

①

$$a) (A^T A + \lambda I) A^T = A^T A A^T + \lambda A^T = A^T (A A^T + \lambda I)$$

$$\therefore (A^T A + \lambda I) A^T = A^T (A A^T + \lambda I)$$

$$\therefore A^T (A A^T + \lambda I)^{-1} = (A^T A + \lambda I)^{-1} A^T$$

b) The LHS of the formula computes more rapidly.

Since  $(A^T A + \lambda I)^{-1}$  is a pseudo-inverse of  $A$ , it has dimension  $A^{-1} \in \mathbb{R}^{100 \times 8000}$ , where  $A \in \mathbb{R}^{8000 \times 100}$

$\therefore$  Computing  $\mathbb{R}^{8000 \times 100} \times \mathbb{R}^{100 \times 8000}$  is faster than  $\mathbb{R}^{8000 \times 100} \times \mathbb{R}^{100 \times 8000}$ .

$$(i) \text{ suppose } G^T = \begin{bmatrix} y_1^T \\ \vdots \end{bmatrix}$$

$$\therefore \text{sol} = \min_w \| \text{sign}(G^T w) - y \|_2^2$$

It has a unique solution iff  $G$  is full-rank, which is unlikely to be the case for real data.

$$(c: i) \min_w \| \text{sign}(G w - y) - y \|_2^2 + \lambda \| w \|_2^2$$

the LHS is more computationally efficient.

②

$$a) w^{(k+1)} = \arg \min_{w_i, i=1, \dots, M} \sum_{i=1}^M (z_i^{(k)} - w_i)^2 + \lambda \tau w_i^2$$

$$b) w^{(k+1)} = \arg \min_{w_i, i=1, \dots, M} \sum_{i=1}^M (z_i^{(k)} - w_i)^2 + \lambda \tau |w_i|.$$

③.