

# CS229 - Problem Set 0

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## Exercise 1

(a)

$$\nabla f(x) = \begin{bmatrix} \frac{\partial}{\partial x_1} f(x) \\ \frac{\partial}{\partial x_2} f(x) \\ \vdots \\ \frac{\partial}{\partial x_n} f(x) \end{bmatrix}$$

For  $f(x) = \frac{1}{2}x^T A x + b^T x$ ,  $A^T = A$ , we'll get

$$\begin{aligned} \frac{\partial}{\partial x_k} f(x) &= \frac{\partial}{\partial x_k} \left( \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n x_i A_{ij} x_j + \frac{1}{2} \sum_{i=1}^n x_i b_i \right) = \frac{1}{2} \frac{\partial}{\partial x_k} \left( \sum_{i \neq k}^n x_k A_{ki} x_i + \sum_{j \neq k}^n x_j A_{jk} x_k + \frac{1}{2} x_k^2 A_{kk} \right) + \\ \frac{\partial}{\partial x_k} \sum_{i=1}^n x_i b_i &= \frac{\partial}{\partial x_k} \sum_{i=1, i \neq k}^n x_k A_{ik} x_i + A_{kk} x_k + b_k = \sum_{i=1}^n A_{ik} x_i + b_k \end{aligned}$$

And we got  $\nabla f(x) = Ax + b$

(b)

By the multivariable chain rule

$$\nabla f(x) = \nabla g(h(x)) = g'(h(x)) \nabla h(x)$$

(c)

From (a) we got  $\frac{\partial}{\partial x_k} f(x) = \sum_{i=1}^n A_{ik} x_i + b_k$ , so

$$\frac{\partial}{\partial x_k x_t} f(x) = \frac{\partial}{\partial x_t} \left( \sum_{i=1}^n A_{ik} x_i + b_k \right) = A_{it}$$

And we got  $\nabla^2 f(x) = A$

(d)

Let  $f(x) = g(a^T x)$ , by (b)

$$\nabla f(x) = g'(a^T x) \nabla h(x) = \nabla(a^T x), \frac{\partial}{\partial x_k} a^T x = \frac{\partial}{\partial x_k} \sum_{i=1}^n a_i x_i = x_k$$

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

If we'll use the multivariable chain rule on  $\nabla f(x) = g'(a^T x) a$ , we'll get  $\nabla^2 f(x) = g''(a^T x) a a^T$ .  
And without the first calculation

$$\nabla^2 f(x) = g'(a^T x) \nabla^2(a^T x) + g''(a^T x) \nabla(a^T x) \nabla(a^T x)^T$$

But  $\frac{\partial}{\partial x_k x_t} a^T x = \frac{\partial}{\partial x_t} a_k = 0$ , thus  $\nabla^2 a^T x = 0$ , and by (c) we got  $\nabla a^T x = a$ , so

$$\nabla^2 g(a^T x) = g''(a^T x) a a^T$$

## Exercise 2

(a)

Let  $z \in \mathbb{R}^n$ ,  $A = zz^T$ , then  $A^T = (zz^T)^T = (z^T)^T z^T = zz^T = A$ , and for  $v \in \mathbb{R}^n$  we got  $\langle Av, v \rangle = \langle zz^T v, v \rangle = \langle z^T v, z^T v \rangle = \|z^T v\|^2 \geq 0$ , thus by definition  $A \succeq 0$

(b)

I'll show that  $\mathcal{N}(A) = W = \{v : \langle z, v \rangle = 0\}$ , indeed, if  $\langle z, v \rangle = 0$  then  $z^T v = 0 \implies Av = 0$ , so  $W \subseteq \mathcal{N}$ , also

$$Av = 0 \implies \|z^T v\|^2 = \langle z^T v, z^T v \rangle = \langle zz^T, v \rangle = zz^T v = 0$$

And thus we got  $\mathcal{N} = \{v : \langle z, v \rangle = 0\}$ .

From the rank-nullity theorem  $\dim \text{Im} T = n - \dim \ker T = n - (n - 1) \stackrel{(1)}{=} 1$

(c)

The statement is true, indeed, if  $A \succeq 0$ , then  $(BAB^T)^T = (B^T)^T A^T B^T = B^T A^T B^T = B^T A B^T$ , and for  $v \in \mathbb{R}^n$  we got  $\langle B^T A B v, v \rangle = \langle A B v, B v \rangle \geq 0$ , while the last claim is true because  $A \succeq 0$

## Exercise 3

(a)

$A = T \Lambda T^{-1} \implies AT = \Lambda T$ , so for each column of  $T$ ,  $t^{(i)}$  we have  $At^{(i)} = [T \Lambda]^{(i)}$ , but

$$[T \Lambda]_k^{(i)} = \sum_{j=1}^n T_{kj} \Lambda_{ji} = T_{ki} \Lambda_{ii} \implies [T \Lambda]^{(i)} = \Lambda_{ii} t^{(i)}$$

And thus  $At^{(i)} = [T \Lambda]^{(i)} \stackrel{(2)}{=} \lambda_i t^{(i)}$

(b)

By the definition of orthogonal matrix, if  $U$  is orthogonal then  $U^T = U^{-1}$ , so  $A = U \Lambda U^{-1}$  and the claim is true from (a)

(c)

Suppose  $A \succeq 0$  and suppose that  $u^{(i)}$  is an eigenvector of  $A$  with eigenvalue  $\lambda_i$ , then

$$0 \leq \langle A u^{(i)}, u^{(i)} \rangle = \langle \lambda_i u^{(i)}, u^{(i)} \rangle = \lambda_i \langle u^{(i)}, u^{(i)} \rangle = \lambda_i \|u^{(i)}\|^2$$

So because  $\|u^{(i)}\|^2 \geq 0$  we got  $\lambda_i \geq 0$