

Problem Set 2

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With reference to Zushun Zong and Winston Xu.

1

i)

$$\|x + y\|^2 - \|x - y\|^2 = \|x\|^2 + \langle x, y \rangle + \langle y, x \rangle + \|y\|^2 - (\|x\|^2 - \langle x, y \rangle - \langle y, x \rangle + \|y\|^2)$$

$$\|x + y\|^2 - \|x - y\|^2 = 2(\langle x, y \rangle + \langle y, x \rangle)$$

$$\text{In } \mathbb{R}, \langle x, y \rangle = \sum_i a_i b_i = \sum_i b_i a_i = \langle y, x \rangle,$$

$$\langle x, y \rangle = \frac{1}{4}(\|x + y\|^2 - \|x - y\|^2)$$

ii)

$$\|x + y\|^2 + \|x - y\|^2 = \|x\|^2 + \langle x, y \rangle + \langle y, x \rangle + \|y\|^2 + \|x\|^2 - \langle x, y \rangle - \langle y, x \rangle + \|y\|^2$$

$$\frac{1}{2}(\|x + y\|^2 + \|x - y\|^2) = \|x\|^2 + \|y\|^2$$

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$$\begin{aligned} \text{RHS} &= \frac{1}{4}[\langle \vec{x} + \vec{y}, \vec{x} + \vec{y} \rangle - \langle \vec{x} - \vec{y}, \vec{x} - \vec{y} \rangle + i\langle \vec{x} - i\vec{y}, \vec{x} - i\vec{y} \rangle - i\langle \vec{x} + i\vec{y}, \vec{x} + i\vec{y} \rangle] \\ &= \frac{1}{4}[\langle \vec{x}, \vec{x} \rangle + \langle \vec{x}, \vec{y} \rangle + \langle \vec{y}, \vec{x} \rangle + \langle \vec{y}, \vec{y} \rangle - \langle \vec{x}, \vec{x} \rangle + \langle \vec{x}, \vec{y} \rangle + \langle \vec{y}, \vec{x} \rangle \\ &\quad - \langle \vec{y}, \vec{y} \rangle + i\langle \vec{x}, \vec{x} \rangle + \langle \vec{x}, \vec{y} \rangle - \langle \vec{y}, \vec{x} \rangle - i\langle \vec{y}, \vec{y} \rangle - i\langle \vec{x}, \vec{x} \rangle + \langle \vec{x}, \vec{y} \rangle \\ &\quad - \langle \vec{y}, \vec{x} \rangle + i\langle \vec{y}, \vec{y} \rangle] \\ &= \frac{1}{4}(4\langle \vec{x}, \vec{y} \rangle) = \langle \vec{x}, \vec{y} \rangle = \text{LHS} \end{aligned}$$

3 We need the following computation:

$$\langle x, x^5 \rangle = \int_0^1 x^6 dx = \frac{1}{7}$$

$$\sqrt{\langle x, x \rangle} = \sqrt{\int_0^1 x^2 dx} = \sqrt{\frac{1}{3}}$$

$$\sqrt{\langle x^5, x^5 \rangle} = \sqrt{\int_0^1 x^{10} dx} = \sqrt{\frac{1}{11}}$$

$$\langle x^2, x^4 \rangle = \int_0^1 x^6 dx = \frac{1}{7}$$

$$\sqrt{\langle x^2, x^2 \rangle} = \sqrt{\int_0^1 x^4 dx} = \sqrt{\frac{1}{5}}$$

$$\sqrt{\langle x^4, x^4 \rangle} = \sqrt{\int_0^1 x^8 dx} = \sqrt{\frac{1}{9}}$$

We now have the following:

1.

$$\theta_1 = \arccos\left(\frac{\langle x, x^5 \rangle}{\|x\| \|x^5\|}\right) = \arccos\left(\frac{\frac{1}{7}}{\sqrt{\frac{1}{3}}\sqrt{\frac{1}{11}}}\right) = \arccos\left(\frac{\sqrt{33}}{7}\right)$$

2.

$$\theta_2 = \arccos\left(\frac{\langle x^2, x^4 \rangle}{\|x^2\| \|x^4\|}\right) = \arccos\left(\frac{\frac{1}{7}}{\sqrt{\frac{1}{5}}\sqrt{\frac{1}{9}}}\right) = \arccos\left(\frac{\sqrt{45}}{7}\right)$$

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1. Observe that $\frac{1}{\pi} \int_{-\pi}^{\pi} \cos(t) \sin(t) dt = 0$, $\frac{1}{\pi} \int_{-\pi}^{\pi} \cos(t) \cos(2t) dt = 0$, $\frac{1}{\pi} \int_{-\pi}^{\pi} \cos(t) \sin(2t) dt = 0$, $\frac{1}{\pi} \int_{-\pi}^{\pi} \sin(t) \cos(2t) dt = 0$, $\frac{1}{\pi} \int_{-\pi}^{\pi} \sin(t) \sin(2t) dt = 0$, and $\frac{1}{\pi} \int_{-\pi}^{\pi} \cos(2t) \sin(2t) dt = 0$.

Moreover, we have $\frac{1}{\pi} \int_{-\pi}^{\pi} \cos(t) \cos(t) dt = 1$, $\frac{1}{\pi} \int_{-\pi}^{\pi} \sin(t) \sin(t) dt = 1$, $\frac{1}{\pi} \int_{-\pi}^{\pi} \cos(2t) \cos(2t) dt = 1$, and $\frac{1}{\pi} \int_{-\pi}^{\pi} \sin(2t) \sin(2t) dt = 1$.

1.

Hence S is an orthonormal set.

2.

$$\|t\| = \sqrt{\frac{1}{\pi} \int_{-\pi}^{\pi} t^2 dt} = \sqrt{\frac{2}{3} \pi^2} = \frac{\sqrt{6}\pi}{3}.$$

3. Observe that $\langle \cos(t), \cos(3t) \rangle = 0$, $\langle \sin(t), \cos(3t) \rangle = 0$, $\langle \cos(2t), \cos(3t) \rangle = 0$, $\langle \sin(2t), \cos(3t) \rangle = 0$.

Hence we have $\text{proj}_X(\cos(3t)) = 0$.

4. Note that $\frac{1}{\pi} \int_{-\pi}^{\pi} \cos(t) t dt = 0$, $\frac{1}{\pi} \int_{-\pi}^{\pi} \sin(t) t dt = 2$, $\frac{1}{\pi} \int_{-\pi}^{\pi} \cos(2t) t dt = 0$, $\frac{1}{\pi} \int_{-\pi}^{\pi} \sin(2t) t dt = -1$. Hence, $\text{proj}_X(t) = 2 \sin(t) - \sin(2t)$.

9 we can convert the rotation transformation into a matrix in the standard basis Q . If we can show that $Q^T Q = I$, then the transformation is orthonormal.

$$Q = \begin{bmatrix} \cos(\theta) & -\sin(\theta) \\ \sin(\theta) & \cos(\theta) \end{bmatrix}$$

\Rightarrow

$$Q^T Q = \begin{bmatrix} \cos(\theta)^2 + \sin(\theta)^2 & 0 \\ 0 & \cos(\theta)^2 + \sin(\theta)^2 \end{bmatrix}$$

\Rightarrow

$$Q^T Q = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} = I$$

Hence, the transformation is orthonormal.

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Proof. Suppose $Q = [\vec{q}_1, \vec{q}_2, \dots, \vec{q}_n]$ and $\vec{x} = [x_1, x_2, \dots, x_n]^T, \vec{y} = [y_1, y_2, \dots, y_n]^T$. Then

$$\langle Q\vec{x}, Q\vec{y} \rangle = \sum_{i=1}^n \sum_{j=1}^n \overline{x_i} y_j \langle \vec{q}_i, \vec{q}_j \rangle.$$

By definition, this equals $\langle \vec{x}, \vec{y} \rangle = \sum_{i=1}^n \sum_{j=1}^n \overline{x_i} y_j$ only when $\langle \vec{q}_i, \vec{q}_j \rangle = 0$ if $i \neq j$ and $\langle \vec{q}_i, \vec{q}_j \rangle = 1$ if $i = j$. This indicates that $Q^H Q = I$ and $Q Q^H = I$.

For the other direction, observe that $Q^H Q = I$ and $Q Q^H = I$ imply $\langle \vec{q}_i, \vec{q}_j \rangle = 0$ if $i \neq j$ and $\langle \vec{q}_i, \vec{q}_j \rangle = 1$ if $i = j$. The result then follows immediately.

$$\begin{aligned} \|Q\vec{x}\| &= \sqrt{\langle x_1 \vec{q}_1 + x_2 \vec{q}_2 + \dots + x_n \vec{q}_n, x_1 \vec{q}_1 + x_2 \vec{q}_2 + \dots + x_n \vec{q}_n \rangle} \\ &= \sqrt{\sum_{i,j} \overline{x_i} x_j \langle \vec{q}_i, \vec{q}_j \rangle} \\ &= \sqrt{\sum_i \overline{x_i} x_i \times 1} = \|\vec{x}\| \end{aligned}$$

To show that Q^{-1} is an orthonormal matrix, observe that $Q Q^H = I$ and $Q Q^{-1} = I$. This implies that $Q^{-1} = Q^H$. Then it is trivially true that $Q^{-1H} Q^{-1} = I$ and $Q^{-1} Q^{-1H} = I$.

The columns of Q are orthonormal have been shown in part 1.

Since Q is an orthonormal matrix, we know $Q^{-1} = Q^H$. Hence, $\det(Q) \det(Q^H) = \det(Q Q^H) = \det(I) = 1$. Since $\det(Q) = \det(Q^H)$, it follows that $|\det(Q)| = 1$. The converse is not true.

Observe that $(Q_1 Q_2)(Q_1 Q_2)^H = Q_1 Q_2 Q_2^H Q_1^H = Q_1 I Q_1^H = Q_1 Q_1^H = I$. Also, $(Q_1 Q_2)^H (Q_1 Q_2) = Q_2^H Q_1^H Q_1 Q_2 = Q_2^H I Q_2 = I$. Hence $Q_1 Q_2$ is also an orthonormal matrix. \square

11 Suppose there are only r independent vectors. Then we would first get r orthonormal vectors and then get $n - r$ zero vectors.

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1) Let $D =$

$$\begin{bmatrix} -1 & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 \\ \vdots & & 1 & \vdots \\ 0 & \dots & \dots & \ddots \end{bmatrix}$$

Then $QD = \begin{bmatrix} -q_1 & q_2 & \dots & q_n \end{bmatrix}$, which is still an orthonormal matrix, and $D^{-1}R$ is still an upper-triangular matrix. Observe that

$$QD \cdot D^{-1}R = Q(DD^{-1})R = QR = A$$

Hence $A = QD(D^{-1}R)$ is another form of QR decomposition., so it is not unique.

2 We need the following lemmas:

1. If Q_1 and Q_2 are orthonormal matrices, then, so is $Q_1^T Q_2$.

Proof.

$$(Q_1^T Q_2)(Q_1^T Q_2)^T = (Q_1^T Q_2)(Q_2^T Q_1) = Q_1^T (Q_2 Q_2^T) Q_1 = Q_1^T Q_1 = I$$

$$(Q_1^T Q_2)^T (Q_1^T Q_2) = Q_2^T (Q_1 Q_1^T) Q_2 = I$$

□

2. If U is an invertible upper-triangular matrix, then so is U^{-1} . The proof follows induction.

3. If U_1 and U_2 are upper-triangular matrices, then so is $U_1 U_2$.

Proof. Let $U_1 = [a_{ij}]$, $U_2 = [b_{ij}]$. Since both are upper triangular, it follows that $a_{ij}, b_{ij} = 0$ if $i > j$. □

Let $C = [c_{ij}] = U_1 U_2$, then $c_{ij} = \sum_{k=1}^n a_{ik} b_{kj}$.

Fix some $i > j$, then

$$c_{ij} = (a_{i1}b_{1j} + a_{i2}b_{2j} + \cdots + a_{i,i-1}b_{i-1,j}) + (a_{ii}b_{ij} + a_{i,i+1}b_{i+1,j} + \cdots + a_{in}b_{nj})$$

Note that in the first term, all $a_{ik} = 0$, and in the second term, all $b_{ki} = 0$.

Hence $c_{ij} = 0$ where $i > j$, $\Rightarrow C$ is upper-triangular.

Now by contradiction, assume that $A = Q_1 R_1$ and $A = Q_2 R_2$, where both R_1 and R_2 have positive diagonal elements.

Then $Q_2 R_2 = Q_1 R_1$, $\Rightarrow Q_1^T Q_2 = R_1 R_2^{-1}$.

Let $M = Q_1^T Q_2 = R_1 R_2^{-1}$, by lemma 1, M is orthonormal. By lemma 2 and 3, M is upper triangular with positive diagonals. It follows that M must be the identity matrix I .

Hence, $R_1 R_2^{-1} = I \Rightarrow R_1 = R_2$, and therefore, $Q_1 = Q_2$.

Thus, the decomposition is unique.

17 Since \hat{R} is an n by n upper-triangular matrix, \hat{R} is invertible, so is \hat{R}^H .

Since $A = \hat{Q} \hat{R}$,

$$\begin{aligned} A^H A \vec{x} &= A^H b \\ (\hat{Q} \hat{R})^H (\hat{Q} \hat{R}) \vec{x} &= (\hat{Q} \hat{R})^H b \\ \hat{R}^H \hat{R} \vec{x} &= \hat{R}^H \hat{Q}^H b \\ \hat{R} \vec{x} &= \hat{Q}^H b \end{aligned}$$

Hence the two systems are equivalent.

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$$\begin{aligned}
\|x - y\|^2 &= \langle x - y, x - y \rangle \\
&= \langle x, x \rangle - \langle x, y \rangle - \langle y, x \rangle + \langle y, y \rangle \\
&\geq \langle x, x \rangle - |\langle x, y \rangle| - |\langle y, x \rangle| + \langle y, y \rangle \\
&\geq \langle x, x \rangle - \|x\| \|y\| - \|y\| \|x\| + \langle y, y \rangle \\
&= \|x\|^2 - 2\|x\| \|y\| + \|y\|^2 \\
&= (\|x\| - \|y\|)^2
\end{aligned}$$

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- 1). 1. $\|f\|_{L^1} \geq 0$ is trivial.

Observe that since $|f(t)| \geq 0$,

$$\int_a^b |f(t)| dt = 0 \iff f(t) = 0 \text{ on } [a, b].$$

$$2. \|\alpha f\|_{L^1} = \int_a^b |\alpha f(t)| dt = |\alpha| \int_a^b |f(t)| dt = |\alpha| \|f\|_{L^1}$$

$$3. \|f + g\|_{L^1} = \int_a^b |f + g| dt \leq \int_a^b |f| + |g| dt = \|f\|_{L^1} + \|g\|_{L^1}$$

- 2). 1. $\|f\|_{L^2} \geq 0$ is trivial.

Observe that since $|f(t)| \geq 0$,

$$\text{original} = 0 \iff f(t) = 0 \text{ on } [a, b].$$

$$2. \|\alpha f\|_{L^2} = \left(\int_a^b |\alpha f(t)|^2 dt \right)^{\frac{1}{2}} = |\alpha| \left(\int_a^b |f(t)|^2 dt \right)^{\frac{1}{2}} = |\alpha| \|f\|_{L^2}$$

$$3. \|f + g\|_{L^1} = \left(\int_a^b |f + g| dt \right)^{\frac{1}{2}} = \left(\int_a^b |f|^2 + |g|^2 + 2|f||g| dt \right)^{\frac{1}{2}}.$$

$$\text{In } \mathbb{L}^2, [a, b], \langle f, g \rangle = \int_a^b (\bar{f}g)^2 dt.$$

By Cauchy-Schwarz,

$$|\langle f, g \rangle| \leq \|f\| \|g\|$$

$$\text{i.e. } \left| \int_a^b \bar{f}g dt \right|^2 \leq \int_a^b |\bar{f}f| dt \cdot \int_a^b |\bar{g}g| dt$$

$$\Rightarrow \left| \int_a^b |f||g| dt \right|^2 \leq \int_a^b |f|^2 dt \cdot \int_a^b |g|^2 dt$$

$$\text{Hence, } \left(\int_a^b |f|^2 + |g|^2 + 2|f||g| dt \right)^{\frac{1}{2}} \leq \left(\int_a^b |f|^2 dt + \int_a^b |g|^2 dt + 2 \left(\int_a^b |f|^2 dt \int_a^b |g|^2 dt \right)^{\frac{1}{2}} \right)^{\frac{1}{2}}$$

$$\int_a^b |f|^2 + |g|^2 + |f||g| dt \leq \left(\sqrt{\int_a^b |f|^2 dt} + \sqrt{\int_a^b |g|^2 dt} \right)^2$$

$$\Rightarrow \|f + g\|_{L^2} \leq \|f\|_{L^2} + \|g\|_{L^2}$$

- 3). 1. $\|f\|_{L^\infty} \geq 0$ is trivial.

Observe that since $|f(t)| \geq 0$,

$$\text{original} = 0 \iff f(t) = 0 \text{ on } [a, b].$$

$$2. \|\alpha f\|_{L^\infty} = \sup_{x \in [a, b]} |\alpha f(x)| = |\alpha| \sup_{x \in [a, b]} |f(x)| = |\alpha| \|f\|_{L^\infty}$$

$$3. \|f + g\|_{L^\infty} \leq \sup_{x \in [a, b]} |f(x)| + \sup_{x \in [a, b]} |g(x)| = \|f\|_{L^\infty} + \|g\|_{L^\infty}$$

26 To prove this is an equivalence relationship:

Proof. 1. $\|\cdot\|$ is topologically equivalent to $\|\cdot\|_a$ by choosing $m = M = 1$.
 2. If $m\|x\|_a \leq \|x\|_b \leq M\|x\|_a$, $\forall \vec{x}$,
 then $\frac{1}{M}\|x\|_b \leq \|x\|_a \leq \frac{1}{m}\|x\|_b$, $\forall \vec{x}$,
 so it is symmetric.
 3. If $m\|x\|_a \leq \|x\|_b \leq M\|x\|_a$, $\forall \vec{x}$, and if $n\|x\|_b \leq \|x\|_c \leq N\|x\|_b$, $\forall \vec{x}$,
 then $mn\|x\|_a \leq \|x\|_c \leq MN\|x\|_a$ $\forall \vec{x}$.
 Thus it is transitive.
 \Rightarrow Thus this is an equivalence relationship. □

1). $\|\vec{x}\|_2^2 = \sum_{i=1}^n x_i^2$

$$\|x\|_1^2 = \sum_{i=1}^n |x_i|^2 \quad (1)$$

$$= \sum_{i=1}^n x_i^2 + \sum_{i \neq j} |x_i| |x_j| \quad (2)$$

$$\geq \sum_{i=1}^n x_i^2 = \|\vec{x}\|_2^2 \quad (3)$$

Thus, $\|\vec{x}\|_1 \geq \|\vec{x}\|_2$

Let $\vec{u} = [\text{sgn}(x_1), \dots, \text{sgn}(x_n)]^T$, $\|\vec{x}\|_1 = \sum_{i=1}^n x_i \cdot \text{sgn}(x_i) = |\langle \vec{u}, \vec{x} \rangle|$.

By Cauchy-Schwarz, $|\langle \vec{u}, \vec{x} \rangle| \leq \|\vec{u}\|_2 \|\vec{x}\|_2 = \sqrt{n} \|\vec{x}\|_2$

Hence, $\|\vec{x}\|_1 \leq \sqrt{n} \|\vec{x}\|_2$

2). Let $|x_k| = \|\vec{x}\|_\infty = \max_{i=1}^n |x_i|$

Then, $\|x\|_2^2 = \sum_{i=1}^n |x_i|^2 = nx_k^2 = \|\vec{x}\|_\infty^2$

Hence, $\|x\|_2 \geq \|x\|_\infty$

Moreover, $\|x\|_2^2 \leq nx_k^2$

$\Rightarrow \|x\|_\infty \leq \|x\|_2 \leq \sqrt{n} \|x\|_\infty$

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i. From the previous exercise, we can get $\sup_{x \neq 0} \frac{\|Ax\|_1}{\|x\|_1} \leq \sup_{x \neq 0} \frac{\|Ax\|_1}{\|x\|_1} \leq \sqrt{n} \sup_{x \neq 0} \frac{\|Ax\|_2}{\|x\|_2}$, and

$\sup_{x \neq 0} \frac{\|Ax\|_1}{\|x\|_1} \geq \sup_{x \neq 0} \frac{\|Ax\|_2}{\|x\|_1} \geq \frac{1}{\sqrt{n}} \sup_{x \neq 0} \frac{\|Ax\|_2}{\|x\|_2}$, which imply that
 $\frac{1}{\sqrt{n}} \|A\|_2 \leq \|A\|_1 \leq \|A\|_2$.

ii. From previous we can get: $\sup_{x \neq 0} \frac{\|Ax\|_2}{\|x\|_2} \leq \sup_{x \neq 0} \frac{\sqrt{n} \|Ax\|_\infty}{\|x\|_\infty}$, and $\sup_{x \neq 0} \frac{\|Ax\|_2}{\|x\|_2} \geq \sup_{x \neq 0} \frac{\|Ax\|_\infty}{\sqrt{n} \|x\|_\infty}$.

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Proof. First, NTS: $\|Q\|_2 = 1$, where Q is orthonormal.

$$\begin{aligned} \|Qx\| &= \|x\| \\ \Rightarrow \sup_{x \neq 0} \frac{\|Qx\|}{\|x\|} &= \|Q\| = 1 \end{aligned}$$

Next, by definition, $\|A\|_2 = \sup_{x \neq 0} \frac{\|Ax\|_2}{\|x\|_2}$,
 $\Rightarrow \|Ax\|_2 \leq \|A\|_2 \|x\|_2$.

Now,

$$\frac{\|Ax\|_2}{\|A\|_2} \leq \frac{\|A\|_2 \|x\|_2}{\|A\|_2} = \|x\|_2$$

Take sup on both sides, we have

$$\|Ax\|_2 = \sup_{\|A\|_2 \neq 0} \frac{\|Ax\|_2}{\|A\|_2} \leq \|x\|_2$$

□

30 (i) Positivity:

Since $\|A\|_S = \|SAS^{-1}\| \geq 0$ and $\|A\|_S = \|SAS^{-1}\| = 0$ if and only if $SAS^{-1} = 0$.

(ii) Scalar Preservation:

$$\|kA\|_S = \|SkAS^{-1}\| = \|kSAS^{-1}\| = k\|SAS^{-1}\| = k\|A\|_S$$

(iii) Triangle Inequality:

$$\|(A+B)\|_S = \|S(A+B)S^{-1}\| = \|SAS^{-1} + SBS^{-1}\| \leq \|SAS^{-1}\| + \|SBS^{-1}\| = \|A\|_S + \|B\|_S$$

(iv) Submultiplicative:

$$\|AB\|_S = \|SAB S^{-1}\| = \|SAS^{-1}SBS^{-1}\| \leq \|SAS^{-1}\| \cdot \|SBS^{-1}\| = \|A\|_S \cdot \|B\|_S$$

Therefore, we have shown that $\|\cdot\|_S$ is a matrix norm,

37 We first find a set of orthonormal basis for V.

Let $p_1 = 1$, $q_1 = \frac{p_1}{\|p_1\|} = \frac{1}{\int_0^1 1 dx} = 1$.

let $p_2 = x - \text{proj}_1 x = x - \frac{1}{2}$, $q_2 = \frac{p_2}{\|p_2\|} = \sqrt{12}(x - \frac{1}{2})$.

Let $p_3 = x^2 - \text{proj}_1 x^2 - \text{proj}_{x-\frac{1}{2}} x^2 = x^2 - x + \frac{1}{6}$, $q_3 = \frac{p_3}{\|p_3\|} = \sqrt{180}(x^2 - x + \frac{1}{6})$.

Then, $q = \sum_{i=1}^3 L(q_i)q_i = 0 + 12(x - \frac{1}{2}) + 180(x^2 - x + \frac{1}{6}) = 180x^2 - 168x + 24$.

It can be referred that $\forall p \in V, L[p] = \langle q \cdot p \rangle$

38 Let $\mathcal{B} = \{1, x, x^2\}$, then:

$$D = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 2 \\ 0 & 0 & 0 \end{bmatrix}$$

Also we have:

$$D^* = -D = \begin{bmatrix} 0 & -1 & 0 \\ 0 & 0 & -2 \\ 0 & 0 & 0 \end{bmatrix}$$

39 (i)

$$\begin{aligned} \langle (S + T)v, w \rangle &= \langle Sv, w \rangle + \langle Tv, w \rangle = \langle v, S^*w \rangle + \langle v, T^*w \rangle = \langle v, (S^* + T^*)w \rangle \\ \langle \alpha T^*v, w \rangle &= \alpha \langle Tv, w \rangle = \alpha \langle v, T^*w \rangle = \langle v, \bar{\alpha} T^*w \rangle \end{aligned}$$

(ii)

$$\langle S^*v, w \rangle = \overline{\langle w, S^*v \rangle} = \overline{\langle Sw, v \rangle} = \langle v, Sw \rangle$$

(iii)

$$\langle STv, w \rangle = \langle Tv, S^*w \rangle = \langle v, T^*S^*w \rangle$$

(iv)

$$\begin{aligned} \text{Since } \langle T^*(T^{-1})^*x, y \rangle &= \langle (T^{-1})^*x, Ty \rangle = \langle x, (T^{-1})Ty \rangle = \langle x, y \rangle \text{ for } \forall x, y \\ \Rightarrow T^*(T^{-1})^* &= I \end{aligned}$$

40 (i)

View A as the operator,

$$\text{since } \langle AB, C \rangle = \text{tr}(AB)^H C = \text{tr} B^H A^H C = \langle B, A^H C \rangle \Rightarrow A^* = A^H$$

(ii)

$$\langle A_2, A_3 A_1 \rangle = \text{tr}(A_2^H A_3 A_1) = \text{tr}(A_1 A_2^H A_3) = \text{tr}(A_2 A_1^H A_3) = \langle A_2 A_1^*, A_3 \rangle$$

(iii)

$$\text{For some } B, C \in \mathbb{M}_n(\mathbb{F}), \text{ we have } \langle B, AC - CA \rangle = \langle B, AC \rangle - \langle B, CA \rangle.$$

$$\text{Applying (ii), we have } \langle B, CA \rangle = \langle BA^*, C \rangle.$$

$$\text{Meanwhile, } \langle B, AC \rangle = \text{tr}(B^H AC) = \text{tr}((A^H B)^H C) = \langle A^H B, C \rangle = \langle A^* B, C \rangle$$

$$\Rightarrow T_A^* = T_{A^*}$$

44 If $b = 0$, then $b \in R(A)$, and $x = 0$ is a solution to $Ax = 0$.

Now if $b \neq 0$, since $\mathbb{F}^n = R(A) + N(A^H)$,

then either $b \in R(A)$ or $b \in N(A^H)$.

If $b \in R(A)$, then $\exists x$ as a solution.

If $b \in N(A^H)$, let $y = b$, since $b \neq 0$, $\langle y, b \rangle = \langle b, b \rangle \neq 0$

45 (i)

First we will show that $\text{Skew}_n(\mathbb{R}) \subset \text{Sym}_n^\perp(\mathbb{R})$.

$$\text{Let } A \in \text{Skew}_n(\mathbb{R}) \text{ Then, } \forall B \in \text{Sym}_n(\mathbb{R}), \langle A, B \rangle = \text{tr}(A^H B) = \text{tr}(-AB) = \text{tr}(-AB^H) = -\overline{\langle A, B \rangle}$$

$$\text{Also } \langle A, B \rangle = -\overline{\langle A, B \rangle} \implies \langle A, B \rangle = 0 \text{ for all } B \in \text{Sym}_n(\mathbb{R})$$

$$\Rightarrow A \in \text{Sym}_n(\mathbb{R})^\perp$$

(ii)

Then we will show that $\text{Sym}_n^\perp(\mathbb{R}) \subset \text{Skew}_n(\mathbb{R})$.

Let $B \in \text{Sym}_n(\mathbb{R})^\perp$. Then for $\forall A \in \text{Sym}_n(\mathbb{R})$,

$\langle B + B^T, A \rangle = \langle B, A \rangle + \langle B^T, A \rangle = 0 + \langle B^T, A \rangle$
 and $\langle B^T, A \rangle = \text{tr}(BA) = \text{tr}(BA^T) = \text{tr}(A^T B) = \text{tr}(B^T A) = \langle B, A \rangle = 0$
 $\Rightarrow \langle B + B^T, A \rangle = 0$ for all $A \in \text{Sym}_n(\mathbb{R})$
 But $B + B^T \in \text{Sym}_n(\mathbb{R}) \Rightarrow \|B + B^T\| = 0 \Rightarrow B + B^T = 0 \Rightarrow B^T = -B$

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1). $\because x \in N(A^H A), \therefore Ax \in R(A)$.

Since $x \in N(A^H A), A^H Ax = 0 \Rightarrow A^H * (Ax) = 0 \Rightarrow Ax \in N(A^H)$.

2). i). NTS: $N(A^H A) \subset N(A)$.

Pick $x \in N(A^H A)$, then $A^H Ax = 0$.

If $x = 0$, then $x = 0 \in N(A)$

If $x \neq 0$, NTS: $Ax = 0$

By contradiction, assum $Ax \neq 0$.

Then, $A^H(Ax) = 0$ implies that $Ax \in N(A^H)$

Since $Ax \in R(A)$ and $Ax \neq 0$, this contradicts with the fact that $R(A)^\perp = N(A^H)$.

Hence $Ax = 0$ and $x \in N(A)$.

Therefore, $N(A^H A) \subset N(A)$

ii). NTS: $N(A) \subset N(A^H A)$.

Pick $x \in N(A)$, then $Ax = 0$. It follows that $A^H Ax = A^H(Ax) = A^H \cdot 0 = 0$.

Hence, $x \in N(A^H A)$ and $N(A^H A) = N(A)$.

$\Rightarrow N(A) = N(A^H A)$

3). Observe that both A and $A^H A$ are both map to the n-dimensional spaces.

By rank-nullity, $\dim(V) = \text{rank}(L) + \dim(N(L))$, where $L : V \rightarrow W$.

Since $N(A^H A) = N(A)$ by 2)., we have $\dim(N(A^H A)) = \dim(N(A))$

It follows that $\text{rank}(A^H A) = \dim(\mathbb{R}^n) - \dim(N(A^H A)) = \dim(\mathbb{R}^n) - \dim(N(A)) = \text{rank}(A)$

4). Since $A \in M_{m \times n}(\mathbb{R}), A^T A \in M_{m \times m}(\mathbb{R})$

If A has linearly independent columns, then $\text{rank}(A) = n$

Since $A^T A$ is an n by n matrix, it is non-singular.

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i). $p^2 = [A(A^H A)^{-1} A^H][A(A^H A)^{-1} A^H] = A(A^H A)^{-1} A^H = p$

ii). lemma: $(A^{-1})^H = (A^T)^{-1}$

proof of lemma:

$(A^{-1} A^H = (A A^{-1})^H) = I^H = I$

$$A^T(A^{-1})^H = (A^{-1}A)^H = I$$

$$\begin{aligned} p^H &= [A(A^H A)^{-1} A^H]^H \\ &= A[(A^H A)^{-1}]^H A^H \\ &= A[(A^H A)^H]^{-1} A^H \\ &= A(A^H A)^{-1} A^H \\ &= p \end{aligned}$$

iii. Since we know that rank will not increase in matrix multiplication, we can infer that $\text{rank}(p) \leq \text{rank}(A) = n$.

Now, $\forall y \in R(A), \exists x \text{ s.t. } Ax = y$.

Observe that $p_y = A(A^H A)^{-1} A^H y = Ax = y$,

$\Rightarrow y \in R(p)$

It follows that $R(A) \subset R(p)$, so $n = \text{rank}(A) \leq \text{rank}(p)$

We can now conclude that $\text{rank}(p) = n$.

48 (i)

let $\alpha \in \mathbb{R}, A, B \in M_n(\mathbb{R})$, then we have:

$$\begin{aligned} P(\alpha(A+B)) &= \frac{(\alpha(A+B)) + (\alpha(A+B))^T}{2} \\ &= \frac{\alpha(A+B) + \alpha(A^T+B^T)}{2} \\ &= \frac{\alpha(A+A^T+B+B^T)}{2} \\ &= \alpha(P(A) + P(B)) \end{aligned}$$

(ii)

$$P^2(A) = \frac{P(A) + P(A)^T}{2} = \frac{\frac{A+A^T}{2} + \frac{A+A^T}{2}}{2} = \frac{A+A^T}{2} = P(A)$$

(iii)

$$\begin{aligned} \langle P(A), B \rangle &= \text{tr}(P(A)^T B) = \text{tr}\left(\frac{A+A^T}{2} \cdot B\right) = \frac{\text{tr}(A^T B + AB)}{2} = \text{tr}(AB) = \frac{\text{tr}(AB + AB^T)}{2} \\ &= \text{tr}\left(A \cdot \frac{B+B^T}{2}\right) = \text{tr}(AP(B)) = \langle A, P(B) \rangle \end{aligned}$$

(iv)

$$A \in \text{Ker}(P) \iff P(A) = 0 \iff A + A^T = 0 \iff A = -A^T \iff A \in \text{Skew}_n(\mathbb{R})$$

(v)

$$\begin{aligned}
A \in \text{Range}(P) &\iff \exists B : A = P(B) \\
&\iff \exists B : B + B^T = 2A \\
&\iff A \in \text{Sym}_n(\mathbb{R})
\end{aligned}$$

(vi)

$$\begin{aligned}
\|A - P(A)\|_F^2 &= \langle A - P(A), A - P(A) \rangle = \langle A - \frac{A + A^T}{2}, A - \frac{A + A^T}{2} \rangle \\
&= \langle \frac{A - A^T}{2}, \frac{A - A^T}{2} \rangle = \text{Tr} \left(\left(\frac{A - A^T}{2} \right)^T \frac{A - A^T}{2} \right) \\
&= \text{Tr} \left(\frac{A^T - A}{2} \frac{A - A^T}{2} \right) = \text{Tr} \left(\frac{A^T A - A^2 - (A^T)^2 + A A^T}{4} \right) \\
&= \text{Tr} \left(\frac{A^T A - A^2 - A^2 + A^T A}{4} \right) = \text{Tr} \left(\frac{A^T A - A^2}{2} \right) = \frac{\text{Tr}(A^T A) - \text{Tr}(A^2)}{2}.
\end{aligned}$$

50 Let

$$A = \begin{bmatrix} x_1^2 & y_1^2 \\ \cdot & \cdot \\ \cdot & \cdot \\ \cdot & \cdot \\ x_n^2 & y_n^2 \end{bmatrix}, \quad x = \begin{bmatrix} r \\ s \end{bmatrix}, \quad b = \begin{bmatrix} 1 \\ \cdot \\ \cdot \\ \cdot \\ 1 \end{bmatrix}$$

Then the normal equation to solve is:

$$AA^T x = A^T b$$