

**Problem Set #[2]**  
OSM Lab, Zachary Boyd  
John Wilson

**Problem 3.1**

i)

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

ii)

$$\begin{aligned}\frac{1}{2}(\|x+y\|^2 + \|x-y\|^2) &= \frac{1}{2}(\langle x+y, x+y \rangle + \langle x-y, x-y \rangle) = \\ &= \frac{1}{2}(\langle x, x \rangle + 2\langle x, y \rangle + \langle y, y \rangle + \langle x, x \rangle - 2\langle x, y \rangle + \langle y, y \rangle) = \|x\|^2 + \|y\|^2\end{aligned}$$

**Problem 3.2**

Expansion of the norms into inner products and then separation by linearity yields

$$\begin{aligned}\frac{1}{4}(\|x+y\|^2 - \|x-y\|^2 + i\|x-iy\|^2 - i\|x+iy\|^2) &= \\ \frac{1}{4}(\langle x, x \rangle + \langle x, y \rangle + \langle y, x \rangle + \langle y, y \rangle - \langle x, x \rangle + \langle x, y \rangle + \langle y, x \rangle - \langle y, y \rangle + i\langle x, x \rangle + \dots \\ \langle x, y \rangle - \langle y, x \rangle + i\langle y, y \rangle - i\langle x, x \rangle + \langle x, y \rangle - \langle y, x \rangle - i\langle y, y \rangle) &= \langle x, y \rangle\end{aligned}$$

**Problem 3.3**

By definition 3.3.18, we have that given vectors  $x$  and  $y$ ,  $\cos\theta = \frac{\langle x, y \rangle}{\|x\|\|y\|}$ .

i) Note  $\sqrt{\int_0^1 x^2 dx} = \frac{1}{\sqrt{3}}$ ,  $\sqrt{\int_0^1 x^{10} dx} = \frac{1}{\sqrt{11}}$ , and  $\int_0^1 x^6 dx = \frac{1}{7}$ . So  $\theta = \cos^{-1}\left(\frac{\sqrt{33}}{7}\right)$

ii) We have  $\sqrt{\int_0^1 x^4 dx} = \frac{1}{\sqrt{5}}$ ,  $\sqrt{\int_0^1 x^8 dx} = \frac{1}{3}$ , and  $\int_0^1 x^6 dx = \frac{1}{7}$ . So  $\theta = \cos^{-1}\left(\frac{3\sqrt{5}}{7}\right)$

**Problem 3.8**

i) Given  $\langle f, g \rangle = \frac{1}{\pi} \int_{-\pi}^{\pi} f(t)g(t)dt$ , we have the following results:  $\langle \cos(t), \cos(t) \rangle = 1$ ,  $\langle \cos(t), \sin(t) \rangle = 0$ ,  $\langle \cos(t), \cos(2t) \rangle = 0$ ,  $\langle \cos(t), \sin(2t) \rangle = 0$ ,  $\langle \sin(t), \sin(t) \rangle = 1$ ,  $\langle \sin(t), \cos(2t) \rangle = 0$ ,  $\langle \sin(t), \sin(2t) \rangle = 0$ ,  $\langle \cos(2t), \cos(2t) \rangle = 1$ ,  $\langle \cos(2t), \sin(2t) \rangle = 0$ ,  $\langle \sin(2t), \sin(2t) \rangle = 1$ . Thus the set is orthonormal.

ii)  $\|t\| = \sqrt{\langle t, t \rangle} = \sqrt{\frac{1}{\pi} \int_{-\pi}^{\pi} t^2 dt} = \frac{\sqrt{6\pi}}{3}$

iii)  $\text{proj}_X(\cos(3t)) = \sum_{f \in S} \langle f, \cos(3t) \rangle f = 0$ . It results that  $\cos(3t)$  is orthogonal to this set.

iv)  $\text{proj}_X t = \sum_{f \in S} \langle f, t \rangle f = 2 \sin t - \sin(2t)$

**Problem 3.9** Let  $\mathbf{x} = [x_1 \ x_2]^T, \mathbf{y} = [y_1 \ y_2]^T$  be real valued vectors. Then  $\langle R_\theta \mathbf{x}, R_\theta \mathbf{y} \rangle = \cos^2 \theta x_1 y_1 - \cos \theta \sin \theta (x_1 y_2 + x_2 y_1) + \sin^2 \theta (x_2 y_2 + x_1 y_1) + \cos \theta \sin \theta (x_1 y_2 +$

$x_2y_1) + \cos^2 \theta x_2y_2 = x_1y_1 + x_2y_2 = \langle x, y \rangle$ , as desired.

**Problem 3.10 i)** Let  $Q$  be an orthonormal matrix. Then  $\langle Qx, Qy \rangle = \langle x, y \rangle \Rightarrow x^H Q^H Q y = x^H y \Rightarrow Q^H Q y = y \Rightarrow Q^H Q = I$ . By Proposition 3.2.12, we have that  $Q$  is invertible, since the field is of finite dimension  $n$ . Thus by uniqueness of inverses, we also have  $Q Q^H = I$ , as desired.

ii) Since i) holds, we have  $\|Qx\| = \sqrt{\langle x^H Q^H Q x \rangle} = \sqrt{\langle x^H x \rangle} = \|x\|$ .

iii) Note that by i),  $Q^{-1} = Q^H$ . We have  $\langle Q^H x, Q^H y \rangle = x^H Q Q^H y = x^H y = \langle x, y \rangle$ , as desired.

iv) Observe that the  $i^{th}$  column of  $Q$  is equal to  $Qe_i$ , where  $e_i$  is the  $i^{th}$  standard basis vector. Then  $\langle Qe_i, Qe_j \rangle = \langle e_i, e_j \rangle = \delta_{i,j}$ , where  $\delta_{i,j}$  is the Kronecker delta. This establishes orthonormality of the columns.

v) Let  $Q$  be orthonormal. Then we know, since  $Q^H Q = I$ , that  $\det Q^H Q = 1$ . So  $1 = \det Q^H Q = (\det Q)^2$ , so  $|\det Q| = 1$ . The converse is not true. Take the matrix

$$A = \begin{bmatrix} 1 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

This matrix has determinant 1 but the second column is not a unit vector, so it is not an orthonormal matrix.

vi) Let  $Q_1, Q_2 \in M_n(\mathbb{F})$  be orthonormal matrices. Then  $\langle Q_1 Q_2 x, Q_1 Q_2 y \rangle = x^H Q_2^H Q_1^H Q_1 Q_2 y = x^H Q_2^H Q_2 y = x^H y = \langle x, y \rangle$ , showing that the product is orthonormal.

**Problem 3.11** Suppose  $x_i$  is a linear combination of the elements  $x_j$  of your basis set with  $j < i$ . When this happens, the difference  $x_i - p_{i-1}$  will equal zero, and division by the norm of this difference will cause the problem to be undefined. Thus each element of the basis set must be linearly independent.

**Problem 3.16 i)** We provide a counterexample. Consider the matrices  $Q$  and  $R$  given in Example 3.3.11. Modify  $Q$  such that

$$Q = \begin{bmatrix} 1 & -1 & 1 & -\sqrt{2} \\ 1 & 1 & -1 & 0 \\ 1 & 1 & 1 & \sqrt{2} \\ 1 & -1 & -1 & 0 \end{bmatrix}$$

We still have that  $A = QR$  and  $Q$  is orthonormal, showing that QR decompositions are not unique.

ii) Let  $A = Q_1 R_1 = Q_2 R_2$  and  $R_1, R_2$  have only positive diagonal elements. Then it follows that  $R_1 R_2^{-1} = Q_1^{-1} Q_2 = Q_1^H Q_2$ . Since upper triangularity and orthonormality are closed under matrix multiplication,  $R_1 R_2^{-1}$  must be an orthonormal, upper triangular matrix with all positive entries along the diagonal. This implies that it must equal the identity matrix. Then  $I = Q_1^H Q_2$ , and  $Q_2^{-1} = Q_2^H = Q_1^H$ . Thus  $Q_2 = Q_1$ . Identical logic shows that  $R_2 = R_1$ . Thus the QR decomposition is unique here.

**Problem 3.17**  $A^H Ax = A^H b \Leftrightarrow \widehat{R}^H \widehat{Q}^H \widehat{Q} \widehat{R} x = \widehat{R}^H \widehat{Q}^H b \Leftrightarrow \widehat{R}^H \widehat{R} x = \widehat{R}^H \widehat{Q}^H b \Leftrightarrow \widehat{R} x = \widehat{Q}^H b$

**Problem 3.23** Note  $\|x\| = \|x + y - y\| \leq \|x - y\| + \|y\|$  by the triangle inequality, so  $\|x\| - \|y\| \leq \|x - y\|$ . Similar logic yields  $\|y\| - \|x\| \leq \|y - x\| = \|x - y\|$ . Since  $\|\|x\| - \|y\|\|$  is one of these two cases, the result is immediate.

**Problem 3.24** Norm properties: 1:  $\|\mathbf{x}\| \geq 0$ , with equality only if  $x = 0$ . 2:  $\|a\mathbf{x}\| = |a|\|\mathbf{x}\|$ . 3:  $\|\mathbf{x} + \mathbf{y}\| \leq \|\mathbf{x}\| + \|\mathbf{y}\|$ .

i) Note  $|\cdot|$  is a norm, so the three properties hold. Then  $\|f\|_{L^1} = \int_a^b |f(t)| dt \geq 0$  since the integrand is non-negative. Similarly,  $\int_a^b |f(t)| dt = 0 \Leftrightarrow |f(t)| = 0 \Leftrightarrow f = 0$ . So property 1 holds. Property 2:  $\|af\|_{L^1} = \int_a^b |af(t)| dt = |a| \int_a^b |f(t)| dt = |a|\|f\|_{L^1}$ . Property 3:  $\|f + g\|_{L^1} = \int_a^b |f(t) + g(t)| dt \leq \int_a^b |f(t)| + |g(t)| dt = \int_a^b |f(t)| dt + \int_a^b |g(t)| dt = \|f\|_{L^1} + \|g\|_{L^1}$

ii) 1:  $\|f\|_{L^2} = \left( \int_a^b |f(t)|^2 dt \right)^{\frac{1}{2}} \geq 0$  since the integrand is non-negative. Similarly,  $\left( \int_a^b |f(t)|^2 dt \right)^{\frac{1}{2}} = 0 \Leftrightarrow |f(t)| = 0 \Leftrightarrow f = 0$ . So property 1 holds. Property 2:  $\|af\|_{L^2} = \left( \int_a^b |af(t)|^2 dt \right)^{\frac{1}{2}} = \left( \int_a^b |a|^2 |f(t)|^2 dt \right)^{\frac{1}{2}} = \left( |a|^2 \int_a^b |f(t)|^2 dt \right)^{\frac{1}{2}} = |a| \left( \int_a^b |f(t)|^2 dt \right)^{\frac{1}{2}} = |a|\|f\|_{L^2}$ . Property 3: First observe that by i), both  $\|f + g\|_{L^2}$  and  $\|f\|_{L^2} + \|g\|_{L^2}$  are positive quantities. Then we can square both sides and show equivalently that  $\|f + g\|_{L^2}^2 \leq \|f\|_{L^2}^2 + 2\|f\|_{L^2}\|g\|_{L^2} + \|g\|_{L^2}^2$ . See that  $\|f + g\|_{L^2}^2 = \int_a^b |f(t) + g(t)|^2 dt \leq \int_a^b |f(t)|^2 + 2|f(t)||g(t)| + |g(t)|^2 dt = \int_a^b |f(t)|^2 dt + 2 \int_a^b |f(t)||g(t)| dt + \int_a^b |g(t)|^2 dt = \|f\|_{L^2}^2 + 2\|f\|_{L^2}\|g\|_{L^2} + \|g\|_{L^2}^2$ . Thus  $\|f + g\|_{L^2}^2 \leq \|f\|_{L^2}^2 + 2\|f\|_{L^2}\|g\|_{L^2} + \|g\|_{L^2}^2$  and  $\|f + g\|_{L^2} \leq \|f\|_{L^2} + \|g\|_{L^2}$  and 3 holds.

iii) 1:  $\|f\|_{L^\infty} = \sup_{x \in [a,b]} |f(t)| \geq 0$  with  $\sup_{x \in [a,b]} |f(t)| = 0$  only when  $f = 0$ , by properties of supremums and norms. 2:  $\|cf\|_{L^\infty} = \sup_{x \in [a,b]} |cf(t)| = \sup_{x \in [a,b]} |c||f(t)| = |c| \sup_{x \in [a,b]} |f(t)| = |c|\|f\|_{L^\infty}$ . Property 3:  $\|f + g\|_{L^\infty} = \sup_{x \in [a,b]} |f(t) + g(t)| \leq \sup_{x \in [a,b]} |f(t)| + \sup_{x \in [a,b]} |g(t)| = \|f\|_{L^\infty} + \|g\|_{L^\infty}$  by supremum and absolute value properties. Thus it is a norm.

**Problem 3.26** We show that it is an equivalence relation. Symmetry: suppose  $\|\cdot\|_a \approx \|\cdot\|_b$ . Then by definition  $m\|x\|_a \leq \|x\|_b \leq M\|x\|_a$  which implies that  $\frac{1}{M}\|x\|_b \leq \|x\|_a \leq \frac{1}{m}\|x\|_b$ , with  $0 < \frac{1}{M} \leq \frac{1}{m}$  as desired.

Reflexiveness: We know  $1\|x\|_a \leq \|x\|_a \leq 1\|x\|_a$ , and thus  $\|\cdot\|_a \approx \|\cdot\|_a$ .

Transitivity: Suppose  $\|\cdot\|_a \approx \|\cdot\|_b$  and  $\|\cdot\|_b \approx \|\cdot\|_c$ . Then there exist  $u, U, m, M$  such that  $0 < u \leq U, 0 < m \leq M$  and  $m\|x\|_a \leq \|x\|_b \leq M\|x\|_a$  and  $u\|x\|_b \leq \|x\|_c \leq U\|x\|_b$ . Multiplication yields  $mu\|x\|_a \leq u\|x\|_b \leq \|x\|_c \leq U\|x\|_b \leq MU\|x\|_a$ , with  $0 < mu \leq MU$ , as desired. Thus  $\|\cdot\|_a \approx \|\cdot\|_c$ , and topological equivalence is an equivalence relation.

i) We have  $\|\mathbf{x}\|_2 = \|x_1 \mathbf{e}_1 + \cdots + x_n \mathbf{e}_n\|_2 \leq \|x_1 \mathbf{e}_1\| + \cdots + \|x_n \mathbf{e}_n\| = \sqrt{x_1^2} + \cdots + \sqrt{x_n^2} = |x_1| + \cdots + |x_n| = \|\mathbf{x}\|_1$ . We proceed to prove the second inequality with the Cauchy-

Schwarz inequality. Define  $y$  to be the vector of all ones, but where the sign of each  $y_i$  is equal to the sign of  $x_i$ . Then by Cauchy-Schwarz,  $\|x\|_1 = |\langle x, y \rangle| \leq \|y\|_2 \|x\|_2 = \sqrt{n} \|x\|_2$ , as desired. Then  $\|x\|_2 \leq \|x\|_1 \leq \sqrt{n} \|x\|_2$ .

ii) Let  $x_i$  be the element of  $x$  with greatest magnitude. Then we have that  $\|x\|_\infty = |x_i| = \sqrt{x_i^2} \leq \sqrt{x_1^2 + \cdots + x_i^2 + \cdots + x_n^2} = \|x\|_2 \leq \sqrt{x_i^2 + \cdots + x_i^2} = \sqrt{nx_i^2} = \sqrt{n} \|x\|_\infty$ .

**Problem 3.28** We proceed by definition of the induced norm and by the properties shown in problem 3.26.

i)  $\frac{1}{\sqrt{n}} \|A\|_2 = \sup \frac{\|Ax\|_2}{\sqrt{n} \|x\|_2} \leq \sup \frac{\|Ax\|_2}{\|x\|_1} \leq \sup \frac{\|Ax\|_1}{\|x\|_1} = \|A\|_1 \leq \sup \frac{\sqrt{n} \|Ax\|_2}{\|x\|_1} \leq \sqrt{n} \sup \frac{\|Ax\|_2}{\|x\|_2} = \sqrt{n} \|A\|_2$   
ii)  $\frac{1}{\sqrt{n}} \|A\|_\infty = \sup \frac{\|Ax\|_\infty}{\sqrt{n} \|x\|_\infty} \leq \sup \frac{\|Ax\|_\infty}{\|x\|_2} \leq \sup \frac{\|Ax\|_2}{\|x\|_2} = \|A\|_2 \leq \sup \frac{\|Ax\|_2}{\|x\|_\infty} \leq \sup \frac{\sqrt{n} \|Ax\|_\infty}{\|x\|_\infty} = \sqrt{n} \|A\|_\infty$

**Problem 3.29** We show  $\sup \frac{\|Rx\|_2}{\|x\|_2} \leq 1$ . We have  $\sup \frac{\|Ax\|_2}{\|A\|_2 \|x\|_2} \leq \sup \frac{\|A\|_2}{\|A\|_2} = 1$ . So  $\|Rx\|_2 \leq \|x\|_2$ . Let  $A = I$ . Then  $\|Ix\|_2 = \|x\|_2$ . So  $\sup(\|Ax\|_2) \geq \|x\|_2$ . Then  $\|Rx\|_2 = \|x\|_2$ .

**Problem 3.30** We show that  $\|\cdot\|_S$  has the properties of non-negativity (with equality only if the interior of the norm is zero), scalar preservation, triangle inequality, and the submultiplicative property. We rely on the fact that the matrix norm  $\|\cdot\|$  has those properties.

Positivity:  $\|A\|_S = \|SAS^{-1}\| = 0 \Leftrightarrow SAS^{-1} = 0 \Leftrightarrow A = 0$ , since  $S$  is invertible. Thus  $\|A\|_S = 0 \Leftrightarrow A = 0$  and similarly  $\|A\|_S \geq 0$ .

Scalar preservation:  $\|cA\|_S = \|ScAS^{-1}\| = |c| \|SAS^{-1}\| = |c| \|A\|_S$

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

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

**Problem 3.37** We first establish an orthonormal basis for the space  $\mathbb{R}[x; 2]$ . Take as a preliminary basis the set  $\{1, x, x^2\}$  and apply the Gram-Schmidt orthonormalization

process. This yields

$$\begin{aligned}
\|1\| &= \int_0^1 1dx = 1 \\
q_1 &= 1 \\
q_2 &= \frac{x - p_1}{\|x - p_1\|} \\
p_1 &= \langle 1, x \rangle = \int_0^1 xdx = \frac{1}{2} \\
\|x - \frac{1}{2}\| &= \left( \int_0^1 x^2 - x + \frac{1}{4} dx \right)^{\frac{1}{2}} = \frac{1}{2\sqrt{3}} \\
q_2 &= 2\sqrt{3}x - \sqrt{3} \\
q_3 &= \frac{x^2 - p_2}{\|x^2 - p_2\|} \\
p_2 &= \langle 1, x^2 \rangle + \langle 2\sqrt{3}x - \sqrt{3}, x^2 \rangle 2\sqrt{3}x - \sqrt{3} = x - \frac{1}{6} \\
\|x^2 - x + \frac{1}{6}\| &= \left( \int_0^1 \left( x^2 - x + \frac{1}{6} \right)^2 dx \right)^{\frac{1}{2}} = \frac{1}{6\sqrt{5}} \\
q_3 &= 6\sqrt{5}x^2 - 6\sqrt{5}x + \sqrt{5}
\end{aligned}$$

We now have an orthonormal basis, and can calculate the adjoint using the formula  $\mathbf{y} = \sum_{i=1}^3 \overline{L(\mathbf{q}_i)} \mathbf{q}_i$ . This process yields  $y = 180x^2 - 168x + 24$ .

**Problem 3.38** We seek a matrix representation of  $D$ .  $D[1] = 0, D[x] = 1, D[x^2] = 2x$ , so

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

We know that for each column of the adjoint, we can calculate  $\langle b_i, D[v] \rangle = \langle c_0 + c_1x + c_2x^2, a_0 + a_1x + a_2x^2 \rangle \forall b_i \in \{1, x, x^2\}$ , where  $v = a_0 + a_1x + a_2x^2$  is an arbitrary polynomial, which will yield a system of equations whose solution will yield the  $i^{th}$  column of the matrix representation of the adjoint. Note  $\langle c_0 + c_1x + c_2x^2, a_0 + a_1x + a_2x^2 \rangle = \int_0^1 (c_0 + c_1x + c_2x^2)(a_0 + a_1x + a_2x^2)dx = \frac{1}{60}(10a_0(6c_0 + 3c_1 + 2c_2) + 5a_1(6c_0 + 4c_1 + 3c_2) + a_2(20c_0 + 15c_1 + 12c_2))$  and  $\langle 1, a_1 + 2a_2x \rangle = a_1 + a_2$ ,  $\langle x, a_1 + 2a_2x \rangle = \frac{a_1}{2} + \frac{2a_2}{3}$ , and  $\langle x, a_1 + 2a_2x \rangle = \frac{a_1}{3} + \frac{a_2}{2}$ . Solving this system yields that

$$D^* = \begin{bmatrix} -6 & 2 & 3 \\ 12 & -24 & -26 \\ 0 & 30 & 30 \end{bmatrix}$$

**Problem 3.39 i)** We have  $\langle w, (S + T)(v) \rangle = \langle w, S(v) + T(v) \rangle = \langle w, S(v) \rangle + \langle w, T(v) \rangle = \langle S^*(w), v \rangle + \langle T^*(w), v \rangle = \langle (S^* + T^*)(w), v \rangle$ . Also,  $\langle w, \alpha T(v) \rangle = \alpha \langle T^*(w), v \rangle = \langle \bar{\alpha} T^*(w), v \rangle$

**ii)**  $\langle w, S^*(v) \rangle = \langle S(w), v \rangle$

**iii)**  $\langle w, S(T(v)) \rangle = \langle S^*(w), T(v) \rangle = \langle T^*(S^*(w)), v \rangle$

**iv)** We show  $T^*(T^{-1})^* = I$  and  $(T^{-1})^* T^* = I$ . Note  $\langle w, v \rangle = \langle w, T^{-1}T(v) \rangle = \langle (T^{-1})^*(v), T(v) \rangle = \langle T^*(T^{-1})^*(w), v \rangle$ . Thus  $T^*(T^{-1})^* = I$ . Also  $\langle w, TT^{-1}(v) \rangle = \langle T^*(w), (T^{-1})^*(v) \rangle = \langle (T^{-1})^*T^*(w), v \rangle$ . So  $(T^{-1})^* = (T^*)^{-1}$

**Problem 3.40 i)**  $\langle B, AC \rangle = \text{tr}(B^H AC) = \langle A^H B, C \rangle$

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

**iii)**  $\langle B, T_A(C) \rangle = \langle B, AC - CA \rangle = \text{tr}(B^H AC - B^H CA) = \text{tr}(B^H AC) - \text{tr}(B^H CA) = \langle A^H B, C \rangle - \langle BA^H, C \rangle = \langle A^* B - BA^*, C \rangle = \langle T_{A^*}(B), C \rangle$

**Problem 3.44** ( $\rightarrow$ ) Suppose  $Ax = b$  has a solution  $x \in \mathbb{F}^n$ . Let  $y \in \mathcal{N}(A^H)$ . Then  $\langle y, b \rangle = \langle y, Ax \rangle = y^H Ax = \langle A^H y, x \rangle = \langle 0, x \rangle = 0$ . ( $\leftarrow$ ) Let  $y \in \mathcal{N}(A^H)$ , and assume  $\langle y, b \rangle \neq 0$ . Then by the Fundamental Subspaces Theorem,  $y \in \mathcal{R}(A)^\perp$ . Then given any  $b \in \mathcal{R}(A)$ , by definition of  $\mathcal{R}(A)^\perp$ ,  $\langle y, b \rangle = 0$ . Since we assume that  $\langle y, b \rangle \neq 0$ ,  $\mathcal{R}(A) = \emptyset$ , and  $Ax = b$  has no solution.

**Problem 3.45** Define a linear transformation  $L : M_n(\mathbb{R}) \rightarrow M_n(\mathbb{R})$  to be  $L(A) = A + A^T$ . Then  $\mathcal{N}(L) = \{A \in M_n(\mathbb{R}) : A + A^T = 0\} = \{A \in M_n(\mathbb{R}) : A = -A^T\} = \text{Skew}_n(\mathbb{R})$ . Note  $(A + A^T)^T = A + A^T$ , so  $\mathcal{R}(L) \subset \text{Sym}_n(\mathbb{R})$ . Also, for  $A \in \text{Sym}_n(\mathbb{R})$ ,  $A = A^T$  so  $A = \frac{1}{2}A + \frac{1}{2}A^T$ , so  $\text{Sym}_n(\mathbb{R}) \subset \mathcal{R}(L)$  and  $\text{Sym}_n(\mathbb{R}) = \mathcal{R}(L)$ . Note also that  $\text{tr}(BA) = \text{tr}(AB) \Leftrightarrow \text{tr}(A^T B^T) = \text{tr}(AB) \Leftrightarrow \text{tr}(A^T B) + \text{tr}(A^T B^T) = \text{tr}(A^T B) + \text{tr}(AB) \Leftrightarrow \text{tr}(A^T(B + B^T)) = \text{tr}((A + A^T)B) \Leftrightarrow \langle A, L(B) \rangle = \langle L(A), B \rangle$ . So  $L = L^*$ . Then by the Fundamental Subspaces Theorem, we know that  $\text{Sym}_n(\mathbb{R})^\perp = \mathcal{R}(L)^\perp = \mathcal{N}(L^*) = \mathcal{N}(L) = \text{Skew}_n(\mathbb{R})$ , as desired.

**Problem 3.46 i)** Let  $x \in \mathcal{N}(A^H A)$ . That  $Ax \in \mathcal{R}(A)$  is immediate. We also know that  $A^H Ax = 0$ . This directly implies that  $Ax \in \mathcal{N}(A^H)$ .

**ii)** Let  $x \in \mathcal{N}(A^H A)$ . By part i) we know that  $x \in \mathcal{N}(A^H)$  and  $x \in \mathcal{R}(A)$ . By the fundamental subspaces theorem, these two spaces are orthogonal and therefore  $Ax=0$ . Then  $x \in \mathcal{N}(A)$ . Let  $x \in \mathcal{N}(A)$ . Then  $Ax = 0 \Rightarrow A^H Ax = 0$ . So  $x \in \mathcal{N}(A^H A)$  and  $\mathcal{N}(A^H A) = \mathcal{N}(A)$ .

**iii)** By the Rank Nullity Theorem, since  $A$  and  $A^H A$  operate on the same space,  $\text{rank}(A) + \text{nullity}(A) = \text{rank}(A^H A) + \text{nullity}(A^H A)$ . In ii) we proved that  $\mathcal{N}(A^H A) = \mathcal{N}(A)$ , so  $\text{nullity}(A) = \text{nullity}(A^H A)$ . It directly follows that  $\text{rank}(A) = \text{rank}(A^H A)$ .

**iv)** Suppose that  $A$  has all linearly independent columns. Then by necessity, since there are  $n$  columns,  $A$  is of rank  $n$ . So by iii)  $A^H A$  is also of rank  $n$ . Since  $A^H A$  has  $n$  columns and is square, it is full rank and therefore is non-singular.

**Problem 3.47 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)  $P^H = A((A^H A)^{-1})^H A^H = A(A^H A)^{-1} A^H = P$

iii) By the results of 2.14(i), we know that  $\text{rank}(P) \leq \min\{\text{rank}(A), \text{rank}((A^H A)^{-1} A^H)\} \leq \text{rank}(A)$ . Let  $y \in \mathcal{R}(A)$ . So  $y = Ax$  for some  $x$ . Then  $P(y) = A(A^H A)^{-1} A^H Ax = Ax$ , implying that  $y \in \mathcal{R}(P)$ . Then  $\mathcal{R}(A) \subset \mathcal{R}(P)$ , which means that  $\text{rank}(A) \leq \text{rank}(P)$ . Thus  $\text{rank}(A) = \text{rank}(P) = n$ .

**Problem 3.48 i)**  $P(A + cB) = \frac{1}{2}(A + cB + A^T + cB^T) = \frac{1}{2}(A + A^T) + \frac{c}{2}(B + B^T) = P(A) + cP(B)$

ii)  $P(P(A)) = \frac{1}{4}(A + A^T + A + A^T) = \frac{1}{4}(2A + 2A^T) = \frac{1}{2}(A + A^T) = P(A)$

iii)  $\langle A, P(B) \rangle = \frac{1}{2} \text{tr}(A^T(B + B^T)) = \frac{1}{2} \text{tr}(A^T B + A^T B^T) = \frac{1}{2} \text{tr}(BA) + \frac{1}{2} \text{tr}(A^T B) = \frac{1}{2} \text{tr}(AB + A^T B) = \langle P(A), B \rangle$

iv) Let  $A \in \mathcal{N}(P)$ . Then  $P(A) = 0 \Rightarrow A + A^T = 0 \Rightarrow A = -A^T \Rightarrow A \in \text{Skew}_n(\mathbb{R})$ . Similarly,  $A \in \text{Skew}_n(\mathbb{R}) \Rightarrow A = -A^T \Rightarrow \frac{1}{2}(A + A^T) = 0 \Rightarrow A \in \mathcal{N}(P)$ . So  $\mathcal{N}(P) = \text{Skew}_n(\mathbb{R})$ .

v) Let  $A \in \mathcal{R}(P)$ . Then  $A = \frac{1}{2}(B + B^T) \Rightarrow A^T = \frac{1}{2}(B + B^T) = A \Rightarrow A \in \text{Sym}_n(\mathbb{R})$ . Similarly,  $A \in \text{Sym}_n(\mathbb{R}) \Rightarrow A = A^T \Rightarrow A = \frac{1}{2}(A + A^T) \Rightarrow A \in \mathcal{R}(P)$ . So  $\mathcal{R}(P) = \text{Sym}_n(\mathbb{R})$ .

vi)  $\|A - P(A)\|_F^2 = \text{tr}((A - P(A))^T(A - P(A))) = \text{tr}(A^T A - A^T P(A) - P(A)^T A - P(A)^T P(A)) = \frac{1}{4} \text{tr}(4A^T A - 2A^T(A + A^T) - 2(A + A^T)A + (A + A^T)(A + A^T)) = \frac{1}{4} \text{tr}(A^T A - A^T A^T - AA + AA^T) = \frac{1}{4} (\text{tr}(A^T A) - \text{tr}(A^T A^T) - \text{tr}(AA) + \text{tr}(AA^T)) = \frac{1}{2} (\text{tr}(A^T A) - \text{tr}(A^2))$ .

So  $\|A - P(A)\|_F = \sqrt{\frac{\text{tr}(A^T A) - \text{tr}(A^2)}{2}}$

**Problem 3.50** The problem can be written as  $Ax = b$ , where

$$A = \begin{bmatrix} x_1^2 & y_1^2 \\ x_2^2 & y_2^2 \\ \vdots & \vdots \\ x_n^2 & y_n^2 \end{bmatrix}, x = \begin{bmatrix} r \\ s \end{bmatrix}, b = \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix}$$

The normal equations are  $A^T A x = A^T b$ . This is simplified to

$$\begin{bmatrix} \sum_{i=1}^n x_i^4 & \sum_{i=1}^n x_i^2 y_i^2 \\ \sum_{i=1}^n x_i^2 y_i^2 & \sum_{i=1}^n y_i^4 \end{bmatrix} \begin{bmatrix} r \\ s \end{bmatrix} = \begin{bmatrix} \sum_{i=1}^n x_i^2 \\ \sum_{i=1}^n y_i^2 \end{bmatrix}$$