

Lecture 1 : Statistics

Defn : Random Sample

If $X_1, X_2, X_3, \dots, X_N$ are mutually independent all w/ marginal dist f then we say these X_n s are a random sample from f .

denoted: $X_n \stackrel{iid}{\sim} f$

indep and identically dist.

Notation:

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

a random vector

a MV rand var.

$$\underline{x} = (x_1, \dots, x_N)$$

a vector in \mathbb{R}^N

Joint dist of a RS (rand. sample)

$$\overset{\text{joint}}{f}(\underline{x}) = f(x_1, x_2, \dots, x_N)$$

$$= f(x_1) f(x_2) f(x_3) \dots f(x_N)$$

$$= \prod_{n=1}^N f(x_n)$$

Ex. $X_n \stackrel{iid}{\sim} \text{Exp}(\lambda)$

What is the joint of \underline{X} .

$$\begin{aligned} f(\underline{x}) &= \prod_{n=1}^N f(x_n) \\ &= \prod_{n=1}^N \lambda e^{-\lambda x_n} \mathbb{1}(x_n > 0) \end{aligned}$$

$$= \lambda^N \prod_{n=1}^N (e^{-\lambda x_n}) \prod_{n=1}^N \mathbb{1}(x_n > 0)$$

$$= \lambda^N e^{-\lambda \sum_{n=1}^N x_n} \prod_{n=1}^N \mathbb{1}(x_n > 0)$$

$$= \lambda^N e^{-\lambda \sum_n x_n} \mathbb{1}(\text{all } x_n > 0)$$

$\text{Exp}(\lambda)$

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

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

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

$$\mathbb{1}(\text{statement}) =$$

$$\begin{cases} 0 & \text{statement false} \\ 1 & \text{statement true} \end{cases}$$

$$e^a e^b = e^{a+b}$$

$$\prod_n e^{a_n} = e^{\sum_n a_n}$$

$$\mathbb{1}(A) \mathbb{1}(B) = \mathbb{1}(A \text{ and } B)$$

$$\prod_n \mathbb{1}(A_n) = \mathbb{1}(\text{all } A_n \text{ true})$$

Defn: Statistic

Given a RS $X_n \stackrel{iid}{\sim} f$ and

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

(typically $d \ll N$)

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

Ex. Arithmetic Mean : ($d=1$)

$$T(\underline{X}) = \frac{1}{N} \sum_{n=1}^N X_n = \bar{X}_N$$

Sample Variance : ($d=1$)

$$S_{N-1}^2 = \frac{1}{N-1} \sum_{n=1}^N (X_n - \bar{X}_N)^2$$

Sample SD:

$$S_{N-1} = \sqrt{S_{N-1}^2}$$

Minimum:

$$X_{(1)} = \min_{n=1, \dots, N} X_n$$

Maximum:

$$X_{(N)} = \max_{n=1, \dots, N} X_n$$

Range: $R = X_{(N)} - X_{(1)}$.

Order Statistic: $X_{(r)} = r^{\text{th}}$ smallest among X_n s

Defn: Sampling Distribution

If $T = T(X)$ is a statistic then the sampling dist of T is just its distribution.

Ex, what is the dist of $X_{(1)}$?

Assuming $X_n \stackrel{iid}{\sim} f$, f cts

F is the CDF

What is the PDF of $X_{(1)}$?

$$\underline{P(X_{(1)} \geq t)} = P(X_1 \geq t, X_2 \geq t, X_3 \geq t, \dots, X_N \geq t)$$

$$\begin{aligned} &= P(X_1 \geq t) P(X_2 \geq t) \cdots P(X_N \geq t) \\ &\quad \rightarrow \text{(by independence)} \end{aligned}$$

$$= \prod_{n=1}^N P(X_n \geq t)$$

$$= \prod_{n=1}^N (1 - F(t))$$

$$= (1 - F(t))^N$$

$$\begin{aligned} P(X_n \geq t) &= 1 - P(X_n < t) \\ &= 1 - F(t) \end{aligned}$$

$$\boxed{P(X_{(1)} \geq t) = (1 - F(t))^N}$$

$$\begin{aligned}
 F_{X_{(1)}}(t) &= P(X_{(1)} \leq t) \\
 &= 1 - P(X_{(1)} \geq t) \\
 &= 1 - (1 - F(t))^N
 \end{aligned}$$

$$f_{X_{(1)}}(t) = \frac{dF_{X_{(1)}}}{dt} = N(1 - F(t))^{N-1} f(t)$$

Play similar game w/ maximum $X_{(N)}$

$$P(X_{(N)} \leq t)$$

you get

$$f_{X_{(N)}}(t) = N F(t)^{N-1} f(t)$$

Famous result from intro stats:

$$X_n \stackrel{\text{iid}}{\sim} N(\mu, \sigma^2) \text{ then } \bar{X}_N \sim N(\mu, \sigma^2/N)$$

Facts: Sums of RVs

Let $g: \mathbb{R} \rightarrow \mathbb{R}$ and $X_n \stackrel{iid}{\sim} f$

$$(1) \mathbb{E}\left[\sum_{n=1}^N g(X_n)\right] = N \mathbb{E}[g(X_n)]$$

↑ any of them

pf.

$$\mathbb{E}\left[\sum_n g(X_n)\right] = \sum_n \mathbb{E}[g(X_n)] = N \mathbb{E}[g(X_n)]$$

$$(2) \text{Var}\left(\sum_n g(X_n)\right) = N \text{Var}(g(X_n))$$

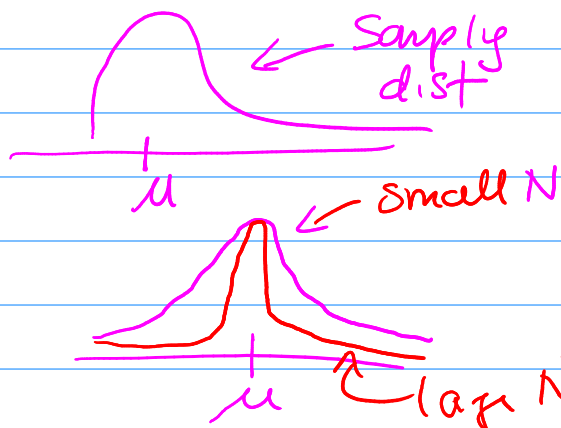
pf. Similar as above — NEED independence

Theorem: If $X_n \stackrel{iid}{\sim} f$ and

$$\mathbb{E}X_n = \mu \text{ and } \text{Var}(X_n) = \sigma^2$$

then

$$(1) \mathbb{E}[\bar{X}_N] = \mu$$



$$(2) \text{Var}(\bar{X}_N) = \frac{\sigma^2}{N}$$

$$(3) \mathbb{E}[S_{N-1}^2] = \sigma^2$$