

LINEAR MODEL NOTES

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1. MATRIX ALGEBRA

1.1. Column and Null Space.

Exercise 1.1. Let $X \in \mathcal{M}_{m,n}$. Then $\mathcal{N}(X) = \mathcal{N}(X^T X)$.

Proof. Let $a \in \mathcal{N}(X)$. Then $Xa = 0$. So $X^T Xa = 0$. Thus $a \in \mathcal{N}(X^T X)$. Conversely, suppose that $a \in \mathcal{N}(X^T X)$. Then $X^T Xa = 0$. So

$$\begin{aligned} 0 &= a^T X^T Xa \\ &= (Xa)^T (Xa) \\ &= \|Xa\|^2 \end{aligned}$$

Hence $Xa = 0$ and $a \in \mathcal{N}(X)$. □

Exercise 1.2. Let $X \in \mathcal{M}_{m,n}$. Then $\mathcal{C}(X^T) = \mathcal{C}(X^T X)$.

Proof.

$$\begin{aligned} \mathcal{C}(X^T) &= \mathcal{N}(X)^\perp \\ &= \mathcal{N}(X^T X)^\perp \\ &= \mathcal{C}(X^T X) \end{aligned}$$

□

Exercise 1.3. Let $X \in \mathcal{M}_{m,n}$. If $X^T X = 0$, then $X = 0$.

Proof. Suppose that $X^T X = 0$. Then

$$\begin{aligned} \text{rank}(X^T) &= \dim \mathcal{C}(X^T) \\ &= \dim \mathcal{C}(X^T X) \\ &= \text{rank}(X^T X) \\ &= 0 \end{aligned}$$

So $X^T = X = 0$. □

Exercise 1.4. Let $X \in \mathcal{M}_{m,n}$ and $A, B \in \mathcal{M}_{n,p}$. Then $X^T X A = X^T X B$ iff $X A = X B$.

Proof. Clearly if $X A = X B$, then $X^T X A = X^T X B$. Conversely, suppose that $X^T X A = X^T X B$. Then $X^T X (A - B) = 0$. So for each $i = 1, \dots, p$, $X^T X (A - B) e_i = 0$. Thus for each $i = 1, \dots, p$, $X (A - B) e_i \in \mathcal{N}(X^T) \cap \mathcal{C}(X) = \{0\}$. Hence $X (A - B) = 0$ and $X A = X B$. □

1.2. Generalized Inverses.

Definition 1.5. Let $A \in \mathcal{M}_{m,n}$ and $G \in \mathcal{M}_{n,m}$. Then G is said to be a **generalized inverse** of A if $AGA = A$.

Theorem 1.6. Let $A \in \mathcal{M}_{m,n}$. Then there exists $G \in \mathcal{M}_{n,m}$ such that G is a generalized inverse of A .

Note 1.7. We will denote a generalized inverse of A by A^- .

Exercise 1.8. Let $X \in \mathcal{M}_{m,n}$. Then $(X^T)^- = (X^-)^T$.

Proof.

$$\begin{aligned} X^T (X^-)^T X^T &= (X X^- X)^T \\ &= X^T \end{aligned}$$

□

Exercise 1.9. Let $X \in \mathcal{M}_{m,n}$. Then $\mathcal{C}(X X^-) = \mathcal{C}(X)$.

Proof. Clearly $\mathcal{C}(X X^-) \subset \mathcal{C}(X)$. Let $b \in \mathcal{C}(X)$. Then there exists $a \in \mathbb{R}^n$ such that $X a = b$. Then

$$\begin{aligned} X X^- b &= X X^- X a \\ &= X a \\ &= b \end{aligned}$$

So $b \in \mathcal{C}(X X^-)$. Thus $\mathcal{C}(X) \subset \mathcal{C}(X X^-)$ and $\mathcal{C}(X) = \mathcal{C}(X X^-)$. □

Exercise 1.10. Let $X \in \mathcal{M}_{m,n}$. Then $\mathcal{N}(X) = \mathcal{N}(X^- X)$

Proof. From the previous exercise, we have that

$$\begin{aligned} \mathcal{N}(X) &= \mathcal{C}(X^T)^\perp \\ &= \mathcal{C}(X^T (X^T)^-)^\perp \\ &= \mathcal{C}(X^T (X^-)^T)^\perp \\ &= \mathcal{C}((X^- X)^T)^\perp \\ &= \mathcal{N}(X^- X) \end{aligned}$$

□

Definition 1.11. Let $A \in \mathcal{M}_{m,n}$ and $b \in \mathbb{R}^m$. Then the system $Ax = b$ is said to be **consistent** if $b \in \mathcal{C}(A)$.

Exercise 1.12. Let $A \in \mathcal{M}_{m,n}$ and $b \in \mathbb{R}^m$. If the system $Ax = b$ is consistent, then $x = A^-b$ satisfies $Ax = b$.

Proof. Suppose that the system $Ax = b$ is consistent. Then $b \in \mathcal{C}(A)$. So there exists $x^* \in \mathbb{R}^n$ such that $Ax^* = b$. Then

$$\begin{aligned} A(A^-b) &= A(A^-Ax^*) \\ &= Ax^* \\ &= b \end{aligned}$$

Hence A^-b satisfies $Ax = b$. □

Exercise 1.13. Let $X \in \mathcal{M}_{m,n}$. Then $X^- = (X^T X)^- X^T$.

Proof. By definition, $X^T X (X^T X)^- X^T X = X^T X$. A previous exercise implies that $X (X^T X)^- X^T X = X$. Thus $X^- = (X^T X)^- X^T$. □

Exercise 1.14. Let $X \in \mathcal{M}_{m,n}$. Then $(X^T)^- = X (X^T X)^-$.

Proof. The previous exercise tells us that $X^- = (X^T X)^- X^T$. Transposing both sides, we obtain $(X^T)^- = X (X^T X)^-$. □

1.3. Projections.

Definition 1.15. Let $A \in \mathcal{M}_{m,m}$. Then A is said to be **idempotent** if $A^2 = A$.

Exercise 1.16. Let $X \in \mathcal{M}_{m,n}$. Then XX^- and X^-X are idempotent

Proof.

$$\begin{aligned} (XX^-)(XX^-) &= (XX^-X)X^- \\ &= XX^- \end{aligned}$$

The case is similar for X^-X . □

Exercise 1.17. Let $A \in \mathcal{M}_{m,m}$. If A is idempotent, then $I - A$ is idempotent.

Proof. Suppose that A is idempotent. Then

$$\begin{aligned} (I - A)(I - A) &= I^2 - IA - AI + A^2 \\ &= I - 2A + A \\ &= I - A \end{aligned}$$

□

Theorem 1.18. Let $A \in \mathcal{M}_{m,m}$. If A is idempotent, then $\text{rank}(A) = \text{tr}(A)$.

Definition 1.19. Let $P \in \mathcal{M}_{m,m}$ and $S \subset \mathbb{R}^m$ a subspace. Then P is said to be a **projection matrix** onto S if

- (1) $\mathcal{C}(X) = S$
- (2) P is idempotent
- (3) for each $x \in S$, $Px = x$

Exercise 1.20. Let $S \subset \mathbb{R}^m$ and P, Q projection matrices onto S . Then $PQ = Q$.

Proof. Let $x \in \mathbb{R}^m$. Then $Qx \in \mathcal{C}(Q) = S$. So $PQx = Qx$. Thus $PQ = Q$. \square

Exercise 1.21. Let $X \in \mathcal{M}_{m,n}$. Then XX^- is a projection onto $\mathcal{C}(X)$.

Proof. A previous exercise tells us that $\mathcal{C}(XX^-) = \mathcal{C}(X)$. Another previous exercises tells us that XX^- is idempotent. Let $b \in \mathcal{C}(X)$. Then there exists $a \in \mathbb{R}^n$ such that $Xa = b$. So

$$\begin{aligned} XX^-b &= XX^-Xa \\ &= Xa \\ &= b \end{aligned}$$

\square

Exercise 1.22. Let $X \in \mathcal{M}_{m,n}$. Then $I - X^-X$ is a projection onto $\mathcal{N}(X)$

Proof. Since X^-X is idempotent, so is $I - X^-X$. Let $b \in \mathcal{C}(I - X^-X)$. Then there exists $a \in \mathbb{R}^n$ such that $(I - X^-X)a = b$. Then

$$\begin{aligned} Xb &= X(I - X^-X)a \\ &= (X - XX^-X)a \\ &= (X - X)a \\ &= 0a \\ &= 0 \end{aligned}$$

So $\mathcal{C}(I - X^-X) \subset \mathcal{N}(X)$. Let $a \in \mathcal{N}(X)$. Then $Xa = 0$ and

$$\begin{aligned} (I - X^-X)a &= a - X^-Xa \\ &= a \end{aligned}$$

So $\mathcal{N}(X) \subset \mathcal{C}(I - X^-X)$ and therefore $\mathcal{C}(I - X^-X) = \mathcal{N}(X)$. \square

Exercise 1.23. Let $S \subset \mathbb{R}^m$ be a subspace and $P \in \mathcal{M}_{m,m}$ be a symmetric projection matrix onto S . Then P is unique.

Proof. Let $Q \in \mathcal{M}_{m,m}$ be a symmetric projection matrix onto S . Then

$$\begin{aligned} (P - Q)^T(P - Q) &= P^TP - P^TQ - Q^TP + Q^TQ \\ &= P^2 - PQ - QP + Q^2 \\ &= P - Q - P + Q \\ &= 0 \end{aligned}$$

Thus $P - Q = 0$ and $P = Q$. \square

Definition 1.24. Let $X \in \mathcal{M}_{m,n}$. We define P_X by

$$P_X = X(X^TX)^-X^T$$

Exercise 1.25. Let $X \in \mathcal{M}_{m,n}$. Then P_X is well defined. That is, independent of the choice of $(X^TX)^-$.

Proof. Suppose that G, H are generalized inverses of $X^T X$. By definition, we have

$$\begin{aligned} X^T X G X^T X &= X^T X H X^T X \Rightarrow X G X^T X = X H X^T X \\ &\Rightarrow X^T X G^T X^T = X^T X H X^T \\ &\Rightarrow X G^T X^T = X H X^T \\ &\Rightarrow X G X^T = X H X^T = P_X \end{aligned}$$

□

Note 1.26. Recall that $X^- = (X^T X)^- X^T$. So that $P_X = X X^-$ is indeed a projection onto $\mathcal{C}(X)$. Since P_X is symmetric, it is the unique symmetric projection onto $\mathcal{C}(X)$.

Note 1.27. Recall that $(X^T)^- = X(X^T X)^-$. So that $P_X = (X^T)^- X^T$. A previous exercises tells us that $I - P_X$ is a projection on $\mathcal{N}(X^T)$. Since $I - P_X$ is symmetric, it is the unique symmetric projection onto $\mathcal{N}(X^T)$.

1.4. Differentiation.

Definition 1.28. Let $Q : \mathbb{R}^n \rightarrow \mathbb{R}$ given by $b \mapsto Q(b)$. Suppose that $Q \in C^1(\mathbb{R}^n)$. We define

$$\frac{\partial Q}{\partial b} = \begin{pmatrix} \frac{\partial Q}{\partial b_1} \\ \vdots \\ \frac{\partial Q}{\partial b_n} \end{pmatrix}$$

Exercise 1.29. Let $a, b \in \mathbb{R}_n$ and $A \in \mathcal{M}_{n,n}$. Then

$$\begin{aligned} (1) \quad & \frac{\partial a^T b}{\partial b} = a \\ (2) \quad & \frac{\partial b^T A b}{\partial b} = (A + A^T)b \end{aligned}$$

Proof.

(1) Since

$$a^T b = \sum_{i=1}^n a_i b_i$$

We have that

$$\frac{\partial a^T b}{\partial b_i} = a_i$$

and therefore

$$\frac{\partial a^T b}{\partial b} = a$$

(2) Since

$$\begin{aligned} b^T A b &= \sum_{i=1}^n b_i \sum_{j=1}^n A_{i,j} b_j \\ &= \sum_{i=1}^n \sum_{j=1}^n b_i A_{i,j} b_j \end{aligned}$$

The terms containing b_i are

$$A_{i,i}b_i^2 + \sum_{\substack{j=1 \\ j \neq i}}^n (A_{i,j} + A_{j,i})b_i b_j$$

This implies that

$$\begin{aligned} \frac{\partial b^T A b}{\partial b_i} &= 2A_{i,i}b_i + \sum_{\substack{j=1 \\ j \neq i}}^n (A_{i,j} + A_{j,i})b_j \\ &= \sum_{j=1}^n (A_{i,j} + A_{i,j}^T)b_j \\ &= [(A + A^T)b]_i \end{aligned}$$

So

$$\frac{\partial b^T A b}{\partial b} = (A + A^T)b$$

□

2. THE LINEAR MODEL

2.1. Model Description.

Definition 2.1. Given $y \in \mathbb{R}_m$ a vector of observed responses to the matrix $X \in \mathcal{M}_{m,n}$ of observed inputs, we will consider the model

$$y = Xb + e$$

where $b \in \mathbb{R}_n$ is a vector of unknown parameters and $e \in \mathbb{R}^m$ is a random vector of unobserved errors with zero mean.

Definition 2.2. For a parameter vector $b \in \mathbb{R}^n$, we have that $e = y - Xb$. For this reason, e is called the **residual vector** or simply the “residuals”.

Note 2.3. The goal will be to find a parameter vector $b \in \mathbb{R}^n$ that makes the causes the residuals to be as small as possible.

2.2. Least Squares Optimization.

Definition 2.4. We define the **cost function**, $Q : \mathbb{R}^n \rightarrow \mathbb{R}$ by

$$\begin{aligned} Q(b) &= \|y - Xb\|^2 \\ &= (y - Xb)^T (y - Xb) \end{aligned}$$

Definition 2.5. Let $b \in \mathbb{R}^n$. Then b is said to be a **least squares solution** for the model if

$$Q(b) = \inf_{c \in \mathbb{R}^n} Q(c)$$

Exercise 2.6. If b is a least squares solution for the model, then $X^T X b = X^T y$.

Proof. Suppose that b is a least squares solution for the model, then Q has a local minimum at b . Thus

$$\frac{\partial Q}{\partial b}(b) = 0$$

By definition,

$$\begin{aligned} Q(b) &= y^T y - y^T Xb - b^T X^T y + b^T X^T Xb \\ &= y^T y - 2y^T Xb + b^T X^T Xb \end{aligned}$$

Thus

$$\begin{aligned} 0 &= \frac{\partial Q}{\partial b}(b) \\ &= -2X^T y + 2X^T Xb \end{aligned}$$

Hence $X^T Xb = X^T y$. □

Definition 2.7. For $y \in \mathbb{R}^m$ and $X \in \mathcal{M}_{m,n}$, we define the **normal equation** to be

$$X^T Xb = X^T y$$

Exercise 2.8. The normal equation is consistent.

Proof. We have that $X^T y \in \mathcal{C}(X^T) = \mathcal{C}(X^T X)$. □

Exercise 2.9. Let $b \in \mathbb{R}^n$. Then b is a least squares solution for the model iff b satisfies the normal equation.

Proof. The previous exercises tells us that if b is a least squares solution for the model, then b satisfies the normal equation. Conversely, suppose that b satisfies the normal equation. Then

$$\begin{aligned} Q(c) &= (y - Xc)^T (y - Xc) \\ &= (y - Xb + Xb - Xc)^T (y - Xb + Xb - Xc) \\ &= (y - Xb)^T (y - Xb) - (y - Xb)^T (X(b - c)) - (b - c)^T X^T (y - Xb) + (b - c)^T X^T (X(b - c)) \\ &= Q(b) - 2(b - c)^T X^T (y - Xb) + \|X(b - c)\|^2 \\ &= Q(b) + \|X(b - c)\|^2 \end{aligned}$$

Thus b minimizes Q . □

Exercise 2.10. Let $b \in \mathbb{R}^n$ be a least squares solution for the model. Then $\|y\|^2 = \|Xb\|^2 + \|e\|^2$

Proof. Since b satisfies the normal equation, we have that $X^T (y - Xb) = 0$. Thus

$$\begin{aligned} Xb \cdot e &= b^T X^T e \\ &= b^T X^T (y - Xb) \\ &= b^T 0 \\ &= 0 \end{aligned}$$

So Xb and e are orthogonal. Therefore

$$\begin{aligned} \|y\|^2 &= \|Xb + e\|^2 \\ &= \|Xb\|^2 + \|e\|^2 \end{aligned}$$

□