Q&A Probabilistic Inference

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$\Theta \sim \mathrm{Ber}(\hat{\theta})$ $\Theta = 0$ or $\Theta = 1$

$x \sim \mathrm{Ber}(\theta)$ F_i

$a, b \sim p$ $x \sim \mathcal{N}(\mu, \sigma^2)$ $p(F_i \mid \theta_i) = \theta_i$

$p(a \mid b)$ $p(x \mid \mu, \sigma^2)$ $p(F_i \mid \tilde{F}_i, \theta_i) = \begin{cases} 1 & \text{if } F_i = \tilde{F}_i \\ 0 & \text{otherwise} \end{cases}$

A, B on $\{0, 1\}$

$p(A, B) = p(A) \cdot p(B)$

B \ A	0	1
0	0.1	0.3
1	0.2	0.4

$p(A, B) \overset{!}{\neq} p(A) \cdot p(B)$

$p(A=0) = 0.3$ $p(B=0) = 0.4$

$p(A=1) = 0.7$ $p(B=1) = 0.6$

$x \sim W(y)$ $y \sim Z(\dots)$

$y \mid x \sim Z(\dots)$ $y \mid x_1 \sim Z(\dots)$

$(y \mid x_1) \mid x_2 \sim Z(\dots)$

$$\log p(\theta|x) = \log \frac{p(x|\theta)\,p(\theta)}{p(x)} = \log p(x|\theta) + \log p(\theta) - \log p(x)$$

$$\log p(\mu|D,\alpha) = \log \frac{p(D|\mu,\alpha)\cdot p(\mu|\alpha)}{p(D)} \qquad p(x|\theta) \propto \exp(\dots)$$

$\gamma \sim N(0, \sigma^2)$

$x \sim W(\gamma)$

MLE: $\gamma_{MLE} = \arg\max_{\gamma} p(x|\gamma)$ $\longleftrightarrow$

MAP: $\gamma_{MAP} = \arg\max_{\gamma} p(\gamma|x) = \arg\max_{\gamma} p(x|\gamma)\cdot\widetilde{p(\gamma)}$

$D = \{x_1, \dots, x_N\}$

$p(x_{n+1}|D) = p(x_{n+1}|\gamma_{MLE})$

$p(x_{n+1}|\gamma_{MAP})$

posterior predictive $\quad \int p(x_{n+1}|\gamma)\,p(\gamma|D)\,d\gamma$

$$p(x_{n+1}|D) = \int p(x_{n+1},\gamma|D)\,d\gamma = \int p(x_{n+1}|\gamma)\cdot p(\gamma|D)\,d\gamma$$

MLE/MAP $\longrightarrow p(x_{n+1}|\gamma_{MLE/MAP})$