

# Econ 583 HW 1 Solutions

Note Title

10/6/2011

Q 1: Let  $X$  be a rv with  $E[X] = \mu$  and  $\text{Var}(X) = \sigma^2 < \infty$ . Then Chebyshev's inequality says

$$\Pr \{ |X - \mu| \geq \epsilon \} \leq \frac{\text{Var}(X)}{\epsilon^2} = \frac{\sigma^2}{\epsilon^2}$$

Suppose  $X \sim N(\mu, \sigma^2)$ . Then Chebyshev's inequality says

$$\Pr \{ |X - \mu| \geq \frac{\epsilon}{\sigma} \} \leq \frac{\sigma^2}{9\sigma^2} = \frac{1}{9}$$

Because  $X \sim N(\mu, \sigma^2)$

$$\Pr \{ |X - \mu| \geq 3\sigma \}$$

$$= \Pr \left\{ \left| \frac{X - \mu}{\sigma} \right| \geq 3 \right\} = 1 - \Pr \{ -3 \leq Z \leq 3 \}$$

for  $Z \sim N(0, 1)$ . Using the normal CDF function in R we get

$$1 - \Pr \{ -3 \leq Z \leq 3 \} = 1 - 0.9973 = 0.0027 \quad \blacksquare$$

# Elem 583 Hw #1 Solutions for Problem 3

Note Title

10/18/2009

## Consistency of Simple estimators

$x_1, \dots, x_n$  iid with  $E[x] = \mu$ ,  $\text{var}(x) = \sigma^2 < \infty$

$$\hat{\sigma}_1^2 = \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2, \quad \bar{x} = \frac{1}{n} \sum_{i=1}^n x_i$$

$$\hat{\sigma}_2^2 = \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2$$

(a) Compute  $E[\hat{\sigma}_i^2]$   $i=1, 2$

$$\hat{\sigma}_1^2 = (n-1)^{-1} \underset{\sim}{e}' \underset{\sim}{M}_1 \underset{\sim}{e}, \quad t_i = x_i - \bar{x}$$

and  $e = (e_1, \dots, e_n)$ ,  $M_1 = I_n - P_1$

and  $P_1 = \underline{1} (\underline{1}' \underline{1})^{-1} \underline{1}'$  with  $\underline{1} = (1, \dots, 1)'$ .

Then

$$E[\underset{\sim}{e}' \underset{\sim}{M}_1 \underset{\sim}{e}] = E[\text{tr}(\overset{\text{scalar}}{\underset{\sim}{e}' \underset{\sim}{M}_1 \underset{\sim}{e}})]$$

$$= E[\text{tr}(\underset{\sim}{M}_1 \underset{\sim}{e} \underset{\sim}{e}')] \quad (\text{tr}(AB) = \text{tr}(BA))$$

$t(\cdot) \in E[\cdot]$   
are linear operators

$$= \text{tr}(E[\underset{\sim}{M}_1 \underset{\sim}{e} \underset{\sim}{e}'])$$

$$= \text{tr}(M_1 E[\underline{e}\underline{e}'])$$

$$= \text{tr}(M_1 \sigma^2 I_n)$$

$$= \sigma^2 \text{tr}(M_1) = \sigma^2 \text{rank}(M_1)$$

$$= \sigma^2 (n-1) \quad \forall (C \text{ } M_1 \text{ is Idempotent})$$

$$\text{Hence, } E[\hat{\sigma}_1^2] = (n-1)^{-1} E[\underline{e}' M_1 \underline{e}]$$

$$= (n-1)^{-1} (n-1) \sigma^2 = \sigma^2$$

$$\text{Next, } \hat{\sigma}_v^2 = \frac{n-1}{n} \cdot \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2$$

$$= \frac{n-1}{n} \hat{\sigma}_1^2$$

$$\Rightarrow E[\hat{\sigma}_v^2] = \frac{n-1}{n} E[\hat{\sigma}_1^2] = \frac{n-1}{n} \sigma^2$$

$$(b) \text{ bias}(\hat{\sigma}_v^2, \sigma^2) = E[\hat{\sigma}_v^2] - \sigma^2$$

$$= \frac{n-1}{n} \sigma^2 - \sigma^2 = \left(\frac{n-1}{n} - 1\right) \sigma^2$$

$$= -\frac{1}{n} \sigma^2$$

Clearly,  $\text{bias}(\hat{\sigma}_2^2, \sigma^2) \rightarrow 0$  as  $n \rightarrow \infty$ .

$$(c) \hat{\sigma}_1^2 = \frac{n}{n-1} \hat{\sigma}_2^2. \quad \text{As } n \rightarrow \infty$$

$$\frac{n}{n-1} \rightarrow 1 \quad \text{and} \quad \hat{\sigma}_2^2 \xrightarrow{p} \sigma^2$$

By Slutsky,  $\hat{\sigma}_1^2 \xrightarrow{p} 1 \cdot \sigma^2 = \sigma^2$ . ■

. Hayashi, Ch 2, pg. 97 #4

Suppose  $\sqrt{n}(\hat{\theta}_n - \theta) \xrightarrow{d} N(0, \sigma^2)$ .

Does it follow that  $\hat{\theta}_n \xrightarrow{p} \theta$ ?

$$\text{Write } \hat{\theta}_n - \theta = \frac{1}{\sqrt{n}} \sqrt{n}(\hat{\theta}_n - \theta)$$

Then  $\frac{1}{\sqrt{n}} \rightarrow 0$ ,  $\sqrt{n}(\hat{\theta}_n - \theta) \xrightarrow{d} N(0, \sigma^2)$

as  $n \rightarrow \infty$ . Therefore by Slutsky

$$\hat{\theta}_n - \theta \xrightarrow{d} 0 \cdot N(0, \sigma^2) = 0$$

Hence  $\hat{\theta}_n \xrightarrow{p} \theta$ . ■

5. Recall Markov's LLN:  $x_1, \dots, x_n$   
uncorrelated with  $E\{x_i\} = \mu_i < \infty$   
and  $\text{var}(x_i) = \sigma_i^2 \leq M < \infty \forall i = 1, \dots, n$ .

$$\begin{aligned}\text{Then } \bar{x} - \bar{\mu} &= \frac{1}{n} \sum_i x_i - \frac{1}{n} \sum_i \mu_i \\ &= \frac{1}{n} \sum_i (x_i - \mu_i) \xrightarrow{P} 0\end{aligned}$$

Chebyshev's inequality says for any r.v

$X$  with  $E\{X\} = \mu$  and  $\text{var}(X) = \sigma^2 < \infty$

$$\Pr(|X - \mu| > \epsilon) \leq \frac{\text{var}(X)}{\epsilon^2}$$

let  $X = \bar{x}$  and  $\mu = \bar{\mu}$ . Then

$$\Pr(|\bar{x} - \bar{\mu}| > \epsilon) \leq \frac{\text{var}(\bar{x})}{\epsilon^2}$$

Now,

$$\begin{aligned} \text{Var}(\bar{x}) &= \text{Var}\left(\frac{1}{n} \sum_{i=1}^n x_i\right) = \frac{1}{n^2} \sum_{i=1}^n \text{Var}(x_i) \\ &= \frac{1}{n^2} \sum_{i=1}^n \sigma_i^2 < \frac{nM}{n^2} = \frac{M}{n} \end{aligned}$$

Therefore,

$$\Pr(|\bar{x} - \bar{\mu}| > \epsilon) \leq \frac{M}{n} \rightarrow 0$$

as  $n \rightarrow \infty$ . ■

6. Hayashi, ch 2, pg. 168 #1

$$Z_n = \begin{cases} 0 & \text{with prob } (n-1)/n \\ n^2 & \text{" " " } 1/n \end{cases}$$

Show that  $\text{plim}_{n \rightarrow \infty} Z_n = 0$  but

$$\lim_{n \rightarrow \infty} \epsilon(Z_n) \neq 0$$

For any  $\epsilon > 0$

$$\Pr(|Z_n| > \epsilon) = \frac{1}{n} \xrightarrow{n \rightarrow \infty} 0$$

Hence  $Z_n \xrightarrow{P} 0$ . However,

$$E[Z_n] = 0 \cdot \frac{(n-1)}{n} + n^2 \cdot \frac{1}{n} = n$$

$\rightarrow \infty$  as  $n \rightarrow \infty$ . □