

## Error Propagation

$$Y = AX + b$$

$\uparrow$  matrix of constants  
 $\nwarrow$  constant vector  
 $\swarrow$  random variable  $\Sigma_{xx}$

$$\Sigma_{yy} = A \Sigma_{xx} A^T$$


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$$Y = Y^0 + J \Delta x \quad \text{Taylor Series}$$

$$\Sigma_{xx}$$

$$\Sigma_{\Delta x}$$

$$\Sigma_{yy} = J \Sigma_{xx} J^T$$

$$\begin{bmatrix} X_a \\ Y_a \\ X_b \\ Y_b \end{bmatrix} \equiv \Sigma_{xx} \begin{bmatrix} \sigma_{X_a}^2 & \sigma_{X_a Y_a} & \cdot & \cdot \\ \sigma_{X_a Y_a} & \sigma_{Y_a}^2 & \cdot & \cdot \\ \sigma_{X_b X_a} & \sigma_{Y_b Y_a} & \sigma_{X_b}^2 & \cdot \\ \sigma_{Y_b X_a} & \sigma_{Y_b Y_a} & \sigma_{Y_b X_b} & \sigma_{Y_b}^2 \end{bmatrix}$$

$$D_x = X_b - X_a \quad \text{what is } \Sigma \begin{pmatrix} D_x \\ D_y \end{pmatrix} ?$$

$$D_y = Y_b - Y_a$$

$$\begin{pmatrix} D_x \\ D_y \end{pmatrix} = \begin{pmatrix} -1 & 0 & 1 & 0 \\ 0 & -1 & 0 & 1 \end{pmatrix} \begin{pmatrix} X_a \\ Y_a \\ X_b \\ Y_b \end{pmatrix}$$

$$\Sigma \begin{pmatrix} D_x \\ D_y \end{pmatrix} = \begin{pmatrix} -1 & 0 & 1 & 0 \\ 0 & -1 & 0 & 1 \end{pmatrix} \Sigma_{xx} \begin{pmatrix} 1 & 0 \\ 0 & -1 \\ 0 & 0 \\ 0 & -1 \end{pmatrix} \begin{pmatrix} X_a \\ Y_a \\ X_b \\ Y_b \end{pmatrix}$$

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$$\Sigma_{\begin{pmatrix} D_x \\ D_y \end{pmatrix}} = \begin{pmatrix} \sigma_{D_x}^2 & \sigma_{D_x D_y} \\ \sigma_{D_x D_y} & \sigma_{D_y}^2 \end{pmatrix}$$

error propagation with either  $\begin{cases} \Sigma & \text{abs. cov. mx} \\ Q & \text{Scaled cov. mx.} \end{cases}$

$$\Sigma = \sigma_0^2 Q$$

$$\Sigma_{xx} = \sigma_0^2 Q_{xx}$$

$$\Sigma_{\hat{x}\hat{x}} = \sigma_0^2 Q_{\hat{x}\hat{x}}$$

$$\Sigma_{\Delta\Delta} = \sigma_0^2 Q_{\Delta\Delta}$$

$$\Sigma_{uv} = \sigma_0^2 Q_{uv}$$

$$\Sigma_{\ell\ell} = \sigma_0^2 Q_{\ell\ell} \quad (Q^* = Q_{\ell\ell})$$

$$\Sigma_{xx} = \sigma_0^2 Q_{xx}$$

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$\sigma_0^2$  either
 }
 prior  $\sigma_0^2$  chosen "a priori"

}
 post adjustment  $\hat{\sigma}_0^2$  estimated "a posteriori"

### Indirect Observation Model

$$Q_{\beta\beta} = N^{-1} = (B^T W B)^{-1}$$

( $Q_{xx}$ )

$$\Sigma_{\beta\beta} = \sigma_0^2 Q_{\beta\beta}$$

$$Q_{\hat{\beta}\hat{\beta}} = ?$$

$$Q_{\hat{\beta}\hat{\beta}} = B^T (B^T W B)^{-1} B^T W \cdot Q \left[ B (B^T W B)^{-1} B^T W \right]^T$$

$$= B (B^T W B)^{-1} B^T W \underbrace{Q W B (B^T W B)^{-1} B^T}_{I}$$

$$Q_{\hat{\beta}\hat{\beta}} = B N^{-1} B^T$$

I/O

$$\sum \hat{\beta} \hat{\beta} = \sigma^2 Q_{\hat{\beta}\hat{\beta}}$$

$$Q_{vv} = ? \quad v = f - B_0$$

$$v = d - l - B N^{-1} B^T W (d - l)$$

$$v = d - l - B N^{-1} B^T W d + B N^{-1} B^T W l$$

$$v = (I - B N^{-1} B^T W) d + (B N^{-1} B^T W - I) l$$

form  
we  
need

✓

$$\hat{l} = l + v, \quad v + B\Delta = f, \quad v = f - B\Delta \quad 13-6$$

$$f = d - l$$

$$\hat{l} = l + f - B\Delta = \underline{l} + d - \underline{l} - B\Delta$$

$$\hat{l} = d - B\Delta \rightarrow \Delta = (B^T W B)^{-1} B^T W (d - l)$$

$$\hat{l} = d - B(B^T W B)^{-1} B^T W (d - l)$$

$$\hat{l} = d - B(B^T W B)^{-1} B^T W d + B(B^T W B)^{-1} B^T W l$$

$$\hat{l} = \left( I - B(B^T W B)^{-1} B^T W \right) d + \underbrace{B(B^T W B)^{-1} B^T W}_{\text{in form we need for error prop.}} \cdot l$$

$$Q_{vv} = (BN^{-1}B^T W - I) Q (BN^{-1}B^T W - I)^T \quad 13-7$$

$$= (BN^{-1}B^T \underline{WQ} - Q) (WBN^{-1}B^T - I)$$

$$= (BN^{-1}B^T - Q) (WBN^{-1}B^T - I)$$

$$\underbrace{BN^{-1}B^T W BN^{-1}B^T} + Q - BN^{-1}B^T - BN^{-1}B^T$$

$$Q_{vv} = Q + \underbrace{BN^{-1}B^T - BN^{-1}B^T}_{-BN^{-1}B^T} - BN^{-1}B^T$$

$$\boxed{Q_{vv} = Q - BN^{-1}B^T}$$

Indirect  
Observation

$$Q_{vv} = Q - Q_{\hat{x}\hat{x}} \quad , \quad Q_{\hat{x}\hat{x}} = Q - Q_{vv}$$

Observations Only

$$\hat{l} = l + v$$

$$Av = f$$

$$v = QA^T k$$

$$k = W_e f$$

$$Av = \underline{\underline{d - A l}}^{13-8}$$

$$Q_e = AQA^T$$

$$W_e = Q_e^{-1}$$

$$Q_{vv} = ? \quad v = QA^T k, \quad = QA^T W_e f$$

$$v = QA^T W_e (d - A l)$$

$$v = \underline{QA^T W_e d} - \underline{QA^T W_e A l}$$

$$Q_{vv} = QA^T W_e A \cdot Q \cdot \underbrace{(QA^T W_e A)^T}_{A^T W_e A Q}$$

$$Q_{vv} = QA^T W_e A Q$$



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$$\hat{l} = l + QA^T W_e d - QA^T W_e A l$$

$$\hat{l} = QA^T W_e d + (I - QA^T W_e A) l \leftarrow$$

$$Q_{\hat{l}\hat{l}} = (I - QA^T W_e A) Q (I - QA^T W_e A)^T \\ (I - A^T W_e A Q)$$

$$= (Q - QA^T W_e A Q) \left( \begin{array}{c} \uparrow \\ \end{array} \right)$$

$$Q_{\hat{l}\hat{l}} = QA^T W_e A Q - QA^T W_e A Q + \\ QA^T W_e A Q \underline{A^T W_e A} Q$$

$$Q_{\hat{l}\hat{l}} = QA^T W_e A Q - \underline{QA^T W_e A Q} + QA^T W_e A Q$$

$$Q_{\hat{\beta}\hat{\beta}} = Q - QA^T W_e A Q$$

$$\underline{Q_{\hat{\beta}\hat{\beta}} = Q - Q_{vv}}, \quad \underline{Q_w = Q - Q_{\hat{\beta}\hat{\beta}}}$$

post adjustment statistics

Global Test (are results consistent w/  
prior assumptions?)

Hypothesis Test

$$H_0: \sigma^2 = \sigma_0^2$$

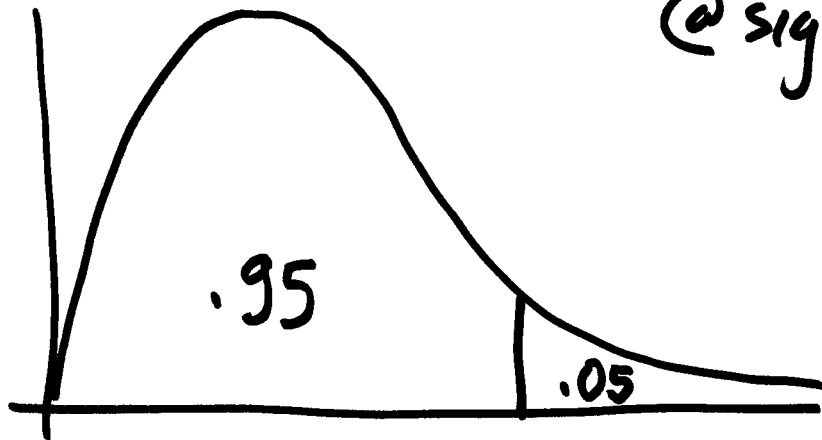
true  
var. of  
unit weight

chosen value

$$H_1: \sigma^2 > \sigma_0^2$$

We know from statistics, if  $\sigma^2 = \sigma_0^2$   
 then  $\frac{VTWV}{\sigma_0^2} \sim \chi^2_r$

@ significance level of .05



test statistic  $\chi^* = \frac{VTWV}{\sigma_0^2}$

Decision Rule:

if  $\chi^* < CV$ , we accept  $H_0$

if  $\chi^* > CV$ , we reject  $H_0$   
accept  $H_1$