

MGFs and CLT

Moments

For RV X , the k -th moment of X is defined as $E(X^k)$. (1st moment of X is $E(X) = \mu$)

↳ The k -th central moment is defined as

$$E((X - \mu)^k), \text{ where } E(X) = \mu$$

$$(2^{\text{nd}} \text{ central moment of } X \text{ is } E((X - \mu)^2) = \sigma^2)$$

Moment Generating Functions

For RV X , we can use moment generating functions (MGFs) to calculate the k -th moment.

• the MGF of X is given as $m(t) = E(e^{tX})$

↳ to get the k th moment of X , we use the following formula

$$E(X^k) = m^{(k)}(0) \quad [k^{\text{th}} \text{ derivative of } m, \text{ at } t=0]$$

Example

Suppose you have X , $P(X=x) = \begin{cases} \frac{1}{4}, & k=2 \\ \frac{3}{4}, & k=4 \end{cases}$. Calculate $E(X^2)$ using MGFs.

$$m_X(t) = \frac{1}{4}e^{2t} + \frac{3}{4}e^{4t}$$

$$m^{(1)}(t) = 2 \cdot \frac{1}{4}e^{2t} + 4 \cdot \frac{3}{4}e^{4t} \\ = \frac{1}{2}e^{2t} + 3e^{4t}$$

$$m^{(2)}(t) = 2 \cdot \frac{1}{2}e^{2t} + 4 \cdot 3e^{4t} \\ = e^{2t} + 12e^{4t}$$

$$E(X^2) = m^{(2)}(0) = 1 + 12 = 13$$

$$E(X^2) = 4^2 \cdot \frac{3}{4} + 2^2 \cdot \frac{1}{4} = 13$$

Properties About MGFs

- For X, Y , if you have $m_x(t), m_y(t)$

$$m_x(t) = m_y(t) \iff X, Y \text{ follow same distribution}$$

Very useful if you want to show equivalence of variables w/ limited info

- Let X_1, X_2, \dots, X_n be independent w/ MGFs and $Y = a_1 X_1 + \dots + a_n X_n$. Then

$$m_Y(t) = m_{X_1}(a_1 t) \times \dots \times m_{X_n}(a_n t)$$

Central Limit Theorem

An incredibly important theorem in statistics

- Suppose you have X_1, \dots, X_n iid RVs. w/ mean μ , variance σ^2

$$\text{Then, for } \bar{X}_n = \frac{1}{n}(X_1 + \dots + X_n)$$

$$\text{w/ } Z_n = \sqrt{n} \left(\frac{\bar{X}_n - \mu}{\sigma} \right)$$

$$\text{then } Z_n \xrightarrow{D} N(0, 1) \quad [Z_n \text{ converges in distribution to } N(0, 1)]$$

$$\text{and } \bar{X}_n \rightarrow N(\mu, \sigma^2/n)$$

Convergence

Consider sequence of continuous RVs X_1, X_2, \dots and RV Y

- X_n converges in probability to Y , as $n \rightarrow \infty$ if $(X_n \xrightarrow{P} Y)$

$$\lim_{n \rightarrow \infty} P(|X_n - Y| \geq \epsilon) = 0, \forall \epsilon > 0$$

- X_n converges in distribution to Y , as $n \rightarrow \infty$, if $(X_n \xrightarrow{D} Y)$

$$\lim_{n \rightarrow \infty} P(X_n \leq x) = P(Y \leq x) \quad \forall x \in \mathbb{R}$$

↳ very useful for approximating probabilities

Q&A

7. b) $X \sim \text{Exp}(1)$, $Y = X^3$ $\text{Gamma}(3n+1, 1)$

$$\begin{aligned}
 E(Y^n) &= E(X^{3n}) \\
 &= \int_0^\infty x^{(3n+1)-1} e^{-x} dx \\
 &= \Gamma(3n+1) \int_0^\infty \frac{1}{\Gamma(3n+1)} x^{(3n+1)-1} e^{-x} dx \\
 &= \Gamma(3n+1) = (3n)!
 \end{aligned}$$

$$E(Y) = 3! = 6$$

$$\begin{aligned}
 V(Y) &= E(Y^2) - (E(Y))^2 \\
 &= 6! - (3!)^2 \\
 &= 720 - 36 = 684
 \end{aligned}$$

8. Weekly Output $\sim U(20, 30)$

$$X_1, X_2, \dots, X_{52} \sim U(20, 30)$$

$$E(X_i) = 25, \text{Var}(X_i) = \frac{100}{12}$$

$$X = \sum_{i=1}^{52} X_i, \quad \bar{X} = \frac{\sum_{i=1}^{52} X_i}{52}$$

$$\begin{aligned}
 \text{want: } P\left(\sum_{i=1}^{52} X_i < 1280\right) &= P\left(\bar{X}_{52} < \frac{1280}{52}\right) \\
 &= P\left(\sqrt{52} \frac{\bar{X}_{52} - 25}{\sqrt{100/12}} < \sqrt{52} \frac{1280/52 - 25}{\sqrt{100/12}}\right) \\
 &= P(Z < -0.961) = \Phi(-0.961)
 \end{aligned}$$

F19 Q5

$$a) V(X_i) = E(X_i^2) - (E(X_i))^2$$

$$E(X_i^2) = V(X_i) + \mu^2$$

$$\frac{1}{n} \sum_{i=1}^n X_i^2 \xrightarrow{P} \sigma^2 + \mu^2$$

$$b) \bar{X}_n \xrightarrow{P} \mu, f(x) = x^2$$

$$(\bar{X}_n)^2 \xrightarrow{P} \mu^2$$

F17 Q5 X, Y independent

$$c) X \sim \text{Exp}(1) \quad \text{want } m_Z$$

$$Y \sim \text{Exp}(2) \quad Z = X + Y$$

$$m_Z(t) = m_{X+Y}(t) = m_X(t) m_Y(t) = \left(\frac{1}{1-t} \right) \left(\frac{2}{2-t} \right)$$

$$h) \text{ want } P(Z > 4 | W = 2) \quad W = \sqrt{X}$$

$$P(Z > 4 | W = 2) = P(X + Y > 4 | \sqrt{X} = 2)$$

$$= P(Y > 4 - X | X = 4)$$

$$= P(Y > 0 | X = 4)$$

$$= P(Y > 0) \quad X, Y \text{ i.i.d.}$$

$$= 1$$