IEOR 241: Homework 10

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November 19, 2022

Exercise 1

1. To verify if f is a density we just need to check that $\int_0^\infty f(t)dt = 1$:

$$\int_{0}^{\infty} f(x)dx = \int_{0}^{\infty} \frac{x}{a} e^{-\frac{x^{2}}{2a}} dx = \left[-e^{-\frac{x^{2}}{2a}} \right]_{0}^{\infty} = 1$$

2. Define $\forall i \in [1; 8], h_i$ to be the height of year i. The likelihood of h is : $\mathcal{L}(a) = \prod_{i=1}^{8} f(h_i)$. We will try to find $\hat{a} = \arg \max(\mathcal{L}(a))$.

$$\hat{a} = \arg \max(\mathcal{L}(a))$$

$$= \arg \max(\log(\mathcal{L}(a)))$$

$$= \arg \max(\sum_{i=1}^{8} \log(h_i) - \frac{h_i^2}{2a} - \log(a))$$

$$= \arg \max \left(\left[\sum_{i=1}^{8} \log(h_i) \right] - \frac{\sum_{i=1}^{8} h_i^2}{2a} - 8\log(a) \right)$$

As \hat{a} is a maximum it implies that $\frac{\sum\limits_{i=1}^8 h_i^2}{2\hat{a}^2} - \frac{8}{\hat{a}} = 0$ thus

$$\hat{a} = \frac{\sum_{i=1}^{8} h_i^2}{16} = 2.42$$

3. Let $t \in \mathbb{R}+$, $\mathbb{P}(H \le t) = \int_0^t \frac{x}{a} e^{-\frac{x^2}{2a}} dx = 1 - e^{\frac{-t^2}{2a}}$. Hence :

$$\forall t \in \mathbb{R}, F(t) = \begin{cases} 0 & \text{if } t < 0\\ 1 - e^{\frac{-t^2}{2\hat{a}}} & \text{otherwise} \end{cases}$$

4. The probability of a disaster is the probability of the event that H > 6.

$$\mathbb{P}(H > 6) = 1 - F(6) = e^{\frac{-6^2}{2\hat{a}} = 0.0006}$$

5. Let N be the number of flood in 100 years. Under the assumption that all years are independent $N \sim \mathcal{B}(100, \mathbb{P}(H > 6))$. We have that

$$P(N=0) = F(6)^{100} = 0.94$$

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Exercise 2

1. Let $t \in \mathbb{R}$. If t < 0 then $\mathbb{P}(S \le t) = 0$ as exp takes only positive values.

If $t \ge 0$ then $\mathbb{P}(S \le t) = \mathbb{P}(X \le \ln(t)) = \int_{-\infty}^{\log(t)} \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} dx$. Differentiating both sides with respect to t we have :

$$f_S(t) = \begin{cases} \frac{1}{t\sigma\sqrt{2\pi}} e^{-\frac{(\log(t)-\mu)^2}{2\sigma^2}} & \text{if } t > 0\\ 0 & \text{otherwise} \end{cases}$$

2.

$$\mathbb{E}(S) = \int_0^\infty \frac{1}{\sigma\sqrt{2\pi}} e^{t - \frac{(t-\mu)^2}{2\sigma^2}} dt = e^{\frac{\sigma^2}{2}(1 + \frac{1}{\sigma^2})^2 - \frac{\mu^2}{2\sigma^2}}$$

3. The means should match:

Exercise 3

Part A

1. Let $\forall i \in [1, N]$, $p_i : t \mapsto p_i(t)$ be the price of the asset i as a function of time.

We have that
$$\pi_i = \frac{p_i(0)}{\sum\limits_{i=1}^{N} p_i(0)} = \frac{p_i(0)}{X(0)}$$
 and $X(T) = \sum\limits_{i=1}^{N} p_i(T)$.

Thus

$$\frac{X(T) - X(0)}{X(0)} = \frac{\sum_{i=1}^{N} p_i(T) - p_i(0)}{X(0)} = \frac{\sum_{i=1}^{N} p_i(0)(1 + R_i) - p_i(0)}{X(0)} = \sum_{i=1}^{N} \pi_i R_i$$

2. Let
$$R = \frac{X(T) - X(0)}{X(0)} = \sum_{i=1}^{N} \pi_i R_i$$
 then $\mathbb{V}(R) \left(\sum_{i=1}^{N} \pi_i R_i \right) = \sum_{i=1}^{N} \pi^2 \mathbb{V}(R_i) = \sum_{i=1}^{N} \pi_i^2 \sigma^2$. Hence:

$$\mathbb{V}(R) = \sigma^2 \sum_{i=1}^{N} \pi_i^2$$

3. We use the Lagrange Multipliers Method: define $\forall \lambda, \pi$, $L(\lambda, \pi) = \sigma^2 \sum_{i=1}^N \pi_i^2 + \lambda \left(1 - \sum_{i=1}^N \pi_i\right)$ to minimize L is equivalent to minimizing $\mathbb{V}(R)$. Differentiating with respect to π we have: $\nabla_{\pi} L(\lambda, \pi) = \left(-2\sigma^2\pi_i - \lambda_i\right)$

$$\begin{pmatrix} 2\sigma^2\pi_1 - \lambda \\ 2\sigma^2\pi_2 - \lambda \\ ... \\ 2\sigma^2\pi_N - \lambda \end{pmatrix}$$
. Let π^* be the optimal distribution, the optimality condition yields $\nabla_{\pi}L(\lambda, \pi^*) = 0$ thus

$$\pi_1^* = \pi_2^* = \dots = \pi_N^* = \frac{1}{N}$$

4.
$$\mathbb{V}(R) = \sigma^2 \sum_{i=1}^{N} (\frac{1}{N})^2 = \frac{\sigma^2}{N}$$
 hence

$$\mathbb{V}(R) \to_{N \to \infty} 0$$

Part B

5.

$$\mathbb{V}(R) = \operatorname{Cov}(R, R) = \operatorname{Cov}(\sum_{i=1}^{N} \pi_i R_i, \sum_{j=1}^{N} \pi_j R_j) = \sum_{i=1}^{N} \pi_i^2 \operatorname{Cov}(R_i, R_i) + \sum_{i \neq j} \pi_i \pi_j \operatorname{Cov}(R_i, R_j)$$
$$= \sigma^2 \sum_{i=1}^{N} \pi_i^2 + \rho \sigma^2 \sum_{i \neq j} \pi_i \pi_j$$

6. Same as question **3.** we use Lagrange Multipliers Method.

Define
$$L(\lambda,\pi) = \sigma^2 \sum_{i=1}^N \pi_i^2 + \rho \sigma^2 \sum_{i \neq j} \pi_i \pi_j + \lambda \left(1 - \sum_{i=1}^N \pi_i\right)$$
 we have $\nabla_{\pi} L(\lambda,\pi) = \begin{pmatrix} 2\sigma^2 \pi_1 + 2\sigma^2 \rho \sum_{1 \neq j} \pi_j - \lambda \\ 2\sigma^2 \pi_2 + 2\sigma^2 \rho \sum_{2 \neq j} \pi_j - \lambda \\ \dots \\ 2\sigma^2 \pi_N + 2\sigma^2 \rho \sum_{N \neq j} \pi_j - \lambda \end{pmatrix}$ We can notice that for each term i fixed, $2\sigma^2 \rho \sum_{i \neq j} \pi_j = 2\sigma^2 \rho \sum_{i \neq j} \pi_j + 2\sigma^2 \rho \pi_i - 2\sigma^2 \rho \pi_i = 1 - 2\sigma^2 \rho \pi_i$. Hence we have the same solution:

$$\boxed{\pi_1^* = \pi_2^* = \ldots = \pi_N^* = \frac{1}{N}}$$

7.
$$\mathbb{V}(R) = \sigma^2 \sum_{i=1}^{N} \pi_i^2 + \rho \sigma^2 \sum_{i \neq j} \pi_i \pi_j = \frac{\sigma^2}{N} + \sigma^2 \rho \frac{N-1}{N}$$

$$\mathbb{V}(R) \to_{N \to \infty} \sigma^2 \rho$$

Part C

8. $\mathbb{V}(R) = \pi_1^2 + 2\pi_2^2 + 4\pi_1\pi_2 = \pi_1^2 + 2(1-\pi_1)^2 + 4\pi_1(1-\pi_1) = \pi_1^2 + 2 - 4\pi_1 + 2\pi_1^2 + 4\pi_1 - 4\pi_1^2 = 2 - \pi_1^2$ which is a decreasing function in π_1 as $\pi_1 > 0$ hence

The optimal portfolio minimizing the risk is : $\pi_1 = 1, \pi_2 = 0$