

## Exercise 6.3

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### 1 6.3

#### 1.1 a

**a6.** Show that  $\theta_{n+1} = \theta_n + \epsilon Y_n$ ,  $Y_n = D(\theta_n) - \xi_n$  satisfies the assumptions of Theorem 6.1.

**Proof**  $E[\delta M_n^\epsilon (\delta M_n^\epsilon)^T 1_{||\theta_n^\epsilon - \theta^*|| = < \rho} | \mathfrak{F}_{n-1}^\epsilon]$  is symmetric matrix Because:

$$\delta M_n^\epsilon = Y_n^\epsilon - g(\xi_{n-1}^\epsilon, \theta_n^\epsilon)$$

And:

$$g(\xi_{n-1}^\epsilon, \theta_n^\epsilon) = E[Y_n^\epsilon | \mathfrak{F}_{n-1}^\epsilon]$$

So:

$$\delta M_n^\epsilon = Y_n^\epsilon - E[Y_n^\epsilon | \mathfrak{F}_{n-1}^\epsilon]$$

Based on:

$$Y_n = D(\theta_n) - \xi_n$$

Then:

$$E[\delta M_n^\epsilon (\delta M_n^\epsilon)^T 1_{||\theta_n^\epsilon - \theta^*|| = < \rho} | \mathfrak{F}_{n-1}^\epsilon] = E[(Y_n^\epsilon - E[Y_n^\epsilon | \mathfrak{F}_{n-1}^\epsilon])(Y_n^\epsilon - E[Y_n^\epsilon | \mathfrak{F}_{n-1}^\epsilon])^T 1_{||\theta_n^\epsilon - \theta^*|| = < \rho} | \mathfrak{F}_{n-1}^\epsilon]$$

Because  $D(\theta_n)$  and  $\xi_n$  are random variable, so  $Y_n$  is random variable also.

$$\begin{aligned} E[\delta M_n^\epsilon (\delta M_n^\epsilon)^T 1_{||\theta_n^\epsilon - \theta^*|| = < \rho} | \mathfrak{F}_{n-1}^\epsilon] &= E[(Y_n^\epsilon - E[Y_n^\epsilon | \mathfrak{F}_{n-1}^\epsilon])(Y_n^\epsilon - E[Y_n^\epsilon | \mathfrak{F}_{n-1}^\epsilon])^T 1_{||\theta_n^\epsilon - \theta^*|| = < \rho} | \mathfrak{F}_{n-1}^\epsilon] \\ &= E[(Y_n^\epsilon - E[Y_n^\epsilon | \mathfrak{F}_{n-1}^\epsilon])((Y_n^\epsilon)^T - (E[Y_n^\epsilon | \mathfrak{F}_{n-1}^\epsilon])^T) 1_{||\theta_n^\epsilon - \theta^*|| = < \rho} | \mathfrak{F}_{n-1}^\epsilon] \\ &= E[(Y_n^\epsilon - E[Y_n^\epsilon | \mathfrak{F}_{n-1}^\epsilon])((Y_n^\epsilon)^T - E[(Y_n^\epsilon)^T]) 1_{||\theta_n^\epsilon - \theta^*|| = < \rho} | \mathfrak{F}_{n-1}^\epsilon] \end{aligned}$$

For simplify, the following processes ignore  $\epsilon$  for a second, but remember it is exist all the time.

$$\begin{aligned} &= E[(Y_n Y_n^T - E[Y_n] Y_n^T - Y_n E[Y_n^T] + E[Y_n] E[Y_n^T]) 1_{||\theta_n^\epsilon - \theta^*|| = < \rho} | \mathfrak{F}_{n-1}^\epsilon] \\ &= E[Y_n Y_n^T - E[E[Y_n] Y_n^T] - E[-Y_n E[Y_n^T]] + E[E[Y_n] E[Y_n^T]]] \\ &= E[Y_n Y_n^T] - E[Y_n] E[Y_n^T] - E[Y_n] E[Y_n^T] + E[Y_n] E[Y_n^T] \end{aligned}$$

Because  $Y_n Y_n^T$  is symmetric matrix,  $E[Y_n]E[Y_n^T]$  is also symmetric matrix, so  $E[\delta M_n^\epsilon (\delta M_n^\epsilon)^T 1_{||\theta_n^\epsilon - \theta^*|| = < \rho} | \mathfrak{F}_{n-1}^\epsilon ]$  is symmetric matrix.

**a7. Where the error term satisfies  $E[\rho_1(\theta, \xi_n^\epsilon)] = \mathcal{O}(\|\theta - \theta^*\|^2)$ , as  $n \rightarrow \infty$   $\epsilon \rightarrow 0$**

$$Y_n = D(\theta_n) - \xi_n$$

because  $Y_n$  is random value, so

$$\begin{aligned} E[Y_n^\epsilon | \mathfrak{F}_{n-1}^\epsilon] &= E[Y_n^\epsilon] \\ &= E[D(\theta_n) - \xi_n] = E[D(\theta_n)] - E[\xi_n | \theta_n] = E[D(\theta_n)] - S(\theta_n) \end{aligned}$$

Then

$$\begin{aligned} \nabla_\theta^2 g(\theta^*, \xi) &= E[\nabla^2 D(\theta^*)] - \nabla^2 S(\theta^*) \\ g(\theta, \xi) &= g(\theta^*, \xi) + \nabla_\theta g(\theta^*, \xi)^T (\theta - \theta^*) + \rho_1(\theta, \xi) \end{aligned}$$

and

$$E[Y_n^\epsilon | \mathfrak{F}_{n-1}^\epsilon] = g(\xi_{n-1}^\epsilon, \theta_n^\epsilon)$$

So

$$g(\theta, \xi) = g(\theta^*, \xi) + \nabla_\theta g(\theta^*, \xi)^T (\theta - \theta^*) + \frac{1}{2} \nabla_\theta^2 g(\theta^*, \xi) (\theta - \theta^*)^2 + \rho_2(\theta, \xi)$$

$$E[\rho_1(\theta, \xi_n^\epsilon)] = E[\frac{1}{2} \nabla_\theta^2 g(\theta^*, \xi) (\theta - \theta^*)^2 + \rho_2(\theta, \xi)]$$

Because  $E[\rho_2(\theta, \xi)] \rightarrow 0$  and  $\nabla_\theta^2 g(\theta^*, \xi) = E[\nabla^2 D(\theta^*)] - \nabla^2 S(\theta^*) > 0$  but limited, so  $E[\rho_1(\theta, \xi_n^\epsilon)] = \mathcal{O}(\|\theta - \theta^*\|^2)$

**a8. There is a Hurwitz matrix  $A$  (i.e. a matrix where all the eigenvalues have a negative real part) such that  $\lim_{m \rightarrow \infty} \frac{1}{m} \sum_{i=n}^{n+m-1} E[\nabla_\theta g(\xi_{n-1}^\epsilon, \theta^*)^T - A] = 0$**

$$\nabla_\theta g(\theta^*, \xi) = E[\nabla D(\theta^*)] - \nabla S(\theta^*)$$

$$E[\nabla_\theta g(\xi_{n-1}^\epsilon, \theta^*)^T] = E[E[\nabla_\theta D(\theta_n^*)]^T] - E[\nabla_\theta S(\theta_n^*)^T] = E[\nabla_\theta D(\theta_n^*)]^T - E[\nabla_\theta S(\theta_n^*)^T] = E[\nabla_\theta D(\theta_n^*)]^T - \nabla_\theta S(\theta_n^*)^T$$

## 1.2 b

Use  $d = 5$  for the demand function. Your economics guru has estimated that  $\theta^* \approx 1$  and  $S'(\theta^*) \approx 4.5$ . With this information, apply Theorem 6.1 to identify the values of  $a$ ,  $\sigma^2$  for the (approximate) limit Orstein Uhlenbeck process  $U(t)$ , and find  $T$  such that  $e^{-aT} \approx 0.0001$

$$D(\theta) = \theta^{-5}$$

$$D(\theta^* \approx 1) \approx S(\theta^* \approx 1)$$

$$S'(\theta^*) \approx 4.5$$

$$D'(\theta^*) < S'(\theta^*)$$

$$D'(\theta^*) < 4.5$$

$$U_n^\epsilon = \frac{\theta_n^\epsilon - 1}{\sqrt{\epsilon}}$$

$$U^\epsilon(t) = U_n^\epsilon, t \in [n\epsilon, (n+1)\epsilon]$$

### 1.3 c

Show that  $\epsilon \approx 0.0005$  yields a precision of 0.01(half width of the approximate confidence interval after  $T/\epsilon$  iterations, with confidence level  $\alpha = 0.05$ ).