

EXAMPLE CLASS

12 NOVEMBER

12:00-13:00PM

MATH3/4/68181

Q1

$$X \sim \text{Exp}(\lambda)$$

$$\left\{ \begin{array}{l} \text{Var}_p(X) = -\frac{1}{\lambda} \log(1-p) \\ \text{ES}_p(X) = -\frac{1}{p\lambda} \left\{ p \cdot \log(1-p) - p - \log(1-p) \right\} \end{array} \right.$$

From example class last week

Suppose x_1, x_2, \dots, x_n is a random sample from $\text{Exp}(\lambda)$.

The MLE of

$$\hat{\lambda} = \frac{1}{\bar{x}} \quad (\text{from Math 20802}).$$

Hence MLEs of Var_p and ES_p are

$$\widehat{\text{Var}}_p(X) = -\bar{x} \cdot \log(1-p)$$

$$\text{and } \widehat{\text{ES}}_p(X) = -\frac{\bar{x}}{p} \left\{ p \cdot \log(1-p) - p - \log(1-p) \right\}$$

Q2

X has PDF $a x^{a-1}$

$$\text{VaR}_p(X) = p^{\frac{1}{a}}$$

$$\text{ES}_p(X) = \frac{p^{\frac{1}{a}}}{\frac{1}{a} + 1}$$

from Example class last week.

Suppose x_1, x_2, \dots, x_n is a random sample on X . The MLE of a is

$$\hat{a} = - \frac{n}{\sum_{i=1}^n \log x_i} \quad \left(\begin{array}{l} \text{from lecture} \\ \text{this morning} \end{array} \right)$$

Hence, the MLEs of VaR_p and ES_p are

$$\widehat{\text{VaR}}_p(X) = p^{-\frac{\sum_{i=1}^n \log x_i}{n}}$$

and

$$\widehat{\text{ES}}_p(X) = \frac{p^{-\frac{\sum_{i=1}^n \log x_i}{n}}}{-\frac{\sum_{i=1}^n \log x_i}{n} + 1}$$

Hence, the MLEs of VaR_p and ES_p are

$$\widehat{\text{VaR}}_p(X) = e^{\hat{\mu}} + \hat{\sigma} \Phi^{-1}(p)$$

and

$$\widehat{\text{ES}}_p(X) = \frac{e^{\hat{\mu}}}{p} \int_0^p e^{\hat{\sigma} \Phi^{-1}(t)} dt.$$

Q3 covered in lectures

Q4

$X \sim LN(\mu, \sigma^2)$
The CDF of X is

$$F(x) = \Phi\left(\frac{\log x - \mu}{\sigma}\right) = p$$

$$\Rightarrow \frac{\log x - \mu}{\sigma} = \Phi^{-1}(p)$$

$$\Rightarrow \log x = \mu + \sigma \Phi^{-1}(p)$$

$$\Rightarrow x = e^{\mu + \sigma \Phi^{-1}(p)}$$

$$\Rightarrow \text{VaR}_p(X) = e^{\mu + \sigma \Phi^{-1}(p)}$$

$$ES_p(X) = \frac{1}{p} \int_0^p e^{\mu + \sigma \Phi^{-1}(t)} dt$$

$$= \frac{e^{\mu}}{p} \int_0^p e^{\sigma \Phi^{-1}(t)} dt$$

Suppose x_1, x_2, \dots, x_n is a random sample from $LN(\mu, \sigma^2)$. The MLEs of μ and σ are

$$\hat{\mu} = \frac{1}{n} \sum_{i=1}^n \log x_i$$

and
$$\hat{\sigma} = \sqrt{\frac{1}{n} \sum_{i=1}^n (\log x_i - \hat{\mu})^2}$$

(from Math 20802)

Q5

X has PDF $f(x) = \theta_2 x^{\theta_2 - 1} \theta_1^{-\theta_2}$,
 $0 < x < \theta_1$

The CDF of X is

$$\begin{aligned} F(x) &= \theta_2 \theta_1^{-\theta_2} \int_0^x y^{\theta_2 - 1} dy \\ &= \theta_2 \theta_1^{-\theta_2} \left[\frac{y^{\theta_2}}{\theta_2} \right]_0^x \\ &= \left(\frac{x}{\theta_1} \right)^{\theta_2} \end{aligned}$$

To find VaR, set

$$\left(\frac{x}{\theta_1} \right)^{\theta_2} = p$$

$$\Rightarrow x = \theta_1 p^{\frac{1}{\theta_2}}$$

$$\Rightarrow \text{VaR}_p(X) = \boxed{\theta_1 p^{\frac{1}{\theta_2}}}$$

$$\Rightarrow \text{ES}_p(X) = \frac{\theta_1}{p} \int_0^p t^{\frac{1}{\theta_2}} dt$$

$$= \frac{\theta_1}{p} \left[\frac{t^{\frac{1}{\theta_2} + 1}}{\frac{1}{\theta_2} + 1} \right]_0^p$$

$$= \boxed{\frac{\theta_1 \theta_2}{1 + \theta_2} p^{1/\theta_2}}$$

Suppose x_1, x_2, \dots, x_n is a random sample on X . The MLEs of θ_1 and θ_2 are

$$\hat{\theta}_1 = \max(x_1, x_2, \dots, x_n)$$

and

$$\hat{\theta}_2 = \frac{n}{n \log \hat{\theta}_1 - \sum_{i=1}^n \log x_i}.$$

(from Math20802)

Hence, the MLEs of VaR_p and ES_p are

$$\widehat{\text{VaR}}_p(X) = \hat{\theta}_1 p^{\frac{1}{\hat{\theta}_2}}$$

and

$$\widehat{\text{ES}}_p(X) = \frac{\hat{\theta}_1 \hat{\theta}_2}{1 + \hat{\theta}_2} p^{\frac{1}{\hat{\theta}_2}}.$$

Q6

$$X \sim \text{Uni}[\mu - \delta, \mu + \delta]$$

$$F(x) = \frac{x - \mu + \delta}{2\delta} = p$$

$$\Rightarrow \text{VaR}_p(X) = \mu - \delta + 2\delta p$$

$$\Rightarrow \text{ES}_p(X) = \mu - \delta + \delta p$$

From Math 20802, the MLEs of μ and δ are

$$\hat{\mu} = \frac{\max x_i + \min x_i}{2}$$

$$\hat{\delta} = \frac{\max x_i - \min x_i}{2}$$

Hence, the MLEs of VaR_p and ES_p are

$$\widehat{\text{VaR}}_p(X) = \hat{\mu} - \hat{\delta} + 2\hat{\delta} p,$$

$$\widehat{\text{ES}}_p(X) = \hat{\mu} - \hat{\delta} + \hat{\delta} p.$$