

Comparing models

①

• Have $f_j, j=1, J$ with $\{f_j = f_{\theta_j} : \theta_j \in \Theta_j\}$, $\dim(\Theta_j) = p_j$

• $\hat{\theta}_j$ is the maximizer of $\sum_{i=1}^n \log f_{\theta_j}(x_i) = \ell_{f_j}(\theta_j)$

• maximum value $\ell_{f_j}(\hat{\theta}_j)$

• θ_{j0} is the maximizer of $E_g[\log f_{\theta_j}(X)]$

• Criterion used to compare f_j

$$Q_j = E_g[\log f_j(X | \hat{\theta}_j)] = E[\log f_j(X | \hat{\theta}_j, X^n)]$$

over

X and

$$\hat{\theta}_j = \hat{\theta}_j(X^n)$$

• we know

$$\sqrt{n}(\hat{\theta}_j - \theta_{j0}) \rightarrow^d N(0, FI_j(\theta_{j0})^{-1} J_j(\theta_{j0}) FI_j(\theta_{j0})^{-1})$$

We will work toward an estimate of θ_j .

(2)

We will start by examining the estimation variance

→ how $\hat{\theta}_j$ varies for different samples of X^n .

We have $l_{f_j}(\theta_j) = \sum_{i=1}^n \log f_j(x_i | \theta_j)$.

• Expand $l_{f_j}(\theta_j)$ near $\hat{\theta}_j$ $\Rightarrow$ by definition

$$l_{f_j}(\theta_j) = l_{f_j}(\hat{\theta}_j) + \frac{1}{\partial \theta_j} l_{f_j}(\theta_j) \Big|_{\hat{\theta}_j} (\theta_j - \hat{\theta}_j)$$

$$+ \frac{1}{2} (\theta_j - \hat{\theta}_j)' \left(\frac{\partial^2}{\partial \theta_j \partial \theta_j'} l_{f_j}(\theta_j) \Big|_{\hat{\theta}_j} \right) (\theta_j - \hat{\theta}_j)$$

where $\|\theta_j - \theta_j^*\| \leq \|\theta_j - \hat{\theta}_j\|$

$$= l_{f_j}(\hat{\theta}_j) - \frac{n}{2} (\theta_j - \hat{\theta}_j)' \left[\textcircled{A} \right] (\theta_j - \hat{\theta}_j)$$

$$\text{where } \textcircled{A} = -\frac{1}{n} \sum_{i=1}^n \frac{\partial^2}{\partial \theta_j \partial \theta_j'} \log f_j(x_i | \theta_j) \Big|_{\theta_j^*}$$

$$\rightarrow E \left[-\frac{\partial^2}{\partial \theta_j \partial \theta_j'} \log f_j(x | \theta_j) \Big|_{\theta_{j0}} \right] = I I_j(\theta_{j0})$$

So we have

③

$$l_f(\theta_j) \approx l_f(\hat{\theta}_j) - \frac{n}{2} (\theta_j - \hat{\theta}_j)' FI_j(\theta_{j0}) (\theta_j - \hat{\theta}_j)$$



(can we simplify this?)



Look at $\theta_j = \theta_{j0}$

$$n (\hat{\theta}_j - \theta_{j0})' FI_j(\theta_{j0}) (\hat{\theta}_j - \theta_{j0})$$

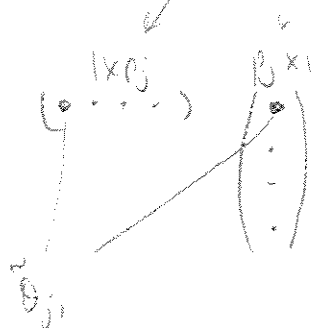
$$= (\sqrt{n} FI_j(\theta_{j0})^{1/2} (\hat{\theta}_j - \theta_{j0}))' (\sqrt{n} FI_j(\theta_{j0})^{1/2} (\hat{\theta}_j - \theta_{j0}))$$

$$= \tilde{\theta}_j' \tilde{\theta}_j \quad \text{where} \quad \tilde{\theta}_j = \sqrt{n} FI_j(\theta_{j0})^{1/2} (\hat{\theta}_j - \theta_{j0})$$

Think of $\tilde{\theta}_j$ as a 'standardized' version of $\hat{\theta}_j$

dim $(\tilde{\theta}_j)$

$$\tilde{\theta}_j' \tilde{\theta}_j = \sum_{p=1}^{P_j} \tilde{\theta}_{jp}^2$$



sum of squares
of components
of $\tilde{\theta}_j$ vector

Now $\tilde{\theta}_j' \tilde{\theta}_j = \sum_{p=1}^{p_j} \tilde{\theta}_{jp}^2 = \text{sum of diagonal elements of } \underbrace{\tilde{\theta}_j \tilde{\theta}_j'}_{p_j \times p_j \text{ matrix}} \quad (4)$

$$\begin{pmatrix} \cdot \\ \cdot \\ \cdot \\ \cdot \end{pmatrix} \begin{pmatrix} \cdot & \cdot & \cdot & \cdot \end{pmatrix} = \begin{pmatrix} \theta_{j1}^2 & \theta_{j1}\theta_{j2} & \dots \\ \theta_{j2}^2 & \dots & \dots \\ \vdots & \vdots & \ddots \end{pmatrix}$$

Trick: We are interested in $E[\tilde{\theta}_j' \tilde{\theta}_j]$

but from above $E[\tilde{\theta}_j' \tilde{\theta}_j] = \text{Trace } E[\tilde{\theta}_j \tilde{\theta}_j']$

Here

$$\text{Trace } E(\tilde{\theta}_j \tilde{\theta}_j') = \text{Trace } E \left[n F_{j,1}(\theta_{j0}) (\hat{\theta}_j - \theta_{j0}) (\hat{\theta}_j - \theta_{j0})' \right]$$

$$= \text{Trace} \left[n F_{j,1}(\theta_{j0}) \underbrace{E[(\hat{\theta}_j - \theta_{j0}) (\hat{\theta}_j - \theta_{j0})']} \right]$$

$$\text{Cov}(\hat{\theta}_j) = \underbrace{F_{j,1}(\theta_{j0})^{-1} J_{j,1}(\theta_{j0}) F_{j,1}(\theta_{j0})^{-1}}_n$$

So

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$$E \left(n (\hat{\theta}_j - \theta_{j0})' F_{L_j}(\theta_{j0}) (\hat{\theta}_j - \theta_{j0}) \right)$$

$$= \text{Trace} \left[n F_{L_j}(\theta_{j0}) \underbrace{(F_{L_j}(\theta_{j0})^{-1})^{-1}}_n J_j(\theta_{j0}) F_{L_j}(\theta_{j0})^{-1} \right]$$

$$= \text{Trace} [J_j(\theta_{j0}) F_{L_j}(\theta_{j0})^{-1}]$$

Back to our approximation

$$l_{f_j}(\theta_j) \approx l_{f_j}(\hat{\theta}_j) - \frac{n}{2} (\hat{\theta}_j - \theta_{j0})' F_{L_j}(\theta_{j0}) (\hat{\theta}_j - \theta_{j0})$$

And specifically at θ_{j0}

$$l_{f_j}(\theta_{j0}) \approx l_{f_j}(\hat{\theta}_j) - \frac{n}{2} (\hat{\theta}_j - \theta_{j0})' F_{L_j}(\theta_{j0}) (\hat{\theta}_j - \theta_{j0})$$

via

$$\approx l_{f_j}(\hat{\theta}_j) - \frac{1}{2} \text{Trace} \{ J_j(\theta_{j0}) F_{L_j}(\theta_{j0}) \}$$

replacing $\dots$

by its expectation

So

⑥

$$l_{f_j}(\theta_{j0}) = \sum_{i=1}^n \log f_j(x_i | \theta_{j0})$$

$$\approx \sum_{i=1}^n \log f_j(x_i | \hat{\theta}_j) - \frac{1}{2} \text{Trace} \{ J_j(\theta_{j0}) F J_j(\theta_{j0})^{-1} \}$$

↓
take expectation over x^n

↓

$$E \left(\sum_{i=1}^n \log f_j(x_i | \theta_{j0}) \right) \approx E \left(l_{f_j}(\hat{\theta}_j) \right) - \frac{1}{2} \text{Trace} \{ J_j(\theta_{j0}) F J_j(\theta_{j0})^{-1} \}$$

$$\approx n E [\log f_j(x | \theta_{j0})]$$

Remember, we are after

$$Q_j = E [\log f_j(x | \hat{\theta}_j(x^n))]$$

• We have 'done' the training part (E over x^n)

• Now, do testing.