

# 8

## Chapter Eight

### Generating Functions

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#### 8.1 Probability Generating Function - Mean and Variance

##### Definition 8.1.

Let  $a_0, a_1, a_2, \dots$  be a sequence of real numbers. Using a variable  $t$ , we define the function

$$A(t) = a_0 + a_1 t + a_2 t^2 + \dots = \sum_{k=0}^{\infty} a_k t^k \quad \dots (8.1.1)$$

If this power series converges in some interval  $-t_0 < t < t_0$ , then  $A(t)$  is called the *generating function* of the sequence  $\{a_k\}$ ,  $k=0,1,2, \dots$

If we differentiate (8.1.1)  $k$  times with respect to  $t$ , and putting  $t = 0$  and dividing by  $k!$ , we get  $a_k$ , i.e.

$$a_k = \frac{1}{k!} \left. \frac{d^k A(t)}{dt^k} \right|_{t=0} \quad \dots (8.1.2)$$

For example, if  $a_k = 1$  for all  $k$ , then

$$A(t) = 1 + t + t^2 + \dots = \sum_{k=0}^{\infty} t^k = \frac{1}{1-t}, \quad |t| < 1.$$

If  $a_k = \frac{1}{k!}$ ,  $k = 0, 1, 2, \dots$ , then

$$A(t) = \sum_{k=0}^{\infty} \frac{t^k}{k!} = e^t.$$

**Definition 8.1.2.**

Suppose that  $X$  is a random variable which assumes non-negative integral - valued  $0, 1, 2, \dots$  and let  $P_k = P\{X=k\}$ ,  $k=0, 1, \dots$  with  $\sum_{k=0}^{\infty} P_k = 1$ . If we let  $a_k = P_k$  in (8.1.1)

then the probability generating function of the r.v.  $X$  (or simply p.g.f.) is defined as

$$P(t) = \sum_{k=0}^{\infty} P_k t^k = \sum_{k=0}^{\infty} P(X = k) t^k = E(t^X) \quad \dots (8.1.3)$$

where  $E(t^X)$  is the expectation of the function  $t^X$  of the r.v.  $X$ .

The series  $\sum_{k=0}^{\infty} P_k t^k$  converges for at least  $|t| < 1$ .

Clearly  $P(0) = P_0$  and  $P(1) = \sum_{k=0}^{\infty} P_k = 1$ .

Now, if we differentiate (8.1.2.) with respect to  $t$ , and put  $t=1$ , we get

$$P'(t) = \sum_{k=1}^{\infty} k P_k t^{k-1} \quad \dots (8.1.4)$$

and

$$P'(1) = \sum_{k=1}^{\infty} k P_k = E(X).$$

Therefore, the mean of the r.v.  $X$  is equal to  $P'(1)$ .  
 Again differentiate (8.1.4) with respect to  $t$ , and put  $t=1$ , we get

$$P''(t) = \sum_{k=2}^{\infty} k(k-1) P_k t^{k-2}$$

and

$$P''(1) = \sum_{k=2}^{\infty} k(k-1) P_k = E(X(X-1)).$$

Thus,  $P''(1) = EX^2 - EX$ , or  
 $EX^2 = P''(1) + P'(1)$

Hence, the variance of  $X$  is given by

$$\text{Var}(X) = EX^2 - (EX)^2 = P''(1) + P'(1) - [P'(1)]^2$$

### Example 8.1.1.

Let  $X$  be a r.v. with a geometric distribution

$$P_k = Pq^k, k = 0, 1, 2, \dots; P + q = 1.$$

Then, the p. g. f. of  $X$  is

$$\begin{aligned} P(t) &= \sum_{k=0}^{\infty} P_k t^k = \sum_{k=0}^{\infty} Pq^k t^k = p \sum_{k=0}^{\infty} (qt)^k \\ &= \frac{p}{1-qt} \end{aligned}$$

Hence

$$P'(t) = \frac{Pq}{(1-qt)^2} \text{ and } P''(t) = \frac{2Pq^2}{(1-qt)^3}$$

Therefore ,

$$E(X) = P'(1) = \frac{q}{p},$$

$$P''(1) = \frac{2q^2}{p^2}, \text{ then}$$

$$\text{Var}(X) = P''(1) + P'(1) - [P'(1)]^2$$

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

$$= q/p^2.$$

### Example 8.1.2.

Let  $X$  have a binomial distribution with parameters  $n$  and  $p$ , then the p.g.f. of  $X$  is

$$P(t) = \sum_{k=0}^n C(n, k) p^k q^{n-k} t^k$$

$$= \sum_{k=0}^n C(n, k) (Pt)^k q^{n-k}$$

$$= (Pt + q)^n, \text{ by binomial theorem.}$$

Hence

$$P'(t) = nP(Pt + q)^{n-1} \text{ and } P''(t) = n(n-1)p^2(Pt + q)^{n-2}$$

Thus

$$EX = P'(1) = np,$$

and

$$P''(1) = n(n-1)p^2$$

Therefore

$$\begin{aligned}\text{Var } (X) &= P''(1) + P'(1) - [P'(1)]^2 \\ &= n(n-1)P^2 + nP - n^2P^2 \\ &= npq.\end{aligned}$$

**Remarks :**

1. The probabilities  $P_k, k \geq 0$  can be uniquely determined from  $P(t)$  as follows

$$P_k = \frac{1}{k!} \left. \frac{d^k P(t)}{dt^k} \right|_{t=0}$$

2. The  $k$ -th factorial moments of  $X, E[X(X-1)\dots(X-k+1)]$  can be found as

$$E[X(X-1)\dots(X-k+1)] = \left. \frac{d^k P(t)}{dt^k} \right|_{t=1}, \text{ for}$$

$$k = 1, 2, 3, \dots$$

**Theorem 8.1.1.**

Let  $Y = mX+n$ , where  $m$  and  $n$  are positive integers, with  $m \neq 0$ , the p.g.f. of  $Y, P_Y(t)$  is given by

$$P_Y(t) = t^n P_X(t^m) \quad \dots (8.1.5)$$

where  $P_X(t)$  is the p. g. f. of  $X$ .

**Proof.** We have

$$\begin{aligned}P_Y(t) &= E(t^Y) = E(t^{mX+n}) \\ &= E(t^n \cdot t^{mX}) = t^n E(t^{mX}) \\ &= t^n E((t^m)^X) = t^n P_X(t^m)\end{aligned}$$

For example, if  $X$  has a binomial distribution with parameters  $n$  and  $p$ , then the p.g.f. of  $Y = 3X + 4$  is given by

$$\begin{aligned} P_Y(t) &= t^4 P_X(t^3) \\ &= t^4 (pt^3 + q)^n. \end{aligned}$$

### Theorem 8.1.2.

Let  $X$  and  $Y$  be two independent r.v.'s with p.g.f.'s  $P_X(t)$  and  $P_Y(t)$ , respectively, Let  $Z=X+Y$ , then the p.g.f. of  $Z$  is

$$P_Z(t) = P_X(t) \cdot P_Y(t) \quad \dots (8.16)$$

### Proof

We have

$$\begin{aligned} P_Z(t) &= E(t^Z) = E(t^{X+Y}) \\ &= E(t^X \cdot t^Y) = E(t^X) \cdot E(t^Y) \text{ since } X \text{ and } Y \text{ are} \\ &\text{independent r.v.'s, then } t^X \text{ and } t^Y \text{ are also independent.} \\ &\text{Therefore,} \end{aligned}$$

$$P_Z(t) = P_X(t) P_Y(t).$$

### Example 8.1.3.

Let  $X_1$  and  $X_2$  be two independent Poisson variates with parameters  $m_1$  and  $m_2$ , respectively, then

$$\begin{aligned} P_{X_1}(t) &= \sum_{k=0}^{\infty} e^{-m_1} \frac{m_1^k t^k}{k!} = e^{-m_1} \sum_{k=0}^{\infty} \frac{(m_1 t)^k}{k!} \\ &= e^{-m_1} \cdot e^{m_1 t} = e^{m_1(t-1)} \end{aligned}$$

In the same way,

$$P_{X_2}(t) = e^{m_2(t-1)}$$

If we let  $Z = X_1 + X_2$  then the p.g.f. of  $Z$  is

$$\begin{aligned} P_Z(t) &= P_{X_1}(t) \cdot P_{X_2}(t) = e^{m_1(t-1)} \cdot e^{m_2(t-1)} \\ &= e^{(m_1+m_2)(t-1)}. \end{aligned}$$

**Remark :**

Theorem 8.1.2. can be extended to the sum of  $n$  independent r.v.'s  $X_1, X_2, \dots, X_n, \dots$ , that is, if  $Z = X_1 + \dots + X_n$ , then

$$\begin{aligned} P_Z(t) &= P_{X_1}(t) P_{X_2}(t) \dots P_{X_n}(t) \\ &= \prod_{i=1}^n P_{X_i}(t) \end{aligned}$$

If  $X_1, X_2, \dots, X_n$  are identically independent distributed random variables with the common p.g.f.  $P(t)$ , then  $Z = X_1 + \dots + X_n$  has a p.g.f.

$$P_Z(t) = [P(t)]^n.$$

## 8.2. Moment Generating Function

### Definition 8.2.1.

The moment generating function (or simply, m.g.f.) of the r.v.  $X$ , is denoted by  $M_X(t)$ , and if it exists, is defined as

$$M_X(t) = E(e^{tX}) \quad \dots (8.2.1)$$

$$\begin{aligned} &= \sum_x e^{tx} \cdot P(x), \text{ when } X \text{ is discrete} \\ &= \int_{-\infty}^{\infty} e^{tx} f(x) dx, \text{ when } X \text{ is continuous,} \end{aligned}$$

where  $t$  is a real parameter. We assume that the right hand side of (8.2.1) is absolutely convergent. Thus

$$\begin{aligned}
 M_X(t) &= E(e^{tX}) \\
 &= E\left[1 + tX + \frac{t^2}{2!} X^2 + \frac{t^3}{3!} X^3 + \dots\right] \\
 &= 1 + tE(X) + \frac{t^2}{2!} E(X^2) + \frac{t^3}{3!} E(X^3) + \dots \\
 &= 1 + tm_1 + \frac{t^2}{2!} m_2 + \frac{t^3}{3!} m_3 + \dots \\
 &= \sum_{r=0}^{\infty} \frac{t^r m_r}{r!} \qquad \dots (8.2.2)
 \end{aligned}$$

where  $m_r = E(X^r)$  is the  $r$ -th moment about the origin of the r.v.  $X$ .

Now, if we differentiate (8.2.2) with respect to  $t$ ,  $k$  times and put  $t=0$ , we get

$$\left. \frac{d^k M_X(t)}{dt^k} \right|_{t=0} = m_k \text{ for } k = 1, 2, \dots$$

**Note**

It is clear that

$$P(t) = E(t^X) = E(e^{X \ln t}) = M_X(\ln t)$$