

LECTURE

20 NOVEMBER

9:00-10:00AM

MATH3/4/68181

b) Non-parametric estimation methods

1) Historical method

Data : x_1, x_2, \dots, x_n

Order the data as

$$x_{(1)} \leq x_{(2)} \leq \dots \leq x_{(n)}$$

Then

$$\hat{ES}_p(x) = \frac{1}{[np]} \sum_{i=1}^{[np]} x_{(i)}$$

where $[x]$ denotes the largest integer less than or equal to x .

Ex $[4.4] = 4, [5.1] = 5$

Ex

-2	8	9	-10	1
-10	-2	1	8	9
"	"	"	"	"
$x_{(1)}$	$x_{(2)}$	$x_{(3)}$	$x_{(4)}$	$x_{(5)}$

$$\begin{aligned}\hat{ES}_{0.4}(x) &= \frac{1}{2} \sum_{i=1}^2 x_{(i)} \\ &= \frac{1}{2} (-10 - 2) \\ &= -6.\end{aligned}$$

2) Bootstrap method

Data x_1, x_2, \dots, x_n

(i) Compute the empirical CDF

$$\hat{F}(x) = \frac{1}{n} \sum_{i=1}^n I\{x_i \leq x\}$$

(ii) Simulate B samples each of size n from \hat{F} .

(iii) Compute \hat{ES}_p for each of the B samples by the historical method, resulting $\hat{ES}_p^{(1)}, \hat{ES}_p^{(2)}, \dots, \hat{ES}_p^{(B)}$.

(iv) Compute \hat{ES}_p as

$$\text{mean}(\hat{ES}_p^{(1)}, \hat{ES}_p^{(2)}, \dots, \hat{ES}_p^{(B)})$$

or

$$\text{median}(\hat{ES}_p^{(1)}, \hat{ES}_p^{(2)}, \dots, \hat{ES}_p^{(B)})$$

3) Jackknife method

Data x_1, x_2, \dots, x_n

(i) Compute \widehat{ES}_p by the historical method for x_2, x_3, \dots, x_n , resulting in $\widehat{ES}_p^{(1)}$.

(ii) Compute \widehat{ES}_p by the historical method for x_1, x_3, \dots, x_n , resulting in $\widehat{ES}_p^{(2)}$

⋮

(iii) Compute \widehat{ES}_p by the historical method for x_1, x_2, \dots, x_{n-1} , resulting in $\widehat{ES}_p^{(n)}$.

(iv) Compute \widehat{ES}_p as

$$\text{Mean} (\widehat{ES}_p^{(1)}, \widehat{ES}_p^{(2)}, \dots, \widehat{ES}_p^{(n)})$$

or

$$\text{Median} (\widehat{ES}_p^{(1)}, \widehat{ES}_p^{(2)}, \dots, \widehat{ES}_p^{(n)}) .$$

4) Kernel method

Data x_1, x_2, \dots, x_n

Order the data as $x_{(1)} \leq x_{(2)} \leq \dots \leq x_{(n)}$

The kernel estimator of $ES_p(x)$ is

$$\widehat{ES}_p(x) = \frac{1}{n_p} \sum_{i=1}^n x_i A_h(\widehat{q}(p) - x_i)$$

where

$h =$ bandwidth

$$\widehat{q}(p) = \sum_{i=1}^n \left[\int_{\frac{i-1}{n}}^{\frac{i}{n}} K_h(t-p) dt \right] x_{(i)}$$

$$K_h(u) = \frac{1}{h} K\left(\frac{u}{h}\right)$$

$$A_h(u) = A\left(\frac{u}{h}\right)$$

$$A(x) = \int_{-\infty}^x K(u) du$$

$K(\cdot)$ = kernel PDF usually chosen as the PDF of $N(0, 1)$

5) Richardson's method (based on Richardson (1911))

Richardson was a professor of applied math in Manchester. His picture is on the front door of G207, ground floor of ATB.

Suppose x_1, x_2, \dots, x_n are the data

(i) Compute the empirical CDF

$$\hat{F}(x) = \frac{1}{n} \sum_{i=1}^n I\{x_i \leq x\}$$

(ii) simulate x_1, x_2, \dots, x_N from $\hat{F}(\cdot)$

(iii) compute \hat{ES}_p by the historical method for the data simulated in (ii)

(iv) Repeat steps (ii) and (iii) 1000 times

(v) Let $m_N =$ the average of the 1000 estimates of ES_p

(vi) Let $S_k = m_{N_k}$, $k = 1, 2, \dots, l+1$

for some l and N_1, N_2, \dots, N_{l+1}

(vii) Compute \widehat{ES}_p as

$$\widehat{ES}_p = \frac{\begin{array}{c} \left(\begin{array}{cccc} s_1 & s_2 & \dots & s_{l+1} \\ 1 & \frac{1}{2} & \dots & \frac{1}{l+1} \\ \vdots & \vdots & \ddots & \vdots \\ 1^l & \left(\frac{1}{2}\right)^l & \dots & \left(\frac{1}{l+1}\right)^l \end{array} \right) \end{array}}{\begin{array}{c} \left(\begin{array}{cccc} 1 & 1 & \cdot & 1 \\ 1 & \frac{1}{2} & \cdot & \frac{1}{l+1} \\ \cdot & \cdot & \cdot & \cdot \\ 1^l & \left(\frac{1}{2}\right)^l & \cdot & \left(\frac{1}{l+1}\right)^l \end{array} \right) \end{array}}$$

Ex

$$k = 1$$

$$N_1 = 100$$

$$N_2 = 1000$$

$$\begin{aligned} \widehat{ES}_p &= \frac{\begin{vmatrix} m_{100} & m_{1000} \\ 1 & \frac{1}{2} \end{vmatrix}}{\begin{vmatrix} 1 & 1 \\ 1 & \frac{1}{2} \end{vmatrix}} \\ &= \frac{\frac{m_{100}}{2} - m_{1000}}{\frac{1}{2} - 1} \end{aligned}$$

Models for Stock Returns

1) Model based on varying
volatility

(Model 1)

2) Model based on additive
random walk

(Model 2)

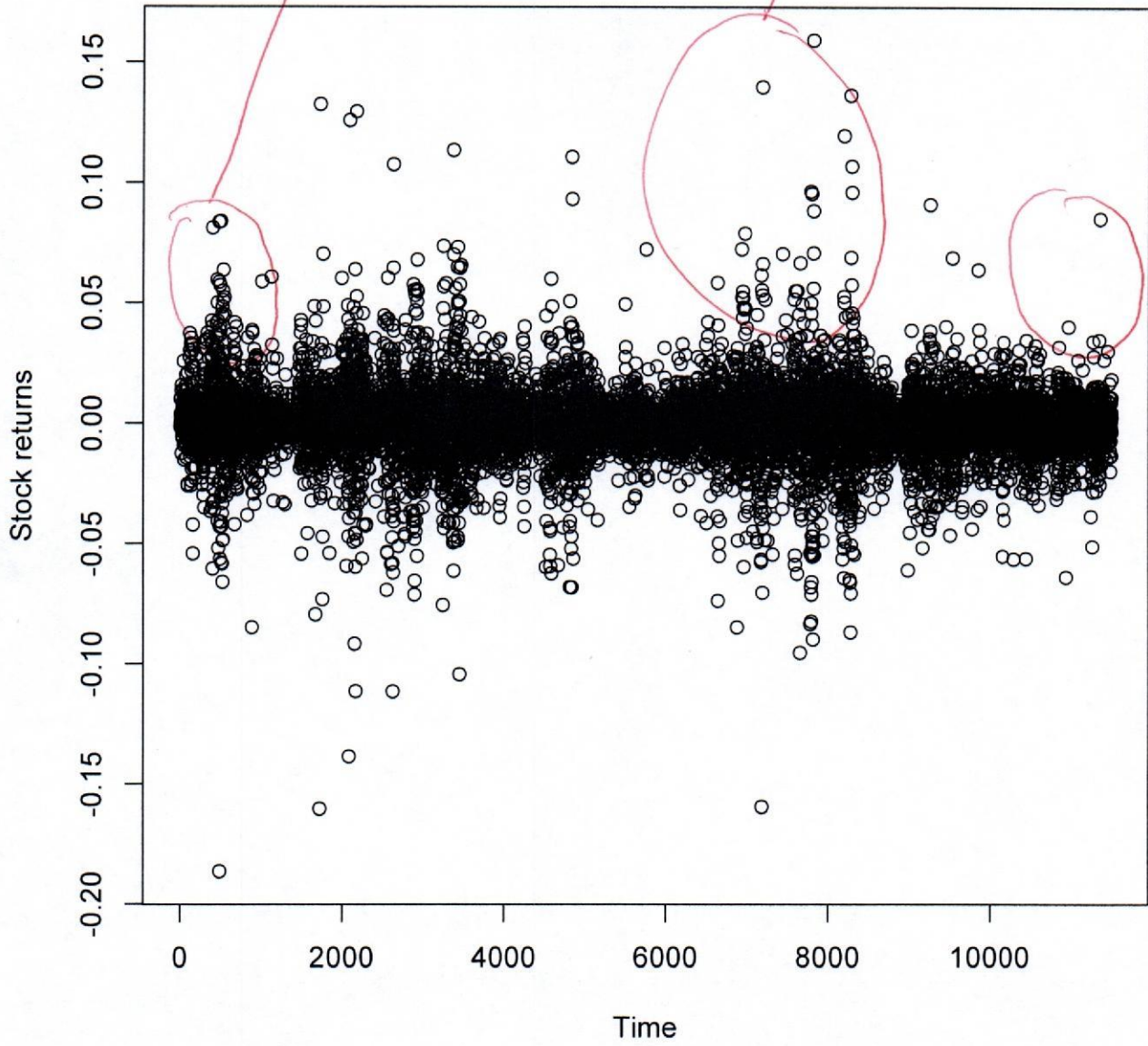
3) Model based on multiplicative
random walk

(Model 3)

Model I

Large

Small



Model 1

X = stock returns

V = variability
(volatility)

V is a random variable itself

V = unobservable

$X | V$ = observable

Hence, the PDF of X is

$$f_X(x) = \int_0^{\infty} \underbrace{f_{X|V}(x|v)}_{\substack{\text{conditional} \\ \text{PDF of } X|V}} \underbrace{f_V(v)}_{\text{PDF of } V} dv$$

The CDF of X is

$$F_X(x) = \int_0^{\infty} F_{X|V}(x|v) f_V(v) dv$$