

CS4780 Lec 24 - kernel SVM

Linear

$$\min_w \sum_{i=1}^n (w^T x_i - y_i)^2$$

$$\min_w (X^T w - y^T)^2$$

with $w = X\alpha = \sum_{i=1}^n \tilde{x}_i \alpha_i$

$$\min_w \left(\underbrace{X^T X}_{K} \alpha - y^T \right)^2$$

$$\min_{\alpha} (K\alpha - y^T)^2$$

$$X = [x_1 \dots x_n]$$

$$y = [y_1 \dots y_n]$$

$$[X^T X]_{ij} = \tilde{x}_i^T \tilde{x}_j$$

$$\begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix}$$

$$\begin{bmatrix} x_1 & x_n \end{bmatrix}$$

complete square

$$\alpha^T K^T K \alpha - 2y^T K \alpha + y^T y$$

minimize

$$\frac{\partial}{\partial \alpha} \Rightarrow 2KK\alpha - 2K^T y^T = 0$$

$$KK\alpha = K^T y^T \quad] \times K^{-1}$$

$$K\alpha = y^T \quad] \times K^{-1}$$

$$\boxed{\alpha = K^{-1} y^T}$$

— No feature importance

Test point:

$$h(z) = w^T z$$

$$= \alpha^T X^T z$$

$$= \underbrace{\alpha^T K}_{K*} z$$

Back to linear classifier during test time
back to n-dimension (dim. of α)

$X^T z$ = inner product to test point z with every

$$K* = \sum x_i^T z \quad \left. \begin{array}{l} \text{single} \\ \text{point } z \\ \text{in} \\ \text{training} \\ \text{data} \end{array} \right\}$$

$$= k(z, x_i)$$

Parametric algorithm - Fixed size of parameter learned.

If more data, you don't learn more parameters.

Non-parametric algo - Model size grows as training data grows
eg. k-NN

SVM:

$$\min_{w, b} w^T w + C \sum_{i=1}^n \xi_i$$

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

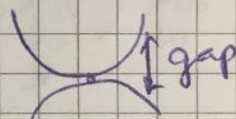
$$\xi_i \geq 0$$

Kernelized version:

Every convex has a dual

minimum has exactly same pt. as maximum
in dual space

primal - dual gap
minimize to zero



$$\min_{\alpha_1, \dots, \alpha_n} \frac{1}{2} \sum_{i,j} \alpha_i \alpha_j y_i y_j k_{ij} - \sum \alpha_i$$

inner product

$$\text{s.t. } 0 \leq \alpha_i \leq C$$

$$\sum_{i=1}^n \alpha_i x_i = 0$$

only those points that
lie on margin have
non zero ~~alpha~~

Solve for w

$$w = \sum_{i=1}^n \alpha_i y_i x_i$$

hypothesis test

$$h(z) = w^T z + b$$

$$= \sum_{i=1}^n \alpha_i y_i k(x_i, z) + b$$