

Random variables

Cumulative distribution function (cdf)

Definition: The **cumulative distribution function (cdf)** of a random variable X , denoted by $F(\cdot)$, is defined by

$$F(x) = P(X \leq x), \quad \text{any } x \in \mathbb{R}$$

Sometimes written with subscript $F_X(x)$

A function $F(x)$, $x \in \mathbb{R}$, is a cdf for some random variable **if and only if** the following hold:

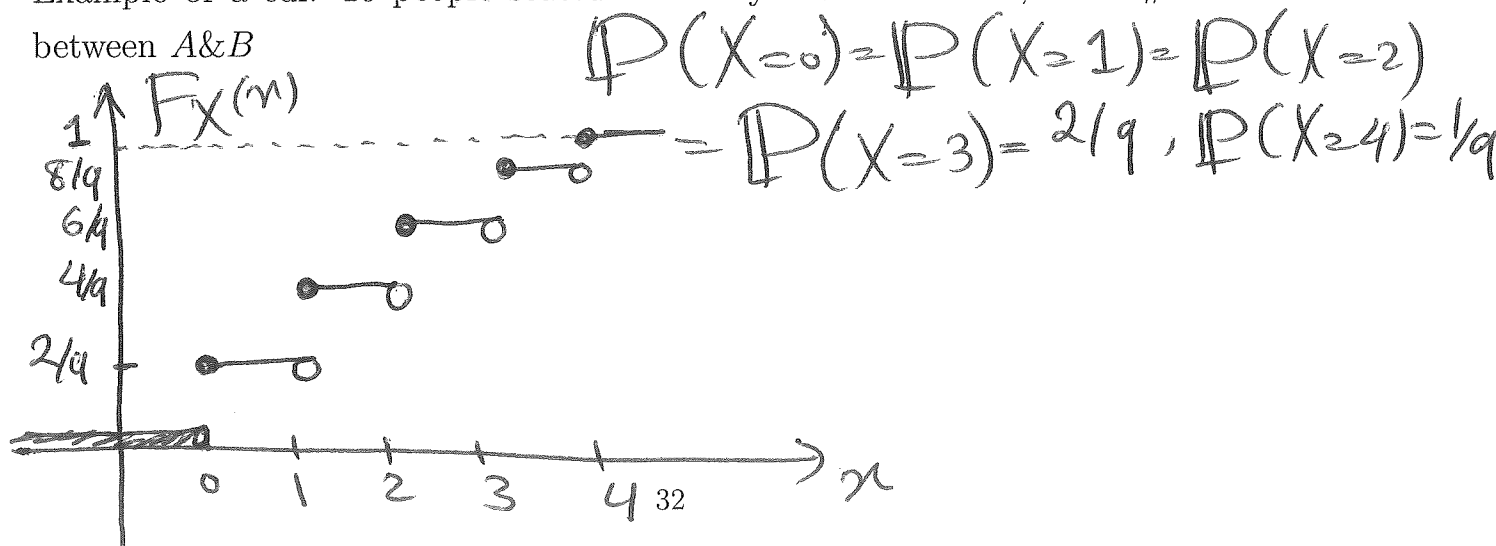
1. $F(x)$ is a nondecreasing function of x
2. $\lim_{x \rightarrow -\infty} F(x) = 0 \quad \lim_{x \rightarrow \infty} F(x) = 1$
3. $F(x)$ is right continuous, i.e., $\lim_{x \downarrow x_0} F(x) = F(x_0)$ for any $x_0 \in \mathbb{R}$

e.g., to show part 1., take $y \geq x$ and $F(y) - F(x) = P(X \leq y) - P(X \leq x)$.

$$y \geq x \Rightarrow \{X \leq x\} \subset \{X \leq y\}$$

$$F(x) = P(X \leq x) \leq P(X \leq y) = F(y)$$

Example of a cdf: 10 people seated randomly around a table; $X = \#$ of seats between A & B



Random variables

Discrete random variables & probability mass functions

- *Definition:* If a cdf F is a step function (with jumps at a countable collection of points $x_i \in \mathbb{R}$), then we say the distribution described by F is **discrete** (with support or range $x_i \in \mathbb{R}$).

If a random variable X has a cdf $F = F_X$ which is a step function, then we say X is a **discrete random variable**.

*X is discrete (i.e. cdf F is step-function)
If $P(X \in \{x_i\}) = 1$ for some set $\{x_i\}$
of countable values in \mathbb{R}*

- Besides the cdf, there are other (equivalent) ways to state the probability distribution for a discrete distribution/discrete r.v. X .

1. The **probability mass function (pmf)** of a discrete random variable X is given by

$$f(x) = P(X = x) \geq 0, \quad \text{for any } x \in \mathbb{R}$$

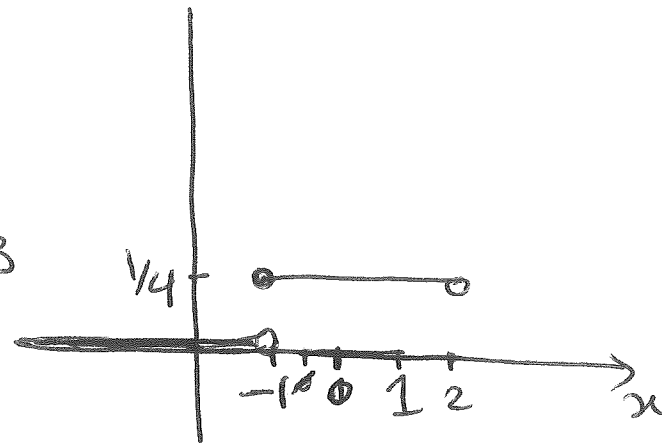
2. Equivalently, the pmf of a discrete r.v. X is

$$f(x) = \underbrace{P(X \leq x) - P(X < x)}_{P(X=x)} = F(x) - \lim_{y \rightarrow x^-} F(y)$$

*e.g. random seating
 $X = \#$ of seats between
A & B*

$$f(x) = P(X=x) = \begin{cases} 2/9 \\ 1/9 \\ 0 \end{cases}$$

$$\begin{aligned} x &= 0, 1, 2, 3 \\ x &= 4 \\ &0.w \end{aligned}$$



$$\text{Note that } F(x) = P(X \leq x) = \sum_{z \leq x} f(z) = \sum_{z \leq x, f(z) > 0} f(z)$$

Random variables

Continuous random variables & probability density functions

- If a cdf F is such that there is a nonnegative function f such that

$$F(x) = \int_{-\infty}^x f(t)dt, \quad \text{for any } x \in \mathbb{R},$$

then the distribution described by F is said to be (absolutely) **continuous** with **probability density function (pdf)** f .

A random variable X with an (absolutely) continuous cdf F , or a pdf f , is said to be a **continuous random variable**.

- If F is (absolutely) continuous then its derivative at $x \in \mathbb{R}$ is its pdf $f(x)$

$$F'(x) = \frac{dF(x)}{dx} = f(x)$$

- If X is a continuous random variable then $P(X = x) = 0$ for any $x \in \mathbb{R}$.

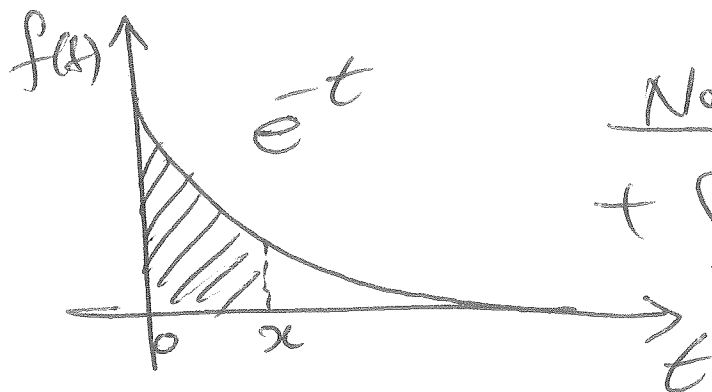
$$\begin{aligned} P(a < X < b) &= P(a \leq X \leq b) \\ &= P(a \leq X \leq b) \\ &= P(a < X < b) = F(b) - F(a) \\ &= \int_a^b f(t)dt \end{aligned}$$

- Technical points: An absolutely continuous cdf has a derivative and so is more than just continuous. We *ignore* the distinction between a continuous & absolutely continuous cdf. Also, the derivative of F might not technically exist for *every* $x \in \mathbb{R}$ but this never matters (i.e., doesn't affect integrals); we just say $F'(x) = f(x)$ in any case.

Random variables

Continuous random variables & probability density functions (cont'd)

A continuous cdf example. Consider the function $f(x) = \begin{cases} e^{-x} & x > 0 \\ 0 & x \leq 0 \end{cases}$



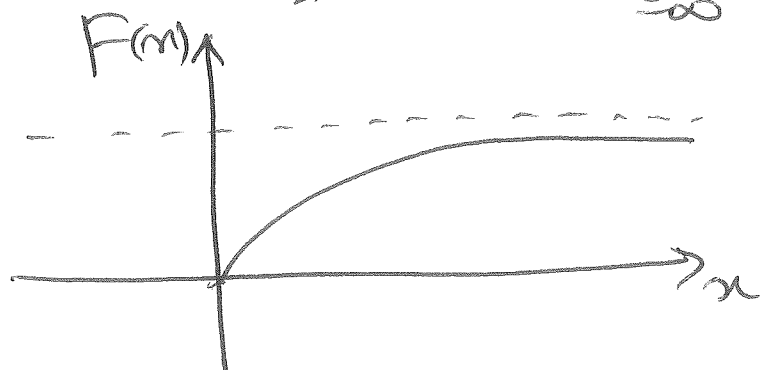
Note: $f(x) \geq 0 \quad \forall x \in \mathbb{R}$

$$+ \int_{-\infty}^{\infty} f(x) dx = \int_0^{\infty} e^{-x} dx = 1$$

p.d.f $f \Rightarrow$ c.d.f F

$$F(x) = \mathbb{P}(X \leq x) = \int_{-\infty}^x f(t) dt =$$

$$\begin{cases} \int_{-\infty}^x 0 dt = 0 & \text{If } x \leq 0 \\ \int_0^x e^{-t} dt = 1 - e^{-x} & \text{If } x > 0 \end{cases}$$



$$\begin{aligned} \mathbb{P}(1 \leq X \leq 2) &= F(2) - F(1) = e^{-1} - e^{-2} \\ &= \int_1^2 f(x) dx \\ &\quad \underbrace{\quad}_{e^{-x}} \end{aligned}$$

$$\mathbb{P}(X=2) = \int_2^2 f(x) dx = 0$$

$$f(x) = \frac{dF(x)}{dx} = \begin{cases} \frac{d0}{dx} = 0 & \text{If } x < 0 \\ \frac{d(1 - e^{-x})}{dx} = e^{-x} & \text{If } x \geq 0 \end{cases}$$

Random variables

Properties of probability density or mass functions

A function $f(x)$ is a pdf (or pmf) for some random variable if and only if

1. $f(x) \geq 0$ for any $x \in \mathbb{R}$
2. $\int_{-\infty}^{\infty} f(x)dx = 1$ (or $\sum_x f(x) = 1$)

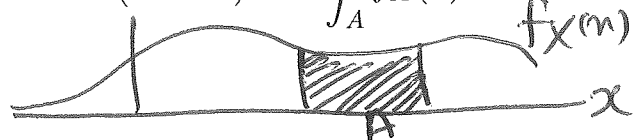
Any nonnegative function having a finite integral (or sum) can be turned into a pdf (or pmf) f by dividing by its integral (or sum)

We will write $X \sim f_X(x)$ (or $X \sim F_X(x)$) to denote that X has a distribution given by f (or F)

To find general probabilities using pmf/pdf, note that for $A \subset \mathbb{R}$,

$$P(X \in A) = \sum_{x \in A} f_X(x) = \sum_{x \in A, f_X(x) > 0} f_X(x) \quad (\text{discrete case using pmf})$$

$$P(X \in A) = \int_A f_X(x)dx \quad (\text{continuous case using pdf})$$



- Discrete r.v. case: Relating cdf to pmf

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

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

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

$$P(a < X < b) = F(b) - F(a) - f(b)$$

- Continuous r.v. case: Relating cdf to pmf

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

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

$$= \int_a^b f(u) du$$

STAT 542: Summary to date

Where we have been & where we are headed

- Completed

- Intro to probability
 - * axioms and properties using set theory
 - * conditional probability and independence
- Random variables
 - * definition
 - * discrete/continuous
 - * cdf, pdf/pmf

- Next

- Transformations (an intro)
"new" r.v. $Y=g(X)$ of "old" r.v. X
- Expected values (mean, variance, moment generating function)
- Probability-moment inequalities (Markov, Chebychev, Jensen)