

$$\psi(\alpha_1, \alpha_2) = \frac{1}{2} (\alpha_1^2 K_{11} + 2\alpha_1 \alpha_2 y_1 y_2 K_{12} + \alpha_2^2 K_{22}) - (\alpha_1 + \alpha_2) + \alpha_1 y_1 V_1 + \alpha_2 y_2 V_2$$

有: $\alpha_1 = (\xi - \alpha_2 y_2) y_1$, 代入:

$$\psi(\alpha_1, \alpha_2) = \frac{1}{2} [(\xi - \alpha_2 y_2)^2 K_{11} + 2(\xi - \alpha_2 y_2) \alpha_2 y_2 K_{12} + \alpha_2^2 K_{22}] - (\xi - \alpha_2 y_2) y_1 - \alpha_2 + (\xi - \alpha_2 y_2) V_1 + \alpha_2 y_2 V_2 + C$$

求导: 有:

$$\frac{\partial \psi}{\partial \alpha_2} = \frac{1}{2} [-2y_2(\xi - \alpha_2 y_2) K_{11} + 2(\xi - \alpha_2 y_2) y_2 K_{12} + (-2y_2) \alpha_2 y_2 K_{12} + 2\alpha_2 K_{22}] + y_1 y_2 - 1 - y_2 V_1 + y_2 V_2$$

整理, 有:

$$\begin{aligned} \frac{\partial \psi}{\partial \alpha_2} &= [\alpha_2 K_{11} - y_2 \xi K_{11} + \xi y_2 K_{12} - \alpha_2 K_{12} - \alpha_2 K_{12} + \alpha_2 K_{22}] + y_1 y_2 - 1 - y_2 V_1 + y_2 V_2 \\ &= \alpha_2 (K_{11} - 2K_{12} + K_{22}) + y_2 \xi K_{12} - y_2 \xi K_{11} + y_1 y_2 - 1 - y_2 (V_1 - V_2) \end{aligned}$$

此处重新考虑 SVM 计算方式: 对于某 x , 预测值为:

$$f(x) = w^T x + b, \text{ 其中 } w \text{ 为权重向量} \rightarrow \|w\| = \sum_{i=1}^n \alpha_i y_i \quad \text{有关系}$$

即 $f(x)$ 为原先的预测值, 对应地, α 为原始权重向量

$$\text{由 } f(x) = \sum_{i=1}^n \alpha_i^{\text{old}} y_i K(x_i, x) + b \text{ 为迭代前的 SVM 估计值}$$

由于 $\alpha_3, \alpha_4 \dots \alpha_n$ 是不变的, 则可以以 $f(x)$ 表示出 V_1, V_2 .

$$\begin{cases} V_1 = \sum_{i=3}^n \alpha_i^{\text{old}} y_i K_{i1} = f(x_1) - \alpha_1^{\text{old}} y_1 K_{11} - \alpha_2^{\text{old}} y_2 K_{12} - b \\ V_2 = \sum_{i=3}^n \alpha_i^{\text{old}} y_i K_{i2} = f(x_2) - \alpha_1^{\text{old}} y_1 K_{12} - \alpha_2^{\text{old}} y_2 K_{22} - b \end{cases} \quad \text{其中 } V_1, V_2$$

取 $\frac{\partial \psi}{\partial \alpha_2} = 0$, 则:

$$\alpha_2 (K_{11} - 2K_{12} + K_{22}) + y_2 \xi (K_{12} - K_{11}) + y_1 y_2 - 1 = y_2 (V_1 - V_2)$$

$$\alpha_2 (K_{11} - 2K_{12} + K_{22}) + y_2 \xi (K_{12} - K_{11}) + y_1 y_2 - 1 = y_2 (V_1 - V_2)$$

$$\text{代入 } V_1 - V_2 = f(x_1) - f(x_2) - \alpha_1^{\text{old}} y_1 (K_{11} - K_{12}) - \alpha_2^{\text{old}} y_2 (K_{12} - K_{22})$$

$$\begin{aligned} \alpha_1 = y_1 (\xi - \alpha_2 y_2) &\rightarrow f(x_1) - f(x_2) - \xi (K_{11} - K_{12}) + \alpha_2^{\text{old}} y_2 (K_{11} - K_{12}) + \alpha_2^{\text{old}} y_2 (K_{22} - K_{12}) \\ &= f(x_1) - f(x_2) - \xi (K_{11} - K_{12}) + \alpha_2^{\text{old}} y_2 (K_{11} - 2K_{12} + K_{22}) \quad (\star_2) \end{aligned}$$

将 \star_2 代入 \star_1 有:

$$\begin{aligned} \frac{\partial \psi}{\partial \alpha_2} &= \alpha_2^{\text{new}} (K_{11} - 2K_{12} + K_{22}) + y_2 \xi (K_{12} - K_{11}) + y_1 y_2 - 1 - y_2 (f(x_1) - f(x_2)) + \xi y_2 (K_{11} - K_{12}) \\ &\quad - \alpha_2^{\text{old}} (K_{11} - 2K_{12} + K_{22}) \end{aligned}$$

$$= (\alpha_2^{\text{new}} - \alpha_2^{\text{old}}) (K_{11} - 2K_{12} + K_{22}) + y_2 (y_1 y_2 - y_2 (f(x_1) - f(x_2))) = 0$$

$$\text{则有: } \alpha_2^{\text{new}} - \alpha_2^{\text{old}} = \frac{y_2 (f(x_1) - f(x_2)) - y_2 (y_1 y_2 - 1)}{K_{11} - 2K_{12} + K_{22}} = y_2 \frac{(f(x_1) - y_1) - (f(x_2) - y_2)}{K_{11} - 2K_{12} + K_{22}}$$

我们取 $E_1 = f(x_1) - y_1$, $E_2 = f(x_2) - y_2$. $\eta = K_{11} - 2K_{12} + K_{22}$, 则

$$\alpha_2^{\text{new}} = \alpha_2^{\text{old}} + y_2 \frac{E_1 - E_2}{\eta}$$

\star 为权重迭代公式。