(11) SVM - 'Kernel Trick' Based Formulation :

Kernel SVM'S :

$$\min \begin{cases} \frac{1}{2} w^T w + C \sum_i \varepsilon_i \\ y_i (w^T x_i + b) \geq 1 - \varepsilon_i \end{cases}$$

In circular classification

$x_i \rightarrow \phi(x_i)$ { computationally expensive

Now

$$\left[y_i (w^T \phi(x_i) + b) \geq 1 - \varepsilon_i \right]$$

Another formulation :

⇒ CS229 Andrew NG :

(Formulation of SVM using the Lagrangian method)

$$\left[\begin{array}{l} \max \left(\sum_i \alpha_i - \frac{1}{2} \sum_{i,j} \alpha_i \alpha_j y_i y_j \phi(x_i)^T \phi(x_j) \right) \\ \sum_i \alpha_i y_i = 0 \end{array} \right]$$

(T = Transpose)

for calculation of ● Kernel Trick is introduced

- Kernel Trick :

Kernel has following properties :

$$K(x_i, x_j) = \phi(x_i)^T \cdot \phi(x_j)$$

Projected vector for ith example

Projected vector for jth example

Three types of kernel provided by SVM :

1. Linear Kernel
2. Radial Basis function Kernel (RBF)
3. Polynomial
4. Sigmoid

$$x \rightarrow \phi(x)$$

1. Radial Basis Kernel

$$K(x_i, x_j) = e^{-\gamma |x_i - x_j|^2}$$

γ : Amplitude

② Polynomial kernel :

$$k(x_i, x_j) = (\gamma x_i^T \cdot x_j + r)^c$$

c = degree of polynomial

③ Sigmoid kernel.

$$k(x_i, x_j) = \frac{1 - e^{-2(\gamma x_i \cdot x_j + r)}}{1 + e^{-2(\gamma x_i \cdot x_j + r)}}$$