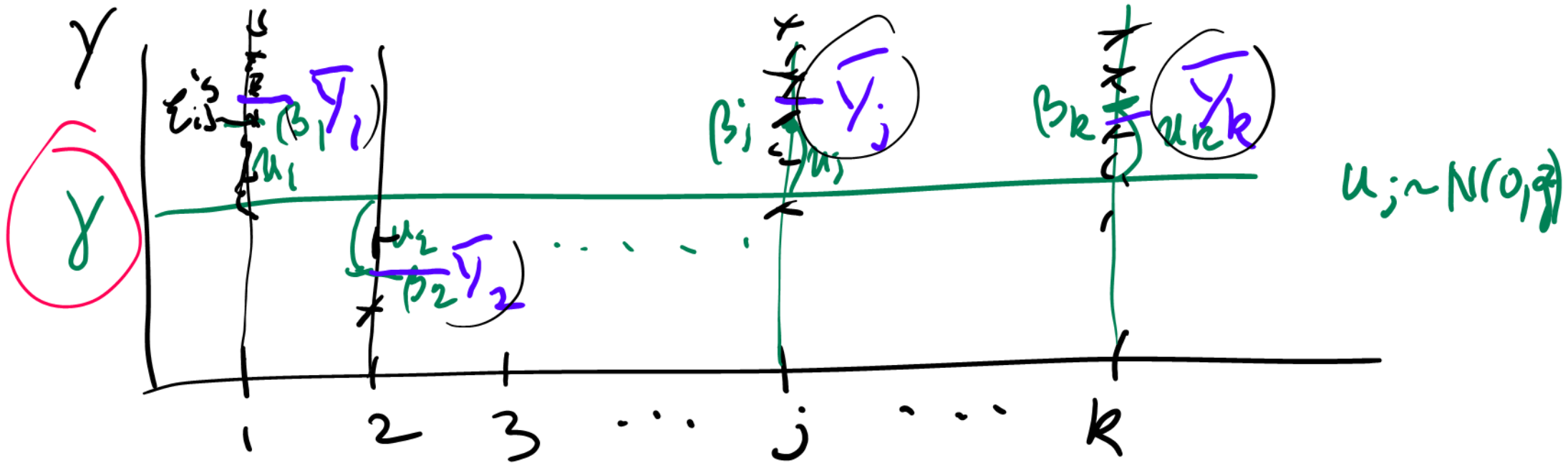


City mean!

$$\begin{array}{ccccccc}
 y_{ij} & = & \gamma & + & u_i & + & \epsilon_{ij} \\
 \uparrow & & \uparrow & & \uparrow & & \uparrow \\
 \text{School} & \text{student} & \text{Fixed param.} & & \text{Var}(u_i) = \tau^2 & & \text{Var}(\epsilon_{ij}) = \sigma^2
 \end{array}$$

lme(  
 $y \sim 1, dd$   
 Random =  
 $\sim 1 | \text{school}$ )

$$y_{ij} = \beta_i + \epsilon_{ij} \quad \beta_i = \gamma + u_i$$



Estimate  $\gamma$ :

$$1) \bar{y}_{GM} = \frac{\sum n_i \bar{y}_i}{\sum n_i} = \frac{\sum w_i \bar{y}_i}{\sum w_i} = \sum_{i=1}^k w_i \bar{y}_i$$

$w_i \propto n_i$

$$2) \bar{y}_{..} = \frac{\sum \bar{y}_i}{k} = \sum_{i=1}^k \frac{1}{k} \bar{y}_i$$

3)  $\bar{Y}_1$  est of  $\gamma$     $\bar{Y}_2$  est of  $\gamma$  ...  $\bar{Y}_k$  est of  $\gamma$

$\bar{Y}_i$  unk for  $\gamma$

$$\bar{Y}_i = \gamma + \underbrace{u_i} + \underbrace{\left( \frac{\sum z_{ij}}{n_i} \right)} \quad \text{EXER}$$

$$E(\bar{Y}_i) = \gamma + 0 + 0 = \gamma$$

$\bar{Y}_i$ 's are independent.

Need weights proportional to inverse of Variance  
Need weights proportional to inverse of Variance

Need weights proportional to inverse of variance

Need weights proportional to inverse of variance  
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Need weights proportional to inverse of variance  
Need weights proportional to inverse of variance

ooo (OO Times

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$$\bar{Y}_i = \gamma + \alpha_i + \frac{\sum \varepsilon_{ij}}{n_i}$$

$$\text{Var}(\bar{Y}_i) = \alpha^2 + \frac{\sigma^2}{n_i}$$

$$w_i \propto \frac{1}{\alpha^2 + \frac{\sigma^2}{n_i}} \propto \frac{1}{\frac{\alpha^2}{\sigma^2} + \frac{1}{n_i}}$$

If  $n_i$  equal  
 $w_i$  are constant  
i.e. are all equal

1)

$\frac{q^2}{\sigma^2}$  very small

$$w_i \propto \left( \frac{q^2}{\sigma^2} + \frac{1}{n_i} \right)^{-1}$$

$$\propto \left( \frac{1}{n_i} \right)^{-1} = n_i$$

i.e.  $\bar{Y}_{GM}$

2)

$\frac{q^2}{\sigma^2}$

very large

$$w_i \propto \left( \frac{q^2}{\sigma^2} + \frac{1}{n_i} \right)^{-1} = \text{constant}$$

$$\text{i.e. } \bar{Y}_{oo} = \frac{\sum \bar{Y}_i}{k}$$

3) Estimate  $\frac{\sigma^2}{\sigma^2}$

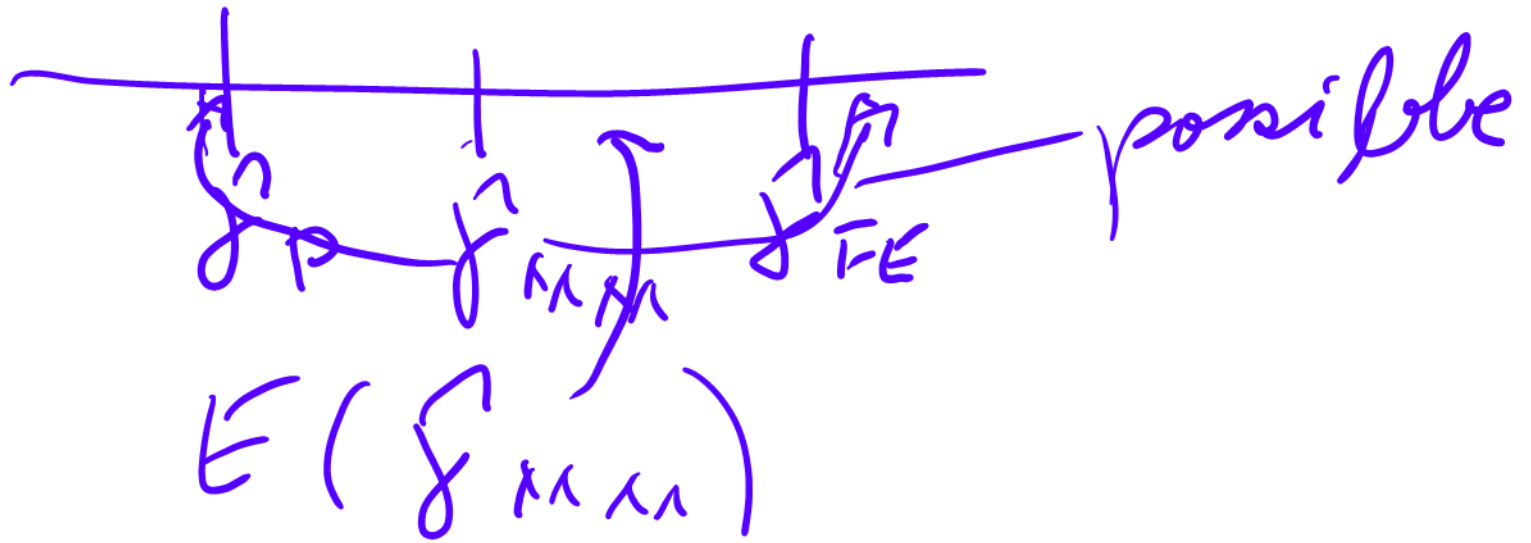
Then use  $w_i \propto \left( \frac{q^2}{\sigma^2} + \frac{1}{n_i} \right)^{-1}$

Mixed Model

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$$\left( \begin{array}{l} \hat{\beta}_P = \frac{\sum y_{ij}}{\sum n_{ij}} = \bar{Y}_{GX} \\ \hat{\beta}_{FE} = \frac{\sum \bar{Y}_i}{R} \end{array} \right.$$

$$\hat{f}_{NNN} = \sum \hat{w}_i \bar{T}_i$$

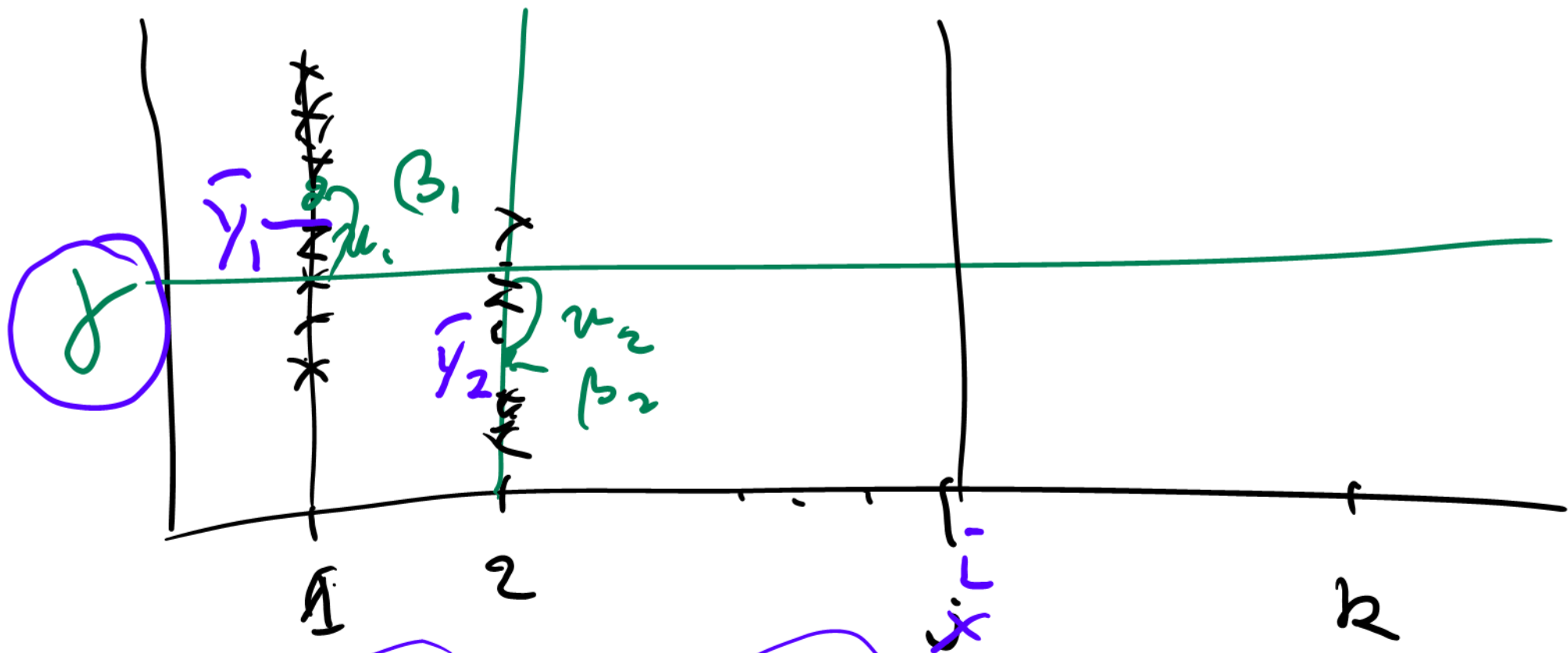












$\bar{y}_i$  est of  $\beta_i$

$E(\bar{y}_i | \beta_i) = \beta_i$  cond'l unbiased for  $\beta_i$

$\bar{y}_i$  is BLUE of  $\beta_i | \beta_i$

$$\text{Var}(\bar{Y}_i - \beta_i) = \text{Var}\left(\cancel{\gamma} + \cancel{u_j} + \frac{\sum \epsilon_{ij}}{n_i} - (\cancel{\gamma} + \cancel{u_j})\right)$$

$$= \text{Var}\left(\frac{\sum \epsilon_{ij}}{n_i}\right) = \frac{\sigma^2}{n_i}$$

Mult req

$$\sigma^2 (X_i' X_i)^{-1}$$

$$= \frac{\sigma^2}{n_i} (\sum x_i)^{-1}$$

Guess  $\beta_i$  - no info except  $\gamma$

$$E(\beta_i - \gamma) = 0$$

$\gamma$  "est" of  $\beta_i$

$$\underline{\beta_i} = \underline{\gamma} + \underline{u_i}$$

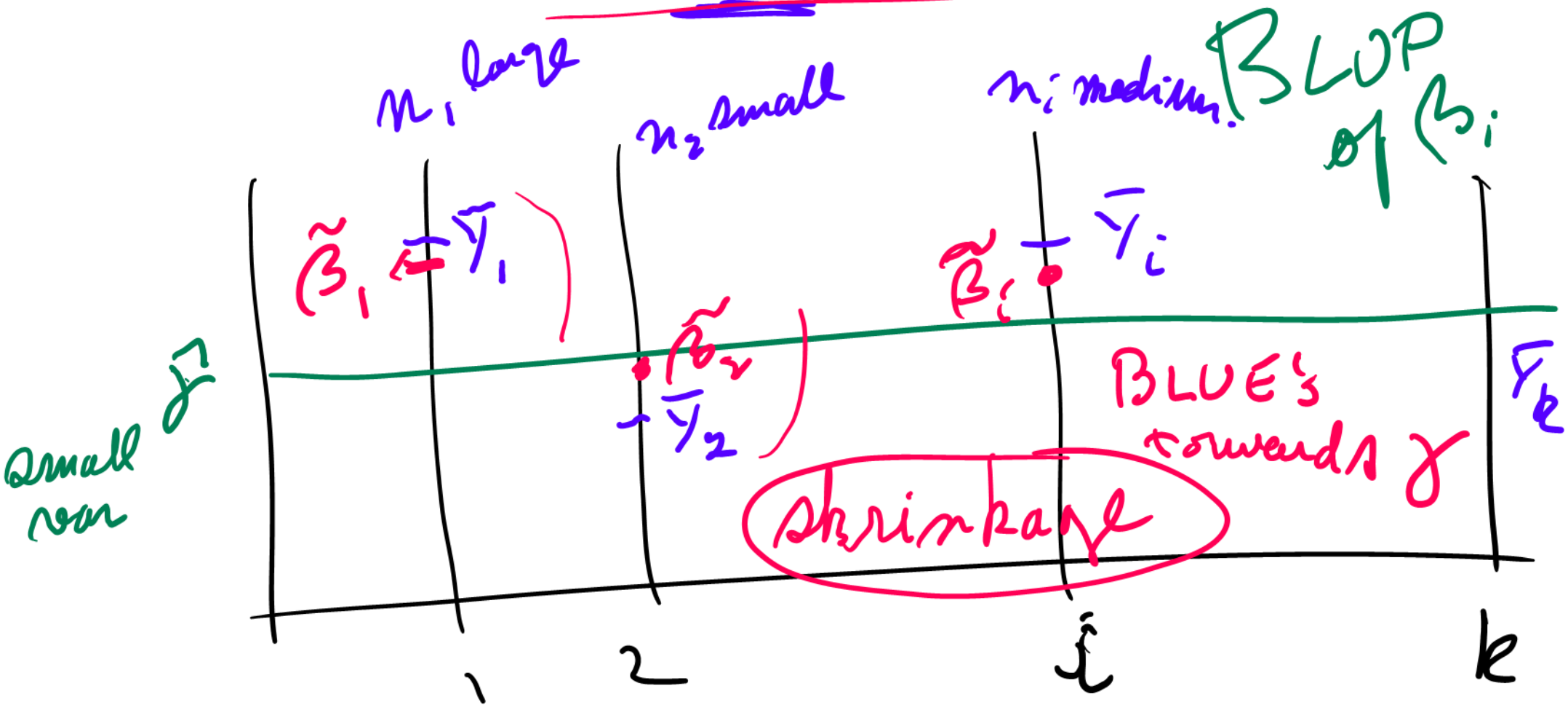
$$\text{Var}(\underline{\beta_i} - \underline{\gamma}) = \sigma^2$$

Two guesses  $\bar{y}_i$   $\sigma^2/n_i$   
 $\gamma$   $\sigma^2$

Prediction  $\underline{\beta_i}$  from  $y_i$ 's +  $\underline{\gamma}$

BLU ~~A~~ Predictor of  $\beta_i$   
random

$$\left( \frac{1}{g^2} + \frac{1}{\sigma^2/n_i} \right)^{-1} \left( \frac{1}{g^2} \gamma + \frac{n_i}{\sigma^2} \bar{y}_i \right) = \tilde{\beta}_i$$



fit ← ~~lme~~ ( ... )

$\beta$ 's:  $\text{coef}(\text{fit})$

$\sigma^2$ :  $\text{var}(\text{fit})$

$\delta$ :  $\text{fixef}(\text{fit})$

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$\hat{\eta}_1, \hat{\eta}_2, \dots, \hat{\eta}_p$

$E(\eta_i) = \eta$

$\text{Var} \begin{pmatrix} \hat{\eta}_1 \\ \hat{\eta}_2 \\ \vdots \\ \hat{\eta}_p \end{pmatrix} = V$



$$(I'V^{-1}I)^{-1}I'V^{-1}\vec{y} \rightarrow$$

Check

$$\text{Var}(y) = \underline{E}(\underline{\text{Var}}(y|x)) \\ + \text{Var}(E(y|x))$$







