

## BF For Model Selection

$$M_0: \underline{\theta} = \{\alpha, \sigma^2\} \quad H_0: \beta = 0$$

$$M_1: \underline{\theta} = \{\alpha, \beta, \sigma^2\} \quad H_1: \beta \neq 0$$

$$B_{0,1} = \frac{\pi(M_0 | x)}{\pi(M_1 | x)} \cdot \frac{P(M_1)}{P(M_0)}$$

NOTE  $P(M)$  is a joint prior  $P(M, \theta)$  which can be factorised in  $P(M_j) \cdot P(\theta | M_j)$

### THEORETICAL REMARKS

$$\pi(\underline{\theta}, M_j | x) \propto f(x | \underline{\theta}, M_j) P(\underline{\theta} | M_j) P(M_j)$$

$\pi(M_j | x)$  is "simply" the MARGINAL POSTERIOR DISTRIBUTION

$$\begin{aligned} \pi(M_j | x) &\propto \int f(x | \underline{\theta}, M_j) P(\underline{\theta} | M_j) P(M_j) d\underline{\theta} \\ &= P(M_j) \int f(x | \underline{\theta}, M_j) P(\underline{\theta} | M_j) d\underline{\theta} = P(M_j) f(x | M_j) \end{aligned}$$

## PROBLEMS

$$\boxed{A} \quad \int f(x|\theta, M_j) P(\theta|M_j) d\theta = f(x|M_j)$$

OFTEN ANALYTICALLY INTRACTABLE

$\boxed{B}$

WITH MANY COMPETING MODELS  
 $B_F$  AND POSTERIOR MODEL

PROBABILITIES ARE  
COMPUTATIONALLY CHALLENGING

## ① SIMPLE MC APPROACH

TARGET  $\hat{\pi}(M_j|x) \propto \hat{f}(x|M_j) P(M_j)$

$$f(x|M_j) = E_{\theta} [f(x|\theta, M_j)]$$

$\Rightarrow \hat{f}(x|M_j)$  BY DRAWING  $K$  SAMPLES FROM THE PRIOR OF THE  
PARAMETERS IN MODEL  $j$  AND THEN USE THEM IN THE MC

ESTIMATE

$$\hat{f}(x|M_j) = \frac{1}{K} \sum_{k=1}^K f(x|\theta^k, M_j)$$

ONCE WE HAVE  $\hat{\pi}(M_j|x)$ , THEN  $\hat{\pi}(M_j|x) \rightarrow \pi(M_j|x)$  AS  $K \rightarrow \infty$

- REPEAT THIS PROCESS FOR ALL  $2^J$  MODELS  
AND RENORMALISE THE ESTIMATES

$$\hat{\pi}(M_j | x) = \frac{\hat{f}(x | M_j) P(M_j)}{\sum_{j=1}^J \hat{f}(x | M_j) P(M_j)}$$

HOWEVER...

THE ESTIMATE  $\hat{f}(x | M_j)$  ARE GENERALLY VERY UNSTABLE  
AS A RESULT OF THE PARAMETERS BEING DRAWN FROM THE PRIOR!

### ALTERNATIVE APPROACHES

- IMPORTANCE SAMPLING (NEXT WEEK)
- REVERSIBLE JUMP MCMC
- BAYESIAN VARIABLE SELECTION
- MODEL COMPARISON CRITERIA (e.g. DIC & WAIC)  $\leftarrow$  NEXT LECTURE!