

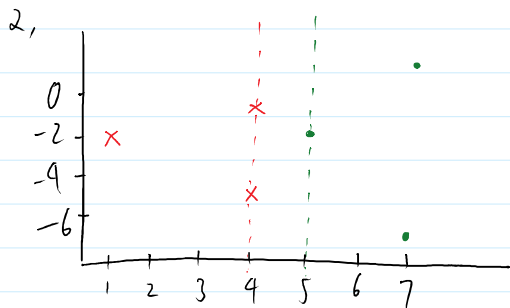
作业5

2017年4月18日 8:14

$$1, \min_{b, w_i} \frac{1}{2} (W^T W + C \sum_{n=1}^N \xi_n)$$

$$s.t. \quad y_n (W^T z_n + b) \geq 1 - \xi_n \quad \text{and} \quad \xi_n \geq 0$$

共 $d+1+N$ 个参数, $2N$ 个约束条件 (C 视为超参数)



$\phi_1(x)$	$\phi_2(x)$	y
1	-2	-1
4	-5	-1
4	-1	-1
5	-2	+1
7	-7	+1
7	1	+1
7	1	+1

易知该超平面为 $z_1 = 4.5$

3, 非线性, 使用 sklearn.svm.SVC 计算得

$$\alpha = [0.69, 0.76, 0.89, 0.23, 0.29]$$

$$b = [-1.67]$$

SV 下标 $[1, 2, 3, 4, 5]$

$$4 \quad \text{决策} \quad g_{svm} = \text{sign} \left(\sum_{SV} \alpha_n y_n k(x_n, x) + b \right)$$

对应的超平面

$$-0.69(1+x_2)^2 - 0.76(1-x_2)^2 + 0.89(1-x_1)^2 + 0.23(1+2x_2)^2 + 0.29(1-2x_2)^2 - 1.67$$

5, 显然不降, 实际上, 两类的 z 空间就不一样

$$\text{对 } Q_2 \quad (x_1, x_2) \rightarrow (x_2^2 - 2x_1 + 3, x_1^2 - 2x_2 - 5)$$

$$\text{对 } Q_4 \quad (x_1, x_2) \rightarrow (1, \sqrt{2}x_1, \sqrt{2}x_2, \sqrt{2}x_1x_2, x_1^2, x_2^2)$$

$$6, \quad L(K, c, \lambda)$$

$$= R^T + \sum_{n=1}^N \lambda_n (||x_n - c||^2 - R^T)$$

7, KKT 条件

$$\textcircled{1} \quad ||x_n - c||^2 \leq R^T$$

$$\textcircled{2} \quad \lambda_n \geq 0$$

$$\textcircled{3} \quad \lambda_n (||x_n - c||^2 - R^T) = 0$$

$$\frac{\partial L}{\partial c_i} = 0 \Rightarrow 2 \sum_{n=1}^N \lambda_n (x_n^{(i)} - c_i) = 0 \Rightarrow c_i \sum_{n=1}^N \lambda_n = \sum_{n=1}^N \lambda_n x_n^{(i)}$$

$$\text{若 } \sum_{n=1}^N \lambda_n \neq 0 \text{ 时} \quad c = \frac{\sum_{n=1}^N \lambda_n x_n}{\sum_{n=1}^N \lambda_n}$$

$$\frac{\partial L}{\partial R} = 0 \Rightarrow 2R - 2R \sum_{n=1}^N \lambda_n = 0 \Rightarrow R(1 - \sum_{n=1}^N \lambda_n) = 0$$

$$8, \quad k > 0 \Rightarrow \sum_{n=1}^N \lambda_n = 1 \quad c = \sum_{n=1}^N \lambda_n x_n$$

$$\text{则} \quad L(K, c, \lambda) = \sum_{n=1}^N \lambda_n ||x_n - c||^2 = \sum_{n=1}^N \lambda_n ||x_n - \sum_{m=1}^N \lambda_m x_m||^2 \quad s.t. \quad \sum_{n=1}^N \lambda_n = 1$$

$$9, \quad L = \sum_{n=1}^N \lambda_n ||x_n - \sum_{m=1}^N \lambda_m x_m||^2 = \sum_{n=1}^N \lambda_n (x_n - \sum_{m=1}^N \lambda_m x_m)^T (x_n - \sum_{m=1}^N \lambda_m x_m)$$

$$= \sum_{n=1}^N \lambda_n x_n^T x_n - 2 \sum_{n=1}^N \sum_{m=1}^N \lambda_n \lambda_m x_m^T x_n + \sum_{n=1}^N \lambda_n \sum_{m=1}^N \sum_{k=1}^N \lambda_m \lambda_k x_m^T x_k$$

$$\begin{aligned}
&= \sum_{n=1}^N \lambda_n x_n^T x_n - 2 \sum_{n=1}^N \sum_{m=1}^N \lambda_n \lambda_m x_m^T x_n + \sum_{n=1}^N \lambda_n \sum_{m=1}^N \sum_{l=1}^N \lambda_m \lambda_l x_m^T x_l \\
&= \sum_{n=1}^N \lambda_n k(x_n, x_n) - 2 \sum_{n=1}^N \sum_{m=1}^N \lambda_n \lambda_m k(x_m, x_n) + \sum_{m=1}^N \sum_{l=1}^N \lambda_m \lambda_l \cdot \sum_{n=1}^N \lambda_n \\
&= \sum_{n=1}^N \lambda_n k(x_n, x_n) - \sum_{n=1}^N \sum_{m=1}^N \lambda_n \lambda_m k(x_m, x_n)
\end{aligned}$$

10, 求 $\{\lambda_i > 0\}$ $\|x_i - c\| - R^2 = 0$

$$\begin{aligned}
R &= \sqrt{(x_i - c)^T C (x_i - c)} = \sqrt{x_i^T x_i - 2 C^T x_i + C^T C} \\
&= \sqrt{x_i^T x_i - 2 \sum_{m=1}^N \lambda_m x_m^T x_i + \sum_{n=1}^N \sum_{m=1}^N \lambda_m \lambda_n x_n^T x_m} \\
&= \sqrt{k(x_i, x_i) - 2 \sum_{m=1}^N \lambda_m k(x_m, x_i) + \sum_{n=1}^N \sum_{m=1}^N \lambda_n \lambda_m k(x_n, x_m)}
\end{aligned}$$

11, min w.b. $\frac{1}{2} w^T w + C \sum_{n=1}^N \xi_n^2 = \min_{w,b} \frac{1}{2} \tilde{w}^T \tilde{w}$

$$\Rightarrow \frac{1}{2} \tilde{w}^T \tilde{w} = \frac{1}{2} w^T w + C \sum_{n=1}^N \xi_n^2 = \frac{1}{2} w^T w + \frac{1}{2} (\sqrt{2C} \xi)^T (\sqrt{2C} \xi)$$

$$\begin{aligned}
\Rightarrow \tilde{w} &= (w, \sqrt{2C} \xi) \quad \{\text{新的特征向量}\} \\
\text{新的函数形式} \quad y_n(w^T x_n + b) + \xi_n &= y_n(\tilde{w}^T \tilde{x}_n + b) \quad \text{令 } \tilde{x}_n = (x_n, v) \\
&= (x_n, v_1, v_2, \dots, v_n) \\
\Rightarrow y_n \sqrt{2C} \xi^T v &= \xi_n
\end{aligned}$$

$$\Rightarrow \xi^T v = \frac{\xi_n}{y_n \sqrt{2C}}$$

$$\Rightarrow v_i = [i=n] \frac{1}{y_n \sqrt{2C}} \quad i \in [1, N] \quad (\text{如何去掉 } y_n?)$$

12, 考虑核函数对应的对称半正定矩阵

$$k_1: [k_1(x_i, x_j)]_{m \times m} \quad k_2: [k_2(x_i, x_j)]_{m \times m}$$

$$\begin{aligned}
a, \quad k_1 + k_2 \text{ 对称半正定} \quad & [k_1(x_i, x_j) + k_2(x_i, x_j)]_{m \times m} \\
&= [k_1(x_i, x_j)]_{m \times m} + [k_2(x_i, x_j)]_{m \times m}
\end{aligned}$$

两个对称半正定矩阵的和仍然是对称半正定矩阵 ✓

b, 不对称 $k_2 = 2k_1$ 则 $k_1 - k_2$ 对应矩阵 $-[k_1(x_i, x_j)]$, 不是半正定的 ✗

$$\begin{aligned}
c, \quad k_1 \cdot k_2 \text{ 对称半正定} \quad & [k_1(x_i, x_j) \cdot k_2(x_i, x_j)]_{m \times m} \\
&= \sum_{i,j=1}^m c_i c_j k_1(x_i, x_j) \cdot k_2(x_i, x_j)
\end{aligned}$$

$$\begin{aligned}
&= \sum_{i,j=1}^m c_i c_j \phi_1(x_i) \phi_1(x_j) \phi_2(x_i) \phi_2(x_j) \\
&= \left(\sum_i c_i \phi_1(x_i) \phi_2(x_i) \right) \left(\sum_j c_j \phi_1(x_j) \phi_2(x_j) \right)
\end{aligned}$$

$$= \| \sum_i c_i \phi_1(x_i) \phi_2(x_i) \|^2 \geq 0 \quad \text{且 } \neq 0 \quad \checkmark$$

$$= (\sum_i c_i \phi_1(x_i) \phi_2(x_i)) (\sum_j c_j \phi_1(x_j) \phi_2(x_j))$$

$$= \|\sum_i c_i \phi_1(x_i) \phi_2(x_i)\|^2 \geq 0 \quad \text{非负定} \quad \checkmark$$

d, 反例 $k_1 = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix}$ $k_2 = \begin{bmatrix} 4/5 & 1/5 \\ 1/5 & 4/5 \end{bmatrix}$ \times

13, a, $k_1 = \begin{bmatrix} 4/5 & 1/5 \\ 1/5 & 4/5 \end{bmatrix}$ $k_2 = \begin{bmatrix} 1/25 & 16/25 \\ 16/25 & 1/25 \end{bmatrix}$ \times 反例

b, 非负定核函数 反例非负定 \checkmark

c, $k_1 = \begin{bmatrix} 4/5 & 1/5 \\ 1/5 & 4/5 \end{bmatrix}$ $k_2 = \begin{bmatrix} e^{-4/5} & e^{-1/5} \\ e^{-1/5} & e^{-4/5} \end{bmatrix}$ \times 反例

d, $\sum_{i,j=1}^m c_i c_j \frac{1}{1 + k_1(x_i, x_j)}$

$$= \sum_{i,j=1}^m c_i c_j \frac{k_1(x_i, x_j)}{(1 + k_1(x_i, x_j)) (1 + k_2(x_i, x_j))} > \sum_{i,j=1}^m c_i c_j k_1(x_i, x_j) \geq 0 \quad \checkmark$$

14, $g_{svm}(x) = \text{sign}(\sum_{SV} \alpha_n y_n k(x_n, x) + y_S - \sum_{SV} \alpha_n y_n k(x_n, x_S))$

$k \rightarrow \tilde{k}$ $g_{svm}(x) = \text{sign}(\sum_{SV} \alpha_n y_n p k(x_n, x) + y_S - \sum_{SV} \alpha_n y_n p k(x_n, x_S))$

为了保持结果不变, 令 $\alpha'_n = \alpha_n / p$

原 α 的求解 $\frac{1}{2} \min_{\alpha} \sum_{n=1}^N \sum_{m=1}^N \alpha_n \alpha_m y_n y_m z_n^T z_m - \sum_{n=1}^N \alpha_n$

s.t. $\sum_{n=1}^N \alpha_n y_n = 0$

$0 \leq \alpha_n \leq C$

则 α_n 与 C 成正比, 取 $\tilde{C} = C/p$

15 ~ 20 参见 F13

15, $C \uparrow$, $\|w\| \uparrow$

16, $C \uparrow$ E_{in} 不变

17, $C \uparrow$ $\sum_{n=1}^N \alpha_n \uparrow$ 与 C 成正比

18, 2d free SV $d = \frac{1}{\|w\|}$ $\|w\|^2 = \alpha^T K \alpha$

($C \uparrow$ $\|w\| \uparrow$ $d \downarrow$) (sklearn.SVC 中如何求?)

19, $\gamma \uparrow$ E_{out} 先降后升 $\log_2 \gamma = 1$ 时取得最佳

20, $\gamma \uparrow$ E_{val} 先降后升 $\log_2 \gamma = 1$ 时取得最佳