

Moment Generating Functions

Definition: The MGF $M_X(t)$ of X is given by

$$M_X(t) = E(e^{tx})$$

for all t for which the expectation is finite.

Theorem: $E(X^n) = M^{(n)}(0)$ when $M(t) < \infty$ over some neighborhood containing 0.

Proof: The Taylor expansion of $M(t)$ about 0 is

$$M(t) = \sum_{n=0}^{\infty} \frac{M^{(n)}(0)}{n!} t^n$$

Also,

$$\begin{aligned} M(t) &= E[e^{tx}] = E\left[\sum_{n=0}^{\infty} \frac{x^n t^n}{n!}\right] \\ &= \sum_{n=0}^{\infty} \frac{E(x^n)}{n!} t^n \Rightarrow M^{(n)}(0) = E(x^n). \end{aligned}$$

Theorem: Let X, Y be rvs having mgfs M_X & M_Y . If $\exists a > 0$ such that $M_X(t) = M_Y(t) \quad \forall t \in (-a, a)$, then X & Y have the same distribution.

Theorem: Continuity theorem

Let $\{X_n\}$ be a sequence of rvs & $\{F_n\}$ be the corresponding distribution functions & $\{M_n\}$ be the mgfs. Suppose $\exists a > 0$ s.t.
 $M_n(t) \rightarrow M_x(t)$ as $n \rightarrow \infty \quad \forall t \in (a, a)$ where $M_x(t)$ denotes the mgf of some rv X .
Then $F_n(x) \rightarrow F(x) \quad \forall x$ at which F is continuous.

Theorem: $X \sim N(\mu, \sigma^2)$. Then

$$M_x(t) = e^{\mu t + \frac{1}{2} \sigma^2 t^2}, \quad \forall t \in \mathbb{R}.$$

The central limit theorem

Consider a sample of random quantities X_1, \dots, X_n . Define the sample mean \bar{X}_n by

$$\bar{X}_n = \frac{\sum_{i=1}^n X_i}{n}.$$

When X_1, \dots, X_n are i.i.d & $E(X_i) = \mu$, $V(X_i) = \sigma^2$,

$$E(\bar{X}_n) = \mu \quad \& \quad V(\bar{X}_n) = \frac{\sigma^2}{n}.$$

The purpose of this section is to investigate

the long run behavior of \bar{X}_n as $n \rightarrow \infty$.

Theorem: The central limit theorem.

Let X_1, X_2, \dots be i.i.d & $E(X_i) = \mu < \infty$,
 $V(X_i) = \sigma^2 < \infty$. Then,

$$\frac{\bar{X}_n - \mu}{\sigma/\sqrt{n}} \xrightarrow{D} Z \sim N(0,1) \text{ as } n \rightarrow \infty.$$

$$\left(\text{or } \frac{S_n - n\mu}{\sqrt{n}\sigma} \xrightarrow{D} Z \sim N(0,1) \text{ as } n \rightarrow \infty \right).$$

Proof: Assume $\mu = 0$, $\sigma^2 = 1$. & that the mgf of X_i , $M(t)$, is finite on some neighborhood $(-a, a)$ of 0.

The mgf of X_i/\sqrt{n} is $M\left(\frac{t}{\sqrt{n}}\right)$

$$\text{Therefore, } M_{\sum \frac{X_i}{\sqrt{n}}}(t) = \left[M\left(\frac{t}{\sqrt{n}}\right) \right]^n.$$

$$\text{Let } L(t) = \ln(M(t)).$$

$$\text{Note that } L(0) = E[e^0] = 1$$

$$L'(0) = \frac{M'(0)}{M(0)} = \frac{E(X_i)}{1} = 0$$

$$L''(0) = \frac{\overbrace{M(0)}^{=1} \overbrace{M''(0)}^{E(X^2)} - \overbrace{[M'(0)]^2}^{=0}}{\underbrace{[M(0)]^2}_{=1}}$$

$$L''(0) = M''(0) = E(X^2) = 1$$

Our goal is to prove that $\left[M\left(\frac{t}{\sqrt{n}}\right)\right]^n \rightarrow e^{t^2/2}$ or

$$\lim_{n \rightarrow \infty} n L\left(\frac{t}{\sqrt{n}}\right) = \lim_{n \rightarrow \infty} \ln \left[M\left(\frac{t}{\sqrt{n}}\right)^n\right] = \frac{t^2}{2}.$$

Note that

$$\lim_{n \rightarrow \infty} n L\left(\frac{t}{\sqrt{n}}\right) = \lim_{n \rightarrow \infty} \frac{L\left(\frac{t}{\sqrt{n}}\right)}{\frac{1}{n}}$$

$$= \lim_{n \rightarrow \infty} \frac{L'\left(\frac{t}{\sqrt{n}}\right) \left(-\frac{1}{2} n^{-\frac{3}{2}} t\right)}{-\frac{1}{n^2}} = \lim_{n \rightarrow \infty} \frac{L\left(\frac{t}{\sqrt{n}}\right) t}{2 n^{-\frac{1}{2}}}$$

$$= \lim_{n \rightarrow \infty} \frac{L''\left(\frac{t}{\sqrt{n}}\right) \cdot \left(-\frac{1}{2} t n^{-\frac{3}{2}}\right) t}{-n^{-\frac{3}{2}}}$$

$$= \lim_{n \rightarrow \infty} \left[L''\left(\frac{t}{\sqrt{n}}\right) \cdot \frac{t^2}{2} \right] = L''(0) \cdot \frac{t^2}{2} = \frac{t^2}{2}$$

Therefore,

$$M_{\frac{\sum X_i}{\sqrt{n}}}(t) \rightarrow e^{\frac{t^2}{2}}.$$

By the continuity theorem,

$$\frac{\sum X_i}{\sqrt{n}} \xrightarrow{D} Z \sim N(0,1) \quad \square$$

Ex: ① Let $X_1, X_2, \dots \sim B(m, p)$ be independent.

$$\text{Let } \bar{X}_n = \frac{\sum_{i=1}^n X_i}{n}$$

$$\text{Then } \frac{\bar{X}_n - mp}{\sqrt{\frac{mp(1-p)}{n}}} \xrightarrow{D} N(0,1)$$

② Let $X_1, \dots, X_{100} \sim U(0,1)$ be independent.

$$E(X_i) = \frac{1}{2}, \quad V(X_i) = \frac{1}{12}. \quad \text{Then,}$$

$$\begin{aligned} P\left[\sum_{i=1}^{100} X_i \leq 55\right] &= P\left[\frac{\sum_{i=1}^{100} X_i}{100} \leq 0.55\right] \\ &= P\left[\frac{\sum_{i=1}^{100} X_i - \frac{1}{2}}{\sqrt{\frac{1}{12(100)}}} \leq \frac{0.55 - \frac{1}{2}}{\sqrt{\frac{1}{12(100)}}}\right] \approx \Phi\left(\frac{0.55 - \frac{1}{2}}{\sqrt{\frac{1}{12(100)}}}\right) \end{aligned}$$

Markov Chains

Definition : Let $\{X_n\}$ be a sequence of random variables taking values in a countable set S , called the state space.

If $\forall n \geq 0$,

$P(X_{n+1} = j \mid X_n = i, X_{n-1} = i_{n-1}, \dots, X_0 = i_0) = P(X_{n+1} = j \mid X_n = i)$,
then X is said to be a Markov Chain,
or to have the Markov Property.

The Markov property states that the next state X_{n+1} only depends on the current state & is independent of past states X_i , $\forall i < n$.

We write

$$p_{ik} = P(X_1 = k \mid X_0 = i)$$

$\{p_{ik}, i, k \in S\}$, are called the transition probabilities of the chain $\{X_n\}$

The MC is called time-homogeneous if

$$P(X_{n+1} = k \mid X_n = i) = p_{ik}, \forall n.$$