

Regression Analysis

2023 Fall HW1

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Problem 1

The problem is solved with the following algorithm:

Algorithm Solve $Rx = b$ with R being upper-triangular

Given: $R = \{r_{ij}\}_{0 \leq i \leq j \leq n} \in \mathbb{R}^{n \times n}$ upper-triangular as stated, $b \in \mathbb{R}^n$

Initialize $x_{n:(n+1)} = []$, for $i = n : 1$

1. We already got $\vec{x}_{n:(i+1)}$
2. Focus on $R_{i,:}$, we have

$$\sum_{j=i}^n r_{ij}x_j = b_i \Rightarrow x_i = \frac{b_i - \sum_{j=i+1}^n r_{ij}x_j}{r_{ii}}$$

3. Solve x_i from $x_{n:(i+1)}$, and now we have $x_{n:i}$

Return: $x_{n:1} = x$

Problem 2

Question 2.(a)

Since we have $m < n$ and A has full row rank, we have its right inverse matrix

$$A_r := A^T(AA^T)^{-1} \in \mathbb{R}^{n \times m}$$

in this way \mathcal{S} could be represented as

$$\mathcal{S} = \{x | x = A^T(AA^T)^{-1}b + \xi, \xi \in \text{Null}(A)\} \subset \mathbb{R}^n$$

and now the optimization problem is formulated as

$$\begin{aligned} \pi_{\mathcal{S}}(y) &:= \arg \min_{x \in \mathcal{S}} \|y - x\|^2 \\ &= \arg \min_{\xi \in \text{Null}(A)} \|y - A^T(AA^T)^{-1}b - \xi\|^2 \end{aligned}$$

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into a constraint optimization problem, and the Lagrangian function is

$$\begin{aligned}\mathcal{L}(\xi, \lambda) &= \|y - A^T(AA^T)^{-1}b - \xi\|^2 + \lambda^T A\xi, \quad \lambda \in \mathbb{R}^m \\ &\Rightarrow \begin{cases} y - A^T(AA^T)^{-1}b - \xi = A^T\lambda \\ A\xi = 0 \end{cases} \\ &\Rightarrow Ay - b = AA^T\lambda \Rightarrow \lambda = (AA^T)^{-1}(Ay - b) \\ &\Rightarrow \xi = (I - A^T(AA^T)^{-1}A)y \\ &\Rightarrow \pi_S(y) = A^T(AA^T)^{-1}b + (I - A^T(AA^T)^{-1}A)y\end{aligned}$$

Question 2.(b)

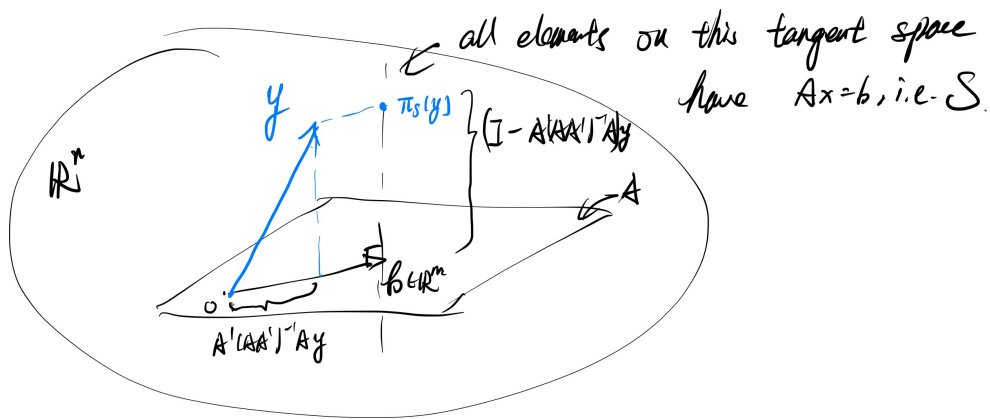


图 1: Illustration of $\pi_S(y)$

Problem 3

Question 3.(a)

Verify directly:

$$\begin{aligned}H'_u &= (I - 2uu')' = I - 2uu' = H_u \\ H'_u H_u &= (I - 2uu')(I - 2uu') = I - 4uu' + 4uu'u'u = I\end{aligned}$$

Question 3.(b)

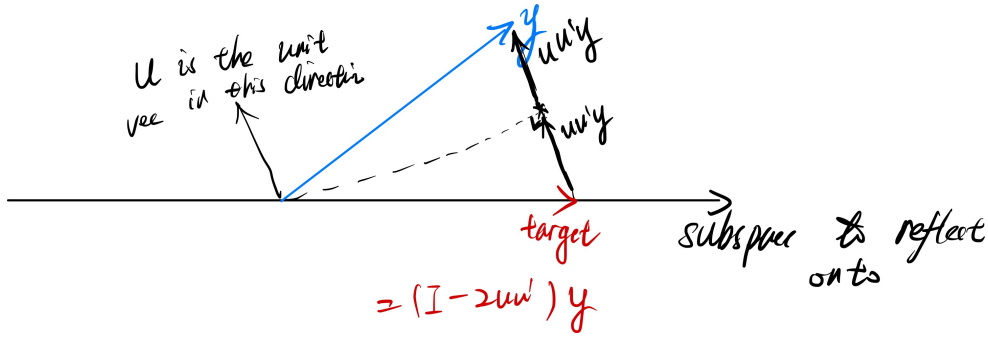


图 2: Illustration of the reflection process

Question 3.(c)

So here e_1 is the ‘direction of subspace’ we want to reflect onto. We can see that here v is just the angular bisector of $\langle x, e_1 \rangle$. Denote $e_x = x / \|x\|$, the unit vector in x direction. Then we have

$$\begin{aligned}
 H_v x &= \left(I - 2 \frac{(e_x + e_1)(e_x + e_1)'}{\|e_x + e_1\|^2} \right) x \\
 &= \frac{\|x\|}{\|e_x + e_1\|^2} \left(\|e_x + e_1\|^2 e_x - 2(e_x + e_1)(e_x + e_1)' e_x \right) \\
 &= \frac{\|x\|}{\|e_x + e_1\|^2} \left((2 + 2e_x \cdot e_1) e_x - 2(1 + e_x \cdot e_1)(e_x + e_1) \right) \\
 &= \frac{\|x\|}{2 + 2e_x \cdot e_1} \times -2(1 + e_x \cdot e_1) e_1 \\
 &= -\|x\| e_1
 \end{aligned}$$

Question 3.(d)

i.e. to prove that operator H is norm-preserving. We have

$$\begin{aligned}
 \|Hx\|_2^2 &= x' H' H x \\
 &= x' H'_{u_k} H'_{u_{k-1}} \cdots H'_{u_1} H_{u_1} \cdots H_{u_{k-1}} H_{u_k} x \\
 &= x' x = \|x\|_2^2
 \end{aligned}$$

Question 3.(e)

as definition

$$u = \frac{a_1 / \|a_1\| + e_1}{\|a_1 / \|a_1\| + e_1\|}, \quad H_u = I - 2uu'$$

Question 3.(f)

Notation: the l^{th} unit vector in \mathbb{R}^m is denoted $e_{m,l}$. We have

$$u_{k+1} = \frac{b_1 / \|b_1\| + e_{k+1,1}}{\|b_1 / \|b_1\| + e_{k+1,1}\|}}, \quad F = I - 2uu'$$

$$\text{Reflection: } S = \begin{bmatrix} I_{(n-k-1) \times (n-k-1)} & 0 \\ 0 & F_{(k+1) \times (k+1)} \end{bmatrix}$$

Question 3.(g)

Use the process in the previous subproblem, say it could reflect the i^{th} column, denoted by S_i . Then we could use

$$\Xi = S_{n-1}S_{n-2} \dots S_1$$

to reflect all n columns. i.e.

$$\Xi A = S_{n-1}S_{n-2} \dots S_1 A = \text{upper triangular}$$

we can write down the Q and R

$$A = QR, \quad Q = S_1S_2 \dots S_{n-1}, \quad R = S_{n-1}S_{n-2} \dots S_1 A$$

Problem 4

Notation: in this section I use v_i in place of s_i , i.e. the eigenvector of A . And further I use the convention that we have S is orthonormal (which can always be valid with some transform to Λ).

Question 4.(a)

To $\text{sgn}(v_1' x^0) \lambda_1 v_1$, i.e. $\pm \lambda_1 v_1$.

Question 4.(b)

Note that in each step $\frac{1}{\|x^k\|}$ just acts as a scalar. So doing n iteration with each step a scalar multiplication IS EQUIVALENT TO doing n iteration with only the last step a scalar (to unitary). So we could express a $n + 1$ steps iteration as

$$x^n = \xi A^n x^0, \quad x^{n+1} = \frac{1}{\|x^n\|} A x^n, \quad \xi \in \mathbb{R}$$

in which we denote the ‘un-scaled’ $A^n x^0$ as \tilde{x}^n , i.e. $x^n = \xi \tilde{x}^n$. Then

$$\tilde{x}^n = A^n x^0 = (S \Lambda S^{-1})^n x^0 = S \Lambda^n S^{-1} x^0, \quad \forall n$$

Then we have

$$x^{n+1} = \frac{1}{\|S\Lambda^n S^{-1}x^0\|} S\Lambda^{n+1}S^{-1}x^0$$

in which spectrum of $\frac{1}{\|S\Lambda^n S^{-1}x^0\|} S\Lambda^{n+1}S^{-1}$ is simply

$$\begin{aligned} \frac{1}{\|S\Lambda^n S^{-1}x^0\|} S\Lambda^{n+1}S^{-1} &\stackrel{(i)}{\sim} \frac{1}{\|\Lambda^n\|} S\Lambda^{n+1}S = S\text{diag}\{\lambda_1, \lambda_2 \left(\frac{\lambda_2}{\lambda_1}\right)^n, \dots, \lambda_n \left(\frac{\lambda_n}{\lambda_1}\right)^n\} S^{-1} \\ &\rightarrow S\text{diag}\{\lambda_1, 0, \dots, 0\} S^{-1} = \lambda_1 v_1 v_1' \end{aligned}$$

in which (i) means only up to a constant $\sim O(1)$

And finally

$$\begin{aligned} x^{n+1} &\rightarrow \propto \lambda_1 v_1 v_1' x^0 \propto v_1 \text{sgn}(v_1' x^0) \\ x^{n+2} &\rightarrow A \frac{x^{n+1}}{\|x^{n+1}\|} = A v_1 \text{sgn}(v_1' x^0) = \text{sgn}(v_1' x^0) \lambda_1 v_1 \end{aligned}$$

Problem 5

Question 5.(a)

$$\begin{cases} x = (A - BD^{-1}C)^{-1}(a - BD^{-1}b) \\ y = (D - CA^{-1}B)^{-1}(b - CA^{-1}a) \end{cases}$$

Question 5.(b)

Using the above fomula, we have

$$\begin{aligned} y &= (C^{-1} + V'A^{-1}U)^{-1}V'A^{-1}z \Rightarrow x = A^{-1}(z - Uy) = (A^{-1} - A^{-1}U(C^{-1} + V'A^{-1}U)^{-1}V'A^{-1})z \\ &\Rightarrow (A + UCV')^{-1} = A^{-1} - A^{-1}U(C^{-1} + V'A^{-1}U)^{-1}V'A^{-1} \end{aligned}$$

Problem 6

Question 6.(a)

Prove it directly

$$\text{L.H.S.} = (a_2 + (a_1 - a_2))b_1 + (a_1 - (a_1 - a_2))b_2 = a_2b_1 + a_1b_2 + (a_1 - a_2)(b_1 - b_2) \geq a_2b_1 + a_1b_2 = \text{R.H.S.}$$

Question 6.(b)

Denote $P_{\text{swap}(i,j)}$ as the operator to swap the i^{th} and j^{th} element.

1. Since $P_{\text{swap}(i,j)}$ keep all other $n - 2$ elements unchanged, we can make use of the above 2-dimensional inequality, we have the following statement:

If $P_{\text{swap}(i,j)}$ is **moving the larger element to a higher larger index, then the inequality is preserved**. Say swapping $v_n @ n \leftrightarrow v_{n-1} @ n - 1$ then the inequality perserve, while $v_n @ n - 1 \leftrightarrow v_{n-1} @ n$ does not.

i.e.

$$u' \tilde{v} \geq u' P_{\text{swap}(i,j)} \tilde{v} \Leftrightarrow \tilde{v}_i \geq \tilde{v}_j \& i > j$$

2. Then we prove that: any permutation matrix $P \in \mathcal{P}_n$ could be represented as products of $P_{\text{swap}(i,j)}$ s, in which each $P_{\text{swap}(i,j)}$ is moving the larger element to a higher larger index for the declared u, \tilde{v} .

We do it by the following iteration process:

Algorithm Decomposition $Pv = \prod P_{\text{swap}(i,j)} v$ which perserce inequality

For $i \leftarrow n : 1$:

- Move v_k to the desired position as in Pv by repeatedly swap it with ‘the first element on its left with subscript smaller than itself’. e.g. to move v_{n-1} which is now at position n to position $n - 3$, with v_n already at position $n - 2$, i.e.

$$\dots, v_{n-3}, v_n, v_{n-2}, v_{n-1}$$

we do by following:

$$\begin{array}{ll} \dots, v_{n-3}, v_n, v_{n-1}, v_{n-2} & \text{swap } v_{n-1} \text{ with } v_{n-2} \\ \dots, v_{n-1}, v_n, v_{n-3}, v_{n-2} & v_n \text{ is skipped, then swap } v_{n-1} \text{ with } v_{n-3} \end{array}$$

Repeat the above operation, which preserve the inquality, until $v_{n:1}$ are all at the right position to become Pv .

Now we have $u'v \geq u'Pv$

Question 6.(c)

According to the above algorithm, we know that $u'v \geq u'Pv, \forall P \in \mathcal{P}_n$. Then we have

$$\begin{aligned} u'v &= u' \left(\sum_{l=1}^k \lambda_l \right) v \geq u' \sum_{l=1}^k \lambda_l P_l, \quad w.r.t. \lambda_l \geq 0, \sum_{l=1}^k \lambda_l = 1 \\ &= u'Sv, \quad \forall S \in \mathcal{S}_n \end{aligned}$$

And also $I \in \mathcal{S}$, thus

$$u'v = \max_{S \in \mathcal{S}_n} u'Sv$$

Problem 7

Question 7.(a)

Say we denote the SVD of A as $A = \tilde{U}\tilde{\Sigma}\tilde{V}$, then we have

$$\text{L.H.S.} = \text{tr}(AB) = \text{tr}(\tilde{U}\tilde{\Sigma}\tilde{V}) = \text{tr}(\tilde{\Sigma}\tilde{V}B\tilde{U})$$

and here we can define $\tilde{B} \leftarrow \tilde{V}B\tilde{U}$. And on the other hand, singular values of a matrix preserve under unitary transformation, thus

$$\sigma(\tilde{B}) = \sigma(\tilde{V}B\tilde{U}) = \sigma(B)$$

so vNti is now

$$\text{tr}(\tilde{\Sigma}\tilde{B}) \leq \sum_{i=1}^n \sigma_i(\tilde{\Sigma})\sigma_i(\tilde{B}) =$$

Now we can re-define $B \leftarrow \tilde{B}$, and $A \leftarrow \tilde{\Sigma}$. So its equivalent to prove

$$\text{tr}(AB) \leq \sum_{i=1}^n \sigma_i(A)\sigma_i(B), \quad \text{with } A \text{ being diagonal}$$

Question 7.(b)

$$\text{tr}(AB) = \text{tr}(AU\Sigma V') = \text{tr}(V'AU\Sigma) = \sum_{i=1}^n \sigma_i v'_i A u_i = \sum_{i,j \leq n} \sigma_i v_{ij} a_j u_{ij}$$

Question 7.(c)

Using $xy \leq \frac{1}{2}(x^2 + y^2)$, we have

$$\text{tr}(AB) = \sum_{i,j \leq n} \sigma_i v_{ij} a_j u_{ij} \leq \frac{1}{2} \sum_{i,j \leq n} \sigma_i a_j (v_{ij}^2 + u_{ij}^2)$$

Question 7.(d)

Since U and V are both orthonormal bases, we have

$$\sum_{j=1}^n v_{ij} v_{kj} = \delta_{ik}, \quad \sum_{j=1}^n u_{ij} u_{kj} = \delta_{ik}$$

so matrix $\{v_{ij}^2\}_{i,j=1}^n$ has row sum 1 & column sum 1 (similar for $\{u_{ij}^2\}_{i,j=1}^n$). Then using notation in the previous problem, in which \mathcal{S}_n is the doubly stochastic matrices, we have

$$\{v_{ij}^2\}_{i,j=1}^n, \{u_{ij}^2\}_{i,j=1}^n \in \mathcal{S}_n \Rightarrow \left\{ \frac{1}{2}(v_{ij}^2 + u_{ij}^2) \right\} \in \mathcal{S}_n$$

then using the inequality $\tilde{u}'\tilde{v} = \max_{S \in S_n} \tilde{u}'S\tilde{v}$, we can place $\sigma_i(A), \sigma_i(B)$ as the \tilde{u}, \tilde{v} , respectively, and then we have

$$\begin{aligned} tr(AB) &\leq \sum_{i,j \leq n} \sigma_i \frac{1}{2} (v_{ij}^2 + u_{ij}^2) a_j \\ &\leq \sum_{i=1}^n \sigma_i(B) \sigma_i(A) \end{aligned}$$

$$\underline{\sum_{i=1}^n}$$

$$\frac{\pi}{6}$$

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