ML Assignment 1 Ankit Kumar 170121 Chaitanya Pathare 19111061 Hemant Kumar 170297 Rahul Ninaji Pakhare 19111068 Raunak Kumar 19111069

1. Given equation

$$argmin_{w \in \mathbb{R}^d} \frac{1}{2} ||\mathbf{w}||_2^2 + C\Sigma_{i=1}^n ([1 - y^i < w, x^i >]_+)^2 \quad (P1)$$

rewritten as new optimization problem

$$argmin_{w \in \mathbb{R}^d} \frac{1}{2} ||\mathbf{w}||_2^2 + C\Sigma_{i=1}^n \xi_i^2$$

$$s.t.y^i < w, x^i > \geqslant 1 - \xi_i, for \quad all \quad i\epsilon[n] \quad (P2)$$

Introducing dual variable α_i for each of the constraints in (P2)

$$\therefore L(w,\xi,\alpha) = \frac{1}{2} ||\mathbf{w}||_2^2 + C\sum_{i=1}^n \xi_i^2 + \sum_{i=1}^n \alpha_i (1 - \xi_i - y^i < w, x^i >)$$
 (P3)

2. To get the dual problem from the above equation (P3) put $\frac{\eth L}{\eth w}=0$ and $\frac{\eth L}{\eth \xi}=0$

$$\frac{\partial L}{\partial w} = ||\mathbf{w}|| - \sum_{i=1}^{n} \alpha_i x_i = 0$$

$$or \quad ||\mathbf{w}|| = \sum_{i=1}^{n} \alpha_i x^i$$

and

$$\frac{\partial L}{\partial \xi} = 2C\xi_i - \sum_{i=1}^n \alpha_i = 0$$

$$or \quad \xi_i = \frac{1}{2C} \sum_{i=1}^n \alpha_i$$

Optimization problem comes down to

$$= \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} (\alpha_{i} \alpha_{j} y^{i} y^{j} < x^{i} x^{j} >) + \frac{1}{4C} \sum_{i=1}^{n} \alpha_{i}^{2} + \sum_{i=1}^{n} \alpha_{i} - \frac{1}{2C} \sum_{i=1}^{n} \alpha_{i}^{2} - \sum_{i=1}^{n} \sum_{j=1}^{n} (\alpha_{i} x^{i} y^{j}) (\alpha_{j} x^{j} y^{j}))$$

$$= argmin(\Sigma_{i=1}^n \alpha_i - \frac{1}{4C}(\Sigma_{i=1}^n \alpha_i^2) - \frac{1}{2}\Sigma_{i=1}^n \Sigma_{j=1}^n (\alpha_i \alpha_j y^i y^j < x^i x^j >)) \quad (D2)$$

All above
$$\mathbf{w} \epsilon R^{d+1}$$
, $\mathbf{x} \epsilon R^{d+1}$

a. Stochastic coordinate descent Given,

P1
$$f = argmin_{w \in \mathbb{R}^d} \frac{1}{2} ||\mathbf{w}||_2^2 + C\sum_{i=1}^n ([1 - y^i < w, x^i >]_+)^2$$

now get gradient for P1

$$\nabla f = ||\mathbf{w}|| + 2C\sum_{i=1}^{n} ([1 - y^{i} < w, x^{i} >]_{+})(-y^{i}x^{i})$$

Note:
$$[1 - y^i < w, x^i >]_+ = \{(1 - y^i < w, x^i >) | if y^i < w, x^i >< 1$$

$$0 \quad if \quad y^i < w, x^i >\geqslant 1\}$$

iterate till the time end for the X

- do 1.find gradient for each data point in the given Batch set B 2.update w for these $w = w - \eta 2C\sum_{i=x}^{x+B} ([1-y^i < w, x^i >]_+)(-y^i x^i)$
- c. Method used for D2 minimization

$$D2 = sargmin(\sum_{i=1}^{n} \alpha_i - \frac{1}{4C}(\sum_{i=1}^{n} \alpha_i^2) - \frac{1}{2}\sum_{i=1}^{n} \sum_{j=1}^{n} (\alpha_i \alpha_j y^i y^j < x^i x^j >))$$

concentrate on α_i

$$argmin(\alpha_i - \frac{1}{4C}(\alpha_i^2) - (\Sigma_{i \neq j}\alpha_j^2) - \frac{1}{2}(\alpha_i^2||x^i||^2) - \alpha_i y^i \Sigma_{i \neq j}(\alpha_j y^j < x^i x^j >))$$

Let
$$x = \alpha_i$$
, $q = ||x^i||^2$, $p = y^i \Sigma_{i \neq j} (\alpha_j y^j < x^i x^j >)$, $r = (\Sigma_{i \neq j} \alpha_j^2)$

$$\therefore argmin(x^2(\frac{1}{2}q+\frac{1}{4C})-x(1-p)+r)$$

Let
$$\frac{q^0}{2} = (\frac{q}{2} + \frac{1}{4C})$$
 : $argmin(\frac{q^0}{2}x^2 - x(1-p) + r)$

minimum at $x^m = \frac{(1-p)}{q^0}$ If $x^m \epsilon[0, \propto]$ then x^m is solution

elseif $x^m < 0$ solution is 0

else solution is \propto or Not defined.

Note:

$$p = y^i \Sigma_{i \neq j} (\alpha_j y^j < x^i x^j >)$$

$$= w^T \mathbf{x}^i - \alpha_i y^i q^0$$

Algorithm minimize:

intialize
$$\alpha^T = \{0, 0, \dots, 0\}_{1Xn}$$
 $w = \{0, 0, \dots, 0\}_{1Xn}$

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

Note: We have appended one extra dimension to our data i.e if $X = \begin{bmatrix} x_{11} & x_{12} & x_{13} & \dots & x_{1n} \\ x_{21} & \dots & \dots & x_{2n} \\ \dots & \dots & \dots & \dots \\ x_{n1} & \dots & \dots & x_{nn} \end{bmatrix}$

and then transformed $X \to X^0 = \begin{bmatrix} x_{11} & x_{12} & x_{13} & . & x_{1n} & 1 \\ x_{21} & . & . & . & . & x_{2n} & 1 \\ . & . & . & . & . & . & 1 \\ . & . & . & . & . & . & 1 \\ . & . & . & . & . & . & . & 1 \\ x_{n1} & . & . & . & . & . & x_{nn} & 1 \end{bmatrix}$

so that w[d-1] = b, d is dimension of each data point in X^0 iterate till time does not end, for each data point in X^0

Do - 1. Calculate
$$\alpha_i$$
 if $\alpha_i \ge 0$ then $\alpha[i] = \alpha_i$ else $\alpha[i] = 0$

2. Update w $w = \sum_{i=1}^{n} \alpha_i y_i x^i$ w will converge after sufficient number of iteration.