

Machine Learning - Assignment 3

Sudip Sinha

May 2, 2014

Exercise 2

Given

- $VV^T = V^TV = I$
- D is an invertible diagonal matrix

Proof

Let $B = VD^{-1}V^T$

- $AB = VDV^TV D^{-1}V^T = VD(V^TV)D^{-1}V^T = VDID^{-1}V^T = V(DD^{-1})V^T = VIV^T = I$
- $BA = VD^{-1}V^TV DV^T = VD^{-1}(V^TV)DV^T = VD^{-1}IDV^T = V(D^{-1}D)V^T = VIV^T = I$

Thus, $A^{-1} = B = VD^{-1}V^T$.

Exercise 3

We just have to show that the square of the norm is a convex function.

By the definition of norm,

$$\begin{aligned} \|tx + (1-t)y\| &\leq \|tx\| + \|(1-t)y\| = t\|x\| + (1-t)\|y\| \\ \implies \|tx + (1-t)y\|^2 &\leq (t\|x\| + (1-t)\|y\|)^2 \leq t^2\|x\|^2 + (1-t)^2\|y\|^2 \end{aligned}$$

Thus, the least squares loss function $\|y - Xw\|^2$ is a convex function of w .

Exercise 4

Let $W = \text{diag}(r_i)$. Therefore, $W^T = W$

Thus, the problem can be reformulated as

$$w = \arg \min_w (e), \text{ where } e = (y - Xw)^T W (y - Xw)$$

Using the rules of Matrix Calculus given [here](#):

$$\begin{aligned} \frac{\partial e}{\partial w} &= (y - Xw)^T W \frac{\partial}{\partial w} (y - Xw) + (y - Xw)^T W^T \frac{\partial}{\partial w} (y - Xw) \\ &= 2(y - Xw)^T W^T (-X) \quad (\text{Since } W^T = W) \\ &= 2(X^T W (Xw - y))^T \end{aligned}$$

For minimum error:

$$\begin{aligned} \frac{\partial e}{\partial w} &= 0^T \\ \implies 2(X^T W (Xw - y))^T &= 0^T \\ \implies X^T W (Xw - y) &= 0 \\ \implies X^T W Xw &= X^T y \\ \implies w &= (X^T W X)^{-1} X^T y \end{aligned}$$