

Ex. 6.10

We wish to show that C_λ is an unbiased estimate for $PE(\lambda)$ e.g.

$$(**) \quad E(C_\lambda) = E\left[ASR(\lambda) + \frac{2\sigma^2}{N} \text{trace}(S_\lambda)\right] = PE(\lambda)$$

Start with $E(ASR(\lambda))$

$$= \frac{1}{N} E\left[\sum_{i=1}^N (y_i - \hat{f}_\lambda(x_i))^2\right] \quad \text{where } y_i = f(x_i) + \varepsilon_i$$

$$= \frac{1}{N} E[(y - S_\lambda y)^T (y - S_\lambda y)] \quad \text{since } \hat{F} = S_\lambda y$$

$$= \frac{1}{N} E[y^T (\mathbb{I} - S_\lambda)^T (\mathbb{I} - S_\lambda) y]$$

$$= \frac{1}{N} E[y^T (\mathbb{I} - S_\lambda)^2 y] \quad \text{since } (\mathbb{I} - S_\lambda) = (\mathbb{I} - S_\lambda)^T$$

Now we will take advantage of some properties of the trace.
Firstly, for a 1×1 matrix K_i we have $K_i = \text{trace}(K_i)$, so:

$$= \frac{1}{N} E[\text{trace}(y^T (\mathbb{I} - S_\lambda)^2 y)]$$

$$= \frac{1}{N} E[\text{trace}((\mathbb{I} - S_\lambda)^2 y y^T)] \quad \text{using the "trace trick"}$$

$$(*) \quad = \frac{1}{N} \text{trace}((\mathbb{I} - S_\lambda)^2) E(y y^T) \quad S_\lambda \text{ depends only on } X \text{ and } \lambda$$

Now $E(y y^T)$

$$= E[(f + \varepsilon)(f + \varepsilon)^T]$$

$$= E[ff^T + \varepsilon f^T + f \varepsilon + \varepsilon \varepsilon^T]$$

$$= ff^T + \sigma^2 \mathbb{I}$$

Returning to (*) we obtain:

$$= \frac{1}{N} \text{trace}((\mathbb{I} - S_\lambda)^2) (ff^T + \sigma^2 \mathbb{I})$$

$$= \frac{1}{N} \text{trace}((\mathbb{I} - S_\lambda)^2) ff^T + \frac{1}{N} \text{trace}((\mathbb{I} - S_\lambda)^2) \sigma^2 \mathbb{I}$$

$$\text{LHS} = \frac{1}{N} F^T (\mathbb{I} - S_\lambda)^2 f \quad \text{trace trick again in reverse.}$$

$$\text{RHS} = \frac{\sigma^2}{N} \text{trace}((\mathbb{I} - S_\lambda)^2)$$

$$= \frac{\sigma^2}{N} \text{trace}(\mathbb{I} - 2S_\lambda + S_\lambda^2)$$

$$= \frac{\sigma^2}{N} [N - 2\text{trace}(S_\lambda) + \text{trace}(S_\lambda^2)]$$

$$= \sigma^2 - \frac{2\sigma^2}{N} \text{trace}(S_\lambda) + \frac{\sigma^2}{N} \text{trace}(S_\lambda^2)$$

Putting this all together we obtain:

$$\mathbb{E}(\text{ASR}(\lambda)) = \frac{1}{N} F^T (\mathbb{I} - S_\lambda)^2 f + \sigma^2 - \frac{2\sigma^2}{N} \text{trace}(S_\lambda) + \frac{\sigma^2}{N} \text{trace}(S_\lambda^2)$$

Therefore, Proving (**) reduces to showing

$$(***) \quad \frac{1}{N} F^T (\mathbb{I} - S_\lambda)^2 f + \sigma^2 + \frac{\sigma^2}{N} \text{trace}(S_\lambda^2) = \text{PE}(\lambda)$$

and to solve this we need to evaluate $\text{PE}(\lambda)$ where

$$\text{PE}(\lambda) = \frac{1}{N} \mathbb{E} \left[\sum_{i=1}^N (y_i^* - \hat{f}_\lambda(x_i))^2 \right]$$

where this time $y_i^* = f(x_i) + \varepsilon_i^*$

$$= \frac{1}{N} E[(f + \varepsilon^* - \hat{f})^T (f + \varepsilon^* - \hat{f})]$$

$$= \frac{1}{N} E[(f - \hat{f})^T (f - \hat{f}) + 2\varepsilon^{*T} (f - \hat{f}) + \varepsilon^{*T} \varepsilon^*]$$

$$= \frac{1}{N} E[(f - S_\lambda y)^T (f - S_\lambda y)] + 0 + \sigma^2 \quad \left(\begin{array}{l} \text{Since } E(\varepsilon^*) = 0 \\ \text{and } E(\varepsilon^{*T} \varepsilon^*) = N\sigma^2 \end{array} \right)$$

$$= \frac{1}{N} E[(f - S_\lambda f - S_\lambda \varepsilon)^T (f - S_\lambda f - S_\lambda \varepsilon)] + \sigma^2$$

$$= \frac{1}{N} E[(f - S_\lambda f)^T (f - S_\lambda f) - (f - S_\lambda f)^T S_\lambda \varepsilon - (S_\lambda \varepsilon)^T (f - S_\lambda f) + (S_\lambda \varepsilon)^T S_\lambda \varepsilon] + \sigma^2$$

(using $y = f + \varepsilon$)

$$\textcircled{1} = \frac{1}{N} E[(f - S_\lambda f)^T (f - S_\lambda f) + (S_\lambda \varepsilon)^T S_\lambda \varepsilon] + \sigma^2 \quad (\text{since } E(\varepsilon) = 0)$$

$$\Rightarrow \text{LHS} = \frac{1}{N} f^T (\mathbb{I} - S_\lambda)^2 f \quad (\text{using "trace trick" as before})$$

$$\text{RHS} = \frac{1}{N} E[\varepsilon^T S_\lambda^2 \varepsilon] \quad (\text{since } S_\lambda^T = S_\lambda)$$

$$= \frac{1}{N} E[\text{trace}(\varepsilon^T S_\lambda^2 \varepsilon)] \quad (\text{as } \varepsilon^T S_\lambda^2 \varepsilon = 1 \times 1 \text{ matrix})$$

$$= \frac{1}{N} E[\text{trace}(S_\lambda^2 \varepsilon \varepsilon^T)] \quad (\text{trace trick})$$

$$= \frac{1}{N} \text{trace}(S_\lambda^2) \sigma^2$$

Therefore $\textcircled{1}$ is equal to:

$$= \frac{1}{N} f^T (\mathbb{I} - S_\lambda)^2 f + \frac{\sigma^2}{N} \text{trace}(S_\lambda^2) + \sigma^2$$

Satisfying (***) as required and thus proving \hat{C}_λ is an unbiased estimate of $PE(\lambda)$.