Recall

Let X, Y be two r.v.s and $\alpha, \beta \in \mathbb{R}$. Then $E[\alpha X + \beta Y] = \alpha E[X] + \beta E[Y]$ (the linearity of $E[\cdot]$) .

Cumulative distribution function

The *cumulative distribution function* (CDF) of a r.v. X is defined by

$$F(t) \coloneqq P(X \le t),\ \forall\, t \in \mathbb{R}$$

which has the following properties:

· Non-decreasing. · Right-continuous. · $\lim_{t\to-\infty} F(t) = 0$ and $\lim_{t\to+\infty} F(t) = 1$.

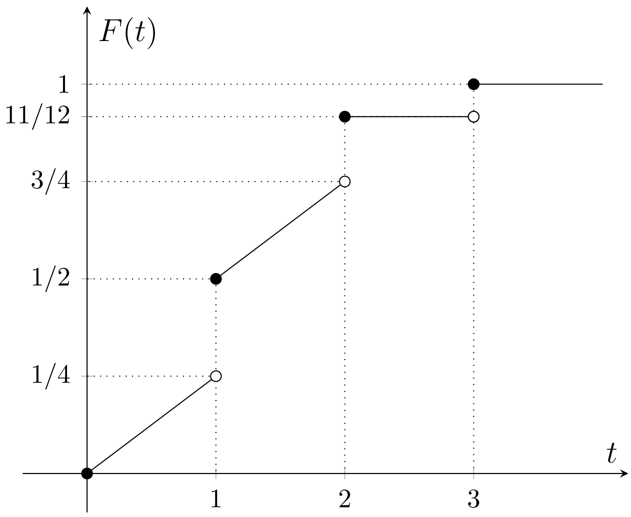
All probability questions about X can be answered in terms of CDF. In particular, for $x \in \mathbb{R}$, $P(X < x) = \lim_{t\to x-} F(t)$.

Example 1. Suppose r.v. X has CDF

$$F(t) = \begin{cases} 0 & t \in (-\infty, 0) \\ t/4 & t \in [0, 1) \\ 1/2 + (t-1)/4 & t \in [1, 2) \\ 11/12 & t \in [2, 3) \\ 1 & t \in [3, +\infty). \end{cases}$$

Find $P(X = i),\ i = 1, 2, 3$ and $P(1 \le X < 3)$.

Solution. Below is the graph of $F(t)$.



Then

$$P(X = 1) = P(X \le 1) - P(X < 1) = F(1) - \lim_{t\to1-} F(t) = \frac{1}{2} - \frac{1}{4} = \frac{1}{4},$$
$$P(X = 2) = P(X \le 2) - P(X < 2) = F(2) - \lim_{t\to2-} F(t) = \frac{11}{12} - \frac{3}{4} = \frac{1}{6},$$

$$P(X=3)=P(X\leq 3)-P(X<3)=F(3)-\lim_{t\to 3-}F(t)=1-\frac{11}{12}=\frac{1}{12}.$$

And

$$P(1\leq X<3)=P(X<3)-P(X<1)=\lim_{t\to 3-}F(t)-\lim_{t\to 1-}F(t)=\frac{11}{12}-\frac{1}{4}=\frac{2}{3}.$$

$\square$

Remark. Since the CDF of discrete r.v.s should be of the shape of step functions, the r.v. X in Example 1 is not discrete. Later we will learn that X is not a *continuous* r.v. either because the CDF of continuous r.v. should be (absolutely) continuous (following Ross' definition of continuous r.v.).

Common discrete random variables

Usually, there are several equivalent ways to characterize a common r.v. X. (1) The story/ backgroud/ definition of X. (2) The explicit PMF/ CDF/ (PDF) of X. (3) Express X in terms of other r.v.s. The story shows the specialty of X and hints us the type of examples that we can use X to model. The PMF or CDF way is concise and allows us to do the computations.

Bernoulli r.v.. with parameter $p\in[0,1]$. Denote $X\sim Bern(p)$.

(1) X is the outcome of a trial that succeeds with probability p and fails with probability $1-p$.

(2) The PMF of X is $p(1)=P(X=1)=p$ and $p(0)=P(X=0)=1-p$.

Note $E[X]=p$ and $\mathrm{Var}(X)=p(1-p)$.

Binomial r.v.. with parameter (n,p). Denote $X\sim Bin(n,p)$.

(1) X is the number of successes that occur in the n independent Bernoulli trials with parameter p.

(2) The PMF of X is $p(k)=P(X=k)=\sum_{k=0}^{n}\binom{n}{k}p^k(1-p)^{n-k}$ for $k=0,\ldots,n$.

(3) Let $X_1,\ldots,X_n$ be independent Bernoulli r.v.s with parameter p. Then $X=\sum_{k=1}^{n}X_k$.

Note $E[X]=np$ and $\mathrm{Var}(X)=np(1-p)$.

Poisson r.v.. with parameter $\lambda>0$. Denote $X\sim Poisson(\lambda)$.

(2) The PMF of X is $p(k)=P(X=k)=\dfrac{\lambda^k e^{-\lambda}}{k!}$ for $k=0,1,2,\ldots$

(1) Approximate binomial r.v. with parameter (n,p) when n large and p small such that np moderate. This story is not precise but flexible to model many examples.

Note $E[X]=\mathrm{Var}(X)=\lambda$.

Geometric r.v. & computing examples

Example 2 (Geometric r.v. with parameter p)**.** Denote $X \sim Geom(p)$.

(1) X is the number of independent Bernoulli trials with parameter $p \in (0,1)$ such that first success occur.

(2) By independence, the PMF is $p(k) = (1-p)^{k-1}p$ for $k = 1, 2, 3, \ldots$

Then we show $E[X] = \dfrac{1}{p}$ and $\mathrm{Var}(X) = \dfrac{1-p}{p^2}$.

By definition, $E[X] = \sum_{k=1}^{\infty} k(1-p)^{k-1}p$. Note that for $x \in (-1,1)$, (by a result about the uniform convergence of power series) we have

$$\sum_{k=1}^{\infty} kx^{k-1} = \sum_{k=0}^{\infty}(x^k)' = (\sum_{k=0}^{\infty} x^k)' = (\frac{1}{1-x})' = \frac{1}{(1-x)^2}.$$

Then setting $x = 1-p$ leads to $E[X] = p\sum_{k=1}^{\infty} k(1-p)^{k-1} = p\dfrac{1}{[1-(1-p)]^2} = \dfrac{1}{p}$.

To obtain $\mathrm{Var}(X)$, it suffices to compute $E[X^2]$

$$\begin{aligned}
E[X^2] &= \sum_{k=1}^{\infty} k^2(1-p)^{k-1}p \\
&= \sum_{k=1}^{\infty}(k-1+1)^2(1-p)^{k-1}p \\
&= \sum_{k=1}^{\infty}(k-1)^2(1-p)^{k-1}p + \sum_{k=1}^{\infty} 2(k-1)(1-p)^{k-1}p + \sum_{k=1}^{\infty}(1-p)^{k-1}p \\
(\text{let } n = k-1) \quad &= (1-p)\sum_{n=1}^{\infty} n^2(1-p)^{n-1}p + 2(1-p)\sum_{k=1}^{\infty} n(1-p)^{n-1}p + 1 \\
&= (1-p)E[X^2] + 2(1-p)E[X] + 1
\end{aligned}$$

Then substitute $E[X] = \dfrac{1}{p}$ and solve the equation to get $E[X^2] = \dfrac{2-p}{p^2}$.

Hence $\mathrm{Var}(X) = E[X^2] - (E[X])^2 = \dfrac{1-p}{p^2}$.

Remark. Observe that we have use two different ways to compute $E[X]$ and $\mathrm{Var}(X)$ in Example 2 both of which can be recursively extended to deal with series like $\sum_{k=1}^{\infty} k^p x^k$ with $p \in \mathbb{N}$.

Example 3. Let $X \sim Bin(n,p)$. Prove

$$E\left[\frac{1}{1+X}\right] = \frac{1-(1-p)^{n+1}}{(n+1)p}$$

Proof. Recall the PMF of $Bin(n,p)$ and by the formula of $E[g(X)]$,

$$E\left[\frac{1}{1+X}\right] = \sum_{k=0}^{n} \frac{1}{k+1}\binom{n}{k}p^k(1-p)^{n-k}$$

$$
\begin{aligned}
&= \frac{1}{(n+1)p} \sum_{k=0}^{n} \frac{1}{k+1} \frac{(n+1)!}{k![(n+1)-(k+1)]!} \cdot p^{k+1}(1-p)^{[(n+1)-(k+1)]} \\
&= \frac{1}{(n+1)p} \sum_{k=0}^{n} \binom{n+1}{k+1} p^{k+1}(1-p)^{[(n+1)-(k+1)]} \\
(\text{let } j = k+1) \quad &= \frac{1}{(n+1)p} \left[\sum_{j=0}^{n} \binom{n+1}{j} p^{j}(1-p)^{[(n+1)-j]} - (1-p)^{n+1} \right] \\
(\text{ by Binomial Thm}) \quad &= \frac{1}{(n+1)p} [1-(1-p)^{n+1}].
\end{aligned}
$$

□

Example 4. Let X be a r.v. with non-negative integral values. Prove

$$\sum_{k=0}^{\infty} kP(X \geq k) = \frac{1}{2}(E[X^2] + E[X]).$$

Proof.

$$
\begin{aligned}
\sum_{k=0}^{\infty} kP(X \geq k) &= \sum_{k=0}^{\infty} \sum_{i=k}^{\infty} kP(X = i) \\
&= \sum_{i=0}^{\infty} \sum_{k=0}^{i} kP(X = i) \\
&= \sum_{i=0}^{\infty} \frac{i(i+1)}{2} P(X = i) \\
&= \frac{1}{2} E[X^2] + \frac{1}{2} E[X],
\end{aligned}
$$

where in the second equality we have changed the order of summation (see e.g. [Tutorial 4, Example 2] for details). □

Remark. Recall for the r.v. X in Example 4 we also have the layer-cake $E[X] = \sum_{k=0}^{\infty} P(X \geq k)$ (see e.g. [Tutorial 4, Example 2]). Together we can express $E[X^2]$ in terms of $P(X \geq k)$ if $E[X] < \infty$, thus $\mathrm{Var}(X)$. This process can recursively continue to express $E[X^p], p \in \mathbb{N}$ in terms of $P(X \geq k)$.