

## M378K Introduction to Mathematical Statistics

### Problem Set #9

#### Moment generating functions.

**Definition 9.1.** The  $k^{\text{th}}$  moment of a random variable  $Y$  taken about the origin is defined as  $\mathbb{E}[Y^k]$  provided that the expectation exists. We write

$$\mu_k = \mathbb{E}[Y^k]$$

when there is no ambiguity about the random variable in question.

**Remark 9.2.**  $\mu_k$  is also referred to as the  $k^{\text{th}}$  raw moment.

**Remark 9.3.** In particular,  $\mu_1 = \mu$  happens to be the **mean** of the random variable  $Y$ .

**Definition 9.4.** The  $k^{\text{th}}$  central moment of a random variable  $Y$  is defined as  $\mathbb{E}[(Y - \mu)^k]$  provided that the expectation exists. We write

$$\mu_k^c = \mathbb{E}[(Y - \mu)^k]$$

when there is no ambiguity about the random variable in question.

**Remark 9.5.**  $\mu_k$  is also referred to as the  $k^{\text{th}}$  moment of a random variable  $Y$  taken about its mean.

**Definition 9.6.** The moment-generating function (mgf)  $m_Y$  for a random variable  $Y$  is defined as

$$m_Y(t) = \mathbb{E}[e^{tY}]$$

for all  $t$  for which the above expectation exists. In fact, we say that the moment-generating function exists if there exists a positive number  $b$  such that  $m_Y(t)$  is finite for all  $t$  such that  $|t| \leq b$ .

**Problem 9.1.** How much is  $m_Y(0)$ ?

$$m_Y(0) = \mathbb{E}[e^{0 \cdot Y}] = 1$$



**Remark 9.7.** On the choice of terminology...

Step 1.

$$\frac{d}{dt} m_Y(t) = ?$$

$$\begin{aligned} \frac{d}{dt} m_Y(t) &= \frac{d}{dt} \mathbb{E}[e^{tY}] = \mathbb{E}\left[\frac{d}{dt} e^{tY}\right] \\ &= \mathbb{E}[Y e^{tY}] \end{aligned}$$

Step 2.

$$m_Y'(0) = ?$$

$$m_Y'(0) = \mathbb{E}[\underbrace{Y e^{0 \cdot Y}}_1] = \mathbb{E}[Y] = \mu_Y$$

Step 3.

$$\frac{d^2}{dt^2} m_Y(t) = ?$$

$$\frac{d}{dt} \left( \frac{d}{dt} m_Y(t) \right) = \frac{d}{dt} \mathbb{E}[Y e^{t \cdot Y}] = \mathbb{E}[Y^2 e^{t \cdot Y}]$$

Step 4.

$$m_Y''(0) = ?$$

$$m_Y''(0) = \mathbb{E}[Y^2] = \mu_2, \text{ i.e., the second moment}$$

Step 5. *What do you suspect the **generalization** of the above would be?*

$$m_Y^{(k)}(0) = \mathbb{E}[Y^k] = \mu_k \quad \text{😊}$$

**Theorem 9.8.** If  $m_Y$  exists, then for  $k \in \mathbb{N}$ , we have

$$m_Y^{(k)}(0) = \mu_k.$$

**Example 9.9.** Let  $Y \sim b(n=1, p)$ , i.e., let  $Y$  model a Bernoulli trial with the probability of success denoted by  $p$ . Find  $m_Y$ .

→:  $m_Y(t) = \mathbb{E}[e^{t \cdot Y}] = e^{t \cdot 0} \cdot (1-p) + e^{t \cdot 1} \cdot p$   
 $= (1-p) + pe^t \quad t \in \mathbb{R}$

**Proposition 9.10.** Let  $Y_1$  and  $Y_2$  be independent random variables with m.g.f.s denoted by  $m_{Y_1}$  and  $m_{Y_2}$ . Define  $Y = Y_1 + Y_2$ . Then, for every  $t$  for which both  $m_{Y_1}$  and  $m_{Y_2}$  are well defined, we have

$$m_Y(t) = ?$$

*Proof.* By definition:

$$m_Y(t) = \mathbb{E}[e^{t \cdot Y}]$$

Using  $Y = Y_1 + Y_2$ , we can substitute  $Y_1 + Y_2$  for  $Y$  in the expression above. So,

$$m_Y(t) = \mathbb{E}[e^{t \cdot (Y_1 + Y_2)}]$$

One of the properties of the exponential function is that  $e^{A+B} = e^A \times e^B$ . Thus, the above becomes:

$$m_Y(t) = \mathbb{E}[e^{t \cdot Y_1} \cdot e^{t \cdot Y_2}]$$

Recall that  $Y_1$  and  $Y_2$  are assumed to be independent random variables. With this in mind, we get:

$$m_Y(t) = \underbrace{\mathbb{E}[e^{t \cdot Y_1}]} \cdot \underbrace{\mathbb{E}[e^{t \cdot Y_2}]}$$

Finally, using the definition of a m.g.f., we have

$$m_Y(t) = m_{Y_1}(t) \cdot m_{Y_2}(t)$$

**Example 9.11.** Let  $Y \sim b(n, p)$ . What is the moment generating function of  $Y$ ?

→:  $m_Y(t) = ?$

$Y = I_1 + I_2 + \dots + I_n$  w/  $I_j, j=1..n$  are all  $B(p)$  and independent

$$m_Y(t) = m_{I_1}(t) \cdots m_{I_n}(t) \stackrel{\text{identically dist'd}}{=} (m_{I_1}(t))^n = (1-p+pe^t)^n$$

**Example 9.12.** Let  $N \sim \text{Poisson}(\lambda)$ . What is the moment generating function  $m_N$  of  $N$ ?

$$\begin{aligned} \rightarrow: m_N(t) &= \mathbb{E}[e^{t \cdot N}] = \sum_{n=0}^{\infty} e^{t \cdot n} \cdot p_N(n) = \sum_{n=0}^{\infty} e^{t \cdot n} \cdot e^{-\lambda} \frac{\lambda^n}{n!} = \\ &= e^{-\lambda} \sum_{n=0}^{\infty} \frac{e^{t \cdot n} \lambda^n}{n!} = e^{-\lambda} \sum_{n=0}^{\infty} \frac{(e^t \lambda)^n}{n!} = e^{-\lambda} \cdot e^{e^t \lambda} = e^{\lambda(e^t - 1)} \end{aligned}$$

**Example 9.13.** Let  $Z \sim N(0, 1)$ . What is the moment generating function  $m_Z$  of  $Z$ ?

$$\begin{aligned} \rightarrow: m_Z(t) &= \mathbb{E}[e^{t \cdot Z}] = \int_{-\infty}^{\infty} e^{t \cdot z} \cdot \varphi(z) dz = \int_{-\infty}^{\infty} e^{t \cdot z} \cdot \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}} dz \\ &= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2} + t \cdot z - \frac{t^2}{2}} e^{\frac{t^2}{2}} dz = e^{\frac{t^2}{2}} \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(z-t)^2} dz = 1 \end{aligned}$$

density  $N(t, \sigma=1)$

$$m_Z(t) = e^{\frac{t^2}{2}}$$

**Example 9.14.** Let the random variable  $Y$  have the mgf  $m_Y$ . Define  $X = aY + b$  for some constants  $a$  and  $b$ . Express the mgf  $m_X$  of  $X$  in terms of  $m_Y$ ,  $a$  and  $b$ .

$$\begin{aligned} \rightarrow: m_X(t) &= \mathbb{E}[e^{t \cdot X}] = \mathbb{E}[e^{t(aY+b)}] = \mathbb{E}[e^{taY+tb}] \\ &= \mathbb{E}[e^{taY} \cdot e^{tb}] = e^{tb} \mathbb{E}[e^{taY}] = e^{tb} \cdot m_Y(ta) \end{aligned}$$

**Example 9.15.** Let  $X \sim N(\mu, \sigma^2)$ . What is the moment generating function  $m_X$  of  $X$ ?

$$\begin{aligned} \rightarrow: X &= \underbrace{\mu}_b + \underbrace{\sigma}_a \cdot Z \quad \text{w/ } Z \sim N(0,1) \\ m_X(t) &= e^{t \cdot \mu} \cdot m_Z(t \cdot \sigma) = e^{t \cdot \mu} \cdot e^{\frac{(t \cdot \sigma)^2}{2}} = e^{t \cdot \mu + \frac{t^2 \sigma^2}{2}} \quad \square \end{aligned}$$

**Problem 9.2.** A random variable  $Y$  is said to be lognormal if there exists a normally distributed random variable  $X \sim N(\mu, \sigma^2)$  such that  $Y \stackrel{(d)}{=} e^X$ . Express the mean and the variance of the lognormal r.v.  $Y$  in terms of the parameters  $\mu$  and  $\sigma$ .

$$\begin{aligned} \rightarrow: \mathbb{E}[Y] &= \mathbb{E}[e^X] = \mathbb{E}[e^{1 \cdot X}] = m_X(1) = e^{\mu + \frac{\sigma^2}{2}} \\ \mathbb{E}[Y^2] &= \mathbb{E}[(e^X)^2] = \mathbb{E}[e^{2 \cdot X}] = m_X(2) = e^{2\mu + \frac{2^2 \cdot \sigma^2}{2}} = e^{2(\mu + \sigma^2)} \\ \text{Var}[Y] &= \mathbb{E}[Y^2] - (\mathbb{E}[Y])^2 = e^{2(\mu + \sigma^2)} - e^{2\mu + \sigma^2} = e^{2\mu + \sigma^2} (e^{\sigma^2} - 1) \quad \square \end{aligned}$$

**Proposition 9.16.** 1. If  $m_Y$  exists for a certain probability distribution, then it is unique.

2. If  $m_{Y_1}$  and  $m_{Y_2}$  are equal on an interval, then  $Y_1 \stackrel{(d)}{=} Y_2$ .

**Corollary 9.17.** Let  $Y_1$  and  $Y_2$  be independent and normally distributed. Define  $Y = Y_1 + Y_2$ . Then, the distribution of  $Y$  is ...

Proof.

□