

问题:

假设数据集为  $\mathcal{D} = \{\mathbf{x}_i, y_i\}_{i=1}^n$ , 其中  $\mathbf{x}_i \in \mathbb{R}^d, d > 1; y_i \in \mathbb{R}$ , 且参数  $\mathbf{w}$  的先验分布为  $\mathbf{w} \sim \mathcal{N}(\mathbf{0}, \alpha^{-1}\mathbf{I})$ , 似然函数为  $P(\mathcal{D}|\mathbf{w}) \triangleq P(\mathcal{Y}|\mathbb{X}, \mathbf{w}) = \mathcal{N}(\mathcal{Y}|\mathbb{X}\mathbf{w}, \sigma^2\mathbf{I})$ ,

证明: MAP(极大后验估计)等同于  $\ell_2$ 正则化(岭回归)

提示: 1、 $P(\mathbf{w}|\mathcal{D}) = \frac{P(\mathcal{D}|\mathbf{w})P(\mathbf{w})}{P(\mathcal{D})} \propto P(\mathcal{D}|\mathbf{w})P(\mathbf{w})$

2、多元高斯概率密度函数:

$$\begin{aligned} f(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Sigma}) \\ = (2\pi)^{-\frac{d}{2}}(\det\boldsymbol{\Sigma})^{-\frac{1}{2}} \exp\left\{-\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu})^T\boldsymbol{\Sigma}^{-1}(\mathbf{x} - \boldsymbol{\mu})\right\} \end{aligned}$$

解答:

由题目,  $\mathbf{w} \sim \mathcal{N}(\mathbf{0}, \alpha^{-1}\mathbf{I}_d)$ , 所以

$$P(\mathbf{w}) = (2\pi)^{-\frac{d}{2}}(\det\alpha^{-1}\mathbf{I})^{-\frac{1}{2}}\exp\left\{-\frac{\alpha}{2}\mathbf{w}^T\mathbf{w}\right\};$$

又  $P(\mathcal{D}|\mathbf{w}) \triangleq P(\mathcal{Y}|\mathbb{X}, \mathbf{w}) = \mathcal{N}(\mathcal{Y}|\mathbb{X}\mathbf{w}, \sigma^2\mathbf{I})$ ,

故  $P(\mathcal{D}|\mathbf{w})$

$$=(2\pi)^{-\frac{n}{2}}(\det\sigma^2\mathbf{I}_n)^{-\frac{1}{2}}\exp\left\{-\frac{1}{2\sigma^2}(\mathcal{Y}-\mathbb{X}\mathbf{w})^T(\mathcal{Y}-\mathbb{X}\mathbf{w})\right\};$$

$$\begin{aligned}\text{所以 MAP} &\triangleq \operatorname{argmax}_{\mathbf{w}} P(\mathbf{w}|\mathcal{D}) \triangleq \operatorname{argmax}_{\mathbf{w}} \frac{P(\mathcal{D}|\mathbf{w})P(\mathbf{w})}{P(\mathcal{D})} \\ &\propto \operatorname{argmax}_{\mathbf{w}} P(\mathcal{D}|\mathbf{w})P(\mathbf{w})\end{aligned}$$

$$=\operatorname{argmax}_{\mathbf{w}} \frac{\exp\left\{-\frac{1}{2\sigma^2}(\mathcal{Y}-\mathbb{X}\mathbf{w})^T(\mathcal{Y}-\mathbb{X}\mathbf{w})-\frac{\alpha}{2}\mathbf{w}^T\mathbf{w}\right\}}{(2\pi)^{\frac{n+d}{2}}(\det\boldsymbol{\alpha}^{-1}\mathbf{I})^{\frac{1}{2}}(\det\sigma^2\mathbf{I}_n)^{\frac{1}{2}}}$$

由于上式分母中不含  $\mathbf{w}$ ，且  $f(x) = e^x$  为单调递增函数，所以

$$\begin{aligned}\text{MAP} &\triangleq \operatorname{argmax}_{\mathbf{w}} \left\{-\frac{1}{2\sigma^2}(\mathcal{Y}-\mathbb{X}\mathbf{w})^T(\mathcal{Y}-\mathbb{X}\mathbf{w})-\frac{\alpha}{2}\mathbf{w}^T\mathbf{w}\right\} \\ &\triangleq \operatorname{argmin}_{\mathbf{w}} \left\{\frac{1}{2\sigma^2}(\mathcal{Y}-\mathbb{X}\mathbf{w})^T(\mathcal{Y}-\mathbb{X}\mathbf{w})+\frac{\alpha}{2}\mathbf{w}^T\mathbf{w}\right\} \\ &\triangleq \operatorname{argmin}_{\mathbf{w}} \{(\mathcal{Y}-\mathbb{X}\mathbf{w})^T(\mathcal{Y}-\mathbb{X}\mathbf{w})+\alpha\sigma^2\mathbf{w}^T\mathbf{w}\},\end{aligned}$$

该式为岭回归形式，式中  $\alpha\sigma^2$  对应岭回归中超参数  $\lambda$ ，因而 MAP 等同于岭回归，原命题得证。