

[Mirror I]

1. we have $N_B = 4$, $p = 0.6$

Natural prior on N is

Uniform ($\{1, 2, \dots, 10\}$) → constant uniform, cancels out

For posterior: $\frac{P(N_B | p, N) P(p)}{P(p)}$

$$P(N | N_B, p) = \frac{P(N_B, p | N) P(p)}{\sum_{i=1}^{10} P(N_B, p | N=i) P(p=i)}$$

$$= \frac{{}^N C_{N_B} p^{N_B} (1-p)^{N-N_B}}{\sum_i {}^N C_{N_B} p^i (1-p)^{i-N_B}}$$

we can evaluate the numerator for values of $N = 4, 5, \dots, 10$ (clearly 0 for $N < 4$)

N	$P(N N_B, p)$
4	0.6^4
5	$5 \times 0.6^4 \times 0.4$
6	$15 \times 0.6^4 \times 0.4^2$
7	$35 \times 0.6^4 \times 0.4^3$
8	$70 \times 0.6^4 \times 0.4^4$
9	$126 \times 0.6^4 \times 0.4^5$
10	$210 \times 0.6^4 \times 0.4^6$

(sum)

$$= 0.6^4 (1 + 5 \times 0.4 + 15 \times 0.4^2 + 35 \times 0.4^3 + 70 \times 0.4^4 + 126 \times 0.4^5 + 210 \times 0.4^6)$$

∴ Posterior is :

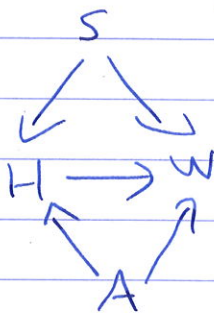
N	$P(N N_B, P)$	
4	1	
5	2	
6	2.4	
7	2.24	11.5824
8	1.792	
9	1.29024	
10	0.86016	

$$\begin{aligned} 2. & P(\alpha, \beta, \sigma | H_i) \\ &= \frac{P(H_i | \alpha, \beta, \sigma) \cdot P(\alpha, \beta, \sigma)}{P(H_i)} \end{aligned}$$

By definition, H_i has no dependence on $\alpha / \beta / \sigma$: this is what discriminative modelling means / assumes. So :

$$= \frac{P(H_i) \cdot P(\alpha, \beta, \sigma)}{P(H_i)} = P(\alpha, \beta, \sigma)$$

3. (a)



(b) $H_i = f(A_i, S_i; \theta)$, or more precisely, the likelihood from the model will be given by $P(H_i | A_i, S_i; \theta)$

Posterior over θ would be

$$P(\theta | \underline{A}, \underline{S}, \underline{H}) = \frac{P(\underline{H} | \underline{A}, \underline{S}; \theta) P(\theta)}{P(\underline{H} | \underline{A}, \underline{S})}$$

(using result from Q2)

with the usual IID assumption:

$$P(\theta | \underline{A}, \underline{S}, \underline{H}) = \frac{[\prod_i P(H_i | A_i, S_i; \theta)] P(\theta)}{\prod_i P(H_i | A_i, S_i)}$$

$$= \frac{[\prod_i P(H_i | A_i, S_i; \theta)] P(\theta)}{\prod_i P(H_i | A_i, S_i)}$$

$$\prod_i \int_{\theta} P(H_i | A_i, S_i; \theta) P(\theta) d\theta$$