

1.1. Let N denote a nonnegative integer-valued random variable. Show that

$$E[N] = \sum_{k=1}^{\infty} P\{N \geq k\} = \sum_{k=0}^{\infty} P\{N > k\}.$$

In general show that if X is nonnegative with distribution F , then

$$E[X] = \int_0^{\infty} \bar{F}(x) dx$$

and

$$E[X^n] = \int_0^{\infty} nx^{n-1} \bar{F}(x) dx.$$

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N : nonnegative integer-valued random variable.

$$\text{Let } I_k = \begin{cases} 1 & \text{if } N \geq k \\ 0 & \text{else.} \end{cases} \quad \text{and} \quad J_k = \begin{cases} 1 & \text{if } N > k \\ 0 & \text{else.} \end{cases}$$

$$\text{Then, } N = \sum_{k=1}^{\infty} I_k = \sum_{k=0}^{\infty} J_k.$$

$$E[N] = \sum_{k=1}^{\infty} E[I_k] = \sum_{k=0}^{\infty} E[J_k]$$

$$\text{Since } E[I_k] = P[N \geq k] \text{ and } E[J_k] = P[N > k],$$

$$E[N] = \sum_{k=1}^{\infty} P\{N \geq k\} = \sum_{k=0}^{\infty} P\{N > k\}.$$

$$E[X] = \int_0^{\infty} x \cdot dF(x) = - \int_0^{\infty} x \cdot d\bar{F}(x)$$

$$E[X] = -x \bar{F}(x) \Big|_0^{\infty} + \int_0^{\infty} \bar{F}(x) dx$$

$$\text{Since } E[X] < \infty, \lim_{x \rightarrow \infty} x \cdot \bar{F}(x) = 0, \text{ giving}$$

$$E[X] = \int_0^{\infty} \bar{F}(x) dx \quad \square$$

1.2. If X is a continuous random variable having distribution F show that.

- (a) $F(X)$ is uniformly distributed over $(0, 1)$,
- (b) if U is a uniform $(0, 1)$ random variable, then $F^{-1}(U)$ has distribution F , where $F^{-1}(x)$ is that value of y such that $F(y) = x$

#1-2 - (a), (b)

Since $F_X(x)$ is a distribution function, $F_X(x) \in [0, 1]$ for all $x \in \mathbb{R}$ so that $Y = F_X(X)$ takes one of the values in $[0, 1]$. Thus for $y \geq 1$, $F_Y(y) = P(Y \leq y) = 1$ and for $y < 0$, $F_Y(y) = P(Y \leq y) = 0$.

Now for $0 \leq y < 1$,

$$\begin{aligned} F_Y(y) &= P(Y \leq y) = P(0 \leq Y \leq y) = P(F_X(X) \in [0, y]) \\ &= P(X \in F_X^{-1}([0, y])). \end{aligned}$$

Note that

$$F_X^{-1}([0, y]) = \{x \in \mathbb{R} \mid F_X(x) \leq y\} = (-\infty, z].$$

for some $z \in \mathbb{R}$, since $F_X(x)$ is a monotone continuous function on \mathbb{R} .

Note that $F_X(z) = y$.

$$\text{Thus, } F_Y(y) = P(X \in F_X^{-1}([0, y])) = P(X \leq z) = F_X(z) = y.$$

and then Y is uniformly distributed over $(0, 1)$

1.8. Let X_1 and X_2 be independent Poisson random variables with means λ_1 and λ_2 .

(a) Find the distribution of $X_1 + X_2$

(b) Compute the conditional distribution of X_1 given that $X_1 + X_2 = n$

1-8 - (a)

$$X_1 \sim P(\lambda_1), \quad X_2 \sim P(\lambda_2)$$

$$P(X_1 + X_2 = n) = \sum_{i=0}^n P(X_1 + X_2 = n, X_1 = i)$$

$$= \sum_{i=0}^n P(X_1 = i, X_2 = n-i) = \sum_{i=0}^n P(X_1 = i) P(X_2 = n-i)$$

$$= \sum_{i=0}^n e^{-\lambda_1} \cdot \frac{\lambda_1^{n-i}}{(n-i)!} \times e^{-\lambda_2} \cdot \frac{\lambda_2^i}{i!}$$

$$= e^{-(\lambda_1 + \lambda_2)} \cdot \frac{1}{n!} \sum_{i=0}^n \frac{n!}{(n-i)! i!} \cdot \lambda_1^{n-i} \cdot \lambda_2^i$$

$$= e^{-(\lambda_1 + \lambda_2)} \cdot \frac{1}{n!} \cdot \sum_{i=0}^n \binom{n}{i} \cdot \lambda_1^{n-i} \cdot \lambda_2^i$$

$$= e^{-(\lambda_1 + \lambda_2)} \cdot \frac{(\lambda_1 + \lambda_2)^n}{n!}$$

$$\therefore X_1 + X_2 \sim P(\lambda_1 + \lambda_2)$$

1-8 - (b)

$$X_1 + X_2 = n.$$

$$P(X_1 = x_1 | X_1 + X_2 = n) = \frac{P(X_1 = x_1 \text{ and } X_1 + X_2 = n)}{P(X_1 + X_2 = n)}$$

$$= \frac{P(X_1 = x_1 \text{ and } X_2 = n - x_1)}{P(X_1 + X_2 = n)} = \frac{P(X_1 = x_1) P(X_2 = n - x_1)}{P(X_1 + X_2 = n)}$$

$$\therefore P(X_1 = x_1 | X_1 + X_2 = n) = \frac{(\lambda_1^{x_1} e^{-\lambda_1} / x_1!) \cdot (\lambda_2^{n-x_1} e^{-\lambda_2} / (n-x_1)!)}{\lambda_1^n \cdot \lambda_2^n \cdot e^{-(\lambda_1 + \lambda_2)} / n!}$$

- 1.11. If X is a nonnegative integer-valued random variable then the function $P(z)$, defined for $|z| \leq 1$ by

$$P(z) = E[z^X] = \sum_{j=0}^{\infty} z^j P\{X = j\},$$

is called the probability generating function of X

(a) Show that

$$\frac{d^k}{dz^k} P(z) \Big|_{z=0} = k! P\{X = k\}.$$

(b) With 0 being considered even, show that

$$P\{X \text{ is even}\} = \frac{P(-1) + P(1)}{2}$$

(c) If X is binomial with parameters n and p , show that

$$P\{X \text{ is even}\} = \frac{1 + (1 - 2p)^n}{2}.$$

(d) If X is Poisson with mean λ , show that

$$P\{X \text{ is even}\} = \frac{1 + e^{-2\lambda}}{2}$$

(e) If X is geometric with parameter p , show that

$$P\{X \text{ is even}\} = \frac{1 - p}{2 - p}.$$

(f) If X is a negative binomial random variable with parameters r and p , show that

$$P\{X \text{ is even}\} = \frac{1}{2} \left[1 + (-1)^r \left(\frac{p}{2 - p} \right)^r \right].$$

1-11-(a)

$$P(z) = \sum_{j=0}^{\infty} z^j P\{X=j\} = P\{X=0\} + z \cdot P\{X=1\} + z^2 P\{X=2\} \\ + \dots + z^k P\{X=k\} + \dots$$

$$\frac{d}{dz} P(z) \Big|_{z=0} = P\{X=1\}, \quad \frac{d^2}{dz^2} P(z) \Big|_{z=0} = 2 P\{X=2\},$$

$$\frac{d^3}{dz^3} P(z) \Big|_{z=0} = 3 \times 2 \times P\{X=3\} = 3! \times P\{X=3\}$$

$$\therefore \frac{d^k}{dz^k} P(z) \Big|_{z=0} = k! P\{X=k\} \quad \square$$

1-11-(b)

$$p(X = \text{even})$$

$$= p(X=0) + p(X=2) + p(X=4) + \dots$$

$$= \frac{p(X=0) + p(X=1) + p(X=2) + p(X=3) + \dots}{2}$$

$$= \frac{p(X=0) - p(X=1) + p(X=2) - p(X=3) + \dots}{2}$$

$$= \frac{1}{2} \sum_{j=0}^{\infty} 1^j p(X=j) + \frac{1}{2} \sum_{j=0}^{\infty} (-1)^j p(X=j)$$

$$= \frac{1}{2} p(1) + \frac{1}{2} p(-1) = \frac{p(1) + p(-1)}{2} \quad \square$$

1-11-(c)

$$X \sim N.B(n, p)$$

$$P(z) = E[z^X] = \sum_{k=0}^n z^k \binom{n}{k} p^k (1-p)^{n-k}$$

$$= (1-p + zp)^n = (1 + (z-1)p)^n$$

$$p(X = \text{even}) = \frac{p(1) + p(-1)}{2} = \frac{1 + (1-2p)^n}{2} \quad \square$$

1-11-(d)

$$X \sim P(\lambda)$$

$$P(z) = E[z^X] = \sum_{k=0}^{\infty} z^k \cdot e^{-\lambda} \cdot \frac{\lambda^k}{k!}$$

$$= e^{-\lambda} \cdot \sum_{k=0}^{\infty} \frac{(\lambda z)^k}{k!} = e^{-\lambda} \times e^{\lambda z} = e^{\lambda(z-1)}$$

$$p(X = \text{even}) = \frac{p(1) + p(-1)}{2} = \frac{1 + e^{-2\lambda}}{2} \quad \square$$

#1-11-(e)

$$X \sim \text{geom}(p)$$

$$P(X=x) = p \cdot (1-p)^{x-1}, \quad x = 1, 2, 3, \dots$$

$$\begin{aligned} P(z) = E[z^x] &= \sum_{k=1}^{\infty} z^k \cdot p(1-p)^{k-1} \\ &= p \cdot z \cdot \sum_{k=1}^{\infty} (z - zp)^{k-1} = \frac{p \cdot z}{1 - z + zp} \end{aligned}$$

$$P(X=\text{even}) = \frac{P(1) + P(-1)}{2}$$

$$= \frac{\frac{p}{p} + \frac{-p}{2-p}}{2} = \frac{1}{2} \left(1 + \frac{-p}{2-p} \right)$$

$$= \frac{1}{2} \times \frac{2-p-p}{2-p} = \frac{1-p}{2-p} \quad \square$$

#1-11-(f)

$$X \sim \text{NB}(r, p)$$

$$P(X=x) = \binom{x-1}{r-1} p^r \cdot (1-p)^{x-r}, \quad x = r, r+1, \dots$$

$$P(z) = E[z^k] = \sum_{k=r}^{\infty} z^k \cdot \binom{k-1}{r-1} p^r \cdot (1-p)^{k-r}$$

$$= (pz)^r \cdot \sum_{k=r}^{\infty} \binom{x-1}{r-1} (z - zp)^{k-r} = \frac{(pz)^r}{(1 - z + zp)^r}$$

$$P(X=\text{even}) = \frac{P(1) + P(-1)}{2}$$

$$= \frac{p + \left(\frac{-p}{2-p} \right)^r}{2} = \frac{1}{2} \left[1 + (-1)^r \cdot \left(\frac{p}{2-p} \right)^r \right] \quad \square$$

1.16. Let $f(x)$ and $g(x)$ be probability density functions, and suppose that for some constant c , $f(x) \leq cg(x)$ for all x . Suppose we can generate random variables having density function g , and consider the following algorithm.

Step 1: Generate Y , a random variable having density function g .

Step 2: Generate U , a uniform $(0, 1)$ random variable.

Step 3: If $U \leq \frac{f(Y)}{cg(Y)}$ set $X = Y$. Otherwise, go back to Step 1.


Assuming that successively generated random variables are independent, show that:

(a) X has density function f

(b) the number of iterations of the algorithm needed to generate X is a geometric random variable with mean c .

#1-16-(a)

$$\begin{aligned} P(Y_n \leq x | E_n) &= P(Y_n \leq x, E_n) / P(E_n) \\ &= c \cdot E[P(Y_n \leq x, E_n | Y_n)] \\ &= c \cdot \int_{-\infty}^x \frac{f(y)}{c g(y)} g(y) dy = F(x), \end{aligned}$$

where $F(x) = \int_{-\infty}^x f(u) du$. On the n th iteration, conditional on the algorithm terminating at that iteration, Y_n has conditional CDF, so X has density f 

#1-16-(b)

Define infinite sequences $\{Y_n, n \geq 1\}$ and $\{U_n, n \geq 1\}$ where Y_n are iid with density g and U_n are iid uniform $(0, 1)$. Define $E_n = \{U_n \leq f(Y_n) / (c \cdot g(Y_n))\}$. E_n is a sequence of independent trials with and the algorithm stops at the first "success". Thus the number of iterations is geometric with parameter

$$P = P(E_n) = E[P(E_n | Y_n)] = \int_{-\infty}^{\infty} \frac{f(y)}{c \cdot g(y)} g(y) dy = \frac{1}{c}, \quad \frac{1}{P} = c$$

1.22. The conditional variance of X , given Y , is defined by

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

Prove the conditional variance formula, namely,

$$\text{Var}(X) = E[\text{Var}(X|Y)] + \text{Var}(E[X|Y]).$$

Use this to obtain $\text{Var}(X)$ in Example 1.5(B) and check your result by differentiating the generating function

1-22

By the definition of Variance,

$$\begin{aligned} \text{Var}[X] &= E[(X - E[X])^2] = E[(X - E[X|Y] + E[X|Y] - E[X])^2] \\ &= E[(X - E[X|Y])^2] + E[(E[X|Y] - E[X])^2] \\ &\quad + 2 \cdot E[(X - E[X|Y])(E[X|Y] - E[X])] \end{aligned}$$

$$E[(X - E[X|Y])(E[X|Y] - E[X])]$$

$$= E[E[(X - E[X|Y]) \cdot (E[X|Y] - E[X]) | Y]]$$

Law of iterated expectation

$$= E[(E[X|Y] - E[X]) E[(X - E[X|Y]) | Y]]$$

$E[X]$ is a constant

$E[X|Y]$: function of Y .

$$= E[(E[X|Y] - E[X])(E[X|Y] - E[X|Y])]$$

$$= 0$$

$$E[E[X|Y] | Y] = E[X|Y]$$

$$= E[X|Y]$$

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

$$= E[E[(X - E[X|Y])^2 | Y]] + E[(E[X|Y] - E[E[X|Y]])^2]$$

$$= E[\text{Var}[X|Y]] + \text{Var}[E[X|Y]]$$

1.36. Use Jensen's inequality to prove that the arithmetic mean is at least as large as the geometric mean. That is, for nonnegative x_i , show that

$$\sum_{i=1}^n x_i / n \geq \left(\prod_{i=1}^n x_i \right)^{1/n}.$$

* Jensen inequality?

$$E[f(x)] \geq f(E[x]).$$

1-36.

Jensen's inequality says that for a convex function $f(x)$ with $c_i \geq 0$, $\sum_{i=1}^n c_i = 1$ if we have arbitrary x_1, x_2, \dots, x_n then

$$f(c_1 x_1 + c_2 x_2 + \dots + c_n x_n) \leq c_1 f(x_1) + c_2 f(x_2) + \dots + c_n f(x_n)$$

(if f is concave \leq turns to \geq)

For an explanation, let $f(x) = \log x$ and $c_1 = c_2 = \dots = c_n = \frac{1}{n}$.

$$\begin{aligned} \log(c_1 x_1 + c_2 x_2 + \dots + c_n x_n) &= \log\left(\frac{1}{n}x_1 + \frac{1}{n}x_2 + \dots + \frac{1}{n}x_n\right) \\ &\geq \frac{1}{n} \log x_1 + \frac{1}{n} \log x_2 + \dots + \frac{1}{n} \log x_n \geq \frac{1}{n} (\log x_1 + \log x_2 + \dots + \log x_n) \end{aligned}$$

$$\log\left(\frac{1}{n} (\log x_1 + \log x_2 + \dots + \log x_n)\right) \geq \frac{1}{n} \log(x_1 \cdot x_2 \cdot \dots \cdot x_n)$$

$$\log\left(\frac{x_1 + x_2 + \dots + x_n}{n}\right) \geq \log(x_1 \cdot x_2 \cdot \dots \cdot x_n)^{\frac{1}{n}}$$

$$\left[\frac{x_1 + x_2 + \dots + x_n}{n}\right] \geq (x_1 \cdot x_2 \cdot \dots \cdot x_n)^{\frac{1}{n}}$$

$$\text{Thus, } \sum_{i=1}^n \frac{x_i}{n} \geq \left(\prod_{i=1}^n x_i \right)^{\frac{1}{n}} \quad \square$$

1.43. For a nonnegative random variable X , show that for $a > 0$,

$$P\{X \geq a\} \leq E[X^t]/a^t$$

Then use this result to show that $n! \geq (n/e)^n$

By Markov Inequality, $P\{X \geq a\} \leq \frac{E[X^t]}{a^t}$, ($X \geq 0$)

Too difficult... $n! \geq (n/e)^n$ //

$$E\left[\frac{n^n}{e^n}\right] = \frac{E[n^n]}{e^n} \sim \frac{E[n^n]}{e^n}$$

$$\underline{P(X \geq e) \leq \frac{E[X^n]}{e^n} \leq \alpha!}$$