<u>Machine Learning</u> 24/11/2014

<u>HW3</u>

(3) from SVM

We know that for dual rep.

$$\operatorname{argmax}_{\lambda} \sum_{n=1}^{N} \lambda_n - \frac{1}{2} \sum_{ij} \lambda_i \lambda_j y_i y_j x_i^T x$$

from the dual Lagrangian form:

$$\sum_{n=1}^{N} \lambda_n - \frac{1}{2} \sum_{n=1}^{N} \sum_{m=1}^{M} \lambda_n \lambda_m y_n y_m x_m^T x_n$$

$$0 < \lambda_n \leq C$$

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

for $K_1(x_1 : x_2)$ this will be

$$\sum_{n=1}^{N} \lambda_n - \frac{1}{2} \sum_{n=1}^{N} \sum_{m=1}^{M} \lambda_n \lambda_m y_n y_m K_1(x_1 : x_2) \quad -($$

$$0 < \lambda_n \leq C$$

$$\sum_{n=1}^{N} \lambda_n y_m = 0$$

for $K_2(x_1 : x_2) = 1 + K_1(x_1 : x_2)$ this will be

$$\sum_{n=1}^{N} \lambda_n - \frac{1}{2} \sum_{n=1}^{N} \sum_{m=1}^{M} \lambda_n \lambda_m y_n y_m K_2(x_1 :$$

$$\Rightarrow \sum_{n=1}^{N} \lambda_n - \frac{1}{2} \sum_{n=1}^{N} \sum_{m=1}^{M} \lambda_n \lambda_m y_n y_m (1 + K_1(x_1 :$$

$$\Rightarrow \sum_{n=1}^{N} \lambda_n - \frac{1}{2} \sum_{n=1}^{N} \sum_{m=1}^{M} y_n y_m \lambda_n \lambda_m - \frac{1}{2} \sum_{n=1}^{N} \sum_{m=1}^{M} y_n y_m \lambda_n \lambda_m K(x_n, x_m)$$

$$0 \le \lambda_n \le 1$$

$$\sum_{n=1}^{N} \lambda_n y_n = 0 \qquad \text{— (2)}$$

The only difference in (1) & (2) is $\Rightarrow$

$$(1) - (2) = -\frac{1}{2} \sum_{n=1}^{N} \sum_{m=1}^{N} y_n y_m \lambda_n \lambda_m \qquad \text{— (3)}$$

As the common constraint is $\sum_{n=1}^{N} y_n \lambda_n = 0$

from that the term at (3) becomes zero.

Hence there is no diff. & Sol^n are essentially equal.