

$$1. (a). f(x) = \frac{1}{2} x^T A x + b^T x$$

CS229

$$\nabla_x f(x) = \nabla_x \left( \frac{1}{2} x^T A x \right) + \nabla_x (b^T x)$$

$$= \frac{\partial}{\partial x} \left[ \frac{1}{2} x^T A x \right] + b$$

$$= Ax + b$$

notes p 10.

$$(b). f(x) = g(h(x)) \quad g \text{ and } h \text{ are both differentiable.}$$

$$\nabla_x f(x) = g'(h(x)) \nabla h(x) \quad \text{chain rule.}$$

$$(c). \nabla^2 f(x) = \nabla (Ax + b)$$

$$= A$$

$$(d). f(x) = g(a^T x)$$

$$\nabla f(x) = \nabla (g(a^T x)) = g'(a^T x) \nabla (a^T x)$$

$$= g'(a^T x) a$$

$$= \begin{bmatrix} g'(\sum a_i x_i) a_1 \\ \vdots \\ g'(\sum a_i x_i) a_n \end{bmatrix}$$

$$\nabla^2 f(x) = \begin{bmatrix} g''(\sum a_i x_i) a_1 a_1 & g''(\sum a_i x_i) a_1 a_2 & \dots \\ g''(\sum a_i x_i) a_2 a_1 & g''(\sum a_i x_i) a_2 a_2 & \dots \\ \vdots & \vdots & \ddots \end{bmatrix}$$

$$= \begin{bmatrix} g''(\sum a_i x_i) a_1 a_1 & g''(\sum a_i x_i) a_1 a_2 & \dots \\ g''(\sum a_i x_i) a_2 a_1 & g''(\sum a_i x_i) a_2 a_2 & \dots \\ \vdots & \vdots & \ddots \end{bmatrix}$$

$$= \begin{bmatrix} g''(\sum a_i x_i) a_1 a_1 & g''(\sum a_i x_i) a_1 a_2 & \dots \\ g''(\sum a_i x_i) a_2 a_1 & g''(\sum a_i x_i) a_2 a_2 & \dots \\ \vdots & \vdots & \ddots \end{bmatrix}$$

$$= \begin{bmatrix} g''(\sum a_i x_i) a_1 a_1 & g''(\sum a_i x_i) a_1 a_2 & \dots \\ g''(\sum a_i x_i) a_2 a_1 & g''(\sum a_i x_i) a_2 a_2 & \dots \\ \vdots & \vdots & \ddots \end{bmatrix}$$

$$= g''(a^T x) a a^T$$

2.  $A$  is PSD.  $x^T A x \geq 0$  if all vectors  $x^T A x \geq 0$ ,  $A = A^T$   
 $A$  PD.  $A > 0$  if all vectors  $x^T A x > 0$ ,  $A = A^T$ .

$I$ . satisfies  $x^T I x = \|x\|_2^2 = \sum_{i=1}^n x_i^2$ .

(a).  $z \in \mathbb{R}^n$  is an  $n$ -vector.

$$A = z z^T$$

$$x^T A x = x^T (z z^T) x$$

$$= x^T z z^T x \quad \text{associative}$$

$$= x^T z x^T z$$

$$= (x^T z)^2 \geq 0.$$

(b).  $z \in \mathbb{R}^n$  non zero.  $n$ -vector

$$A = z z^T.$$

$$N(A) = \{x \in \mathbb{R}^n : A x = 0\}$$

$$z z^T x = 0.$$

Since  $z$  is nonzero,  $z^T x = 0$ .

$$N(A) = \{x \in \mathbb{R}^n : z^T x = 0\} \quad x \text{ is orthogonal to } z^T.$$

$$z^T \cdot z = z \cdot z^T \text{ is nonzero.}$$

$$\text{rank}(A) = n - \text{nul}(A)$$

$$= n - (n-1).$$

$$= 1.$$



(c)  $A$  PSD.  $x^T A x \geq 0$ ,  $A = A^T$ .  
 $B$  arbitrary.

$$\begin{aligned} x^T (B A B^T) x &= x^T B A B^T x \\ &= (x^T B) A (B^T x) \\ &= (B x^T) A (B^T x) \\ &= (B^T x)^T A (B^T x) \end{aligned}$$

$\therefore A$  is PSD.

$$\therefore (B^T x)^T A (B^T x) \geq 0.$$

$\therefore B A B^T$  is PSD.

3.  $A \in \mathbb{R}^{n \times n}$   $Ax = \lambda x$   
 $\uparrow$   
 eigenvalue

(a).  $\Lambda = \text{diag}(\lambda_1, \dots, \lambda_n)$

$$T = [t^{(1)} \ t^{(2)} \ \dots \ t^{(n)}]$$

show  $A t^{(i)} = \lambda_i t^{(i)}$

$$A = T \Lambda T^{-1}$$

$$AT = T \Lambda$$

$$A \begin{bmatrix} t^{(1)} \\ t^{(2)} \\ \dots \\ t^{(n)} \end{bmatrix} = \begin{bmatrix} t^{(1)} \\ t^{(2)} \\ \dots \\ t^{(n)} \end{bmatrix} \begin{bmatrix} \lambda_1 & & 0 \\ & \lambda_2 & \\ 0 & & \ddots \\ & & & \lambda_n \end{bmatrix}$$

$$\begin{bmatrix} A t^{(1)} \\ A t^{(2)} \\ \dots \\ A t^{(n)} \end{bmatrix} = \begin{bmatrix} \lambda_1 t^{(1)} & \lambda_2 t^{(2)} & \dots & \lambda_n t^{(n)} \end{bmatrix}$$

$$\therefore A t^{(i)} = \lambda_i t^{(i)}$$

(b).  $U$  is orthogonal if  $U^T U = I$ .

$A$  is symmetric if  $A = A^T$ .

$$U^T A U = \Lambda$$

$$A = U \Lambda U^T$$

$\lambda_i = \lambda_i(A)$   $i^{\text{th}}$  eigenvalue of  $A$ .

$$AU = UA$$

From (a) we know  $A u^{(i)} = \lambda_i u^{(i)}$

$u^{(i)}$  is an eigenvector of  $A$ .

Show that

(c). If  $A$  is PSD, that is  $x^T A x \geq 0$ ,  
then  $\lambda_i(A) \geq 0$  for each  $i$ .

$$A t^{(i)} = \lambda_i t^{(i)}$$

$$t^{(i)T} A t^{(i)} = t^{(i)T} \lambda_i t^{(i)} \geq 0$$

$A$  is PSD.

$$A \text{ is PSD} = \lambda_i \cdot t^{(i)T} t^{(i)}$$

$$t^{(i)T} t^{(i)} \geq 0$$

$$\therefore t^{(i)T} A t^{(i)} = \lambda_i \geq 0$$

$$\therefore \lambda_i \geq 0$$



$$4. \quad X = (X_1 \dots X_n)$$

$$X \sim N(\mu, \Sigma)$$

$$(a) \quad Y = X_1 + X_2 + \dots + X_n$$

$$\begin{aligned} E[Y] &= E[X_1 + X_2 + \dots + X_n] \\ &= \sum_{i=1}^n \mu_i = a^T \mu \end{aligned}$$

$$a = \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix} \quad a \in \mathbb{R}^n$$

$$\begin{aligned} \text{Var}(Y) &= E[Y^2] - E[Y]^2 = \sum_{i,j=1}^n \Sigma_{ij} \\ &= a^T E[XX^T] a - a^T \mu \mu^T a \end{aligned}$$

$$\begin{aligned} Y &\sim N(\mu_Y, \Sigma_Y) = a^T (\text{Cov}(\vec{X})) a \quad Y \text{ is Gaussian distribution.} \\ &= \sum_{i=1}^n \Sigma_{ii} \end{aligned}$$

$$\begin{aligned} (b). \quad E[X^T \Sigma^{-1} X] \\ &= E[X^T A^T (A A^T)^{-1} A Y] \\ &= E[X^T A^T (A^T A)^{-1} A Y] \\ &= E[Y^T Y] \\ &= E\left[\sum_{i=1}^n Y_i^2\right] \end{aligned}$$

$$\begin{aligned} \Sigma &= A A^T \\ \text{Let } Y &= A^T X \\ X &= A Y \end{aligned}$$

$$\begin{aligned} E[X^T \Sigma^{-1} X] \\ &= E[\text{tr}(X X^T \Sigma^{-1})] \\ &= \text{tr}(E[XX^T] \Sigma^{-1}) \\ &= \text{tr}((\mu \mu^T + \Sigma) \Sigma^{-1}) \\ &= \text{tr}(\mu \mu^T \Sigma^{-1}) + n \\ &= \text{tr}(\mu^T \Sigma^{-1} \mu) + n = \mu^T \Sigma^{-1} \mu + n \end{aligned}$$