

Math 4260 Tutorial 9

1. Assume that the normal random variables X_1, X_2, \dots, X_n of mean μ and variance σ^2 are uncorrelated. If $S_n = \frac{1}{n} \sum_{i=1}^n X_i$, find $E[S_n]$, $\text{Var}(S_n)$.

Solution:

Recall: for $C_i \in \mathbb{R}$,

$$E\left[\sum_{i=1}^n C_i X_i\right] = \sum_{i=1}^n C_i \cdot E[X_i]$$

$$\text{Var}\left(\sum_{i=1}^n C_i X_i\right) = \sum_{i=1}^n C_i^2 \cdot \text{Var}(X_i) + 2 \sum_{1 \leq i < j \leq n} C_i \cdot C_j \cdot \text{Cov}(X_i, X_j)$$

Hence,

$$E[S_n] = E\left[\frac{1}{n} \sum_{i=1}^n X_i\right] = \sum_{i=1}^n \frac{1}{n} \cdot \mu = \mu.$$

$$\text{Var}(S_n) = \sum_{i=1}^n \frac{1}{n^2} \cdot \text{Var}(X_i) + 2 \cdot \sum_{1 \leq i < j \leq n} \frac{1}{n^2} \cdot \text{Cov}(X_i, X_j).$$

$$= \sum_{i=1}^n \frac{1}{n^2} \cdot \sigma^2$$

$$= \frac{\sigma^2}{n}.$$

2. If X_1, X_2, \dots, X_n are independent normal random variables with parameter μ_i, σ_i^2 ($X_i \sim N(\mu_i, \sigma_i^2)$), if $Y = \sum_{i=1}^n X_i$, then Y is still a normal random variable with parameters $(\sum_{i=1}^n \mu_i, \sum_{i=1}^n \sigma_i^2)$.

Solution:

Recall

if X is normal r.v. \Leftrightarrow characteristic function
 μ, σ^2 $\varphi_X(\theta) = E[e^{i\theta X}]$
 $= e^{i\theta\mu - \frac{\theta^2\sigma^2}{2}}$

Since $Y = \sum_{i=1}^n X_i$.

The characteristic function of Y is

$$\varphi_Y(\theta) = E[e^{i\theta Y}] = E[e^{i\theta(\sum_{i=1}^n X_i)}]$$

$$= E[e^{i\theta X_1}] \cdot E[e^{i\theta X_2}] \cdots E[e^{i\theta X_n}]$$

$$= e^{i\theta\mu_1 - \frac{\theta^2\sigma_1^2}{2}} \cdot e^{i\theta\mu_2 - \frac{\theta^2\sigma_2^2}{2}} \cdots e^{i\theta\mu_n - \frac{\theta^2\sigma_n^2}{2}}$$

$$= e^{i\theta(\sum_{i=1}^n \mu_i) - \frac{\theta^2(\sum_{i=1}^n \sigma_i^2)}{2}}$$

which is a characteristic function of a normal r.v. with parameter $(\sum \mu_i, \sum \sigma_i^2)$.

$$\Rightarrow Y \sim N\left(\sum_{i=1}^n \mu_i, \sum_{i=1}^n \sigma_i^2\right)$$

3. A random variable S is log-normal if

$$\ln S \sim N(\mu, \sigma^2)$$

(a) Find the probability density function of S .

(b) If $S(t)$ has log-normal distribution with drift r and volatility σ . Find $E[\frac{S(t+\Delta t)}{S(t)}]$, $E[(\frac{S(t+\Delta t)}{S(t)})^2]$.

Solution:

$$P(S \leq x). \quad \text{If } x \leq 0. \quad P(S \leq x) = 0.$$

If $x > 0$.

$$P(S \leq x) = P(\ln S \leq \ln x).$$

$$= P(Y \leq \ln x)$$

$$= \int_{-\infty}^{\ln x} \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(y-\mu)^2}{2\sigma^2}} dy$$

$$P_S(x) = \frac{dP(S \leq x)}{dx} = \frac{d \int_{-\infty}^{\ln x} \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(y-\mu)^2}{2\sigma^2}} dy}{dx}$$

$$= \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(\ln x - \mu)^2}{2\sigma^2}} \cdot \frac{d \ln x}{dx}$$

$$= \frac{1}{\sqrt{2\pi}\sigma \cdot x} e^{-\frac{(\ln x - \mu)^2}{2\sigma^2}}$$

(b)

$$\ln \frac{S(t+\Delta t)}{S(t)} \sim N\left(\left(r - \frac{\sigma^2}{2}\right)\Delta t, \sigma^2 \Delta t\right)$$

$$Y_t = \frac{S(t+\Delta t)}{S(t)}$$

$$E[Y_t] = \int_{\mathbb{R}} y \cdot f_Y(y) dy$$

$$= \int_0^{\infty} y \cdot \frac{e^{-\frac{(ny - (r - \frac{\sigma^2}{2})\Delta t)^2}{2\sigma^2 \Delta t}}}{\sqrt{2\pi\sigma^2 \Delta t}} dy$$

$$= \int_0^{\infty} \frac{1}{\sqrt{2\pi\sigma^2 \Delta t}} e^{-\frac{(ny - (r - \frac{\sigma^2}{2})\Delta t)^2}{2\sigma^2 \Delta t}} dy$$

$$= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi\sigma^2 \Delta t}} e^{-\frac{z^2}{2\sigma^2 \Delta t}} e^{(r - \frac{\sigma^2}{2})\Delta t} \cdot e^z dz$$

$$= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi\sigma^2 \Delta t}} e^{-\frac{z^2}{2\sigma^2 \Delta t} + z + (r - \frac{\sigma^2}{2})\Delta t} dz$$

$$= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi\sigma^2 \Delta t}} e^{-\frac{(z - \sigma^2 \Delta t)^2}{2\sigma^2 \Delta t}} \cdot e^{r \Delta t} dz$$

$$= e^{r \Delta t}$$

$$\begin{aligned}
 E\left[\left(\frac{S(t+\Delta t)}{S(t)}\right)^2\right] &= E[Y_t^2] = \int_0^\infty y^2 f_Y(y) dy \\
 &= \int_0^\infty y^2 \cdot \frac{1}{\sqrt{2\pi\sigma^2\Delta t}} e^{-\frac{(\ln y - (r - \frac{\sigma^2}{2})\Delta t)^2}{2\sigma^2\Delta t}} dy \\
 &= e^{2r\Delta t + \sigma^2\Delta t}
 \end{aligned}$$

Alternatively,

Since t is log-normal r.v.,
 $\ln Y_t = X$. $X \sim N\left((r - \frac{\sigma^2}{2})\Delta t, \sigma^2\Delta t\right)$

$$Y_t = e^X$$

$$E[Y_t] = E[e^X] = e^{(r - \frac{\sigma^2}{2})\Delta t + \frac{\sigma^2\Delta t}{2}} = e^{r\Delta t}$$

Recall in Tutorial 1, $E[e^{\theta X}] = e^{\theta\mu + \frac{\theta^2\sigma^2}{2}}$
 $X \sim N(\mu, \sigma^2)$

$$\begin{aligned} E[Y_t^2] &= E[(e^X)^2] = E[e^{2X}] = e^{2 \cdot (r - \frac{\sigma^2}{2}) \Delta t + 2 \cdot \sigma^2 \Delta t} \\ &= e^{2r \Delta t + \sigma^2 \Delta t} \end{aligned}$$