

Differential Geometry

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1 Regression

$$\min_{\omega \in \mathbb{R}^m} \frac{1}{2N} \|\Phi\omega - y\|^2 + \lambda C(\omega) \quad (1.1)$$

Lasso: $C = \|\omega\|_1$. **Ridge regression:** $C = \|\omega\|_2$.

subgradient of f :

$$\partial f(x_0) = \{g | f(x) \geq f(x_0) + g^T(x - x_0)\}$$

In particular,

$$\partial|x| = \begin{cases} 1, & x > 0 \\ -1, & x < 0 \\ [-1, 1], & x = 0 \end{cases}$$

1.1 Binary classification problem

one-hot encoding for the output $\left\{\begin{pmatrix} 1 \\ 0 \end{pmatrix}, \begin{pmatrix} 0 \\ 1 \end{pmatrix}\right\}$. It can be understood as the probability for each class and can take continuous values.

A **linear hypothesis space** is $\{u(x) : u = \omega^T x, x \in \mathbb{R}^n, \omega \in \mathbb{R}^n\}$.

Softmax: Map the extracted feature u to the space of one-hot codes

$$\mu = \frac{1}{1 + e^{-u}}, \quad 1 - \mu = \frac{e^{-u}}{1 + e^{-u}} = \frac{1}{1 + e^u}$$

$$KL(p, q) = \int p(\log p - \log q) \quad (1.2)$$

For p real probability, to minimize (1.2), suffices to minimize

$$-\int p \log q_\theta dx = -\sum_{x_i} \log q_\theta(x_i)$$

which is called **Maximum likelihood (cross entropy)**

$$-\sum \log p(y_i | x_i, \omega) = \sum -y_i \log \mu_i - (1 - y_i) \log(1 - \mu_i)$$

We reduce to minimize the thing above.

1.2 Gradient Descent

$$J(\theta) = \sum_{i=1}^N L(f_{\theta}(x_i), y_i), \quad \theta^{t+1} = \theta^t - \eta_t \frac{\partial J(\theta)}{\partial \theta} \Big|_{\theta=\theta^t}$$

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