

Proof for CI of bridge model

Part (2)

$$\text{Var}(\hat{y}_{\text{future}}) = \text{Var}(\sigma^2)$$

Future CI,

$$\text{Var}(y_{\text{future}}) = \sigma^2 + \text{Var}(x_{\text{future}} \beta) \quad \text{where } \sigma^2 = \text{Var}(\varepsilon)$$

Consider lower total Variance

$$\text{Var}(x_{\text{future}} \hat{\beta}) = E(\text{Var}(x_{\text{future}} \hat{\beta} | x_{\text{future}})) + \text{Var}(E[x_{\text{future}} \hat{\beta} | x_{\text{future}}])$$

Consider the second term,

$$E[x_{\text{future}} \hat{\beta} | x_{\text{future}}] = x_{\text{future}} E[\hat{\beta}] = x_{\text{future}} E[\beta]$$

$$\text{Var}(x_{\text{future}} E[\beta]) = E[\beta]' \text{Var}(x_{\text{future}}) E[\beta]$$

Consider the first term,

$$\text{Var}(x_{\text{future}} \hat{\beta} | x_{\text{future}}) = x_{\text{future}}' \sigma^2 (X'X)^{-1} x_{\text{future}}$$

$$E[x_{\text{future}}' \sigma^2 (X'X)^{-1} x_{\text{future}}] = \sigma^2 \text{tr}((X'X)^{-1} \sum x_{\text{future}}) + E[x_{\text{future}}]' \sigma^2 (X'X)^{-1} E[x_{\text{future}}]$$

$$\text{Var}(y_{\text{future}}) = \sigma^2 + E[\beta]' \sum x_{\text{future}} E[\beta] + \sigma^2 \text{tr}((X'X)^{-1} \sum x_{\text{future}}) + E[x_{\text{future}}]' \sigma^2 (X'X)^{-1} E[x_{\text{future}}]$$

Part (1)

$$\text{Var}(\hat{y}_{\text{future}}) = \text{Var}(x_{\text{future}} \hat{\beta}) = x_{\text{future}}' \text{Var}(\hat{\beta}) x_{\text{future}} = \sigma^2 x_{\text{future}}' (X'X)^{-1} x_{\text{future}}$$

For simplicity and since we use independent models to predict each component of x_{future}

$$x_{\text{future}} \sim N\left(\mu, \begin{pmatrix} \text{Var}(x_1) \\ \vdots \\ \text{Var}(x_n) \end{pmatrix}\right), \text{ with predicted value, } \text{Var}(x_{\text{future}}) = \text{var-cov matrix of } x_{\text{future}}$$

$$\sum x_{\text{future}} = \begin{pmatrix} \text{var}(x_1) & 0 & \dots & 0 \\ 0 & \text{var}(x_2) & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \text{var}(x_n) \end{pmatrix}, \text{ should be a diagonal matrix.}$$

Can say that $x_{\text{future}} \hat{\beta}$ follows normal distribution (1)

We assume Lindeberg condition is true as we have many terms and all variances are similar

$x_{\text{future}}' \hat{\beta} = x_{\text{future}}' (X'X)^{-1} X'y$ thus $= \sum_{i=1}^n \sum_{j=1}^n x_{\text{future},i} y_j [(X'X)^{-1}]_{ji}$. Thus the predicted sum of many independent variables, & by CLT

$$y_{\text{future}} \sim N\left(x_{\text{future}}' \hat{\beta}, \sigma^2 + E[\beta]' \sum x_{\text{future}} E[\beta] + \sigma^2 \text{tr}[(X'X)^{-1} \sum x_{\text{future}}] + \sigma^2 E[x_{\text{future}}]' (X'X)^{-1} E[x_{\text{future}}]\right)$$