

# ANLY561 Homework 9

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### Question 1

Let  $f(\mathbf{x}) = \|\mathbf{y} - \mathbf{x}\|_2^2$  and  $g(\mathbf{x}) = \mathbf{v}^T \mathbf{x} - b$

Then we have  $\nabla f(\mathbf{x}) = 2(\mathbf{x} - \mathbf{y})$  and  $\nabla g(\mathbf{x}) = \mathbf{v}$

Since  $\mathbf{v}$  is nonzero all the time, there is always a  $\lambda$  such that  $\nabla f(\mathbf{x}) = \lambda \nabla g(\mathbf{x})$

Then we have  $2(\mathbf{x} - \mathbf{y}) = \lambda \mathbf{v}$  and  $\mathbf{x} = \frac{\lambda \mathbf{v}}{2} + \mathbf{y}$

Plug  $\mathbf{x}$  into  $\mathbf{v}^T \mathbf{x} - b = 0$ , we get  $\mathbf{v}^T (\frac{\lambda \mathbf{v}}{2} + \mathbf{y}) - b = 0$ , therefore  $\lambda = \frac{2}{\|\mathbf{v}\|_2^2} (b - \mathbf{v}^T \mathbf{y})$

$$\mathbf{x} = \frac{\lambda \mathbf{v}}{2} + \mathbf{y} = \frac{\frac{2\mathbf{v}}{\|\mathbf{v}\|_2^2} (b - \mathbf{v}^T \mathbf{y})}{2} + \mathbf{y} = \frac{\mathbf{v}}{\|\mathbf{v}\|_2^2} (b - \mathbf{v}^T \mathbf{y}) + \mathbf{y}$$

$$\mathbf{x}^* = \frac{\mathbf{v}}{\|\mathbf{v}\|_2^2} (b - \mathbf{v}^T \mathbf{y}) + \mathbf{y}$$

### Question 2

a)

We know that  $\mathbf{x}_i$  is the  $i$ th row of data matrix  $X$  and it has  $d$  columns.

$$\text{Therefore, } \mathbf{x}_i = \begin{pmatrix} X_{i,1} \\ X_{i,2} \\ \cdot \\ \cdot \\ \cdot \\ X_{i,d} \end{pmatrix}$$

$$\begin{aligned}
\sum_{i=1}^n ||\mathbf{x}_i - c_i \mathbf{u}||_2^2 &= \sum_{i=1}^n (\sqrt{|\mathbf{x}_i - c_i \mathbf{u}|})^2 \\
&= \sum_{i=1}^n |\mathbf{x}_i - c_i \mathbf{u}| \\
&= \sum_{i=1}^n ((X_{i,1} - c_i \mathbf{u}_1)^2 + (X_{i,2} - c_i \mathbf{u}_2)^2 + \dots + (X_{i,d} - c_i \mathbf{u}_d)^2) \\
&= \sum_{i=1}^n \sum_{j=1}^d (X_{i,j} - c_i \mathbf{u}_j)^2 \\
&= \sum_{i=1}^n \sum_{j=1}^d (X - \mathbf{c} \mathbf{u}^T)_{i,j}^2 \\
&= ||X - \mathbf{c} \mathbf{u}^T||_{Fro}^2
\end{aligned}$$

**b)**

Let  $f(c) = ||\mathbf{x}_i - c_i \mathbf{u}||_2^2$ .

Then we have  $\nabla f(c) = 2\mathbf{u}^T(c_i \mathbf{u} - \mathbf{x}_i)$  and  $\nabla^2 f(c) = ||\mathbf{u}||_2^2$ , therefore,  $f(c)$  is strictly convex, which implies the program has a unique solution.

Let  $\nabla f(c) = 0$ , then we have  $c^* = \mathbf{u}^T \mathbf{x}_i = \mathbf{x}_i^T \mathbf{u}$

Therefore,  $c^* = \mathbf{x}_i^T \mathbf{u}$  is the unique solution to minimize  $f(c)$ .

**c)**

From part a) we know that  $\sum_{i=1}^n ||\mathbf{x}_i - c_i \mathbf{u}||_2^2 = ||X - \mathbf{c} \mathbf{u}^T||_{Fro}^2$

From part b) we know that  $c^* = \mathbf{x}_i^T \mathbf{u}$  is the unique solution to minimize  $||\mathbf{x}_i - c_i \mathbf{u}||_2^2$

In other words,  $c_i^* = \mathbf{x}_i^T \mathbf{u}$  is the solution to minimize  $||\mathbf{x}_i - c_i \mathbf{u}||_2^2$ , where  $\mathbf{x}_i$  is the  $i$ th row of matrix  $X$ .

$$\text{Let } \mathbf{c}^* = \begin{pmatrix} c_1 \\ c_2 \\ \vdots \\ \vdots \\ c_n \end{pmatrix}$$

Therefore,  $\mathbf{c}^* = X\mathbf{u}$  is the solution to minimize  $\sum_{i=1}^n ||\mathbf{x}_i - c_i \mathbf{u}||_2^2$

Therefore,  $\mathbf{c}^* = X\mathbf{u}$  is the solution to minimize  $||X - \mathbf{c} \mathbf{u}^T||_{Fro}^2$

Plug  $\mathbf{c}^*$ , we get  $\sum_{i=1}^n ||\mathbf{x}_i - c_i \mathbf{u}||_2^2 = ||X - X\mathbf{u}\mathbf{u}^T||_{Fro}^2$

With the same constraint, the two program are same.

d)

To simplify the process, any value that is not on the diagonal entries of  $A^T A$  is represented by a.

Matrix  $A \in M_{m,n}$  and  $A^T A \in M_{n,n}$

$$A^T A = \begin{pmatrix} \sum_{i=1}^m A_{i,1}^2 & \cdot & \cdot & \cdot & a \\ a & \sum_{i=1}^m A_{i,2}^2 & \cdot & \cdot & a \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ a & \cdot & \cdot & \cdot & \sum_{i=1}^m A_{i,n}^2 \end{pmatrix}$$

Therefore,

$$\text{trace}(A^T A) = \sum_{i=1}^m A_{i,1}^2 + \sum_{i=1}^m A_{i,2}^2 + \dots + \sum_{i=1}^m A_{i,n}^2 = \sum_{i=1}^m (A_{i,1}^2 + A_{i,2}^2 + \dots + A_{i,n}^2) = \sum_{i=1}^m \sum_{j=1}^n A_{i,j}^2$$

$$\text{Since } \|A\|_{Fro}^2 = \sum_{i=1}^m \sum_{j=1}^n A_{i,j}^2, \|A\|_{Fro}^2 = \text{trace}(A^T A)$$

$$A^T B = \begin{pmatrix} \sum_{i=1}^m A_{i,1} B_{i,1} & \cdot & \cdot & \cdot & a \\ a & \sum_{i=1}^m A_{i,2} B_{i,2} & \cdot & \cdot & a \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ a & \cdot & \cdot & \cdot & \sum_{i=1}^m A_{i,n} B_{i,n} \end{pmatrix}$$

$$\text{trace}(A^T B) = \sum_{i=1}^m \sum_{j=1}^n A_{i,j} B_{i,j}$$

$$B A^T = \begin{pmatrix} \sum_{j=1}^n A_{1,j} B_{1,j} & \cdot & \cdot & \cdot & a \\ a & \sum_{j=1}^n A_{2,j} B_{2,j} & \cdot & \cdot & a \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ a & \cdot & \cdot & \cdot & \sum_{j=1}^n A_{m,j} B_{m,j} \end{pmatrix}$$

$$\text{trace}(B A^T) = \sum_{j=1}^n (A_{1,j} B_{1,j} + A_{2,j} B_{2,j} + \dots + A_{m,j} B_{m,j}) = \sum_{i=1}^m \sum_{j=1}^n A_{i,j} B_{i,j}$$

$$\text{Therefore, } \text{trace}(A^T B) = \text{trace}(B A^T)$$

e)

$$\begin{aligned}
\min_{u \in R^d} ||X - X\mathbf{u}\mathbf{u}^T||_{Fro}^2 &= \min_{u \in R^d} \text{trace}((X - X\mathbf{u}\mathbf{u}^T)(X - X\mathbf{u}\mathbf{u}^T)^T) \\
&= \min_{u \in R^d} \text{trace}((X - X\mathbf{u}\mathbf{u}^T)(X^T - \mathbf{u}\mathbf{u}^T X^T)) \\
&= \min_{u \in R^d} \text{trace}(XX^T - X\mathbf{u}\mathbf{u}^T X^T - X\mathbf{u}\mathbf{u}^T X^T + X\mathbf{u}\mathbf{u}^T \mathbf{u}\mathbf{u}^T X^T) \\
&= \min_{u \in R^d} \text{trace}(XX^T - X\mathbf{u}\mathbf{u}^T X^T) \\
&= \min_{u \in R^d} \text{trace}(XX^T - \mathbf{u}^T X^T X \mathbf{u}) \\
&= \min_{u \in R^d} (\text{trace}(XX^T) - \text{trace}(\mathbf{u}^T X^T X \mathbf{u})) \\
&= \text{trace}(XX^T) - \max_{u \in R^d} \text{trace}(\mathbf{u}^T X^T X \mathbf{u}) \\
&= \max_{u \in R^d} (\mathbf{u}^T X^T X \mathbf{u})
\end{aligned}$$

Therefore, the minimization program and the maximization program are equivalent.

f)

The program

$$\min_{u \in R^d, c \in R^n} \sum_{i=1}^n ||\mathbf{x}_i - c_i \mathbf{u}||_2^2$$

subject to  $||\mathbf{u}||_2^2 = 1$

is equivalent to the program

$$\min_{u \in R^d, c \in R^n} ||X - X\mathbf{u}\mathbf{u}^T||_{Fro}^2$$

subject to  $||\mathbf{u}||_2^2 = 1$

and then is equivalent to the program

$$\max_{u \in R^d} (\mathbf{u}^T X^T X \mathbf{u})$$

subject to  $||\mathbf{u}||_2^2 = 1$

From part c), we know that  $\mathbf{c}^* = X\mathbf{u}$  can solve the program

$$\min_{c \in R^n} \sum_{i=1}^n ||\mathbf{x}_i - c_i \mathbf{u}||_2^2$$

subject to  $||\mathbf{u}||_2^2 = 1$ , therefore,  $\mathbf{c}^*$  is part of the solution for the program

$$\max_{u \in R^d} (\mathbf{u}^T X^T X \mathbf{u})$$

subject to  $||\mathbf{u}||_2^2 = 1$

Since  $\mathbf{u}^*$  is a normalized eigenvector of  $X^T X$  corresponding to the largest eigenvalue of  $X^T X$ , then  $\mathbf{u}^*$  is a solution for the program  $\max_{u \in R^d} (\mathbf{u}^T X^T X \mathbf{u})$  subject to  $||\mathbf{u}||_2^2 = 1$

Plug  $\mathbf{u}^*$  into  $\mathbf{c}^* = X\mathbf{u}$ , we have  $\mathbf{c}^* = X\mathbf{u}^*$ . Therefore,  $\mathbf{c}^*$  and  $\mathbf{u}^*$  together solve the program

$\max_{u \in R^d} (\mathbf{u}^T X^T X \mathbf{u})$  subject to  $||\mathbf{u}||_2^2 = 1$ , which is equivalent to the program  $\min_{u \in R^d, c \in R^n} \sum_{i=1}^n ||\mathbf{x}_i - c_i \mathbf{u}||_2^2$