Chapter 43: Moment Generating Functions

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Learning Objectives

- 1. Learn the definition of a moment-generating function.
- 2. Find the moment-generating function of a Moonidal random variable.
- 3. Use a moment-generating function to find the mean and variance of a random variable.

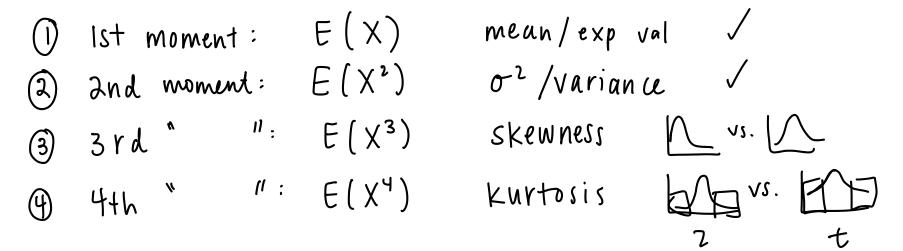
What are moments?

Definition 1

The j^{th} moment of a r.v. X is $\mathbb{E}[X^j]$

Example 1

 $1^{st} - 4^{th}$ moments



What is a *moment generating function* (mgf)??

Definition 3

If X is a r.v., then the moment generating function (mgf) associated with X is:

$$M_X(t) = \mathbb{E}[e^{tX}]$$

Remarks

ullet For a discrete r.v., the mgf of X is

$$M_X(t) = \mathbb{E} \underbrace{e^{tX}}_{all\ x} = \sum_{all\ x} \underbrace{e^{tx}}_{p_X(x)}$$

• For a continuous r.v., the mgf of X is

$$M_X(t) = \mathbb{E}[e^{tX}] = \int_{-\infty}^{\infty} e^{tx} f_X(x) dx$$

• The mgf $M_X(t)$ is a function of t, not of X, and it might not be defined (i.e. finite) for all values of t. We just need it to be defined for t=0.

Example

Example 4

What is $M_X(t)$ for t=0?

$$M_x(t) = E[e^{tX}]$$

$$M_x(t=0) = E(e^{0 \cdot X}) = E(e^0) = 1$$

when t=0, mgf is I for all RVs

Theorem

Theorem 5

The moment generating function uniquely specifies a probability distribution.

Theorem 6

$$\mathbb{E}[X^r] = M_X^{(r)}(0)$$

r=1 : M'_x(0)

 $oxed{(r)}$ in this equation is the rth derivative with respect to t

 $V = 4 : M_{\times}^{(4)}(0)$

- ullet When r=1, we are taking the first derivative
- When r=4, we are taking the fourth derivative

Using the mgf to uniquely describe a probability distribution

Let
$$X \sim Poisson(\lambda)$$

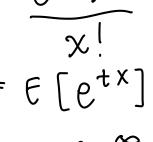
- 1. Find the mgf of X
- 2. Find $\mathbb{E}[X]$

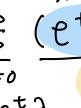
2. Find
$$\mathbb{E}[X]$$

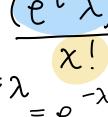
3. Find $Var(X)$

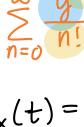
$$f_{\mathbb{X}}(x) = \underbrace{e^{-\lambda} \lambda^{x}}_{\chi!}$$

 $0 M_{x}(t) = E[e^{tx}] = \sum_{k=0}^{\infty} e^{tx} \frac{e^{-\lambda} \lambda^{k}}{2}$









 $\textcircled{2} E(X): M'_{X}(t) = \frac{d}{dt} e^{\lambda(e^{t}-1)}$

$$= e^{\lambda(e^{t}-1)} \cdot \frac{dt}{dt} \left(\frac{\lambda(e^{t}-1)}{2} \right) = e^{-\lambda} e^{e^{t}\lambda} = e^{-\lambda + \lambda e^{t}}$$

$$= e^{\lambda(e^{t}-1)} \cdot \frac{dt}{dt} \left(\frac{\lambda(e^{t}-1)}{2} \right) = e^{-\lambda} e^{e^{t}\lambda} = e^{-\lambda + \lambda e^{t}}$$

$$= \lambda e^{t} e^{\lambda(e^{t}-1)}$$

$$= \lambda e^{t$$

Theorem

Remark: Finding the mean and variance is sometimes easier with the following trick

Theorem 8

Let
$$R_X(t) = \ln[M_X(t)]$$
. Then,

$$\mu=\mathbb{E}[X]=R_X'(0), ext{ and }$$
 $\sigma^2=Var(X)=R_X''(0)$

Proof.

$$R'_{x}(t) = \frac{d}{dt} \ln \left(\underbrace{M_{x}(t)}_{g(x)} \right) = \frac{1}{M_{x}(t)} \cdot \underbrace{M'_{x}(t)}_{g'(x)}$$

$$R'_{x}(t=6) = \frac{1}{M_{x}(6)} \underbrace{M'_{x}(0)}_{h_{x}(0)} = E(x)^{\frac{1}{g(x)}}$$

Using $R_X(t)$ to uniquely describe a probability distribution

Example 9

Let $X \sim Poisson(\lambda)$.

- 1. Find $\mathbb{E}[X]$ using $R_X(t)$
- 2. Find Var(X) using $R_X(t)$

$$\begin{array}{ll}
\text{Tr} R_{x}(t) = \ln \left(M_{x}(t) \right) = \ln \left(e^{\lambda e^{\tau} - \lambda} \right) = \lambda e^{t} - \lambda \\
R_{x}'(t) = \frac{d}{dt} \left(\lambda e^{t} - \lambda \right) = \underline{\lambda} e^{t} \\
R_{x}'(0) = \lambda e^{0} = \lambda
\end{array}$$

$$\mathbb{E}(x) = \lambda$$

$$Var(X) = R''_X(0) = \lambda e^0 = \lambda$$

Using the mgf to uniquely describe the standard normal distribution

Example 10

Let Z be a standard normal random variable, i.e.

 $Z \sim N(0,1)$.

- 1. Find the mgf of ${\it Z}$
- 2. Find $\mathbb{E}[Z]$
- 3. Find Var(Z)

$$M_{Z}(t) = E[e^{tZ}] = \int_{-\infty}^{\infty} e^{tz} \int_{2\pi}^{-z^{2}} e^{-z^{2}} dz$$

$$= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{tz-z^{2}} dy$$

$$= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{tz-z^{2}} dy$$

$$= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{tz-(z-t)^{2}} dy$$

$$= e^{t^{2}/2} \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-(z-t)^{2}} dy \quad \text{let } u = z - t$$

$$= e^{t^{2}/2} \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-u^{2}/2} du = e^{t^{2}/2} = M_{Z}(t)$$

$$R_2(t) = R_2(0)$$

$$R_2(t) = R_2(0)$$

$$R_2(t) = ln (M_2(0))$$

$$R_2(t) = R_2(0)$$

 $R_2(t) = ln(M_2(t)) = ln(e^{t^2/2}) = \frac{t^2}{2}$

$$R_{z}(t) = ln (M_{z}(t)) = ln (e')$$

$$R'_{z}(t) = \frac{d}{dt} (t'_{z}) = \frac{dt}{dt} = t$$

$$E(z) =$$

$$E(z) = R'_{z}(0) = 0$$

$$Var(Z) = \dot{R}_2''(0)$$

$$R_2^{"}(t)$$

$$R_2^{"}(t)$$

$$R_{2}^{"}(t)$$

$$J'(t) = \mathcal{A}$$

$$R_2''(t) = \frac{d}{dt}(t) = 1$$

$$Var(z)=1$$

$$\int_{-\infty}^{\infty} x f_{x}(x) dx$$

$$Var(x) =$$

 $vs. \in (x) =$

$$Var(X) = \int_{-\infty}^{\infty} (x-\mu)^2 f_X(x) dx$$

$$\int_{-\infty}^{\infty} (x-\mu)^{2} f_{x}(x) dx$$

Mgf's of sums of independent RV's

Theorem 9

If X and Y are independent RV's with respective mgf's $M_X(t)$ and $M_Y(t)$, then

$$M_{X+Y}(t) = E[e^{t(X+Y)}] = E[e^{tX}e^{tY}] = E[e^{tX}]E[e^{tY}] = M_X(t)M_Y(t)$$

$$M'_{X+Y}(t) = M'_{X}(t)M'_{Y}(t)$$

Main takeaways

- Mgf's are a purely mathematically definition
 - We can't really relate it to our real world analysis
- They are helpful mathematically because they are unique to a probability distribution
 - We can find the unique mgf from for a probability distribution
 - And we can find a distribution from an mgf
- Mgf's can sometimes make it easier to find the mean and variance of an RV
- Mgf's are most helpful when we are finding a joint distribution that is a sum or transformation of two RV's
 - Make the calculation easier!
- Mgf's are often used to prove certain distribution are sums of other ones!

More resources

- https://online.stat.psu.edu/stat414/book/export/html/676
- https://www.youtube.com/watch/ez_vq23xWrQ
- https://www.youtube.com/watch/2p9J9ChTeFI
- https://www.youtube.com/watch/A5bWU8xcQkE
- https://www.youtube.com/watch/QeUrTGFTFm4
- https://www.youtube.com/watch/HhrkwyyRtgl