

## 6.3 Confidence interval for the model based mean, prediction interval

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Normal linear model  $Y|X \sim \mathcal{N}_m(X\beta, \sigma^2 I_m)$

$$\Rightarrow \forall i \quad Y_i|X_i \sim \mathcal{N}(X_i^T \beta, \sigma^2)$$

$$\varepsilon_i = Y_i - X_i^T \beta \stackrel{iid}{\sim} \varepsilon, \quad \varepsilon \sim \mathcal{N}(0, \sigma^2)$$

$\mathcal{X} \subseteq \mathbb{R}^k$ : sample space of  $X_1, \dots, X_n$

Take  $x_{new} \in \mathcal{X}$ ,  $\varepsilon_{new} \sim \mathcal{N}(0, \sigma^2)$

$$\varepsilon_{new} \perp \varepsilon = (\varepsilon_1, \dots, \varepsilon_n)^T$$

$$Y_{new} = x_{new}^T \beta + \varepsilon_{new}$$

→ "new" observation being sampled (obtained) independently of the "old" observations

$$Y = (Y_1, \dots, Y_n)^T$$

$$Y_{new}|X_{new} = x_{new} \sim \mathcal{N}(x_{new}^T \beta, \sigma^2)$$

Problems: Interval estimation of <sup>being assured</sup>

$$(i) \quad \mu_{new} = E(Y_{new}|X_{new} = x_{new}) \stackrel{\text{being assured}}{\downarrow} = x_{new}^T \beta$$

(ii)  $Y_{new}$  itself (prediction)

Theorem 6.3 Confidence interval for the model based mean, prediction interval

Let  $Y|X \sim N_n(X\beta, \sigma^2 I_n)$ ,  $\text{rank}(X_{n \times k}) = k$ ,  $\hat{\beta} = (X^T X)^{-1} X^T Y$  is the LSE of the regression parameters  $\beta$ .  
Let  $x_{\text{new}} \in X$ ,  $x_{\text{new}} \neq 0$ . Let  $\epsilon_{\text{new}} \sim N(0, \sigma^2)$  is independent of  $E = Y - X\beta$ . Finally, let  $Y_{\text{new}} = x_{\text{new}}^T \beta + \epsilon_{\text{new}}$ . The following then holds:

(i) The quantity  $\hat{\mu}_{\text{new}} = x_{\text{new}}^T \hat{\beta}$  is the BLUE of  $\mu_{\text{new}} = x_{\text{new}}^T \beta$ . The standard error of  $\hat{\mu}_{\text{new}}$  is  $\text{S.E.}(\hat{\mu}_{\text{new}}) = \sqrt{\text{MSE } x_{\text{new}}^T (X^T X)^{-1} x_{\text{new}}}$  and the lower and the upper bound of the  $(1-\alpha)$  100% confidence interval for  $\mu_{\text{new}}$  are

$$(\mu_{\text{new}}^L, \mu_{\text{new}}^U) = \hat{\mu}_{\text{new}} \pm \text{S.E.}(\hat{\mu}_{\text{new}}) t_{n-k} \left(1 - \frac{\alpha}{2}\right)$$

PROOF: Point (i) of

- BLUE property: Theorem 2.5 (Gauss-Markov for linear comb.)
- Point (ii), Theorem 6.2

$$\forall \beta^0 \quad P\left(\hat{\mu}_{\text{new}} \pm \sqrt{\text{MSE } x_{\text{new}}^T (X^T X)^{-1} x_{\text{new}}} \cdot t_{n-k} \left(1 - \frac{\alpha}{2}\right) \ni x_{\text{new}}^T \beta^0 ; \beta = \beta^0\right) = 1 - \alpha$$

(ii) A (random) interval with the bounds

$$(Y_{new}^L, Y_{new}^U) = \hat{\mu}_{new} \pm S.E.P.(x_{new}) \pm n-k (1-\frac{\alpha}{2}),$$

where  $S.E.P.(x_{new}) = \sqrt{MSE (1 + x_{new}^T (X^T X)^{-1} x_{new})}$ ,  
covers with the probability of  $(1-\alpha)$  the  
value of  $Y_{new}$ .

That is  $\forall \beta^0 \in \mathbb{R}^k \forall \sigma_0^2 > 0$

$$P((Y_{new}^L, Y_{new}^U) \ni Y_{new}; \beta = \beta^0, \sigma^2 = \sigma_0^2) = 1-\alpha.$$

Quick but INCORRECT "proof":

$$Y_{new} = x_{new}^T \beta + \epsilon_{new}$$

$$\hat{Y}_{new} = x_{new}^T \hat{\beta} + \hat{\epsilon}_{new}$$

indep.  $\hat{\epsilon}_{new} = 0$  since  $E(\epsilon_{new} | x_{new} = x_{new}) = 0$

$$\text{var}(\hat{Y}_{new} | X) = \text{var}(x_{new}^T \hat{\beta} | X) + \text{var}(\hat{\epsilon}_{new} | X) =$$

$$= x_{new}^T \underbrace{\text{var}(\hat{\beta} | X)}_{\sigma^2 (X^T X)^{-1}} x_{new} + \sigma^2 \quad (? \text{ since } \text{var}(\epsilon_{new} | X) = \sigma^2)$$

$$= \sigma^2 (1 + x_{new}^T (X^T X)^{-1} x_{new})$$

$\rightarrow$  S.E.P. ( $x_{new}$ ) replace unknown  $\sigma^2$  by MSE

$\Rightarrow$  "prediction":  $\hat{Y}_{new} \pm$  S.E.P. ( $x_{new}$ )  $\cdot$  quantile

Proof: All statements given  $X_1, \dots, X_n, X_{new}$ :

$$Y_{new} \sim N(\mu_{new}, \sigma^2)$$

$$\hat{\mu}_{new} \sim N(\mu_{new}, \sigma^2 v) \quad , \quad v = \underbrace{X_{new}^T (X^T X)^{-1} X_{new}}_{> 0 \text{ (WHY?)}}$$

" LSE of  $\mu_{new}$  based on  $(Y, X)$

$$Y \perp\!\!\!\perp Y_{new} \Rightarrow Y_{new} \perp\!\!\!\perp \hat{\mu}_{new}$$

$$\Rightarrow Y_{new} - \hat{\mu}_{new} \sim N(0, \sigma^2(1+v))$$

Further, SSE is a function of  $Y$  (and  $X$ )

$$Y \perp\!\!\!\perp Y_{new} \Rightarrow Y_{new} \perp\!\!\!\perp SSE$$

We also know (Theorem 0.2(v)) :  $\hat{\mu}_{new} \perp\!\!\!\perp SSE$

$$\Rightarrow Y_{new} - \hat{\mu}_{new} \perp\!\!\!\perp SSE$$

Finally,  $\frac{SSE}{\sigma^2} \sim \chi^2_{n-k}$

hence  $\frac{Y_{new} - \hat{\mu}_{new}}{\sqrt{\sigma^2(1+v)}} \sim N(0,1) \perp\!\!\!\perp \chi^2_{n-k}$

$$\frac{\sqrt{SSE}}{\sqrt{(n-k)\sigma^2}} \sim \chi^2_{n-k}$$

$$\frac{Y_{new} - \hat{\mu}_{new}}{\sqrt{MSE(1+v)}}$$

$$\Rightarrow \exists \beta^0 \in \mathbb{R}^k \quad \exists \sigma_0^2 > 0, \quad Y_{new}^0 = X_{new}^T \beta^0 + \epsilon_{new}^0, \quad \epsilon_{new}^0 \sim N(0, \sigma_0^2)$$

$$1-\alpha = P \left( \left| \frac{Y_{new}^0 - \hat{\mu}_{new}^0}{\sqrt{MSE(1+v)}} \right| < t_{n-k}(1-\frac{\alpha}{2}); \beta = \beta^0, \sigma^2 = \sigma_0^2 \right)$$

$$= P \left( \hat{\mu}_{new} \pm \sqrt{MSE(1+v)} t_{n-k}(1-\frac{\alpha}{2}) \ni Y_{new}^0; \beta = \beta^0, \sigma^2 = \sigma_0^2 \right)$$

S.E.P. ( $X_{new}$ )



Confidence interval for the model based mean:

$$CIM(x_{new}) := \hat{\mu}_{new} \pm \sqrt{MSE \cdot v} \cdot t_{n-k} \left(1 - \frac{\alpha}{2}\right), \quad v = x_{new}^T (X^T X)^{-1} x_{new}$$

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Prediction interval:

$$PI(x_{new}) := \hat{\mu}_{new} \pm \underbrace{\sqrt{MSE(1+v)}}_{S.E.P.(x_{new})} \cdot t_{n-k} \left(1 - \frac{\alpha}{2}\right)$$

Sequence of CIM's and PI's for a grid of values  $x_{new} \in \mathcal{X}$

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→ confidence band AROUND the regression function

→ prediction band

Illustration: Kojeri  
Hori  $\emptyset$

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- width of the band

CIM  
MSE,  $v$   
precis. of LSE

PI  
MSE,  $v$  + MSE  
precis. of LSE  $\equiv \text{var}(Y|X)$

→ what is going to happen if  $n \rightarrow \infty$ ?

Importance of normality assumption  
for a valid prediction (also homosced.)

