

# Support Vector Machines (SVM)

$$T = \{(x_1, y_1), \dots, (x_N, y_N)\}$$

$$x_i \in \mathbb{R}^D$$

$$y_i \in \{-1, +1\}$$

$$d_i(w, b) = \frac{(w^T x_i + b) y_i}{\|w\|} \quad \text{"signed" distance}$$

$$(w^*, b^*) = \arg \max_{w, b} \min_i d_i$$

$$\text{s.t. } (w^T x_i + b) y_i > 0 \quad \forall i$$

$$(w^*, b^*) = \arg \max_{w, b, d} d$$

$$\text{s.t. } \frac{(w^T x_i + b) y_i}{\|w\|} \geq d \quad \forall i$$

2d = margin

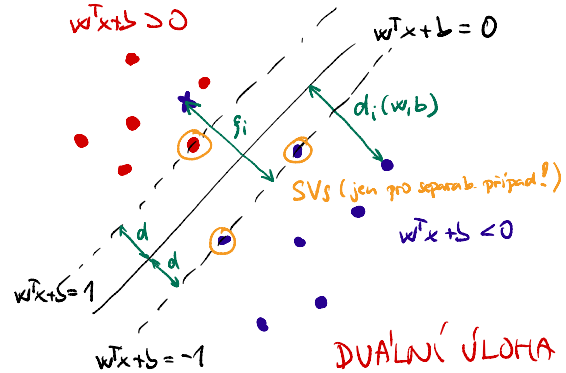
$$\min_i d_i \rightarrow \max d$$

$$\text{s.t. } d \leq d_i \quad \forall i$$

optimalni optimalni

$$(w, b) \rightarrow (sw, sb) \quad s > 0$$

$$d_i(sw, sb) = \frac{(sw^T x_i + sb) y_i}{\|sw\|} = \frac{s(w^T x_i + b) y_i}{s \|w\|}$$



DUALNÍ ÚLOHA

$\|w\| = 1$  let

$$(w^*, b^*) = \arg \max_{w, b} \frac{1}{\|w\|} = \arg \min_{w, b} \frac{1}{2} \|w\|^2$$

$$\text{s.t. } (w^T x_i + b) y_i \geq 1$$

nesep. data

$$(w^*, b^*) = \arg \min_{w, b} \frac{1}{2} \|w\|^2 + C \sum_i \xi_i$$

$$\text{s.t. } (w^T x_i + b) y_i \geq 1 - \xi_i \quad \forall i$$

$$\xi_i \geq 0 \quad \forall i$$

PRIMAŘNÍ ÚLOHA

support vectors

$$SV = \{i : 0 < \alpha_i \leq C\}$$

$$w^* = \sum_{i \in SV} \alpha_i y_i x_i$$

$$b^* = \frac{1}{|I|} \sum_{i \in I} (y_i - \sum_{j \in I} \alpha_j y_j x_j^T x_i)$$

$$I = \{i : 0 < \alpha_i < C\}$$

↑  
může být  $I = \emptyset$ !

převážně

$$\alpha^* = \arg \max_{\alpha} \sum_{i=1}^N d_i - \frac{1}{2} \sum_{i=1}^N \sum_{j=1}^N \alpha_i \alpha_j y_i y_j x_i^T x_j$$

$$\text{s.t. } \sum_{i=1}^N d_i y_i = 0$$

$$0 \leq \alpha_i \leq C \quad \forall i$$

DÚ: přečíst exercise 4

(viz text cvičení)

klasifikace:

$$q(x) : \sum_{i=1}^N \alpha_i y_i x_i^T x + b^* \geq 0$$

$$R_{\text{emp}}(q(x)) = \frac{1}{N} \sum_{i=1}^N w(q(x_i), y_i) \quad \text{empirické riziko}$$

## PERCEPTRON

$v^T x$

$$\underbrace{w^T x_i}_{z_i} \leq 0 \rightarrow \text{chyba}$$

$$\tilde{R}_p(w) = \sum_{\substack{i=1 \\ w^T x_i \leq 0}}^N -w^T x_i = \sum_{i=1}^N \max(-w^T x_i, 0)$$

## LOG. REGRESSE

$$E(w) = \sum_{i=1}^N \ln(1 + e^{\overbrace{-y_i w^T x_i}^{z_i}})$$

diferencovatelné  $\rightarrow$  GD

## SVM

$$(w^*, b^*) = \underset{w, b}{\operatorname{argmin}} \frac{1}{2} \|w\|^2 + C \sum_i \xi_i$$

$$\text{s.t. } (w^T x_i + b) y_i \geq 1 - \xi_i \quad \forall i$$

$$\xi_i \geq 0 \quad \forall i$$

fix:  $\xi_j$  pro  $j \neq i$ ,  $w, b$

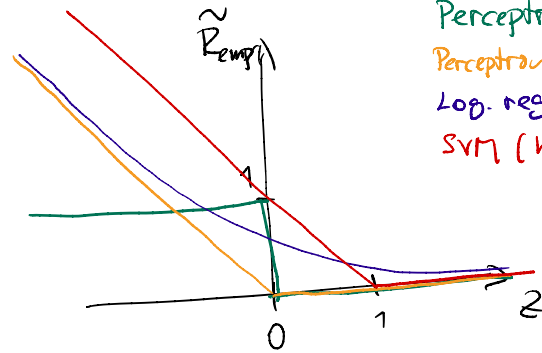
optimalní  $\xi_i$ ?

$$\min_{\xi_i} \xi_i + \left[ \frac{1}{2} \left( \sum_{i=1}^N \xi_i + \frac{1}{2} \|w\|^2 \right) \right] \text{const}$$

$$\xi_i \geq 1 - \underbrace{(w^T x_i + b) y_i}_{z_i}$$

$$\xi_i \geq 0$$

$$\xi_i^* = \max(0, 1 - z_i)$$



Perceptron

Perceptron opt.

Log. regrese

SVM (hinge loss)