

- We call  $\mathcal{F} = \frac{1}{\sigma^2} \sum_{\tilde{\mathbf{z}}}^T \sum_{\tilde{\mathbf{z}}} S$  the Fisher information matrix (FIM).
- Note that if  $\sum_{\tilde{\mathbf{z}}}$  is one-to-one, the  $\mathcal{F} = \frac{1}{\sigma^2} \sum_{\tilde{\mathbf{z}}}^T \sum_{\tilde{\mathbf{z}}} S$  will have full rank.
- $\mathcal{F}$  is  $p \times p$ , where  $p$  is the number of parameters.
- If  $\mathcal{F}$  is full rank, all parameters are identifiable

- Note that if  $\mathbf{E} \sim \mathcal{N}(\mathbf{0}, \Sigma)$ , where  $\Sigma$  is the covariance

$$\mathcal{F} = \sum_{\tilde{\mathbf{z}}}^T \Sigma \sum_{\tilde{\mathbf{z}}}, \text{ where } \Sigma \text{ contains } \text{Var}(\mathbf{E}_i) = \sigma_i^2 \text{ on the diagonal}$$

### Sensitivity Identifiability

- Let  $y_i = f(\mathbf{z}_i; \vec{\theta})$ ,  $i=1, \dots, N_y$  + assume  $\vec{\theta}^*$  minimizes

$$J(\vec{\theta}) = \frac{1}{N_y} \sum_{i=1}^{N_y} (y_i - \underline{f(\mathbf{z}_i; \vec{\theta})})^2$$

- If  $f$  is continuously differentiable w.r.t.  $\vec{\theta}$ , then

$$\nabla_{\vec{\theta}} f \Big|_{\vec{\theta}^*} = \left[ \frac{\partial f}{\partial \theta_1}, \dots, \frac{\partial f}{\partial \theta_p} \right] \Big|_{\vec{\theta} = \vec{\theta}^*}$$

- A linear approximation from  $\vec{\theta}^* \rightarrow \vec{\theta}$  is given by

$$f(\mathbf{z}; \vec{\theta}) \approx f(\mathbf{z}; \vec{\theta}^*) + \nabla_{\vec{\theta}} f \Big|_{\vec{\theta}^*} \cdot \Delta \vec{\theta}, \quad \Delta \vec{\theta} = \vec{\theta}^* - \vec{\theta}$$

- Then we write

$$\Delta y = f(\mathbf{z}; \vec{\theta}^*) - f(\mathbf{z}; \vec{\theta}) \approx \sum_{\tilde{\mathbf{z}}} \Delta \vec{\theta}$$

## Def Sensitivity Identifiability

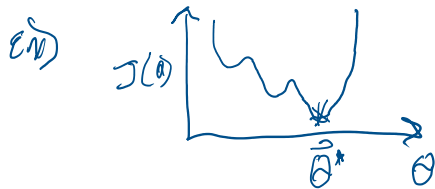
- The parameters  $\vec{\theta} \in \mathbb{R}^p$ , are sensitivity identifiable if  $\sum_{\vec{\theta} \sim \vec{\theta}^*}$  is a one-to-one mapping.

• Note: the null space of  $\sum$  is the nonidentifiable subspace of  $\vec{\theta}$

- This gives the following relationship

$$\nabla_{\vec{\theta}}^2 LL(\vec{\theta}^* | \vec{y}) = -\frac{1}{\sigma^2} \sum^T(\vec{\theta}^*) \sum(\vec{\theta}^*) = -F(\vec{\theta}^*)$$

•  $F(\vec{\theta})$  is full rank  $\Rightarrow \sum$  is one-to-one  $\Rightarrow$  MLE (or OLS) is unique.



UQ Crime Correlation  $\Rightarrow$  identifiability issues.

- A correlation  $= \pm 1$  does imply non-identifiability, but correlation  $\neq \pm 1$  does not.

## Parameter Influence

- A parameter,  $\theta_i$ , is deemed functionally non-influential if there is a manifold,  $NI(\vec{\theta})$ , where  $|f(\vec{\theta}, \theta_i) - f(\vec{\theta}, \theta_i + \Delta \theta_i)| < \eta$ ,  $\eta > 0$  for all  $\theta_i \in NI(\vec{\theta})$ .

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## Local Sensitivity (Chapter 8)

- Sensitivity analysis (SA) is the process of quantifying the relative contributions of inputs ( $\vec{\theta}$ ) to responses,  $\vec{y}$ .

• we call  $\vec{y}$  the "quantity of interests" QoI

the relative contributions of inputs  $(\theta)$  to responses,  $y$ .

. we call  $\vec{y}$  the "quantity of interests"  $QoI$ .