Support Vector Machine Vectorized proof

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Abstract

This is the proof of the vectorized form of SVM, I do this with lots of Matrix Math, I hope you like my latex skills

1 proof

$$loss = \frac{1}{N} \sum_{i=0}^{N-1} loss_i + \lambda \|W\|_2$$
 (1)

$$loss_i = \sum_{k=0}^{C-1} T_{ik} \tag{2}$$

$$T_{ik} = \begin{cases} 0 & , margin_{ik} \le 0 \\ S_{ik} - S_{iy_j} + 1 & , margin_{ik} > 0 \end{cases}$$
 (3)

(4)

Where

$$margin_{ik} = S_{ik} - S_{iy_i} + 1 \tag{5}$$

(6)

And

$$S_{ik} = X_i W_k \tag{7}$$

$$W_k \to \text{k-Coloum vector of W matrix}$$
 (8)

$$W_k = W u_k \tag{9}$$

$$u_k \to \text{Unit coloum vector in direction of k}$$
 (10)

$$S_{ik} = X_i W u_k \tag{11}$$

$$\nabla_W loss = \frac{1}{N} \nabla_W loss_i + \lambda \nabla_W ||W||_2^2$$
 (12)

$$\nabla_W ||W||_2^2 = 2W \tag{13}$$

$$\nabla_W T_{ik} = \begin{cases} 0 &, margin_{ik} \le 0 \\ \nabla_W S_{ik} - \nabla_W S_{iy_j} &, margin_{ik} > 0 \end{cases}$$
 (14)

$$(\nabla_W)_{lm} = \frac{\partial}{\partial W_{lm}} \tag{15}$$

$$(\nabla_W S_{ik})_{lm} = \frac{\partial}{\partial W_{lm}} (X_i W u_k)$$

$$= X_i \frac{\partial}{\partial W_{lm}} (W u_k)$$

$$= X_i \frac{\partial}{\partial W_{lm}} (u_k^T W^T)$$

$$= X_i u_k^T \frac{\partial}{\partial W_{lm}} (W^T)$$
(16)

$$\frac{\partial}{\partial W_{lm}} \left(W^T \right) = \omega_{lm}^T \tag{17}$$

Where ω_{lm} is a matrix full of zeros except at $index_{lm}$ which is 1 from ... in ...

$$X_i u_k^T \omega_{lm}^T = X_i \omega_{lm} u_k \tag{18}$$

$$\omega_{lm}u_k = \begin{cases} 0 & k \neq l \\ u_m & k = l \end{cases} \tag{19}$$

$$X_i \omega_{lm} u_k = \begin{cases} 0 & k \neq l \\ X_i u_m = X_{im} & k = l \end{cases}$$
 (20)

Where X_{im} is mth element in X_i

So
$$\nabla_W (S_{ik}) = \begin{bmatrix} 0 & 0 & | & 0 \\ 0 & 0 & X_i & 0 \\ 0 & 0 & | & 0 \\ 0 & 0 & k_{th} - col & 0 \end{bmatrix}$$
 (21)

Simlarly
$$\nabla_W (S_{y_j}) = \begin{bmatrix} 0 & 0 & | & 0 \\ 0 & 0 & X_i & 0 \\ 0 & 0 & | & 0 \\ 0 & 0 & y_{j-th}col & 0 \end{bmatrix}$$
 (22)

$$So \nabla_{W} T_{ik} = \begin{cases} \begin{bmatrix} | & 0 & | & 0 \\ X_{i} & 0 & X_{i} & 0 \\ | & 0 & | & 0 \\ k_{th} - col & 0 & y_{j-th} - col & 0 \end{bmatrix}, margin_{ik} \leq 0 \\ \text{zero-matrix}, margin_{ik} > 0 \end{cases}$$
(23)

$$\nabla_{W} loss_{i} = \begin{bmatrix} & & & 0 & & & & 0 \\ X_{i} \text{ if } morgin_{ik} > 0 \text{ else zeros} & 0 & -m_{i}X_{i} & 0 \\ & & & 0 & & & 0 \\ k_{th} - col & & 0 & y_{j-th} - col & 0 \end{bmatrix}$$
(24)

Where m_i is the number of $margin_{ik}$ in ith example that is greater than zero, So we can assume C the cost matrix where C_{ic} corresponds to the ith example and cth class cost where

$$C_{in} = \begin{cases} -m_i & n = y_j \text{ n is the correct label for } example_i \\ 1 & margin_{in} > 0 \\ 0 & \text{otherwise} \end{cases}$$
 (25)

$$\left(\sum_{i}^{N} \nabla_{W} loss_{i}\right)_{lm} = \sum_{i}^{N} C_{im} X_{il}$$
(26)

(27)

So
$$\sum_{i}^{N} \nabla_{W} loss_{i} = X^{T} C$$
 (28)

So the final loss expression
$$\nabla_W loss = \frac{1}{N} (X^T C) + 2\lambda W$$
 (29)

How about this (1) Equation label