

Review 9/26: Support Vector Machines



$$\min_{w, b, \epsilon_i \geq 0} \frac{1}{2} w \cdot w + C \sum_{i=1}^m \epsilon_i$$

$$y_1 (w \cdot x_1 + b) \geq 1 - \epsilon_1$$

$$\vdots$$

$$y_m (w \cdot x_m + b) \geq 1 - \epsilon_m$$

① separate

② large margin $\gamma = \frac{1}{\|w\|}$

③ soften margin: $\sum \epsilon_i$ is upper bound on # of training errors

$$\min_{w, b, \epsilon_i \geq 0} \frac{1}{2} w \cdot w + 10 \sum \epsilon_i$$

$$\text{s.t. } y_1 (w \cdot x_1 + b) \geq 1 - \epsilon_1$$

$$y_2 (w \cdot x_2 + b) \geq 1 - \epsilon_2$$

$$y_3 (w \cdot x_3 + b) \geq 1 - \epsilon_3$$

$$y_4 (w \cdot x_4 + b) \geq 1 - \epsilon_4$$

$$1 \left(\begin{pmatrix} 3 \\ 0 \\ 0 \end{pmatrix} \cdot \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix} + 0 \right) \geq 1 - 0$$

$$-1 \left(\begin{pmatrix} \dots \\ \dots \\ 1 \end{pmatrix} \cdot \begin{pmatrix} \dots \\ \dots \\ 1 \end{pmatrix} \right) \geq 1 - 2$$

① $\text{err}_S(h_{w_1, b_1}) = 2$ and $\sum \epsilon_i = 4$

$$\|w_1\| = \sqrt{w_1 \cdot w_1} = \sqrt{2} \rightarrow \gamma_1 = \frac{1}{\sqrt{2}} = \frac{1}{\|w_1\|} = 0.71$$

\rightarrow underfitting

② $\text{err}_S(h_{w_2, b_2}) = 0$ and $\sum \epsilon_i = 0$

$$\|w_2\| = \sqrt{4} \rightarrow \gamma_2 = \frac{1}{2}$$

③ $\text{err}_S(h_{w_3, b_3}) = 0$ and $\sum \epsilon_i = 0$

$$\|w_3\| = \sqrt{2} \rightarrow \gamma_3 = \frac{1}{\sqrt{2}} = 0.71$$

④ $\text{err}_S(h_{w_4, b_4}) = 0$ and $\sum \epsilon_i = 0$

$$\|w_4\| = \sqrt{3} \rightarrow \gamma_4 = \frac{1}{\sqrt{3}} = 0.58$$

⑤ $\text{err}_S(h_{w_5, b_5}) = 0$ and $\sum \epsilon_i = 0$

$$\|w_5\| = \sqrt{1.815} \rightarrow \gamma_5 = 0.74$$

⑥ $\|w_6\| = \sqrt{1.33} \rightarrow \gamma_6 = 0.87$

$$w_{\text{final}} = 0 + \gamma_1 x_1 + \gamma_5 x_5 + \gamma_{18} x_{18} + \gamma_5 x_5 + \gamma_{23} x_{23}$$

Updates: 1, 5, 18, 5, 23

$$\rightarrow w_k = \sum_{j=1}^m \text{"Number of updates on } (x_j, y_j)\text{"} \cdot y_j \cdot x_j$$

Idea:

- Do not store w , but record update steps

- store \mathcal{L}_i to contain "Number of updates on (x_i, y_i) "

$$(w_k \cdot x_i) = \left[\sum_{j=1}^m \alpha_j y_j x_j \right] \cdot x_i = \sum_{j=1}^m \alpha_j y_j (x_j \cdot x_i)$$

Two equivalent representations

- Primal: w, b
- Dual: $\alpha_1 \dots \alpha_m$ and $(x_1, y_1) \dots (x_m, y_m)$

$$+ \alpha_i = 0 \quad + \alpha_i = 0$$

$$+ \alpha_i = 0 \quad + \alpha_i \leq C$$

$$+ \alpha_i \leq C$$

$$0 \leq \alpha_i \leq C$$

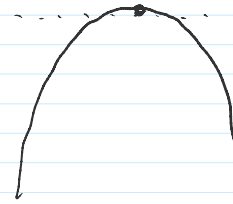
$$- \alpha_i = 0$$

$$- \alpha_i = 0 \quad + \alpha_i = C$$

Computing b :

find some (x_i, y_i) with $0 < \alpha_i < C$:

$$y_i (w \cdot x_i + b) = 1 \rightarrow b = y_i - x_i \cdot w$$



Theorem: If $P(w^*, b^*, \xi^*)$ is solution of Primal and $D(\alpha^*)$ is solution of Dual, then $P(w^*, b^*, \xi^*) = D(\alpha^*)$

Theorem: The leave-one-out error of an SVM is bounded by

$$\text{err}_{loo}(\text{SVM}) = \frac{\text{\# of Support Vectors}}{n}$$

\rightarrow small number of Support Vectors means that estimated generalization error is low!