

## PI 背景 变分推断 Variational Inference

频率角度  $\rightarrow$  优化问题

线性回归:

① 模型:  $f(w) = w^T x$

② 策略: loss function: 
$$\begin{cases} L(w) = \sum_{i=1}^N \|w^T x_i - y_i\|^2 \\ \hat{w} = \operatorname{argmin} L(w). \end{cases}$$
 无约束.

③ 算法: 
$$\begin{cases} \text{解析解: } \frac{\partial L(w)}{\partial w} \triangleq 0 \Rightarrow w^* = (x^T x)^{-1} x^T y. \\ \text{数值解: } GD \rightarrow \text{Gradient Descent.} \end{cases}$$

支持向量机 (SVM)

① 模型:  $f(w) = \operatorname{sign}(w^T x + b)$ .

② 策略: loss function: 
$$\begin{cases} \min \frac{1}{2} w^T w \\ \text{s.t. } y_i (w^T x_i + b) \geq 1, i=1, \dots, N \end{cases}$$
 有约束, SGD 优化

③ 算法: QP.

贝叶斯角度  $\rightarrow$  积分问题

$$P(\theta|x) = \frac{P(x|\theta) \cdot P(\theta)}{P(x)}.$$

贝叶斯 Inference.

贝叶斯决策  $X$ :  $N$  个样本

$\tilde{x}$  新的样本, 求  $P(\tilde{x}|X)$ .

$$\begin{aligned} P(\tilde{x}|X) &= \int_{\theta} P(\tilde{x}, \theta|X) d\theta = \int_{\theta} P(\tilde{x}|\theta, X) \cdot P(\theta|X) d\theta. \\ &= \int_{\theta} P(\tilde{x}|\theta) \cdot \underbrace{P(\theta|X)}_{\text{后验}} d\theta. \quad (\tilde{x} \perp X|\theta) \\ &= E_{\theta|X} [P(\tilde{x}|\theta)] \end{aligned}$$

Inference: 
$$\begin{cases} \text{精确推断} \\ \text{近似推断: } \begin{cases} \text{确定性近似} - VI \\ \text{随机近似} - MCMC. \end{cases} \end{cases}$$

## P2 变分推断.

$X$ : Observed data.  $Z$ : Latent variable. + parameter.

$(X, Z)$ : complete data.

$$\log P(X) = \log P(X, Z) - \log P(Z|X).$$

$$= \log \frac{P(X, Z)}{q(Z)} - \log \frac{P(Z|X)}{q(Z)}$$

=

$$\text{左边} = \int_Z \log P(X) q(Z) dZ = \log P(X) \int_Z q(Z) dZ = \log P(X)$$

$$\text{右边} = \int_Z q(Z) \log \frac{P(X, Z)}{q(Z)} dZ - \int_Z q(Z) \log \frac{P(Z|X)}{q(Z)} dZ$$

ELBO (evidence lower bound)

$KL(q||p)$

$$= \underbrace{L(q)}_{\text{变分}} + \underbrace{KL(q||p)}_{\geq 0}$$

$$\tilde{q}(Z) = \arg \max_{q(Z)} L(q) \Rightarrow \tilde{q}(Z) \approx P(Z|X).$$

$$q(Z) = \prod_{i=1}^M q_i(Z_i) \rightarrow \text{mean theory} \rightarrow q_j(Z_j).$$

$$q_j(Z_j) = \hat{P}(X, Z_j).$$

$$L(q) = \underbrace{\int_Z q(Z) \log P(X, Z) dZ}_{\text{①}} - \underbrace{\int_Z q(Z) \log q(Z) dZ}_{\text{②}}.$$

$$\text{①} = \int_Z \prod_{i=1}^M q_i(Z_i) \log P(X, Z) dZ_1 \dots dZ_M$$

$$= \int_{Z_j} q_j(Z_j) \left( \int_{\substack{Z_1 \dots Z_M \\ (i \neq j)}} \prod_{i=1}^M q_i(Z_i) \cdot \log P(X, Z) \cdot dZ_1 \dots dZ_M \right) dZ_j$$

$$= \int_{Z_j} q_j(Z_j) \left( \int_{\substack{Z_1 \dots Z_M \\ (i \neq j)}} \log P(X, Z) \prod_{i=1}^M q_i(Z_i) dZ_i \right) dZ_j$$

$$= \int_{Z_j} q_j(Z_j) \cdot \underbrace{E_{\prod_{i=1}^M q_i(Z_i)} \left[ \log P(X, Z) \right]}_{\hookrightarrow \log \hat{P}(X, Z_j)} dZ_j$$

$$\text{②} = \int_Z q(Z) \log q(Z) dZ = \int_Z \prod_{i=1}^M q_i(Z_i) \cdot \sum_{i=1}^M \log p_i(Z_i) dZ.$$

$$= \int_Z \prod_{i=1}^M q_i(Z_i) \left[ \log q_1(Z_1) + \dots + \log q_M(Z_M) \right] dZ.$$

$$= \sum_{i=1}^M \int_{Z_i} q_i(Z_i) \log q_i(Z_i) dZ_i = \int_{Z_j} q_j(Z_j) \log q_j(Z_j) dZ_j + C.$$

$$\begin{aligned}
\int_{\mathbf{z}} \prod_{i=1}^M q_i(z_i) \cdot \log q_i(z_i) d\mathbf{z} &= \int_{\mathbf{z}} q_1 q_2 \dots q_M \cdot \log q_1 dz_1 \dots dz_M \\
&= \int_{z_1} q_1 \log q_1 dz_1 \cdot \underbrace{\int_{z_2} q_2 dz_2}_{=1} \dots \underbrace{\int_{z_M} q_M dz_M}_{=1} \\
&= \int_{z_1} q_1 \log q_1 dz_1
\end{aligned}$$

$$\textcircled{1} - \textcircled{2} = \int_{z_j} q_j(z_j) \cdot \log \frac{\hat{p}(x, z_j)}{q_j(z_j)} dz_j = -\text{KL}(q_j \| \hat{p}(x, z_j)) \leq 0$$