

MLE MAP

M 回顾 Likelihood: 有 N 个 i.i.d 样本: $D = \{x^{(1)}, \dots, x^{(N)}\}$ of r.v. X

L 若 X 离散, PMF 为 $p(x|\theta)$, 则 Likelihood of D is:

E
$$L(\theta) = \prod_{n=1}^N p(x^{(n)}|\theta)$$

若 X 连续, PDF 为 $f(x|\theta)$, 则:

$$L(\theta) = \prod_{n=1}^N f(x^{(n)}|\theta)$$

考虑 toss coin: $P(\text{Head}) = \theta$ $P(\text{Tail}) = 1 - \theta$

$$\hat{\theta} = \underset{\theta}{\operatorname{argmax}} P(D|\theta) = \underset{\theta}{\operatorname{argmax}} \prod_{i=1}^N P(x_i|\theta)$$

$$= \underset{\theta}{\operatorname{argmax}} \theta^{d_H} (1-\theta)^{d_T} \mathcal{J}(\theta)$$

$$\frac{\partial \mathcal{J}(\theta)}{\partial \theta} = 0 \Rightarrow \hat{\theta}_{MLE} = \frac{d_H}{d_H + d_T}$$

考虑 $X \sim \text{Gaussian}(\mu, \sigma)$, 欲 $\underset{\mu, \sigma}{\operatorname{argmax}}: \left(\frac{1}{\sqrt{2\pi}\sigma}\right)^n e^{-\sum_{i=1}^n (x_i - \mu)^2 / 2\sigma^2}$

$$\frac{\partial \mathcal{J}}{\partial \mu} = \sum_{i=1}^n (x_i - \mu) / \sigma^2 = 0; \quad \frac{\partial \mathcal{J}}{\partial \sigma^2} = -n + \frac{1}{\sigma^2} \sum_{i=1}^n (x_i - \mu)^2 = 0$$

$$\therefore \hat{\mu}_{MLE} = \frac{1}{n} \sum_{i=1}^n x_i \quad \hat{\sigma}_{MLE}^2 = \frac{1}{n} \sum_{i=1}^n (x_i - \hat{\mu})^2$$

Δ 附: MLE 推出的 σ^2 有 bias! $\hat{\sigma}^2_{unbiased} = \frac{1}{n-1} \sum_{i=1}^n (x_i - \hat{\mu})^2$

why? 因为 $\hat{\sigma}^2_{MLE}$ 中用的是 sample mean 而非 true mean

M : The Bayesian Way :

A
$$P(\theta|D) = \frac{P(D|\theta) P(\theta)}{P(D)}$$

P
$$= \frac{\text{Likelihood} \cdot \text{prior}}{\text{or: 后验}}$$

*: 若 $X \sim \text{Beta}(\alpha, \beta)$,
则 $P(X) \max: x^* = \frac{\alpha-1}{\alpha+\beta-2}$
 $E(X) = \frac{\alpha}{\alpha+\beta}$

$$\text{欲 } \underset{\theta}{\operatorname{argmax}} P(D|\theta) P(\theta) \Leftrightarrow \underset{\theta}{\operatorname{argmax}} [\log P(D|\theta) + \log p(\theta)]$$

考虑 flip coin: $P(D|\theta) = \binom{n}{d_H} \theta^{d_H} (1-\theta)^{d_T}$, if $p(\theta) \sim \text{Beta}(\beta_H, \beta_T)$

则 $P(\theta|D) \sim \text{Beta}(\beta_H + d_H, \beta_T + d_T)$, $\hat{\theta}_{MAP}^* = \frac{d_H + \beta_H - 1}{d_H + \beta_H + d_T + \beta_T - 2}$

($\hat{\theta}_{MAP} = \underset{\theta}{\operatorname{argmax}} P(\theta|D)$)

总结: Frequentist: Sample 少时表现不好; Bayesians: 不同 prior 不同 answer