## 1. Empirical Distribution Function

**7.3 Theorem.** At any fixed value of 
$$x$$
,

$$\mathbb{E}\left(\widehat{F}_n(x)\right) = F(x),$$

$$\begin{split} \mathbb{V}\left(\widehat{F}_n(x)\right) &=& \frac{F(x)(1-F(x))}{n},\\ \text{MSE} &=& \frac{F(x)(1-F(x))}{n} \to 0, \end{split}$$

$$\widehat{F}_n(x) \stackrel{\mathrm{P}}{\longrightarrow} F(x).$$

$$= E\left(\frac{\sum_{i=1}^{n} I(x_i \leq x)}{D}\right) =$$

$$= E\left(\frac{\sum_{i=1}^{n} I(x_i \leq x)}{n}\right) = \frac{1}{n} E\left(\sum_{i=1}^{n} I(x_i \leq x)\right)$$

$$=\frac{1}{N}\sum_{i=1}^{N}P(X_{i}\leq X)$$

$$= F(x)$$
  $\frac{1}{2}$ ?

(a) 
$$V(\hat{F}_{n}(x)) = \frac{F(x)(1-F(x))}{N}$$

$$= E[\hat{F}_n(x)^2] - E[\hat{F}_n(x)]^2$$

$$= \sum_{i=1}^{n} \sum_{j=1}^{n} P(X_i \leq X_j \leq X_j) - \sum_{i=1}^{n} \sum_{j=1}^{n} P(X_i \leq X_j \leq X_j) - \sum_{i=1}^{n} \sum_{j=1}^{n} P(X_i \leq X_j) = \sum_{i=1}^{n} P(X_i \leq X_i) = \sum_{i=1}^{n} P(X_i$$

= 
$$\frac{1}{N^2}$$
  $\sum \left[ P(X; \leq x, X_j \leq x) - P(X; \leq x) P(X; \leq x) \right]$ 

$$\geq \frac{F(x)(1-F(x))}{n}$$

Def. of CDF  $\rightarrow$   $F_X(x) = \mathbb{P}(X \leq x)$ .

7.1 Definition. The empirical distribution function 
$$\widehat{F}_n$$
 is the CDF that puts mass  $1/n$  at each data point  $X_i$ . Formally, 
$$\widehat{F}_n(x) = \frac{\sum_{i=1}^n I(X_i \leq x)}{n} \tag{7}$$
 where 
$$I(X_i \leq x) = \begin{cases} 1 & \text{if } X_i \leq x \\ 0 & \text{if } X_i > x. \end{cases}$$

$$n \cdot \hat{F}_n(x) = \sum_{i=1}^n I(x_i \le x) \sim Bin(n, F(x))$$

$$= \frac{1}{n} \sum_{i=1}^{n} E[I(X_i \leq X)]$$

 $\text{MSE} = \frac{F(x)(1-F(x))}{n} \to 0, \quad \begin{cases} X_n \text{ converges to } X \text{ in probability, written } X_n \overset{\text{P}}{\longrightarrow} X, \text{ if, for every } \\ \epsilon > 0, \end{cases}$   $\stackrel{\text{P}}{\widehat{F}_n(x)} \to F(x). \quad \text{as } n \to \infty.$  (5.1)(5.1)

$$\widehat{F}_n(x) \stackrel{\mathrm{P}}{\longrightarrow} F(x).$$
 as  $n \to \infty$ 

$$\mathbb{P}(|X-\mu| \geq t) \leq rac{\sigma^2}{t^2}$$
 They chev's inequality

$$P(|\hat{F}_n(x) - F(x)| \ge \epsilon) \le \frac{\frac{F(x)(+F(x))}{n}}{\epsilon^2} = \frac{F(x)(+F(x))}{n\epsilon^2} = 0.22428$$

$$\therefore \hat{F}_n(x) \xrightarrow{P} F(x)$$

http://www.win.tue.nl/~rmcastro/AppStat2013/files/lecture1.pdf

9. 100 people are given a standard antibiotic to treat an infection and another 100 are given a new antibiotic. In the first group, 90 people recover; in the second group, 85 people recover. Let  $p_1$  be the probability of recovery under the standard treatment and let  $p_2$  be the probability of recovery under the new treatment. We are interested in estimating  $\theta = p_1 - p_2$ . Provide an estimate, standard error, an 80 percent confidence interval, and a 95 percent confidence interval for  $\theta$ .

Destimate  $\Theta = P_1 - P_2 \Rightarrow \hat{P_1} - \hat{P_2} = 0.05$ 

$$Var(\hat{p_1} - \hat{p_2}) = Var(\hat{p_1}) + Var(\hat{p_2}) - (aV(\hat{p_1}, \hat{p_2}))$$

$$Se(\hat{p_1} - \hat{p_2}) = Var(\hat{p_1}) + Var(\hat{p_2}) = 0.04663689 \approx 0.047$$

3 80 percent interval 0.05 ± 1.28 × 0.047 ⇒ -0.01 ~ 0.11

$$\Theta$$
 95 percent interval  
 $0.05\pm2\times0.047$   $\Rightarrow -0.04\sim0.14$