

ECE 302: Lecture 6.1 Moment Generating Function

Prof Stanley Chan

School of Electrical and Computer Engineering
Purdue University



Moment Generating Function

Definition

For any random variable X , the **moment generating function** (MGF) $M_X(s)$ is

$$M_X(s) = \mathbb{E} \left[e^{sX} \right]. \quad (1)$$

Discrete:

$$M_X(s) = \sum_{x \in \Omega} e^{sx} p_X(x) \quad (2)$$

Continuous:

$$M_X(s) = \int_{-\infty}^{\infty} e^{sx} f_X(x) dx \quad (3)$$

Interpretation: Laplace transform:

$$\mathcal{L}[f](s) = \int_{-\infty}^{\infty} f(t) e^{st} dt.$$

Example 1

Example. Consider a random variable X with three state 0, 1, 2 with probability masses $\frac{2}{6}, \frac{3}{6}, \frac{1}{6}$ respectively. Find MGF.

Solution.

$$M_X(s) =$$

$$= \frac{1}{3} + \frac{e^s}{2} + \frac{e^{2s}}{6}.$$

Example 2

Example. Find the MGF for a Poisson random variable.

Solution. The MGF is

$$M_X(s) =$$

$$= e^{\lambda e^s} e^{-\lambda}.$$

Example 3

Example. Find the MGF for an exponential random variable.

Solution. The MGF is

$$M_X(s) =$$

$$= \frac{\lambda}{\lambda - s}, \quad \text{if } \lambda > s.$$

Getting Moments from MGF

Theorem

The MGF has the property that

- $M_X(0) = 1$,
- $\frac{d^k}{ds^k} M_X(s)|_{s=0} = \mathbb{E}[X^k]$, for any positive integer k .

Proof. The first property can be proved by noting that

$$M_X(0) = \mathbb{E}[e^{0X}] = \mathbb{E}[1] = 1.$$

The second property holds because

$$\frac{d^k}{ds^k} M_X(s) = \int_{-\infty}^{\infty} \frac{d^k}{ds^k} e^{sx} f_X(x) dx = \int_{-\infty}^{\infty} x^k e^{sx} f_X(x) dx.$$

Setting $s = 0$ yields

$$\frac{d^k}{ds^k} M_X(s)|_{s=0} = \int_{-\infty}^{\infty} x^k f_X(x) dx = \mathbb{E}[X^k].$$

Moment Generating Functions

Distribution	PMF/ PDF	$\mathbb{E}[X]$	$\text{Var}[X]$	$M_X(s)$
Bernoulli	$\mathbb{P}[X = 1] = p$	p	$p(1 - p)$	$M_X(s) = 1 - p + pe^s$
Binomial	$p_X(k) = \binom{n}{k} p^k (1 - p)^{n-k}$	np	$np(1 - p)$	$M_X(s) = (1 - p + pe^s)^n$
Geometric	$p_X(k) = p(1 - p)^{k-1}$	$\frac{1}{p}$	$\frac{1-p}{p^2}$	$M_X(s) = \frac{pe^s}{1-(1-p)e^s}$
Poisson	$p_X(k) = \frac{\lambda^k e^{-\lambda}}{k!}$	λ	λ	$M_X(s) = e^{\lambda(e^s - 1)}$
Gaussian	$f_X(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$	μ	σ^2	$M_X(s) = e^{\mu s + \frac{\sigma^2 s^2}{2}}$
Exponential	$f_X(x) = \lambda \exp\{-\lambda x\}$	$\frac{1}{\lambda}$	$\frac{1}{\lambda^2}$	$M_X(s) = \frac{\lambda}{\lambda - s}$
Uniform	$f_X(x) = \frac{1}{b-a}$	$\frac{a+b}{2}$	$\frac{(b-a)^2}{12}$	$M_X(s) = \frac{e^{sb} - e^{sa}}{s(b-a)}$

Table: Moment generating functions of common random variables.

Independent random variables

Theorem

Let X and Y be independent random variables. Let $Z = X + Y$. Then,

$$M_Z(s) = M_X(s)M_Y(s). \quad (4)$$

Proof. By definition of MGF, we have that

$$M_Z(s) = \mathbb{E} \left[e^{s(X+Y)} \right] \stackrel{(a)}{=} \mathbb{E} \left[e^{sX} \right] \mathbb{E} \left[e^{sY} \right] = M_X(s)M_Y(s),$$

where (a) holds because X and Y are independent. □

Many Independent Random Variables

Corollary

- independent random variables X_1, \dots, X_N
- $Z = \sum_{n=1}^N X_n$

Then, the MGF of Z is

$$M_Z(s) = \prod_{n=1}^N M_{X_n}(s).$$

If X_1, \dots, X_N are i.i.d., then the MGF is

$$M_Z(s) = (M_{X_1}(s))^N.$$

Example 4

Theorem (**Sum of Bernoulli = Binomial**)

- X_1, \dots, X_N be a sequence of *i.i.d.* Bernoulli random variables with parameter p
- $Z = X_1 + \dots + X_N$

Then Z is a binomial random variable with parameters (N, p) .

Proof

MGF of Z is

$$\begin{aligned}M_Z(s) &= \mathbb{E}[e^{s(X_1 + \dots + X_N)}] = \prod_{n=1}^N \mathbb{E}[e^{sX_n}] \\ &= \prod_{n=1}^N (pe^{s1} + (1-p)e^{s0}) = (pe^s + (1-p))^N.\end{aligned}$$

MGF of a binomial random variable: If $Z \sim \text{Binomial}(N, p)$, then

$$\begin{aligned}M_Z(s) &= \mathbb{E}[e^{sZ}] = \sum_{k=0}^N e^{sk} \binom{N}{k} p^k (1-p)^{N-k} \\ &= \sum_{k=0}^N \binom{N}{k} (pe^s)^k (1-p)^{N-k} = (pe^s + (1-p))^N,\end{aligned}$$

Example 5

Theorem (Sum of Gaussian = Gaussian)

Let X_1, \dots, X_N be a sequence of Gaussian random variables with parameters $(\mu_1, \sigma_1), \dots, (\mu_N, \sigma_N)$. Let $Z = X_1 + \dots + X_N$ be the sum. Then, Z is a Gaussian random variable:

$$Z = \text{Gaussian}\left(\sum_{n=1}^N \mu_n, \sum_{n=1}^N \sigma_n^2\right). \quad (5)$$

Proof

Proof. We skip the proof of the MGF of a Gaussian. It can be shown that

$$M_X(s) = e^{\mu s + \frac{\sigma^2 s^2}{2}}. \quad (6)$$

When we have a sequence of Gaussian random variables, then

$$\begin{aligned} M_Z(s) &= \mathbb{E}[e^{s(X_1 + \dots + X_N)}] \\ &= M_{X_1}(s) \dots M_{X_N}(s) \\ &= \left(e^{\mu_1 s + \frac{\sigma_1^2 s^2}{2}} \right) \dots \left(e^{\mu_N s + \frac{\sigma_N^2 s^2}{2}} \right) \\ &= \exp \left\{ \left(\sum_{n=1}^N \mu_n \right) s + \left(\sum_{n=1}^N \sigma_n^2 \right) \frac{s^2}{2} \right\}. \end{aligned}$$

Therefore, the resulting random variable Z is also a Gaussian. The mean and variance are $\sum_{n=1}^N \mu_n$ and $\sum_{n=1}^N \sigma_n^2$, respectively. □

What is a moment generating function?

- $\mathbb{E}[e^{sX}]$
- Can generate moments
- Useful for sum of random variables

Questions?