Morris' Screening

- Morris' Screening looks at coarse derivatives + their Statistics
- Given $\vec{\theta} \in \Gamma$, the "Elementary Effects"

$$d_i^j = \frac{F(\vec{\theta}^j + \delta \vec{e}_i) - F(\vec{\theta}^j)}{\delta}$$

where $\vec{e}_i$ is a unit vector in the i-th direction, + δ is the step size.

- we care about the following measures, with R random samples

$$\mu_i = \frac{1}{R} \sum_{j=1}^{R} d_i^j(\vec{\theta}^j), \quad \mu_i^* = \frac{1}{R} \sum_{j=1}^{R} |d_i^j(\vec{\theta}^j)|, \quad \sigma = \left(\frac{1}{R-1} \sum_{j=1}^{R} \left(d_i^j(\vec{\theta}^j) - \mu_i\right)^2\right)^{1/2}$$

- We use μ_i^* more often because d_i^j may not be strictly positive
- μ_i^* measures the average magnitude of change in f w.r.t. θ_i.
- σ_i^2 (or $\sigma_i = \sqrt{\sigma_i^2}$) measures nonlinear or interaction effects.

* we say that if μ_i^* + σ_i^2 are "small", then θ_i is functionally non-influential *

Frequntist Inference

- Frequentist Statistics, also called "classical stats", assumes that unknown parameters in a system are *fixed, + the observations are random*.
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$$y_i = f(\underset{\sim}{x}_i ; \vec{\theta}^0) + \vec{\varepsilon}$$

where y_i is measurement, f is our model, + $\vec{\varepsilon}$ is our measurement error.

. We let $\vec{\theta}^0$ denote the true, unknown parameter.

- In vector form

$$\vec{y} = f(\underset{\sim}{\vec{x}} ; \vec{\theta}^0) + \vec{\varepsilon}$$

- Let's examine a linear model (e.g., regression)

$$\vec{y} = \underset{\sim}{X} \vec{\theta}^0 + \vec{\varepsilon}, \quad \text{where } \underset{\sim}{X} \in \mathbb{R}^{N_y \times p}, \text{ is}$$

the design matrix

- The "inverse problem" is stated as follows:

. Given values of $\underset{\sim}{x}$ corresponding $\vec{y}$, which may be noisy, we seek calibration parameters $\vec{\theta}$ that best describe our data.

Linear Regression

- Let $f(\underset{\sim}{x} ; \vec{\theta}) = \underset{\sim}{X} \vec{\theta}$, where $\underset{\sim}{X} \in \mathbb{R}^{N_y \times p}$ + $\vec{\theta} \in \Gamma \subseteq \mathbb{R}^p$.

- Let $\vec{\theta}^0$ be the true, unknown value of parameters.

- Lets assume the following:

$$\left.\begin{array}{l} \text{i) } E[\varepsilon_i] = 0 \quad , i = 1, \ldots, N_y \\ \text{ii) } Var[\varepsilon_i] = \sigma_0^2 , \quad i = 1, \ldots, N_y \\ \text{iii) } c[\varepsilon_i \, \varepsilon_j] = 0 \quad \text{if } i \neq j \end{array}\right\} \overset{iid}{\sim} N(0, \sigma_0^2)$$

ii) $Var[\varepsilon_i] = \sigma_0$, $i=1, \ldots, n$

iii) $Cov[\varepsilon_i, \varepsilon_j] = 0$, if $i \neq j$

Goal: get estimators, $\hat{\vec{\Theta}}$ + $\hat{\sigma}^2$, for $\vec{\Theta}^0$ + σ_0^2, + then estimates, $\vec{\Theta}_{OLS}$ + s^2, with their sampling distributed.