

# 人工智能基础作业 9

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1.

根据所给数据, 对偶问题为:

$$\begin{aligned} \min_{\alpha} \quad & \frac{1}{2} \sum_{i=1}^N \sum_{j=1}^N \alpha_i \alpha_j y_i y_j (\mathbf{x}_i \cdot \mathbf{x}_j) - \sum_{i=1}^N \alpha_i \\ & = \frac{5}{2} \alpha_1^2 + \frac{13}{2} \alpha_2^2 + 9 \alpha_3^2 + \frac{5}{2} \alpha_4^2 + \frac{13}{2} \alpha_5^2 + 8 \alpha_1 \alpha_2 + 9 \alpha_1 \alpha_3 - 4 \alpha_1 \alpha_4 - 7 \alpha_1 \alpha_5 + 15 \alpha_2 \alpha_3 \\ & \quad - 7 \alpha_2 \alpha_4 - 12 \alpha_2 \alpha_5 - 9 \alpha_3 \alpha_4 - 15 \alpha_3 \alpha_5 + 8 \alpha_4 \alpha_5 - (\alpha_1 + \alpha_2 + \alpha_3 + \alpha_4 + \alpha_5) \\ \text{s.t.} \quad & \alpha_1 + \alpha_2 + \alpha_3 - \alpha_4 - \alpha_5 = 0 \\ & \alpha_i \geq 0, i = 1, 2, 3, 4, 5 \end{aligned}$$

将  $\alpha_1 + \alpha_2 + \alpha_3 - \alpha_4 = \alpha_5$  代入目标函数, 得到:

$$\begin{aligned} \ell(\alpha) &= 2\alpha_1^2 + \alpha_2^2 + \frac{1}{2}\alpha_3^2 + \alpha_4^2 + 2\alpha_1\alpha_2 - 2\alpha_1\alpha_4 + \alpha_2\alpha_3 + \alpha_3\alpha_4 - 2(\alpha_1 + \alpha_2 + \alpha_3) \\ &= \frac{1}{2} \alpha^T \begin{pmatrix} 4 & 2 & 0 & -2 \\ 2 & 2 & 1 & 0 \\ 0 & 1 & 1 & 1 \\ -2 & 0 & 1 & 2 \end{pmatrix} \alpha - 2(1 \ 1 \ 1 \ 0) \alpha \end{aligned}$$

对  $\alpha$  求导, 得到:

$$\frac{\partial \ell}{\partial \alpha} = \begin{pmatrix} 4 & 2 & 0 & -2 \\ 2 & 2 & 1 & 0 \\ 0 & 1 & 1 & 1 \\ -2 & 0 & 1 & 2 \end{pmatrix} \alpha - \begin{pmatrix} 2 \\ 2 \\ 2 \\ 0 \end{pmatrix} = \begin{pmatrix} 4\alpha_1 + 2\alpha_2 - 2\alpha_4 - 2 \\ 2\alpha_1 + 2\alpha_2 + \alpha_3 - 2 \\ \alpha_2 + \alpha_3 + \alpha_4 - 2 \\ -2\alpha_1 + \alpha_3 + 2\alpha_4 \end{pmatrix}$$

令导数为 0, 方程无解, 故只能在边界上取到最小值:

- 当  $\alpha_1 = 0$  时, 最小值  $\ell(0, 0, 2, 0) = -2$ ;
- 当  $\alpha_1 \neq 0, \alpha_2 = 0$  时, 最小值  $\ell(\frac{1}{2}, 0, 2, 0) = -\frac{5}{2}$ ;
- 当  $\alpha_1 \neq 0, \alpha_2 \neq 0, \alpha_3 = 0$  时, 最小值  $\ell(\frac{1}{2}, \frac{1}{2}, 0, \frac{1}{2}) = -1$ ;
- 当  $\alpha_1 \neq 0, \alpha_2 \neq 0, \alpha_3 \neq 0, \alpha_4 = 0$  时, 无最小值.

因此,  $\ell(\alpha)$  在  $\alpha^* = (\frac{1}{2}, 0, 2, 0)^T$  时达到最小, 此时  $\alpha_5 = \alpha_1 + \alpha_2 + \alpha_3 - \alpha_4 = \frac{5}{2}$ , 说明实例点  $\mathbf{x}_1, \mathbf{x}_3, \mathbf{x}_5$  为支持向量. 求得最优化问题的解  $\mathbf{w}^*$  和  $b^*$  为

$$\begin{aligned} \mathbf{w}^* &= \frac{1}{2} \mathbf{x}_1 + 2 \mathbf{x}_3 - \frac{5}{2} \mathbf{x}_5 = \begin{pmatrix} -1 \\ 2 \end{pmatrix} \\ b^* &= 1 - \frac{1}{2} \times 5 - 2 \times 9 + \frac{5}{2} \times 7 = -2 \end{aligned}$$

因此, SVM 的最大间隔分离超平面为

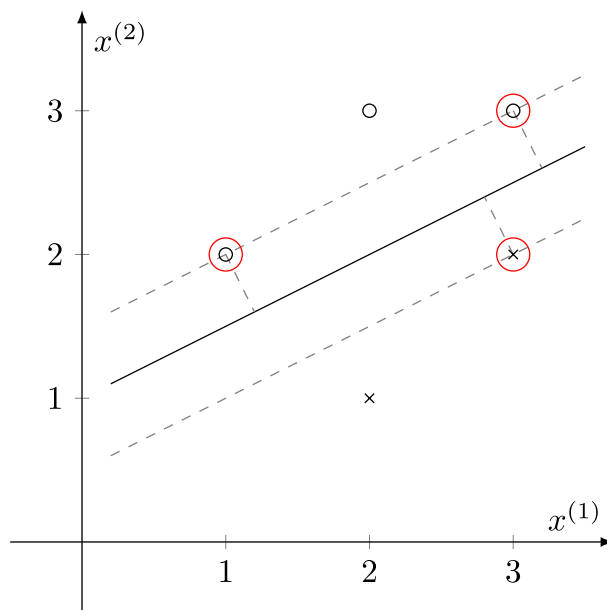
$$-x^{(1)} + 2x^{(2)} - 2 = 0 \Leftrightarrow x^{(2)} = \frac{1}{2}x^{(1)} + 1$$

分类决策函数为

$$f(\mathbf{x}) = \text{sgn}(-x^{(1)} + 2x^{(2)} - 2)$$

由上面的分析, 作出图像如下, 其中

- 圆圈表示正例点, 叉表示负例点;
- 实线表示分离超平面, 虚线表示其间隔边界;
- 支持向量用红色圆圈圈出:



## 2.

首先, 有

$$\begin{aligned}\frac{\partial}{\partial z}\sigma(z) &= \frac{\partial}{\partial z} \frac{1}{1+e^{-z}} = \sigma(z)(1-\sigma(z)) \\ \frac{\partial}{\partial z}(1-\sigma(z)) &= \frac{\partial}{\partial z} \frac{e^{-z}}{1+e^{-z}} = e^{-z} \frac{\partial}{\partial z}\sigma(z) + \sigma(z) \frac{\partial}{\partial z}e^{-z} = -e^{-z}\sigma^2(z) = -\sigma(z)(1-\sigma(z))\end{aligned}$$

记  $g = \mathbf{w}\mathbf{x} + b$ ,  $f(g) = L_{\text{CE}}(\mathbf{w}, b) = -[y \log(\sigma(g)) + (1-y) \log(1-\sigma(g))]$ , 则有

$$\begin{aligned}\frac{\partial g}{\partial \mathbf{w}} = \mathbf{x}^T &\Leftrightarrow \frac{\partial g}{\partial w_j} = x_j \\ \frac{\partial}{\partial g}f(g) &= -\left[y \frac{1}{\sigma(g)} \frac{\partial}{\partial g}\sigma(g) + (1-y) \frac{1}{1-\sigma(g)} \frac{\partial}{\partial g}(1-\sigma(g))\right] \\ &= -[y(1-\sigma(g)) - (1-y)\sigma(g)] \\ &= -y + \cancel{y\sigma(g)} + \sigma(g) - \cancel{y\sigma(g)} \\ &= \sigma(g) - y = \sigma(\mathbf{w}\mathbf{x} + b) - y\end{aligned}$$

由链式法则, 有

$$\frac{\partial L_{\text{CE}}}{\partial w_j} = \frac{\partial L_{\text{CE}}}{\partial g} \cdot \frac{\partial g}{\partial w_j} = (\sigma(\mathbf{w}\mathbf{x} + b) - y)x_j$$