

$$\text{Var}[X] = E[X^2] - (E[X])^2$$

proof “same”

$$\text{Let } f(x) = \begin{cases} 1 & \text{for } 0 < x < 1 \\ 0 & \text{elsewhere} \end{cases}$$



$$F(a) = \int_{-\infty}^a f(x) dx$$

$$= \begin{cases} 0 & \text{if } a \leq 0 \\ a & \text{if } 0 < a \leq 1 \text{ (since } a = \int_0^a 1 dx \text{)} \\ 1 & \text{if } 1 < a \end{cases}$$

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$$\text{Var}[X] = E[X^2] - (E[X])^2 = \frac{1}{3} - \frac{1}{4} = \frac{1}{12} \quad (\sigma \approx 0.29)$$

continuous random variables: summary

Continuous random variable X has density $f(x)$, and

$$\Pr(a \leq X \leq b) = \int_a^b f(x) dx$$

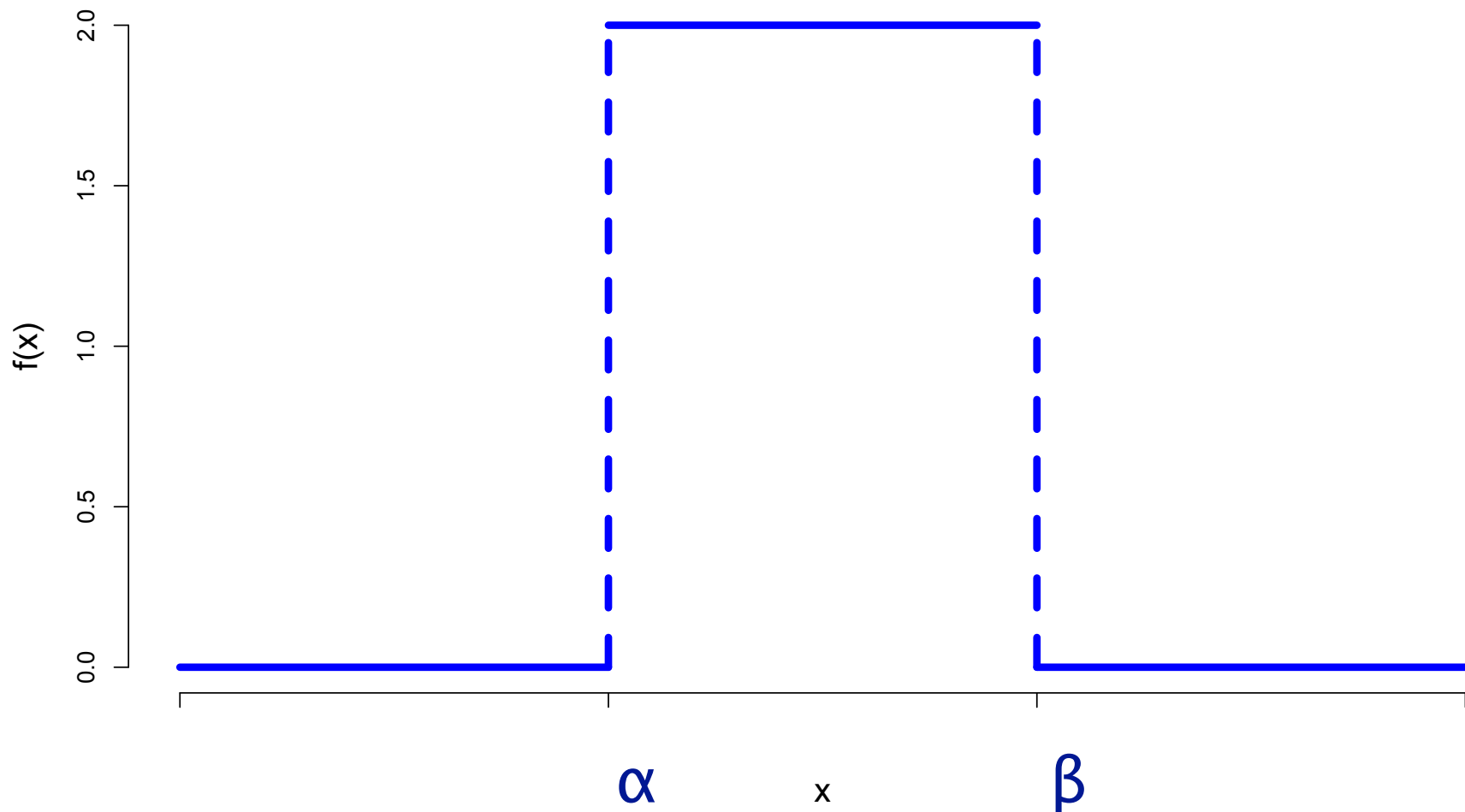
$$E[X] = \int_{-\infty}^{\infty} x \cdot f(x) dx$$

$$E[X^2] = \int_{-\infty}^{\infty} x^2 \cdot f(x) dx$$

uniform random variable

$$X \sim \text{Uni}(\alpha, \beta) \text{ is uniform in } [\alpha, \beta] \quad f(x) = \begin{cases} \frac{1}{\beta - \alpha} & x \in [\alpha, \beta] \\ 0 & \text{otherwise} \end{cases}$$

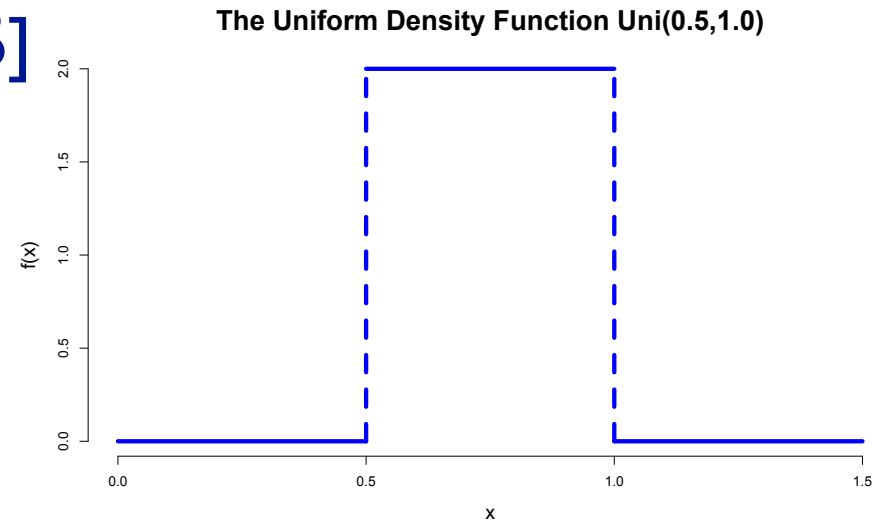
The Uniform Density Function Uni(0.5,1.0)



uniform random variable

$X \sim \text{Uni}(\alpha, \beta)$ is uniform in $[\alpha, \beta]$

$$f(x) = \begin{cases} \frac{1}{\beta - \alpha} & x \in [\alpha, \beta] \\ 0 & \text{otherwise} \end{cases}$$



$$\Pr(a \leq X \leq b) = \int_a^b f(x) dx = \frac{b - a}{\beta - \alpha}$$

if $\alpha \leq a \leq b \leq \beta$:

$$E[X] = \int_{-\infty}^{\infty} x \cdot f(x) dx = \frac{\alpha + \beta}{2}$$