

Recap: Dual form of SVM:

$$\hookrightarrow \min_{\underline{\alpha}} \underbrace{\frac{1}{2} \sum_{n,m} \alpha_n \alpha_m y_n y_m \underline{x}_n^T \underline{x}_m}_{-L(\underline{\alpha})} - \sum_{n=1}^N \alpha_n$$

$$\text{s.t. } \alpha_n \geq 0, \forall n$$

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

$$\text{QP solver} \rightarrow \underline{\alpha}^*$$

$$\hookrightarrow \text{Then } \underline{w}^* = \sum_{n=1}^N \alpha_n^* y_n \underline{x}_n = \sum_{\{n: \alpha_n^* > 0\}} \alpha_n^* y_n \underline{x}_n$$

$$b^* = y_s - \sum_{\{n: \alpha_n^* > 0\}} y_n \alpha_n^* \underline{x}_n^T \underline{x}_s, \text{ for some SV } \{\underline{x}_s, y_s\}$$

\hookrightarrow Decision rule:

$$\hat{y} = \text{sign}(\underline{w}^{*T} \underline{x} + b^*)$$

$$\underline{w}^{*T} \underline{x} = \sum_n \alpha_n^* y_n \underline{x}_n^T \underline{x}$$

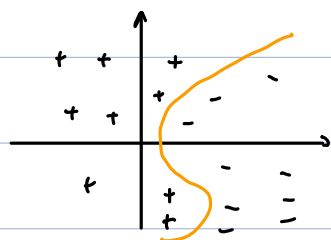
\hookrightarrow key observation:

Dual problem and decision rule depends on $\{\underline{x}_1, \dots, \underline{x}_N\}$

only through $\underline{x}_n^T \underline{x}_m$

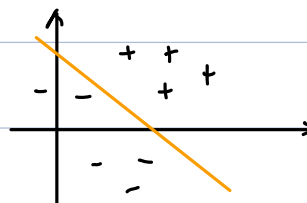
1. SVM and non-linear transform: (ch 8.3)

e.g.



$$\underline{z} = (1, x_1, x_2, x_1^2, x_2^2, x_1 x_2)$$

(quadratic transform)



z-space

↳ In z-space:

$$\mathcal{L}(\underline{\alpha}) = -\frac{1}{2} \sum_{n=1}^N \sum_{m=1}^N y_n y_m \alpha_n \alpha_m \underline{z}_n^T \underline{z}_m + \sum_{n=1}^N \alpha_n$$

Computing of QP: $\mathbf{Q} \in \mathbb{R}^{N \times N}$

essentially unchanged!

Higher dimensional $\underline{z} \equiv$ better fit into dataset

SVM built-in defense against over-fitting.

↳ But is it costly to compute $\underline{z}_n^T \underline{z}_m$?

"kernel" $\triangleq k(\underline{x}_n, \underline{x}_m)$

⇒ Can we compute the kernel $k(\underline{x}_n, \underline{x}_m)$ w/out computing \underline{z}_n or \underline{z}_m ?

⇒ "kernel method"

2. kernel Method:

① Polynomial kernel

e.g. $k(\underline{x}, \underline{x}') = (1 + \underline{x}^T \underline{x}')^2$

// $d=2$, $\underline{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$

$$= (1 + x_1 x_1' + x_2 x_2')^2$$

$$= 1 + x_1^2 x_1'^2 + x_2^2 x_2'^2 + 2x_1 x_1' + 2x_2 x_2' + 2x_1 x_1' x_2 x_2'$$

$$= \underline{z}^T \underline{z}' \text{ if}$$

$$\underline{z} = (1, x_1^2, x_2^2, \sqrt{2} x_1, \sqrt{2} x_2, \sqrt{2} x_1 x_2)$$

$$\underline{z}' = (1, x_1'^2, x_2'^2, \sqrt{2} x_1', \sqrt{2} x_2', \sqrt{2} x_1' x_2')$$

Identical to quadratic transform w/ properly re-scaled \underline{w} .

↳ General polynomial kernel:

$$\text{Use } k(\underline{x}, \underline{x}') = (1 + \underline{x}^T \underline{x}')^Q \quad // Q \text{ means integer}$$

$$= (1 + x_1 x_1' + \dots + x_d x_d')^Q \quad // Q\text{-th polynomial}$$

= inner product of Q -th order polynomial

By running SVM:

$$\mathcal{J}(\underline{\alpha}) = -\frac{1}{2} \sum_{n=1}^N \sum_{m=1}^N y_n y_m \alpha_n \alpha_m \underline{k}(\underline{x}_n, \underline{x}_m) + \sum_{n=1}^N \alpha_n$$

$$\hat{y} = \text{sign} \left(\sum_n \alpha_n y_n \underline{k}(\underline{x}_n, \underline{x}) + b \right)$$

$$b = y_s - \sum_n \alpha_n y_n \underline{k}(\underline{x}_n, \underline{x}_s)$$

② Fancier kernel:

$$k(\underline{x}, \underline{x}') = e^{-r(\|\underline{x} - \underline{x}'\|^2)}, \text{ for some const } r > 0$$

Fact: z -space is infinite dimensional

e.g. $r=1, d=1$

$$k(x, x') = e^{-(x-x')^2} = e^{-x^2} e^{-x'^2} e^{2xx'}$$

$$= e^{-x^2} e^{-x'^2} \sum_{k=0}^{\infty} \frac{2^k x^k x'^k}{k!} \quad \leftarrow \text{Taylor expansion}$$

$$\therefore \underline{z} = e^{-x^2} \left[1, \frac{\sqrt{2}x}{\sqrt{1!}}, \frac{\sqrt{2}^2 x^2}{\sqrt{2!}}, \frac{\sqrt{2}^3 x^3}{\sqrt{3!}}, \dots \right]$$

$$\underline{z}' = e^{-x'^2} \left[1, \frac{\sqrt{2}x'}{\sqrt{1!}}, \dots \right]$$