

Indicator Functions

$$\mathbb{1}(\text{statements}) = \begin{cases} 0 & \text{statement false} \\ 1 & \text{statement true} \end{cases}$$

Ex. $\mathbb{1}(x \in A) = \begin{cases} 0 & x \notin A \\ 1 & x \in A \end{cases}$

PDF of a RV $X \sim \text{Exp}(\lambda)$

$$f(x) = \begin{cases} \lambda e^{-\lambda x}, & x > 0 \\ 0, & x \leq 0 \end{cases}$$

$$f(x) = \lambda e^{-\lambda x} \text{ for } x > 0$$

$$f(x) = \lambda e^{-\lambda x} \mathbb{1}(x > 0)$$

More generally,

$$f(x) = \sim \mathbb{1}(x \in \text{Support})$$

Fact:

$$\mathbb{I}(A \text{ and } B) = \mathbb{I}(A) \mathbb{I}(B)$$

Independence:

$$X \perp Y \iff f(x, y) = f(x) f(y)$$

Ex: $f(x, y) = c e^{-x} e^{-y}$ for $x > 0$ and $y > 0$

$$= c e^{-x} e^{-y} \mathbb{I}(x > 0 \text{ and } y > 0)$$

$$= c e^{-x} e^{-y} \mathbb{I}(x > 0) \mathbb{I}(y > 0)$$

$$= \left[c e^{-x} \mathbb{I}(x > 0) \right] \left[e^{-y} \mathbb{I}(y > 0) \right]$$

fn of x

fn of y

Defn: Random Sample

If $X_1, X_2, X_3, \dots, X_n \stackrel{iid}{\sim} f$

we call this a random sample of size n from f .

Fact:

$$\underline{X} = (X_1, \dots, X_n)$$

$$\underline{x} = (x_1, \dots, x_n) \in \mathbb{R}^n$$

$$f(\underline{X}) = f(x_1, \dots, x_n)$$

$$= f(x_1) f(x_2) \dots f(x_n)$$

$$= \prod_{i=1}^n f(x_i)$$

Defn: Statistic

If $(X_i)_{i=1}^n$ are a rand. sample and

$$T: \mathbb{R}^n \rightarrow \mathbb{R}^d$$

then $T(\underline{X})$ is called a statistic.

Ex. ① arithmetic mean

$$\bar{X} = \frac{1}{n} (X_1 + X_2 + X_3 + \dots + X_n)$$

② Sample variance

$$S^2 = \frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})^2$$

$$- \quad n-1 \quad 1=1$$

③ Order Statistics

$X_{(1)}$ = minimum of X_i

$X_{(n)}$ = maximum of X_i

$X_{(r)}$ = r^{th} smallest of X_i

④ range: $R = X_{(n)} - X_{(1)}$.

Defn: Sampling Distribution of a Statistic

The sampling dist. of $T(\underline{X})$ is
simply the dist. of $T(\underline{X})$.

Theorem: Central Limit Theorem

Intro stats: $\bar{X} \approx N(\mu, \sigma^2/n)$
for large n

451 statement:

If X_i are a random sample

w/ mean $\mathbb{E}X_i = \mu$ and $\text{Var} X_i = \sigma^2 < \infty$

then

$$Y = \sqrt{n} \left(\frac{\bar{X} - \mu}{\sigma} \right) \xrightarrow{d} N(0, 1)$$

$$\bar{X} \approx N(\mu, \sigma^2/n) \Rightarrow \sqrt{n} \left(\frac{\bar{X} - \mu}{\sigma} \right) \approx N(0, 1)$$

CDF/MGF of left
converges to CDF/MGF of Right

Ex. CLT

$X_i \stackrel{iid}{\sim} \text{Bernoulli}(p)$

$$\mu = \mathbb{E}X_i = p \text{ and } \text{Var} X_i = p(1-p) = \sigma^2$$

CLT says:

$$\rightarrow \sqrt{n} \left(\frac{\bar{X} - p}{\sqrt{p(1-p)}} \right) \xrightarrow{d} N(0, 1)$$

practically: $\left[\bar{X} \approx N\left(p, \frac{p(1-p)}{n}\right) \right]$

practically: $X \approx N(p, \frac{p(1-p)}{n})$

$$\bar{X} - p \approx N(0, \frac{p(1-p)}{n})$$

$$\text{Var}(aX) = a^2 \text{Var}(X)$$

$$\frac{\bar{X} - p}{\sqrt{\frac{p(1-p)}{n}}} \approx N(0, 1)$$

Intro stats: 95% CI: $\bar{X} \pm 2 \sqrt{\frac{\bar{X}(1-\bar{X})}{n}}$

$$Y = \sqrt{n} \left(\frac{\bar{X} - \mu}{\sigma} \right)$$

$$= \sqrt{n} \left(\frac{\frac{1}{n} \sum_{i=1}^n X_i - \mu}{\sigma} \right)$$

$$= \frac{\left(\frac{\sqrt{n}}{n} \sum_{i=1}^n X_i - \sqrt{n} \mu \right)}{\sigma}$$

$$= \frac{\frac{1}{\sqrt{n}} \sum_{i=1}^n X_i - \frac{n}{\sqrt{n}} \mu}{\sigma} = \frac{\sum_{i=1}^n X_i}{\sqrt{n}} - \sum_{i=1}^n \mu$$

$$= \frac{1}{\sqrt{n}} \left(\sum_{i=1}^n (X_i - \mu) \right) = \frac{1}{\sqrt{n}} \sum_{i=1}^n \left(\frac{X_i - \mu}{\sigma} \right)$$

$$\begin{aligned} & ; E X_i = \mu \\ & \text{Var } X_i = \sigma^2 \end{aligned}$$

$$Y_i = \frac{X_i - \mu}{\sigma}$$

$$\text{then } E Y_i = 0$$

$$\text{Var } Y_i = 1$$

(0)

$$\boxed{\frac{1}{\sqrt{n}} \sum_{i=1}^n Y_i = Y} \leftarrow$$

Going to show that MGF of $Y \rightarrow$ MGF of $N(0,1)$

$$M_{\sum X_i}(t) = M_{X_1}(t) M_{X_2}(t) \dots$$

$$M_{aX}(t) = M_X(at)$$

$$M_Y(t) = M_{\frac{1}{\sqrt{n}} \sum_{i=1}^n Y_i}(t) = M(t/\sqrt{n})^n$$

Taylor Series

$g: \mathbb{R} \rightarrow \mathbb{R}$ that is k -times differentiable

then

$$T_k(x) = \sum_{r=0}^k \frac{g^{(r)}(0)}{r!} x^r$$

$$\text{then } R = g(x) - T_k(x) \rightarrow 0 \text{ as } x \rightarrow 0$$

Approx M w/ a Taylor series

$$M(t) = (1) + t^0 + M^{(1)}(0)t + M^{(2)}(0)t^2$$

$$M(t) = \frac{(1)t^0}{0!} + \frac{M^{(1)}(0)t^1}{1!} + \frac{M^{(2)}(0)t^2}{2!} + \dots$$

$$= 1 + \underbrace{E[Y]}_c t + \frac{E[Y^2]}{2} t^2 + \dots$$

$$= 1 + \frac{t^2}{2} + \dots$$

$$M_Y(t) = M\left(\frac{t}{\sqrt{n}}\right)^n = \left(1 + \frac{t^2/2}{n}\right)^n$$

$$\xrightarrow{n} e^{t^2/2}$$

↑ MGF of $N(0,1)$

$$\lim_{n \rightarrow \infty} \left(1 + \frac{c}{n}\right)^n = e^c$$