

# ATML HW2 - written Exercises

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Q1)

Applying the Lagrange multiplier,  $L(x, y, \lambda) = f(x, y) - \lambda g(x, y)$ ,

We can define  $h(a) = a^T B a - \lambda (a^T W a - 1)$

Take derivative with respect to  $a$ ,

$$\frac{dh}{da} = (B + B^T)a - \lambda(W + W^T)a$$

Let it equal to 0, then we have  $[(W + W^T)]^{-1}(B + B^T)a = \lambda a$ ,

which is the standard eigenvalue problem. Assuming  $W$  and  $B$  symmetric, we have  $W^{-1}B a = \lambda a$ .

Q2a)

From equation 4.11 in HTF, the LDA rule classifies to class 2

$$\text{if } \mathcal{L}^T \hat{\Sigma}^{-1}(\hat{\mu}_2 - \hat{\mu}_1) > \frac{1}{2} \hat{\mu}_2^T \hat{\Sigma}^{-1} \hat{\mu}_2 - \frac{1}{2} \hat{\mu}_1^T \hat{\Sigma}^{-1} \hat{\mu}_1 + \log\left(\frac{N_1}{N}\right) - \log\left(\frac{N_2}{N}\right)$$

Q2b)

By least squares criterion,

$$\sum_{i=1}^N (y_i - \beta_0 - \beta^T x)^2 = (Y - \beta_0 \mathbf{1} - X\beta)^T (Y - \beta_0 \mathbf{1} - X\beta)$$

$$2X^T X \beta - 2X^T Y + 2\beta_0 X^T \mathbf{1} = 0$$

$$2N\beta_0 - 2\mathbf{1}^T(Y - X\beta) = 0$$

$$\hat{\beta}_0 = \frac{1}{N} \mathbf{1}^T (Y - X\beta)$$

Q2d)

If the results calculated in 2b are arbitrary and distinct, the result holds.

Q3.

$$M = \begin{bmatrix} 1 & 0 & 3 \\ 3 & 7 & 2 \\ 2 & -2 & 8 \\ 0 & -1 & 1 \\ 5 & 8 & 7 \end{bmatrix}$$

a)

$$MM^T = \begin{bmatrix} 10 & 9 & 26 & 3 & 26 \\ 9 & 62 & 8 & -5 & 85 \\ 26 & 8 & 72 & 10 & 50 \\ 3 & -5 & 10 & 2 & -1 \\ 26 & 85 & 50 & -1 & 138 \end{bmatrix} \quad M^T M = \begin{bmatrix} 39 & 57 & 60 \\ 57 & 118 & 53 \\ 60 & 53 & 127 \end{bmatrix}$$

b)  $\text{eigval}(MM^T) = \text{solv}(\det(MM^T - I \cdot \lambda) = 0)$  ← same for  $M^T M$

$$\lambda_{MM^T} = \underset{\lambda_1}{214.7}, \underset{\lambda_2}{0}, \underset{\lambda_3}{69.3}, \underset{\lambda_4}{0}, \underset{\lambda_5}{0}$$

$$\lambda_{M^T M} = 214.7, 0, 69.3$$

c)  $\text{eigvec}(MM^T) = x_i | (MM^T - \lambda_i I) \cdot x_i = 0$  for each eigen  $\lambda$

$$X_{(MM^T)} = \begin{matrix} & x_1 & x_2 & x_3 & x_4 & x_5 \\ \begin{bmatrix} -0.165 & -0.955 & 0.245 & -0.065 & -0.107 \\ -0.472 & -0.035 & 0.453 & 0.750 & -0.047 \\ -0.336 & 0.271 & 0.829 & 0.328 & -0.174 \\ 0.003 & 0.044 & 0.169 & 0.046 & 0.971 \\ -0.798 & 0.104 & -0.133 & -0.568 & 0.119 \end{bmatrix} \end{matrix}$$

$\text{eigvec}(M^T M) = x_i | (M^T M - \lambda_i I) \cdot x_i = 0$  for each eigen  $\lambda$ :

$$X_{(M^T M)} = \begin{matrix} & x_1 & x_2 & x_3 \\ \begin{bmatrix} 0.426 & 0.904 & -0.015 \\ 0.615 & -0.302 & -0.729 \\ 0.663 & -0.302 & 0.685 \end{bmatrix} \end{matrix}$$

$$d) MM^T = (U \Sigma V^T)(U \Sigma V^T)^T = U \Sigma V^T \cdot U \Sigma V^T = U \Sigma^2 U^T$$

$$\Sigma(M) = \sqrt{\Sigma^2}$$

$$U(M) = \text{eigvec}(MM^T)$$

$$\Sigma = \begin{bmatrix} \sqrt{214.7} & 0 \\ 0 & \sqrt{69.3} \end{bmatrix} = \begin{bmatrix} 8.326 & 0 \\ 0 & 14.76 \end{bmatrix}$$

$\lambda_2, \lambda_4, \lambda_5 = 0$  so we can ignore them

$$U = \begin{bmatrix} | & | \\ v_1 & v_3 \\ | & | \end{bmatrix} = \begin{bmatrix} -0.244 & 0.165 \\ 0.453 & 0.471 \\ -0.829 & 0.336 \\ -0.169 & 0.003 \\ -0.133 & 0.798 \end{bmatrix}$$

$$M^T M = (U \Sigma V^T)^T (U \Sigma V^T) = V \Sigma U^T U \Sigma V^T = V \Sigma^2 V^T$$

$$V(M) = \text{eigvec}(M^T M)$$

$$V = \begin{bmatrix} - & v_1 & - \\ - & v_3 & - \end{bmatrix} = \begin{bmatrix} 0.015 & 0.728 & 0.685 \\ -0.426 & 0.615 & 0.663 \end{bmatrix}$$

$$e) \text{ Set } \Sigma_{\text{new}} = \begin{bmatrix} 14.65 & 0 \\ 0 & 0 \end{bmatrix} \text{ and compute } U \Sigma_{\text{new}} V^T$$

$$\hat{M} = U \Sigma_{\text{new}} V^T \cong \begin{bmatrix} 1 & 2 & 2 \\ 3 & 4 & 5 \\ 2 & 3 & 3 \\ 0 & 0 & 0 \\ 5 & 7 & 8 \end{bmatrix}$$