

CSL003P1M : Probability and Statistics
Lecture 24 (Moment Generating Function)

Sumit Kumar Pandey

November 09, 2021

Moment Generating Function

The moment generating function (mgf) $M(t)$ of the random variable X is defined for all real values of t by

$$M(t) = E[e^{tX}] = \sum_x e^{tx} p(x)$$

We call $M(t)$ the moment generating function because all of the moments of X can be obtained successively differentiating $M(t)$ and then evaluating the result at $t = 0$.

Moment Generating Function

$$\begin{aligned}M'(t) &= \frac{d}{dt}E[e^{tX}] \\&= E\left[\frac{d}{dt}(e^{tX})\right] \\&= E[Xe^{tX}]\end{aligned}$$

Hence, the above equation evaluated at $t = 0$ yields

$$M'(0) = E[X]$$

Moment Generating Function

Similarly,

$$\begin{aligned}M''(t) &= \frac{d}{dt} M'(t) \\&= \frac{d}{dt} E[Xe^{tX}] \\&= E\left[\frac{d}{dt}(Xe^{tX})\right] \\&= E[X^2 e^{tX}]\end{aligned}$$

Thus,

$$M''(0) = E[X^2]$$

Moment Generating Function

In general, the n th derivative of $M(t)$ is given by

$$M^n(t) = E[X^n e^{tX}] \quad n \geq 1$$

implying that

$$M^n(0) = E[X^n] \quad n \geq 1$$

Exercise-1

If X is a binomial random variable with parameters n and p , then find $E[X]$ and $Var(X)$ using mgf.

$$\begin{aligned}M(t) &= E[e^{tX}] \\&= \sum_{k=0}^n e^{tk} \binom{n}{k} p^k (1-p)^{n-k} \\&= \sum_{k=0}^n \binom{n}{k} (pe^t)^k (1-p)^{n-k} \\&= (pe^t + 1 - p)^n\end{aligned}$$

After differentiation, we obtain

$$M'(t) = n(pe^t + 1 - p)^{n-1} pe^t$$

Thus,

$$E[X] = M'(0) = np.$$

Exercise-1

After differentiating again, we obtain

$$M''(t) = n(n-1)(pe^t + 1 - p)^{n-2}(pe^t)^2 + n(pe^t + 1 - p)^{n-1}pe^t$$

So,

$$E[X^2] = M''(0) = n(n-1)p^2 + np$$

Thus,

$$\begin{aligned} \text{Var}(X) &= E[X^2] - (E[X])^2 \\ &= n(n-1)p^2 + np - n^2p^2 \\ &= np(1-p). \end{aligned}$$

Exercise-2

If X is a Poisson random variable with parameter λ , then find $E[X]$ and $\text{Var}(X)$ using mgf.

$$\begin{aligned}M(t) &= E[e^{tX}] \\&= \sum_{n=0}^{\infty} \frac{e^{tn} e^{-\lambda} \lambda^n}{n!} \\&= e^{-\lambda} \sum_{n=0}^{\infty} \frac{(\lambda e^t)^n}{n!} \\&= e^{-\lambda} e^{\lambda e^t}\end{aligned}$$

After differentiation, we obtain

$$M'(t) = \lambda e^t e^{-\lambda} e^{\lambda e^t}$$

Thus,

$$E[X] = M'(0) = \lambda.$$

Exercise-2

After differentiating again, we obtain

$$M''(t) = \{(\lambda e^t)^2 + \lambda e^t\}(e^{-\lambda} e^{\lambda e^t})$$

So,

$$E[X^2] = M''(0) = \lambda^2 + \lambda$$

Thus,

$$\begin{aligned} \text{Var}(X) &= E[X^2] - (E[X])^2 \\ &= \lambda \end{aligned}$$

Exercise-3

If X is a geometric random variable with parameter p , then find $E[X]$ and $Var(X)$ using mgf.

$$\begin{aligned}M(t) &= E[e^{tX}] \\&= \sum_{k=1}^{\infty} e^{tk}(1-p)^{k-1}p \\&= pe^t \sum_{k=1}^{\infty} e^{t(k-1)}(1-p)^{k-1} \\&= pe^t \sum_{k=1}^{\infty} \{e^t(1-p)\}^{k-1} \\&= \frac{pe^t}{1 - (1-p)e^t}\end{aligned}$$

Exercise-3

After differentiation, we obtain

$$M'(t) = \frac{pe^t}{\{1 - (1 - p)e^t\}^2}$$

Thus,

$$E[X] = M'(0) = \frac{1}{p}$$

After differentiating again, we obtain

$$M''(t) = \frac{pe^t\{1 + (1 - p)e^t\}}{\{1 - (1 - p)e^t\}^3}$$

Thus,

$$E[X^2] = M''(0) = \frac{2 - p}{p^2}$$

$$\text{So, } \text{Var}(X) = E[X^2] - (E[X])^2 = \frac{1 - p}{p^2}.$$

Exercise-4

If X is a negative binomial random variable with parameters r and p , then find $E[X]$ and $Var(X)$ using mgf.

$$\begin{aligned}M(t) &= E[e^{tX}] \\&= \sum_{k=r}^{\infty} e^{tk} \binom{k-1}{r-1} (1-p)^{k-r} p^r \\&= (pe^t)^r \sum_{k=r}^{\infty} \binom{k-1}{r-1} \{e^t(1-p)\}^{k-r} \\&= \left[\frac{pe^t}{1 - (1-p)e^t} \right]^r\end{aligned}$$

using the identity for positive integer r ,

$$(1-x)^{-r} = \sum_{l=0}^{\infty} \binom{r+l-1}{l} x^l$$

Exercise-4

Try!!

$$E[X] = M'(0) = \frac{r}{p}$$

and,

$$\text{Var}(X) = E[X^2] - (E[X])^2 = \frac{r(1-p)}{p^2}$$

Thank You