

## Binary observations

Bayesian logistic regression

$$p(\beta) = N(\beta; b, B)$$

$$p(y_i | x_i, \beta) = \frac{e^{(x_i^T \beta) y_i}}{1 + e^{(x_i^T \beta)}}$$

$\Downarrow$  augment  $w_i \sim \text{LG}$

$$p(w_i | \beta) = \text{LG}(w_i; 1, x_i^T \beta)$$

$$p(\beta) = N(\beta; b, B)$$

$$p(y_i | x_i, \beta, w_i) \propto \exp\left(K_i x_i^T \beta - \frac{w_i (x_i^T \beta)^2}{2}\right)$$

$$K_i = y_i - \frac{1}{2}$$

GP Classification

$$p(f) = \text{GR}(f; 0, h(\cdot, \cdot))$$

$$p(y_i | x_i, f) = \frac{e^{f(x_i) \cdot y_i}}{1 + e^{f(x_i)}}$$

$\Downarrow$  augment  $w_i \sim \text{LG}$

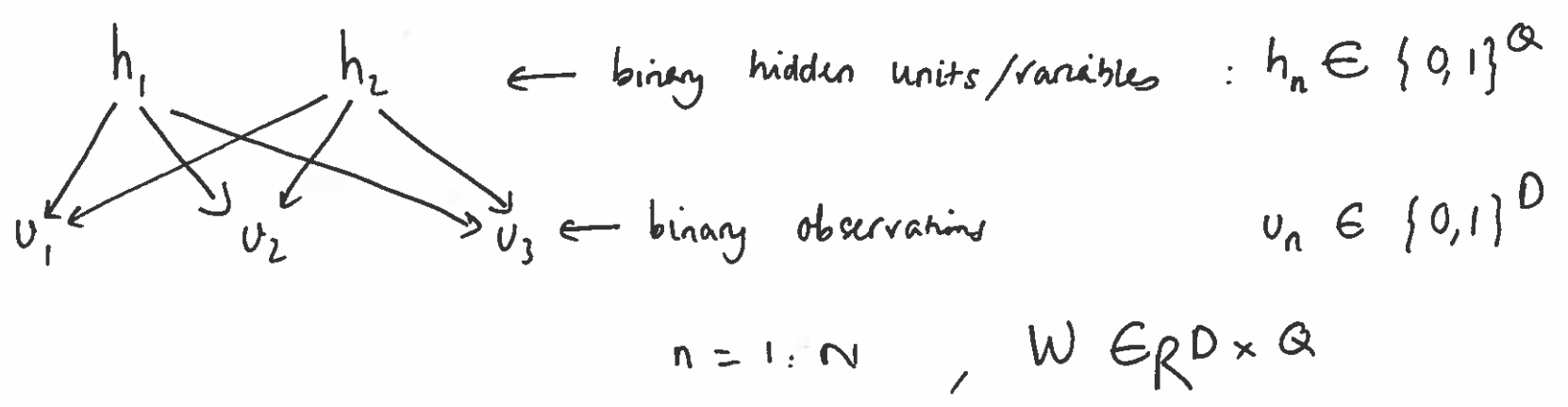
$$p(w_i | f) = \text{LG}(w_i; 1, f(x_i))$$

$$p(f) = \text{GR}(f; 0, h(\cdot, \cdot))$$

$$p(y_i | x_i, w_i, f) \propto \exp\left(K_i f(x_i) - \frac{w_i (f(x_i))^2}{2}\right)$$

$$K_i = y_i - \frac{1}{2}$$

# SBNS



$$p(h_{nq} = 1 \mid b_q) = \sigma(b_q)$$

$$p(v_{nd} = 1 \mid h_n, w_d, c_d) = \sigma(w_d^T \cdot h_n + c_d)$$

$$p(b_q) = N(b_q; 0, \theta_b)$$

$$p(c_d) = N(c_d; 0, \theta_c)$$

$$p(W_d) = N(W_d; 0, \text{diag}(\theta_w))$$

Augment LG variables  $\gamma_h \in \mathbb{R}^Q$  and  $\gamma_v \in \mathbb{R}^{N \times D}$

Similar to BayesLgReg :

$$P(\gamma_{h,q} | -) = PG(\gamma_{h,q}; 1, b_q)$$

$$P(\gamma_{v,nd} | -) = PG(\gamma_{v,nd}; 1, w_d^T h_n + c_d)$$

$$p(b_q) = N(b_q; 0, \Phi_b)$$

$$p(h_{nq} | b_q, \gamma_{h,q}) \propto \exp\left(K_h \cdot b_q - \frac{\gamma_{h,q} b_q^2}{2}\right) \quad \Bigg| \Rightarrow p(b_q | -) = N(b_q; \dots)$$

$$p(w_d) = N(w_d; 0, \text{diag}(\Phi_w))$$

$$p(v_{nd} | w_d, \gamma_{v,nd}, -) \propto \exp\left(K_v \cdot w_d^T \cdot h_n - \gamma_{v,nd} \cdot \frac{(w_d^T h_n)^2}{2}\right) \quad \Bigg| \Rightarrow p(w_d | -) = N(w_d; \dots)$$