

CHAPTER01

MLE

Consider the following very simple model for stock pricing. The price at the end of each day is the price of the previous day multiplied by a fixed, but unknown, rate of return, a , with some noise, w . For a two-day period, we can observe the following sequence:

$$y_2 = ay_1 + w_1$$

$$y_1 = ay_0 + w_0$$

where the noises w_0, w_1 are iid with the distribution $N(0, \sigma^2)$, $y_0 \sim N(0, \lambda)$ is independent of the noise sequence. σ^2 and λ are known, while a is unknown.

1. Find the MLE of the rate of return, a , given the observed price at the end of each day y_2, y_1, y_0 . In other words, compute for the value of a that maximizes $p(y_2, y_1, y_0 | a)$.

Hint: This is a Markov process, e.g. y_2 is independent of y_0 given y_1 . In general, a process is Markov if $p(y_n | y_{n-1}, y_{n-2}, \dots) = p(y_n | y_{n-1})$.

$$p(y_2, y_1, y_0 | a) = p(y_2 | y_1; a) \times p(y_1 | y_0; a) \times p(y_0)$$

$$p(y_2, y_1, y_0 | a) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(y_2 - ay_1)^2}{2\sigma^2}} \times \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(y_1 - ay_0)^2}{2\sigma^2}} \times \frac{1}{\sqrt{2\pi\lambda}} e^{-\frac{y_0^2}{2\lambda}}$$

$$\text{or } L(a | y_2, y_1, y_0)$$

take \ln

$$\begin{aligned} \ln(p(y_2, y_1, y_0 | a)) &= \ln\left(\frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(y_2 - ay_1)^2}{2\sigma^2}}\right) + \ln\left(\frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(y_1 - ay_0)^2}{2\sigma^2}}\right) + \ln\left(\frac{1}{\sqrt{2\pi\lambda}} e^{-\frac{y_0^2}{2\lambda}}\right) \\ &= \left[\ln\left(\frac{1}{\sqrt{2\pi\sigma^2}}\right) + \ln\left(e^{-\frac{(y_2 - ay_1)^2}{2\sigma^2}}\right)\right] + \left[\ln\left(\frac{1}{\sqrt{2\pi\sigma^2}}\right) + \ln\left(e^{-\frac{(y_1 - ay_0)^2}{2\sigma^2}}\right)\right] \\ &\quad + \left[\ln\left(\frac{1}{\sqrt{2\pi\lambda}}\right) + \ln\left(e^{-\frac{y_0^2}{2\lambda}}\right)\right] \\ &= \left[\ln(2\pi\sigma^2)^{-1/2} - \frac{(y_2 - ay_1)^2}{2\sigma^2} \ln(e)\right] + \left[\ln(2\pi\sigma^2)^{-1/2} - \frac{(y_1 - ay_0)^2}{2\sigma^2} \ln(e)\right] \\ &\quad + \left[\ln(2\pi\lambda)^{-1/2} - \frac{y_0^2}{2\lambda} \ln(e)\right] \\ &= \left[-\frac{1}{2}(\ln(2\pi) + \ln(\sigma^2)) - \frac{(y_2 - ay_1)^2}{2\sigma^2}\right] + \left[-\frac{1}{2}(\ln(2\pi) + \ln(\sigma^2)) - \frac{(y_1 - ay_0)^2}{2\sigma^2}\right] \\ &\quad + \left[-\frac{1}{2}(\ln(2\pi) + \ln(\lambda)) - \frac{y_0^2}{2\lambda}\right] \end{aligned}$$

$$= \left[-\frac{1}{2} \ln(2\pi) - \frac{1}{2} \ln(\sigma^2) - \frac{(y_2 - ay_1)^2}{2\sigma^2} \right] + \left[-\frac{1}{2} \ln(2\pi) - \frac{1}{2} \ln(\sigma^2) - \frac{(y_1 - ay_0)^2}{2\sigma^2} \right]$$

$$\left[-\frac{1}{2} \ln(2\pi) - \frac{1}{2} \ln(\sigma^2) - \frac{y_0^2}{2\lambda} \right]$$

$$= -\frac{1}{2} \ln(2\pi) - \ln(\sigma) - \frac{(y_2 - ay_1)^2}{2\sigma^2} - \frac{1}{2} \ln(2\pi) - \ln(\sigma) - \frac{(y_1 - ay_0)^2}{2\sigma^2} - \frac{1}{2} \ln(2\pi) - \ln(\sigma) - \frac{y_0^2}{2\lambda}$$

$$\ln(P(y_2, y_1, y_0 | a)) = -\frac{3}{2} \ln(2\pi) - 3 \ln(\sigma) - \frac{(y_2 - ay_1)^2}{2\sigma^2} - \frac{(y_1 - ay_0)^2}{2\sigma^2} - \frac{y_0^2}{2\lambda}$$

find derivative

$$\frac{\partial}{\partial a} \ln(P(y_2, y_1, y_0 | a)) = 0 - 0 - \frac{1}{\cancel{2}\sigma^2} \cdot \overset{\text{chain rule}}{(y_2 - ay_1)(0 - y_1)} - \frac{1}{\cancel{2}\sigma^2} \cdot (y_1 - ay_0)(0 - y_0)$$

$$= \frac{1}{\sigma^2} (y_2 - ay_1)(y_1) + \frac{1}{\sigma^2} (y_1 - ay_0)(y_0)$$

$$= \frac{1}{\sigma^2} (y_2 y_1 - ay_1^2 + y_1 y_0 - ay_0^2)$$

$$= \frac{1}{\sigma^2} (y_2 y_1 + y_1 y_0 - a(y_1^2 + y_0^2))$$

Since $\frac{\partial}{\partial a} = 0$ from MLE we have a max: \uparrow slope = 0 at stationary curve

$$0 = \frac{1}{\sigma^2} (y_2 y_1 + y_1 y_0 - a(y_1^2 + y_0^2))$$

$$0 = y_2 y_1 + y_1 y_0 - a(y_1^2 + y_0^2)$$

$$a = \frac{y_2 y_1 + y_1 y_0}{y_1^2 + y_0^2} \quad \underline{\text{Ans}}$$