

Lesson 18: Moment Generating Functions

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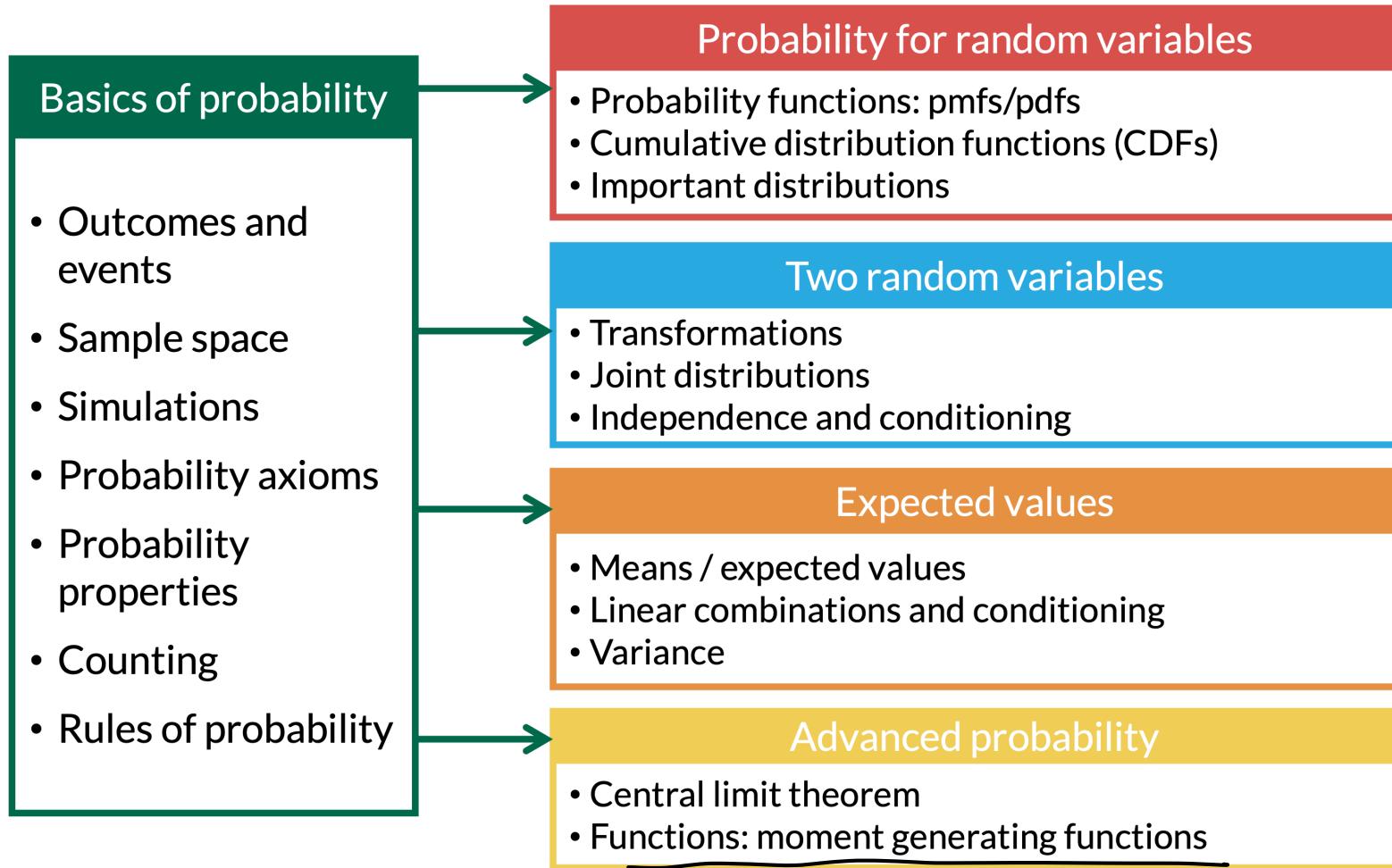
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Learning Objectives

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

$$E(X) = \int_{-\infty}^{\infty} x f(x) dx$$

Where are we?



What are moments?

Definition 1

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

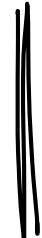
Okay, but what are they?

Gamma (α, β)

Example 1

$1^{st} - 4^{th}$ moments  jth moment : $E(X^j)$

1. 1st moment: $E(X)$ mean

2. 2nd moment: $E(X^2)$ \rightarrow variance : $E(X^2) - [E(X)]^2$ 

3. 3rd moment: $E(X^3)$ \rightarrow skewness 

4. 4th moment: $E(X^4)$ \rightarrow kurtosis 

$$\hookrightarrow E(g(x)) = \int_{-\infty}^{\infty} g(x) f(x) dx^2 \quad \text{OR} \quad \sum_{\text{all } x} g(x) p(x)$$

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:

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

$g(x)$

Remarks

- For a discrete r.v., the MGF of X is

$$M_X(t) = \mathbb{E}[e^{tX}] = \sum_{\text{all } x} e^{tx} p_X(x)$$

- 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 $t = 0$?

$$\begin{aligned}M_X(t) &= E(e^{tX}) \\M_X(t=0) &= E(e^{0 \cdot X}) = E(e^0) \\&= E(1) = 1\end{aligned}$$

when $t=0$, MGF is 1 for ALL RVs

How do MGFs give us moments?

Theorem 5

The moment generating function uniquely specifies a probability distribution. AKA **all moments can be found from the MGF through its derivatives at $t = 0$** .

Theorem 6

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

(r) in this equation is the r th derivative with respect to t . We calculate the derivative at $t = 0$

- When $r = 1$, we are taking the first derivative $\rightarrow M'_X(0) \quad M'_X(t=0)$
- When $r = 4$, we are taking the fourth derivative $\rightarrow M_X^{(4)}(0)$

M'' M''' $M^{(4)}$

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

Using the MGF to uniquely describe a probability distribution

Example 7

Let $X \sim \text{Poisson}(\lambda)$

1. Find the MGF of X
2. Find $\mathbb{E}[X]$
3. Find $\text{Var}(X)$

$$\textcircled{2} \quad \mathbb{E}(X) = M'(t=0)$$

$$M'_X(t) = \frac{d}{dt} e^{\lambda(e^t - 1)}$$

$$= e^{\lambda(e^t - 1)} \frac{d}{dt} \lambda(e^t - 1) = e^{\lambda(e^t - 1)} \lambda e^t = \underline{\lambda e^t e^{\lambda(e^t - 1)}}$$

$$M'(t=0) = \lambda e^0 e^{\lambda(e^0 - 1)} = \lambda$$

$$= 1 \quad = 1$$

$$P_X(x) = \frac{e^{-\lambda} \lambda^x}{x!}$$

$$\textcircled{1} \quad M_X(t) = \mathbb{E}[e^{tx}] = \sum_{x=0}^{\infty} e^{tx} \frac{e^{-\lambda} \lambda^x}{x!}$$

$$= e^{-\lambda} \sum_{x=0}^{\infty} \frac{\lambda^x e^{tx}}{x!}$$

$$= e^{-\lambda} \sum_{x=0}^{\infty} \frac{(\lambda e^t)^x}{x!} = e^{-\lambda} (e^{e^t \lambda})$$

RULE

$$\sum_{n=0}^{\infty} \frac{z^n}{n!} = e^z$$

$$\textcircled{3} \quad \text{Var}(X) = \underbrace{E(X^2)}_{M''(t=0)} - \underbrace{[E(X)]^2}_{\lambda}$$

$$\hookrightarrow M''_X(t) = \lambda e^{\underbrace{t + \lambda(e^t - 1)}_{1}} (1 + \lambda e^t)$$

$$M''(t=0) = \lambda (1 + \lambda) = \lambda + \lambda^2$$

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

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,

$$\mu = \mathbb{E}[X] = R'_X(0), \text{ and} \\ \sigma^2 = \text{Var}(X) = R''_X(0) \\ @ t = 0$$

Proof.

$$R'_X(t) = \frac{d}{dt} \ln(M_X(t)) = \frac{1}{M_X(t)} M'_X(t) = \frac{M'_X(t)}{M_X(t)} = 1 \\ \hookrightarrow @ t = 0$$

$$R'_X(t=0) = \frac{M'_X(0)}{1} = E(X)$$

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 $R_X(t)$

$$\textcircled{1} \quad R_X(t) = \ln(M_X(t)) = \ln(e^{\lambda e^t - \lambda})$$

$$R_X(t) = \lambda e^t - \lambda$$

$$E(X) = R'_X(t=0)$$

$$R'_X(t) = \lambda e^t \quad R'_X(t=0) = \lambda$$

$$Var(X) = R''_X(t=0)$$

$$E(X) = \lambda$$

$$\textcircled{2} \quad R''_X(t) = \frac{d}{dt}(\lambda e^t) = \lambda e^t$$

$$Var(X) = R''_X(t=0) = \lambda$$

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 Z
2. Find $\mathbb{E}[Z]$
3. Find $\text{Var}(Z)$

$$\textcircled{1} \quad M_Z(t) = E[e^{tZ}] = \int_{-\infty}^{\infty} e^{tz} \frac{1}{\sqrt{2\pi}} e^{-z^2/2} dz$$

$$= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{tz - z^2/2} dz \quad \begin{matrix} \text{tz - } z^2/2 \\ \rightarrow \\ = t^2 - (z-t)^2/2 \end{matrix}$$

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

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

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

$$u = \frac{z-t}{\sqrt{2\pi}} \quad du = dz$$

$$= 1$$

$$M_Z(t) = e^{t^2/2}$$

Using the MGF to uniquely describe the standard normal distribution

$$\textcircled{2} \quad E(Z) = R'_Z(t=0) \quad R_Z(t) = \ln(M_X(t)) = \ln(e^{t^2/2}) = t^2/2$$

$$R'_Z(t) = \frac{d}{dt} \left(\frac{t^2}{2} \right) = \frac{2t}{2} = \underline{t}$$

vs.

$$E(Z) = R'_Z(t=0) = 0 \rightarrow \begin{matrix} \text{std normal} \\ \mu = 0 \end{matrix}$$

$$E(Z) = \int_{-\infty}^{\infty} z f_Z(z) dz$$

$$\textcircled{3} \quad \text{Var}(Z) = R''_Z(t=0)$$

$$R''_Z(t) = \frac{d}{dt} (\underline{t}) = 1$$

$$\text{Var}(Z) = \int_{-\infty}^{\infty} (z-\mu)^2 f_Z(z) dz$$

$$\text{Var}(Z) = 1 \rightarrow \text{var of std normal} = 1$$

MGFs of sums of independent RV's

Theorem 9

If X and Y are independent RV's with respective MGFs $M_X(t)$ 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

- MGFs 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
- MGFs can *sometimes* make it easier to find the mean and variance of an RV
- MGFs are most helpful when we are finding a joint distribution that is a sum or transformation of two RV's
 - Make the calculation easier!
- MGFs 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/HhrkwyyRtgI>