

## Geometric and Negative Binomial Distributions

**Definition 6 Geometric distribution** A random variable  $X$  is defined to have *geometric* (or *Pascal*) *distribution* if the density of  $X$  is given by

$$f_X(x) = f_X(x; p) = \begin{cases} p(1-p)^x & \text{for } x = 0, 1, \dots \\ 0 & \text{otherwise} \end{cases} = p(1-p)^x I_{\{0, 1, \dots\}}(x), \quad (11)$$

where the parameter  $p$  satisfies  $0 < p \leq 1$ . (Define  $q = 1 - p$ .) ////

**Definition 7 Negative binomial distribution** A random variable  $X$  with density

$$f_X(x) = f_X(x; r, p) = \begin{cases} \binom{r+x-1}{x} p^r q^x = \binom{-r}{x} p^r (-q)^x & \text{for } x = 0, 1, 2, \dots \\ 0 & \text{otherwise} \end{cases} \quad (12)$$

$$= \binom{r+x-1}{x} p^r q^x I_{\{0, 1, \dots\}}(x),$$

where the parameters  $r$  and  $p$  satisfy  $r = 1, 2, 3, \dots$  and  $0 < p \leq 1$  ( $q = 1 - p$ ), is defined to have a *negative binomial distribution*. The density given by Eq. (12) is called a *negative binomial density*.

**Remark** If in the negative binomial distribution  $r = 1$ , then the negative binomial density specializes to the geometric density. ////

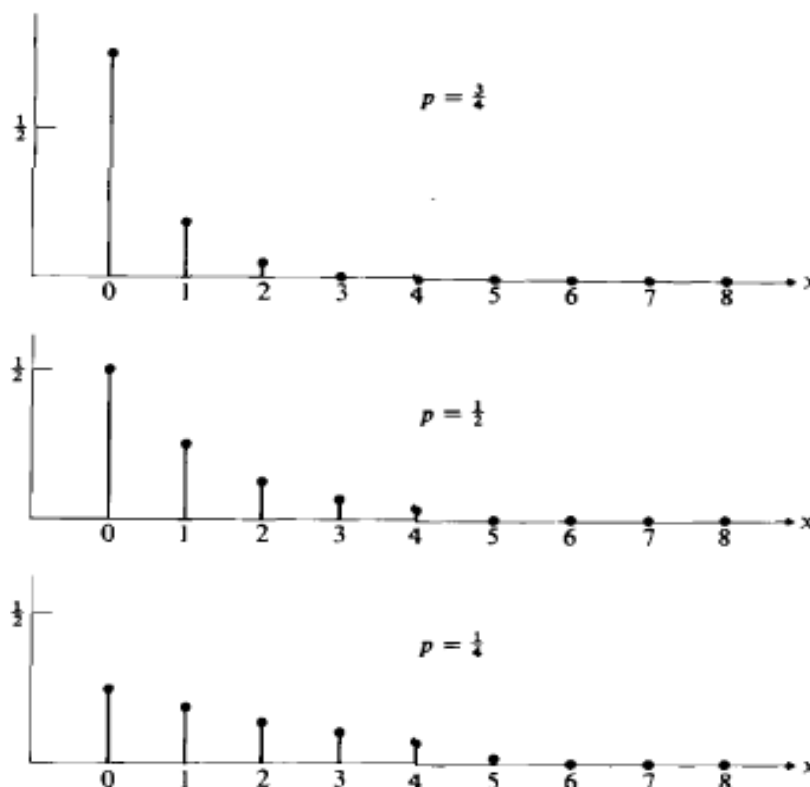


FIGURE 7  
Geometric densities

**Theorem 9** If the random variable  $X$  has a geometric distribution, then

$$E[X] = \frac{q}{p}, \quad \text{var}[X] = \frac{q}{p^2}, \quad \text{and} \quad m_X(t) = \frac{p}{1 - qe^t}. \quad (13)$$

Before leaving the geometric distribution, we note that some authors define the geometric distribution by assuming 1 (instead of 0) is the smallest mass point. The density then has the form

$$f(x; p) = p(1 - p)^{x-1} I_{(1, 2, \dots)}(x), \quad (14)$$

and the mean is  $1/p$ , the variance is  $q/p^2$ , and the moment generating function is  $pe^t/(1 - qe^t)$ .

**Theorem 11** Let  $X$  have a negative binomial distribution; then

$$\mathcal{E}[X] = \frac{rq}{p}, \quad \text{var}[X] = \frac{rq}{p^2}, \quad \text{and} \quad m_X(t) = \left[ \frac{p}{1 - qe^t} \right]^r. \quad (15)$$

**PROOF**

$$\begin{aligned} m_X(t) &= \mathcal{E}[e^{tX}] = \sum_{x=0}^{\infty} e^{tx} \binom{-r}{x} p^r (-q)^x \\ &= \sum_{x=0}^{\infty} \binom{-r}{x} p^r (-qe^t)^x = \left[ \frac{p}{1 - qe^t} \right]^r \end{aligned}$$

[see Eq. (33) in Appendix A].

$$m'_X(t) = p^r (-r)(1 - qe^t)^{-r-1} (-qe^t)$$

and

$$m''_X(t) = rqp^r [q(r+1)e^{2t}(1 - qe^t)^{-r-2} + e^t(1 - qe^t)^{-r-1}];$$

hence

$$\mathcal{E}[X] = m'_X(t) \Big|_{t=0} = \frac{rq}{p}$$

and

$$\begin{aligned} \text{var}[X] &= m''_X(t) \Big|_{t=0} - (\mathcal{E}[X])^2 = rqp^r [qp^{-r-2}(r+1) + p^{-r-1}] - \left( \frac{rq}{p} \right)^2 \\ &= \frac{rq^2}{p^2} + \frac{rq}{p} = \frac{rq}{p^2}. \end{aligned} \quad \text{////}$$

**EXAMPLE 10** Consider a sequence of independent, repeated Bernoulli trials with  $p$  equal to the probability of success on an individual trial. Let the random variable  $X$  represent the number of failures prior to the  $r$ th success; then  $X$  has the negative binomial density given by Eq. (12), as the following argument shows: The last trial must result in a success, having probability  $p$ ; among the first  $x + r - 1$  trials there must be  $r - 1$  successes and  $x$  failures, and the probability of this is

$$\binom{x+r-1}{r-1} p^{r-1} q^x = \binom{r+x-1}{x} p^{r-1} q^x,$$

which when multiplied by  $p$  gives the desired result. ////

A random variable  $X$  having a negative binomial distribution is often referred to as a discrete *waiting-time* random variable. It represents how long (in terms of the number of failures) one waits for the  $r$ th success.