

# EX 1 : CHEESE STORES DATASETS

- $p = \#$  stores, each store has  $n$  observations.  $\Rightarrow i = 1, \dots, p$
- for each observation we have:  $j = 1, \dots, n$

$Q$  = quantity demanded

$P$  = price

$d$  = dummy variable for displacement in the store

from economic theory we have:

$$Q = a P^{\beta} \rightarrow \text{price elasticity.}$$

and we would like to identify  $\beta$ .

$\Rightarrow$  we take:

$$\underbrace{\log Q}_q = \log a + \beta \underbrace{\log P}_p$$

But consider a more comprehensive model allowing us to identify the different role of covariates:

$$q_{ij} = \beta_{0i} + \beta_{1i} p_{ij} + \beta_{2i} \mathbb{1}(d_{ij}=1) + \beta_{3i} \mathbb{1}(d_{ij}=1) \cdot p_{ij} + \varepsilon_{ij}$$

goal: fit this model using a hierarchical regression.

proposal:

→ Specification of the model:

$$q_{ij} | \beta_i \sim N(X_{ij} \beta_i, \sigma^2) \quad , \quad \forall i = 1, \dots, P$$

$$\forall j = 1, \dots, n$$

$$\beta_i | \gamma \sim N(\gamma, \tau^2 \sigma^2)$$

with hyperpriors:  $p(\gamma) \propto c$

$$p(\tau^2) \sim \text{Inv-Ga} \left( \frac{1}{\Sigma}, \frac{1}{\Sigma} \right)$$

$$p(\sigma^2) \sim \text{Jeffreys}: \frac{1}{\sigma^2}$$

⇒ posterior inference strategy: Gibbs sampling.

posterior conditional:

$$p(\beta_i | \gamma) \propto \prod_{j=1}^n p(y_{ij} | X_{ij} \beta_i, \sigma^2) \cdot p(\beta_i)$$

$$\propto \exp \left\{ -\frac{1}{2} (y_i - X_i \beta_i)' (y_i - X_i \beta_i) \right\} \cdot \exp \left\{ -\frac{1}{2\sigma^2 \tau^2} (\beta_i - \gamma)' (\beta_i - \gamma) \right\}$$

$$\propto \exp \left\{ -\frac{1}{2\sigma^2} (-2\beta_i' X_i' y_i + \beta_i' X_i X_i' \beta_i) - \frac{1}{2\sigma^2 \tau^2} (-2\beta_i' \gamma + \beta_i' \beta_i) \right\}$$

$$\propto \exp \left\{ -\frac{1}{2} \left[ -2\beta_i' \left( \frac{X_i' y_i}{\sigma^2} + \frac{\gamma}{\tau^2 \sigma^2} \right) + \beta_i' \left( \frac{X_i X_i'}{\sigma^2} + \frac{I}{\sigma^2 \tau^2} \right) \beta_i \right] \right\}$$

$$\Rightarrow \beta_i \sim N(m^*, V^*); \quad V^* = \left( \frac{X_i X_i'}{\sigma^2} + \frac{I}{\sigma^2 \tau^2} \right)^{-1}; \quad m^* = V^* \left( \frac{X_i' y_i}{\sigma^2} + \frac{\gamma}{\tau^2 \sigma^2} \right)$$

$$\cdot p(\beta^2 | -) \propto \left( \prod_{i=1}^P \left( \prod_{j=1}^n p(y_{ij} | \beta_i, \sigma^2) \right) \cdot p(\beta_i | \sigma^2, \tau^2, f) \right) \cdot p(\sigma^2)$$

$$\propto \left( \prod_{i=1}^P \left( \prod_{j=1}^n \frac{1}{\sigma} \cdot \exp \left\{ -\frac{1}{\sigma^2} (y_{ij} - x_{ij} \beta_i)^2 \right\} \cdot \frac{1}{\sigma} \exp \left\{ -\frac{1}{2\sigma^2 \tau^2} (\beta_i - f)' (\beta_i - f) \right\} \right) \right) \cdot \frac{1}{\sigma^2}$$

$$= \left( \prod_{i=1}^P \left( \frac{1}{\sigma^n} \cdot \exp \left\{ -\frac{1}{2\sigma^2} (y_i - x_i \beta_i)' (y_i - x_i \beta_i) \right\} \right) \right. \\ \left. \times \frac{1}{\sigma} \cdot \exp \left\{ -\frac{1}{2\sigma^2} (\beta_i - f)' (\tau^2 I)^{-1} (\beta_i - f) \right\} \right) \cdot \frac{1}{\sigma^2}$$

$$= (\sigma^2)^{\frac{-N+P}{2} - 1} \cdot \exp \left\{ -\frac{1}{2\sigma^2} \left[ \sum (y_i - x_i \beta_i)' (y_i - x_i \beta_i) + (\beta_i - f)' (\tau^2 I)^{-1} (\beta_i - f) \right] \right\}$$

$$\Rightarrow \sigma^2 \sim \text{Inv-Gre} \left( \frac{N+P}{2}; \frac{\sum ((y_i - x_i \beta_i)' (y_i - x_i \beta_i) + (\beta_i - f)' (\tau^2 I)^{-1} (\beta_i - f))}{2} \right)$$

$$\cdot p(\tau^2 | -) \propto p(\tau^2) \cdot \left( \prod_{i=1}^P p(\beta_i | f, \tau^2, \sigma^2) \right)$$

$$\propto \left( \frac{1}{\tau^2} \right)^P \cdot \exp \left\{ -\frac{1}{2\tau^2} \left( \sum (\beta_i - f)' (\sigma^2 I)^{-1} (\beta_i - f) \right) \right\} \cdot \tau^2 \cdot \exp \left\{ -\frac{1}{2} \tau^2 \right\} \\ = (\tau^2)^{-P - \frac{1}{2} - 1} \cdot \exp \left\{ -\frac{1}{\tau^2} \left[ \frac{\sum (\beta_i - f)' (\sigma^2 I)^{-1} (\beta_i - f) + 1}{2} \right] \right\}$$

$$\Rightarrow \tau^2 \sim \text{Inv-Gre} \left( p + \frac{1}{2}; \frac{\sum (\beta_i - f)' (\sigma^2 I)^{-1} (\beta_i - f) + 1}{2} \right)$$

$$\bullet p(\beta|-) \propto \left( \prod_{i=1}^P p(\beta_i | y_i, \sigma^2, \tau^2) \right) p(\beta)$$

$$\propto \exp \left\{ - \frac{1}{2\sigma^2\tau^2} \sum_{i=1}^P (\beta_i - y_i)' (\beta_i - y_i) \right\}$$

$$\propto \exp \left\{ - \frac{1}{2\sigma^2\tau^2} \left[ y' I y - 2 y' \sum_{i=1}^P \beta_i \right] \right\}$$

$$= \exp \left\{ - \frac{1}{2} \left[ \frac{y' y}{\sigma^2 \tau^2} - 2 \frac{y' \sum_{i=1}^P \beta_i}{\sigma^2 \tau^2} \right] \right\}$$

$$\Rightarrow y|- \sim N(M, K)$$

$$K = \left( \frac{P \cdot I}{\sigma^2 \tau^2} \right)^{-1} \quad ; \quad M = K \cdot \left( \frac{\sum_{i=1}^P \beta_i}{\sigma^2 \tau^2} \right)$$

## EX 2: PRESIDENTIAL SURVEY

Dataset:  $y$ : binary  $\rightarrow$  1: voting for Bush  
 $\rightarrow$  0: not voting for Bush

$S = \# \text{ states}$

$X$ : predictors

Model: Probit model:

$$P(y_{ij} = 1) = \Phi(z_{ij}) \quad i = 1 \dots S, \quad j = 1 \dots n_i$$
$$z_{ij} = \mu_i + x_{ij}^T \beta_i = \underbrace{x_{ij}^T}_{\text{design matrix with intercept}} \underbrace{\beta_i}_{\mu_i, \beta_i}$$

problem: posterior  $p(\gamma_i | y)$  is intractable:

$$p(\gamma_i | y) \propto p(\gamma_i) \cdot \prod_{j=1}^{n_i} [\Phi(x_{ij}' z_i)]^{y_{ij}} \cdot [1 - \Phi(x_{ij}' z_i)]^{1 - y_{ij}}$$

~  
not prior such that  
the posterior is tractable.

↓

solution: Augmented Model:

$S = \# \text{ states}$   
 $P = \# \text{ parents}$

$$y_{ij} = \mathbb{1}(z_{ij} \geq 0)$$

$$z_{ij} \sim N(x_{ij} \beta_i, 1) \quad \leftarrow \text{auxiliary variable}$$

$$\beta_i \sim N(m, \tau^2)$$

hyper-params:

$$\begin{cases} p(m) \propto \mathcal{C} \\ p(\tau^2) \propto \text{Inv-gc}(\frac{1}{2}, \frac{1}{2}) \end{cases}$$

this augmentation works, indeed:

1) the implied marginal model for  $y_{ij}$  is the original one:

$$p(y_{ij} = 1) = p(z_{ij} > 0) = \Phi(x_{ij} \beta_i) \quad \checkmark$$

2) We obtain tractable conditional posteriors which we can use to construct a Gibbs sampler to conduct posterior inference:

(indeed, we are back to a neural-neural model):

follows derivation of the full conditionals:

$$\bullet \quad p(z_{ij} | -) = p(y_{ij} | z_{ij}) \cdot p(z_{ij})$$

truncated normal

$$\Rightarrow \begin{cases} \mathbb{1}(y_{ij} = 1) \cdot N(x_{ij} \beta_i, 1) \\ \mathbb{1}(y_{ij} = 0) \cdot N(x_{ij} \beta_i, 1) \end{cases}$$

$$p(z_{ij} > 0) = p(y_{ij} = 1) = \int_{-\infty}^{x_{ij} \beta_i} \phi(z | 0, 1) dz = \Phi(x_{ij} \beta_i)$$

$$\bullet p(\gamma_i) \propto p(\gamma_i) \cdot \prod_{j=1}^{n_i} p(z_{ij} | x_{ij}, \gamma_i)$$

$$\propto \exp \left\{ -\frac{1}{2} (\gamma_i - m)' (I \tau^2)^{-1} (\gamma_i - m) \right\} \cdot \exp \left\{ -\frac{1}{2} (z_i - \overset{\text{vector}}{x_i} \overset{\text{matrix}}{\gamma_i})' (z_i - \overset{\text{vector}}{x_i} \gamma_i) \right\}$$

$$\propto \exp \left\{ -\frac{1}{2} (\gamma_i' (I \tau^2)^{-1} \gamma_i - 2 \gamma_i' (I \tau^2)^{-1} m) - \frac{1}{2} (\gamma_i' x_i' x_i \gamma_i - 2 \gamma_i' x_i' z_i) \right\}$$

$$\propto \exp \left\{ -\frac{1}{2} (\gamma_i' (x_i' x_i + (I \tau^2)^{-1}) \gamma_i - 2 \gamma_i' (x_i' z_i + \gamma_i' I \tau^2 m)) \right\}$$

$$\Rightarrow \gamma_i \sim N_p(m^*, V^*)$$

$$V^* = (x_i' x_i + (I \tau^2)^{-1})^{-1}$$

$$m^* = V^* \times (x_i' z_i + (I \tau^2)^{-1} m)$$

$$\bullet p(\tau^2 | -) \propto p(\tau^2) \cdot \prod_{i=1}^S p(\gamma_i | m, \tau^2)$$

$$\propto \tau^2^{-\frac{1}{2} - 1} \cdot \exp \left\{ -\frac{1}{2} \tau^2 \right\} \cdot \left( \frac{1}{\tau^2} \right)^S \cdot \exp \left\{ -\frac{1}{2 \tau^2} \sum_{i=1}^S (\gamma_i - m)' (\gamma_i - m) \right\}$$

$$\propto (\tau^2)^{-S - \frac{1}{2} - 1} \cdot \exp \left\{ -\frac{1}{\tau^2} \left( \frac{\sum_{i=1}^S (\gamma_i - m)' (\gamma_i - m) + 1}{2} \right) \right\}$$

$$\Rightarrow \tau^2 \sim \text{Inv-Gre} \left( S + \frac{1}{2}, \frac{\sum_{i=1}^S (\gamma_i - m)' (\gamma_i - m) + 1}{2} \right)$$

$$\bullet p(m|-) \propto p(m) \cdot \prod_{i=1}^S p(y_i | m, \gamma^2)$$



$$\propto \exp \left\{ -\frac{1}{2\gamma^2} \sum_{i=1}^S (y_i - m)'(y_i - m) \right\}$$

$$= \exp \left\{ -\frac{1}{2\gamma^2} \sum_{i=1}^S (y_i' y_i - 2y_i' m + m' m) \right\}$$

$$\propto \exp \left\{ -\frac{1}{2} \left( \frac{S}{\gamma^2} \cdot m' m - \frac{2}{\gamma^2} m' \sum_{i=1}^S y_i \right) \right\}$$

$$\Rightarrow m|- \sim N(N, K)$$

$$K = \frac{\gamma^2}{S} I \quad ; \quad N = K \times \left( \frac{\sum_{i=1}^S y_i}{\gamma^2} \right)$$