# Math Problem Set #2: Inner Product Spaces

OSM Lab - University of Chicago Geoffrey Kocks

# Problem 1: HJE 3.1.

#### Solution.

(i). The right side of the polarization identity is equivalent to:

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

Therefore we have verified the polarization identity that:

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

(ii). The left side of the parallelogram identity is equivalent to:

$$\|\mathbf{x}\|^2 + \|\mathbf{y}\|^2 = \langle \mathbf{x}, \mathbf{x} \rangle + \langle \mathbf{y}, \mathbf{y} \rangle.$$

The right side of the parallelogram identity is equivalent to:

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

Therefore we have verified the parallelogram identity that:

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

## Problem 2: HJE 3.2.

**Solution.** The right side of the polarization identity for complex numbers is equivalent to:

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

Therefore we have verified the complex inner product space identity that:

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

#### Problem 3: HJE 3.3.

#### Solution.

(i). The angle  $\theta$  between x and  $x^5$  is given by:

$$\cos \theta = \frac{\langle x, x^5 \rangle}{\|x\| \|x^5\|} = \frac{\int_0^1 x^6 dx}{\sqrt{(\int_0^1 x^2 dx)(\int_0^1 x^{10} dx)}} = \frac{\frac{1}{7}}{\sqrt{(\frac{1}{3})(\frac{1}{11})}} = \frac{\sqrt{33}}{7}.$$

$$\theta = \arccos \frac{\sqrt{33}}{7}.$$

(ii). The angle  $\theta$  between  $x^2$  and  $x^4$  is given by:

$$\cos \theta = \frac{\langle x^2, x^4 \rangle}{\|x^2\| \|x^4\|} = \frac{\int_0^1 x^6 dx}{\sqrt{(\int_0^1 x^4 dx)(\int_0^1 x^8 dx)}} = \frac{\frac{1}{7}}{\sqrt{(\frac{1}{5})(\frac{1}{9})}} = \frac{\sqrt{45}}{7}.$$

$$\theta = \arccos \frac{\sqrt{45}}{7}.$$

#### Problem 4: HJE 3.8.

# Solution.

(i). A collection S of  $\{x_i\}_{i\in J}$  is an orthonormal set if for all  $i, j \in J$  we have  $\langle \mathbf{x}_i, \mathbf{x}_j \rangle = 1$  if i = j and 0 if  $i \neq j$ . With the given inner product definition, we verify this definition as follows (all integrals solved using Wolfram Alpha):

$$\langle \cos(t), \cos(t) \rangle = \frac{1}{\pi} \int_{-\pi}^{\pi} (\cos(t))(\cos(t))dt = 1.$$

$$\langle \cos(t), \cos(2t) \rangle = \frac{1}{\pi} \int_{-\pi}^{\pi} (\cos(t))(\cos(2t))dt = 0.$$

$$\langle \cos(t), \sin(t) \rangle = \frac{1}{\pi} \int_{-\pi}^{\pi} (\cos(t))(\sin(t))dt = 0.$$

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

$$\langle \sin(t), \sin(t) \rangle = \frac{1}{\pi} \int_{-\pi}^{\pi} (\sin(t))(\sin(t))dt = 1.$$

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

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

$$\langle \sin(2t), \sin(2t) \rangle = \frac{1}{\pi} \int_{-\pi}^{\pi} (\sin(2t))(\sin(2t))dt = 1.$$

(ii). The norm of t is given by:

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

(iii). The projection is given by:

$$proj_X(\cos(3t)) = \langle \cos t, \cos 3t \rangle \cos t + \langle \sin t, \cos 3t \rangle \sin t + \langle \cos 2t, \cos 3t \rangle \cos 2t + \langle \sin 2t, \cos 3t \rangle \sin 2t$$
$$= 0 + 0 + 0 + 0 = \boxed{0}.$$

(iv). The projection is given by:

$$proj_X(t) = \langle \cos t, t \rangle \cos t + \langle \sin t, t \rangle \sin t + \langle \cos 2t, t \rangle \cos 2t + \langle \sin 2t, t \rangle \sin 2t$$
$$= 0 + 2\sin t + 0 + -\sin 2t = 2\sin t - \sin 2t.$$

#### Problem 5: HJE 3.9.

**Solution.** Define  $\mathbf{x} = (x_1, x_2)$  and  $\mathbf{y} = (y_1, y_2)$ . Then the standard inner product space of the column vectors is  $x_1y_1 + x_2y_2$ . The rotation transformation is orthonormal if the standard inner product space of the transformation preserves the original inner product space. The transformations result in the following:

$$\begin{pmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = \begin{pmatrix} x_1 \cos \theta - x_2 \sin \theta \\ x_1 \sin \theta + x_2 \cos \theta \end{pmatrix}$$
$$\begin{pmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{pmatrix} \begin{pmatrix} y_1 \\ y_2 \end{pmatrix} = \begin{pmatrix} y_1 \cos \theta - y_2 \sin \theta \\ y_1 \sin \theta + y_2 \cos \theta \end{pmatrix}$$

Taking the standard inner product space (dot product) of the two resulting column vectors gives:

$$(x_1 \cos \theta - x_2 \sin \theta)(y_1 \cos \theta - y_2 \sin \theta) + (x_1 \sin \theta + x_2 \cos \theta)(y_1 \sin \theta + y_2 \cos \theta) =$$

$$x_1 y_1(\cos \theta)^2 + x_2 y_2(\sin \theta)^2 - \sin \theta \cos \theta(x_1 y_2 + x_2 y_1) + x_1 y_1(\sin \theta)^2$$

$$+ x_2 y_2(\cos \theta)^2 + \sin \theta \cos \theta(x_1 y_2 + x_2 y_1) =$$

$$x_1 y_1((\sin \theta)^2 + (\cos \theta)^2) + x_2 y_2((\sin \theta)^2 + (\cos \theta)^2) = x_1 y_1 + x_2 y_2.$$

The resulting inner product space is the same as the original inner product space so the rotation transformation is orthonormal.

# Problem 6: HJE 3.10. Solution.

- (i.) The matrix Q being orthonormal is equivalent to  $\langle Q\mathbf{x}, Q\mathbf{y} \rangle = \langle \mathbf{x}, \mathbf{y} \rangle$ . This implies that  $Q^H Q \langle \mathbf{x}, \mathbf{y} \rangle = \langle \mathbf{x}, \mathbf{y} \rangle$ . Because these are equal, then  $Q^H Q = I$ . By the properties of matrix inverses, AB = I implies BA = I, so we also have that  $QQ^H = I$ . The same reasoning applies for the converse, so that if the product is I, then it directly follows that  $\langle Q\mathbf{x}, Q\mathbf{y} \rangle = \langle \mathbf{x}, \mathbf{y} \rangle$ . Therefore a matrix Q is orthonormal if and only if  $Q^H Q = QQ^H = I$ .
- (ii.)  $\|Q\mathbf{x}\| = \sqrt{\langle \mathbf{x}^H Q^H, Q\mathbf{x} \rangle} = \sqrt{\langle QQ^H \rangle \langle \mathbf{x}^H, \mathbf{x} \rangle} = \sqrt{\langle \mathbf{x}^H, \mathbf{x} \rangle}$  by the property proved in part (i). The last square root is equivalent to  $\|\mathbf{x}\|$ . Therefore if Q is an orthonormal matrix, then  $\|Q\mathbf{x}\| = \|\mathbf{x}\|$ .
- (iii.) By part (i) of this problem  $Q^HQ = QQ^H = I$ . By the definition of the matrix inverse:  $Q^{-1}Q = QQ^{-1} = I$ . Therefore, for an orthonormal matrix Q:  $Q^{-1} = Q^H$ . We also have that for any Q by definition,  $(Q^{-1})^{-1} = Q$  and  $(Q^H)^H = Q$ . Thus:  $(Q^{-1})^{-1} = (Q^H)^H = (Q^{-1})^H$ . Because the H and inverse of  $Q^{-1}$  are equal,  $Q^{-1}$  is also an orthogonal matrix.
- (iv.) By part (i) of this problem,  $QQ^H = I$ . Each entry in the product  $QQ^H$  is an inner product space of columns of Q, and this inner product space equals 1 along the diagonals and 0 elsewhere. This implies that  $\langle \mathbf{x}_i, \mathbf{x}_j \rangle = 1$  only when i = j and 0 any other time, satisfying the definition of an orthonormal set.
- (v.) By definition,  $\det I = 1$ . By part (i), since  $Q^HQ = I$ ,  $\det Q^HQ = 1$ . By the properties of determinants, this implies that  $\det Q^2 = 1 \implies |\det Q| = 1$ . However the converse is not true because there are matrices that have a determinant of 1 that are not orthonormal. One example is the matrix:  $\begin{pmatrix} 2 & 1 \\ 2 & 1 \end{pmatrix}$  which has a determinant of 1 but does not satisfy the property proved in part (i) of this problem.
- (vi.) Let  $Q_1$  and  $Q_2$  both be orthonormal matrices. Then  $(Q_1Q_2)^{-1} = (Q_2)^{-1}(Q_1)^{-1}$ . By part (i) this is equivalent to  $(Q_2)^H(Q_1)^H = (Q_1Q_2)^H$ . Since the H is the same as the transpose, the product  $Q_1Q_2$  is also orthonormal.

#### Problem 7: HJE 3.11.

**Solution.** We show below that attempting to apply the Gram-Schmidt orthonormalization process to a collection of linearly dependent vectors will not work because we will end up dividing by 0.

Denote the set of linearly dependent vectors as  $\mathbf{x_1}, \mathbf{x_2}, ..., \mathbf{x_n}$ . Let  $\mathbf{x_j}$  be the first vector that is a linear combination of preceding vectors. The beginning of the Gram-Schmidt process gives:

$$q_1 = \frac{x_1}{\left\|x_1\right\|}$$

Projecting  $\mathbf{x_2}$  onto  $\mathbf{q_1}$  gives:

$$\mathbf{p_1} = \langle \mathbf{q_1}, \mathbf{x_2} \rangle \mathbf{q_1}.$$

Define  $\mathbf{r_i} = \mathbf{x_i} - \mathbf{p_{i-1}}$ . Then the next vector in the construction of the orthonormal set is defined by:

$$\mathbf{q_2} = rac{\mathbf{r_2}}{\|\mathbf{r_2}\|}.$$

We continue this process until we get to  $\mathbf{r_j} = \mathbf{x_j} - \mathbf{p_{j-1}} = \mathbf{x_j} - \langle \mathbf{q_{j-1}}, \mathbf{x_j} \rangle \mathbf{q_{j-1}} = 0$ . Then in the next step, we will be dividing by 0, and cannot construct an orthonormal set.

#### Problem 8: HJE 3.16.

#### Solution.

(i.) The QR decomposition is not unique because if there are two matrices Q and R that multiply to equal another matrix A, then we can obtain the same product by multiplying every value in Q by  $\alpha$  and every value in R by  $\frac{1}{\alpha}$ . As an example, we take the Matrix A from Example 3.3.11 of the textbook. We can obtain a decomposition of the same matrix by multiplying Q and R each by -1, obtaining:

$$Q = \begin{pmatrix} -1/2 & 1/2 & -1/2 \\ -1/2 & -1/2 & 1/2 \\ -1/2 & -1/2 & -1/2 \\ -1/2 & 1/2 & 1/2 \end{pmatrix}$$
$$R = \begin{pmatrix} -2 & -1 & -3 \\ 0 & -5 & 1 \\ 0 & 0 & -3 \end{pmatrix}$$

(ii.) Assume that A is invertible and has two different QR decompositions with only positive diagonal elements. Then  $A=Q_1R_1=Q_2R_2 \implies Q_2^{-1}Q_1=R_2R_1^{-1}$ . The matrix  $Q_2^{-1}Q_1$  is orthonormal and  $R_2R_1^{-1}$  is upper triangular. This means that each of the matrix products will be upper triangular and orthonormal, which occurs if the product is I or -I. We are assuming that there are positive diagonals so the product must be I. Then:  $Q_2^{-1}Q_1=I \implies Q_2=Q_1$ .  $R_2R_1^{-1}=I \implies R_1=R_2$ .

Therefore there is a unique QR decomposition.

#### Problem 9: HJE 3.17.

**Solution.** We start with the assumption that  $A^H A \mathbf{x} = A^H b$ . When A can be decomposed as  $A = \hat{Q}\hat{R}$ :

$$A^{H}A\mathbf{x} = A^{H}b \implies (\hat{Q}\hat{R})^{H}(\hat{Q}\hat{R})\mathbf{x} = (\hat{Q}\hat{R})^{H}\mathbf{b}$$

$$\implies \hat{R}^{H}\hat{Q}^{H}\hat{Q}\hat{R}\mathbf{x} = \hat{R}^{H}\hat{Q}^{H}\mathbf{b}$$

$$\implies \hat{R}^{H}\hat{R}\mathbf{x} = \hat{R}^{H}\hat{Q}^{H}\mathbf{b}$$

$$\implies \hat{R}\mathbf{x} = \hat{Q}^{H}\mathbf{b}.$$

Problem 10: HJE 3.23.

**Solution.** By the triangle inequality:

$$||x|| = ||x - y + y|| \le ||x - y|| + ||y|| \implies ||x|| - ||y|| \le ||x - y||.$$

$$||y|| = ||y - x + x|| \le ||x - y|| + ||x|| \implies ||y|| - ||x|| \le ||x - y||.$$

Therefore  $|||x|| - ||y||| \le ||x - y||$ .

#### Problem 11: HJE 3.24.

**Solution.** There are three necessary conditions for a map to be considered a norm:

- (1) Positivity:  $\|\mathbf{x}\| \ge 0$  and  $\|\mathbf{x}\| = 0$  only if  $\mathbf{x} = 0$ .
- (2) Scale preservation:  $||a\mathbf{x}|| = |a|||\mathbf{x}||$ .
- (3) Triangle Inequality:  $\|\mathbf{x} + \mathbf{y}\| \le \|\mathbf{x}\| + \|\mathbf{y}\|$ .
- (i.)  $||f||_{L^1} = \int_a^b |f(t)| dt$ . (1)  $|f(t)| \ge 0$  for all f(t) so the integral from a to b will always be at least 0. The integral will also only equal 0 when f(t) = 0 for all t in the domain.
  - (2)  $\|\alpha \mathbf{x}\|_{L^1} = \int_a^b |\alpha f(t)| dt = |\alpha| \int_a^b |f(t)| dt = |\alpha| \|\mathbf{x}\|_{L^1}$
  - (3)  $||f + g||_{L^1} = \int_a^b |f(t) + g(t)| dt \le \int_a^b |f(t)| dt | + \int_a^b |g(t)| dt = ||f|| + ||g||.$
  - (ii.)  $||f||_{L^2} = (\int_a^b |f(t)|^2 dt)^{1/2}$ .
- (1) Once again, |f(t)| is non-negative, so its square will be non-negative, as well as the integral of this value and its square root.  $||f||_{L^2} = 0$  implies that |f(t)| = 0which only occurs when f(t) = 0 for all t in the domain.
  - (2)  $\|\alpha f\|_{L^2} = (\int_a^b |\alpha f(t)|^2 dt)^{1/2} = |\alpha|((\int_a^b |f(t)|^2 dt)^{1/2} = |\alpha|\|f\|_{L^2}.$
  - (3)

$$||f+g||_{L^{2}}^{2} = \int_{a}^{b} |f+g|^{2} dt \le \int_{a}^{b} (|f|^{2} + 2|f||g| + |g|^{2}) dt$$

$$\le ||f||_{L^{2}}^{2} + ||g||_{L^{2}}^{2} + 2||f||_{L^{2}}||g||_{L^{2}} = ||f||_{L^{2}}^{2} + ||g||_{L^{2}}^{2}$$

$$\implies ||f+g||_{L^{2}}^{2} \le ||f||_{L^{2}}^{2} + ||g||_{L^{2}}^{2}.$$

- (iii.)  $||f||_{L^{\infty}} = \sup_{x \in [a,b]} |f(x)|.$
- (1) Because each norm |f(x)| is always non-negative, its supremum will also be non-negative. The norm will only equal 0 when f(x) is always 0 in the domain.
  - $(2) \|\alpha f(x)\|_{L^{\infty}} = \sup_{x \in [a,b]} |\alpha f(x)| = |\alpha| \sup_{x \in [a,b]} |f(x)| = |\alpha| \|f(x)\|_{L^{\infty}}.$
  - (3)

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

#### Problem 12: HJE 3.26.

**Solution.** First we note that topological equivalence is an equivalence relation. Topological equivalence is an equivalence relation because it if norm  $\|.\|_a$  and  $\|.\|_b$  are topologically equivalent, and  $\|.\|_b$  and  $\|.\|_c$  are topologically equivalent, then it is also true that  $\|.\|_a$  and  $\|.\|_c$  are topologically equivalent. The equivalences imply:

$$m_1 \|x\|_b \le \|x\|_a \le M_1 \|x\|_b.$$

$$m_2 \|x\|_b \le \|x\|_c \le M_2 \|x\|_b.$$

$$\frac{m_1}{m_2} \le \frac{\|x\|_a}{\|x\|_c} \le \frac{M_1}{M_2}.$$

$$\frac{m_1 \|x\|_c}{m_2} \le \|x\|_a \le \frac{M_1 \|x\|_c}{M_2}.$$

Therefore we also will have an equivalence between  $\|.\|_a$  and  $\|.\|_c$ .

We now show that the p-norms for  $p = 1, 2, \infty$  are topologically equivalent:

(i.) Let  $||x||_2$  denote the p-norm for p = 2 and let  $||x||_1$  denote the p-norm for p=1 on  $\mathbb{F}^n$ . First, by the Cauchy-Schwartz inequality:

$$(\sum |x_j|)^2 \le n \sum |x_j^2|.$$

$$\sum |x_j| \le \sqrt{n \sum |x_j^2|}.$$

$$||x||_1 \le \sqrt{n}||x||_2.$$

It also holds that:

$$(\sum x_i)^2 = \sum_{i=1}^n \sum_{j=1}^n x_i x_j = \sum_{i=1}^n x_i^2 + \sum_i \sum_{j \neq i} x_i x_j \ge \sum x_i^2.$$

$$\sum |x_i| \ge \sqrt{\sum |x_i|^2}.$$

$$||x||_1 \ge ||x||_2.$$

Therefore the p-norms for p=1 and p=2 are topologically equivalent.

(ii.) Let  $||x||_2$  denote the p-norm for p = 2 and let  $||x||_{\infty}$  denote the p-norm for  $p = \infty$  on  $\mathbb{F}^n$ . First, we have:

$$||x||_2^2 = \sum |x_i|^2 \le n \sup |x_i|^2 = n(\sup |x_i|)^2 = n||x||_{\infty}^2.$$

$$||x||_2 \le \sqrt{n} ||x||_{\infty}.$$

where sup  $|x_i|$  is shorthand for sup( $|x_1|, |x_2|, ..., |x_n|$ ). We also have:

$$(\sup |x_i|)^2 = (\sup |x_i|^2) \le |x_i^2| + \sum_{j \ne i} |x_j^2| = ||x||_2^2.$$

$$||x||_{\infty} \le ||x||_2.$$

Therefore the p-norms for  $p = \infty$  and p = 2 are also topologically equivalent.

# Problem 13: HJE 3.28.

#### Solution.

(i.) Let  $||A||_2$  denote the operator 2-norm and let  $||A||_1$  denote the operator 1-norm. Then by the properties proven in Exercise 3.26:

$$\frac{1}{\sqrt{n}} \|A\|_{2} = \frac{1}{\sqrt{n}} \sup \frac{\|A\mathbf{x}\|_{2}}{\|\mathbf{x}\|_{2}} \le \sup \frac{\|A\mathbf{x}\|_{2}}{\|\mathbf{x}\|_{1}} \le \sup \frac{\|A\mathbf{x}\|_{1}}{\|\mathbf{x}\|_{1}} = \|A\|_{1}$$

Similarly:

$$||A||_1 \le \sup \frac{\sqrt{n}||A\mathbf{x}||_2}{||\mathbf{x}||_1} \le \sqrt{n}\sup \frac{||A\mathbf{x}||_2}{||\mathbf{x}||_2} = \sqrt{n}||A||_2$$

(ii.) Let  $||A||_2$  denote the operator 2-norm and let  $||A||_{\infty}$  denote the operator  $\infty$ -norm. Then by the properties proved in Exercise 3.26:

$$\frac{1}{\sqrt{n}} \|A\|_{\infty} = \frac{1}{\sqrt{n}} \sup \frac{\|A\mathbf{x}\|_{\infty}}{\|\mathbf{x}\|_{\infty}} \le \sup \frac{\|A\mathbf{x}\|_{\infty}}{\|\mathbf{x}\|_{2}} \le \sup \frac{\|A\mathbf{x}\|_{2}}{\|\mathbf{x}\|_{2}} = \|A\|_{2}$$

Similarly:

$$||A||_2 \le \sup \frac{\sqrt{n} ||A\mathbf{x}||_{\infty}}{||\mathbf{x}||_2} \le \sqrt{n} \sup \frac{||A\mathbf{x}||_{\infty}}{||\mathbf{x}||_{\infty}} = \sqrt{n} ||A||_{\infty}$$

#### Problem 14: HJE 3.29.

# Solution.

We first show that the induced norm of the transformation is equal to  $\|\mathbf{x}\|_2$ . In Exercise 3.10(ii), we showed that if Q is an orthonormal matrix, then  $\|Q\mathbf{x}\| = \|\mathbf{x}\|$  for all  $\mathbf{x}$ . Therefore, when Q is orthonormal, the 2-norm is given by:

$$||Q||_2 = \sup \frac{||Q\mathbf{x}||_2}{||\mathbf{x}||_2} = \sup \frac{||\mathbf{x}||_2}{||\mathbf{x}||_2} = 1.$$

We now show that the induced norm of the transformation  $R_x$  is equal to  $\|\mathbf{x}\|_2$ . By definition,  $\|\mathbf{x}\|_2^2 = \mathbf{x}^H \mathbf{x}$ . Then  $\|A\mathbf{x}\|_2^2 = (A\mathbf{x})^H (A\mathbf{x}) = \mathbf{x}^H A^H A\mathbf{x} = \mathbf{x}^H \mathbf{x} = \|\mathbf{x}\|_2^2$ . Therefore the induced norm of the transformation is equal to  $\|\mathbf{x}\|_2$ .

#### Problem 15: HJE 3.30.

**Solution.** There are three necessary conditions for a map to be considered a norm:

- (1) Positivity:  $\|\mathbf{x}\| \ge 0$  and  $\|\mathbf{x}\| = 0$  only if  $\mathbf{x} = 0$ .
- (2) Scale preservation:  $||a\mathbf{x}|| = |a|||\mathbf{x}||$ .
- (3) Triangle Inequality:  $\|\mathbf{x} + \mathbf{y}\| \le \|\mathbf{x}\| + \|\mathbf{y}\|$ .
- (1) We already know that  $\|.\|$  is a matrix norm so it satisfies the conditions of a norm. Therefore  $\|\mathbf{x}\|_S \geq 0$ . We also know that it will only equal 0 if  $SAS^{-1} = 0$ , which only occurs when A = 0. Therefore positivity holds.

(2) 
$$\|\alpha A\|_{S} = \|\alpha S A S^{-1}\| = |\alpha| \|S A S^{-1}\| = |\alpha| \|A\|_{S}$$

The steps above follow from the fact that  $\|.\|$  is a matrix norm. Therefore scale preservation holds.

(3)

$$||A + B||_S = ||S(A + B)S^{-1}|| = ||(SA + SB)S^{-1}||$$
  
=  $||SAS^{-1} + SBS^{-1}|| \le ||SAS^{-1}|| + ||SBS^{-1}|| = ||A||_S + ||B||_S.$ 

The steps above hold by the triangle inequality of  $\|.\|$  because it is already a matrix norm. Therefore the triangle inequality also holds for  $\|.\|_S$ . Because all three properties hold,  $\|.\|_S$  is considered a matrix norm.

#### Problem 16: HJE 3.37.

**Solution.** The Riesz representation theorem tells us that there will be a unique  $q \in V$  such that  $L(p) = \langle q, p \rangle$  but it does not tell us what this q will be. Define a generic  $q = ex^2 + fx + g$  and  $p = ax^2 + bx + c$ . We want to find e, f, g such that  $\langle q, p \rangle = \int_0^1 qp dx = L(p) = 2a + b$ . This gives us:

$$\int_0^1 (ex^2 + fx + g)(ax^2 + bx + c)dx = 2a + b$$

$$\int_0^1 aex^4 + (be + af)x^3 + (ce + bf + ag)x^2 + (cf + bg)x + cg = \frac{ae}{5} + \frac{be + af}{4} + \frac{ce + bf + ag}{3} + \frac{cf + bg}{2} + cg = a(\frac{e}{5} + \frac{f}{4} + \frac{g}{3}) + b(\frac{e}{4} + \frac{f}{3} + \frac{g}{2}) + c(\frac{e}{3} + \frac{f}{2} + g)$$

We then set this equation equal to 2a + b and solve the following system of equations:

$$0.2e + 0.25f + (1/3)g = 2$$
$$0.25e + (1/3)f + 0.5g = 1$$
$$(1/3)e + 0.5f + q = 0$$

This yields solution e = 180, f = -168, g = 24. Therefore, the unique q guaranteed by the Riesz representation theorem is:  $180x^2 - 168x + 24$ .

#### Problem 17: HJE 3.38.

**Solution.** With respect to the power basis, we seek a D such that:

$$D(1,0,0) = (0,0,0).$$

$$D(0,1,0) = (1,0,0).$$

$$D(0,0,1) = (0,2,0).$$

This is satisfied by:

$$D = \left(\begin{array}{ccc} 0 & 1 & 0 \\ 0 & 0 & 2 \\ 0 & 0 & 0 \end{array}\right)$$

Following example 3.7.8 in the textbook, the adjoint is given by the Hermitian conjugate  $D^H$  so:

$$D^* = \left(\begin{array}{ccc} 0 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 2 & 0 \end{array}\right)$$

Problem 18: HJE 3.39.

Solution.

(i.)

$$\langle \mathbf{v}, (S+T)^*, \mathbf{w} \rangle = \langle (S+T)\mathbf{x}, \mathbf{w} \rangle = \langle S\mathbf{v}, \mathbf{w} \rangle + \langle T\mathbf{v}, \mathbf{w} \rangle$$
$$= \langle \mathbf{v}, T^*\mathbf{w} \rangle + \langle \mathbf{v}, S^*\mathbf{w} \rangle = \langle \mathbf{v}, (T^* + S^*)\mathbf{w} \rangle.$$

Therefore, we have that  $(S+T)^* = S^* + T^*$ . Additionally,  $\langle Q_1, \alpha T(Q_2) \rangle = \alpha \langle T^*(Q_1), Q_2 \rangle = \langle \overline{\alpha} T^*(Q_1), Q_2 \rangle$ .

(ii.) We have that  $\langle \mathbf{v}, S\mathbf{w} \rangle = \langle S^*\mathbf{v}, \mathbf{w} \rangle$ . By reflexive properties, we therefore also have that  $\langle S\mathbf{w}, \mathbf{v} \rangle = \langle \mathbf{w}, S^*\mathbf{w} \rangle$ . Finally, by the definition of the adjoint:  $\langle \mathbf{w}, S^*\mathbf{v} \rangle = \langle (S^*)^*\mathbf{w}, \mathbf{v} \rangle$ . Therefore,  $(S^*)^* = S$ .

(iii.)

$$\langle Q_1, (ST)^*Q_2 \rangle = \langle STQ_1, Q_2 \rangle = \langle TQ_1, S^*Q_2 \rangle = \langle Q_1, T^*S^*Q_2 \rangle.$$

Therefore  $(ST)^* = T^*S^*$ .

(iv.) We have that:

$$\langle T^*(T^{-1})^*Q_1, Q_2 \rangle = \langle Q_1, T^{-1}TQ_2 \rangle = \langle Q_1, Q_2 \rangle = \langle Q_1, Q_2 \rangle.$$

Therefore, because the product of  $T^*$  and  $(T^{-1})^*$  is the identity matrix, they are each the inverse of each other, so:  $(T^{-1})^* = (T^*)^{-1}$ .

# Problem 19: HJE 3.40.

Solution.

- (i.)  $\langle A^*Q_1, Q2 \rangle = \langle Q_1, AQ_2 \rangle = tr(Q_1^HAQ_2)$ . Equivalently,  $\langle A^HQ_1, Q_2 \rangle = tr(Q_1^HAQ_2)$ . Therefore  $A^* = A^H$ .
  - (ii.) For any  $A_1, A_2, A_3$ :

$$\langle A_2, A_3 A_1 \rangle = tr(A_2^H A_3 A_1) = tr(A_1 A_2^H A_3) = \langle A_2 A_1^H, A_3 \rangle = \langle A_2 A_1^*, A_3 \rangle.$$

Therefore  $\langle A_2, A_3 A_1 \rangle = \langle A_2 A_1^*, A_3 \rangle$ .

(iii.) Define  $T_A(X) = AX - XA$ . First we have:

$$\langle T_{A^*}(Q_1), Q_2 \rangle = \langle A^*Q_1 - Q_1A^*, Q_2 \rangle = \langle A^HQ_1 - Q_1A^H, Q_2 \rangle = tr(Q_1^HAQ_2 - Q_1^HQ_2A).$$

We also have:

$$\langle T_A^*(Q_1), Q_2 \rangle = \langle Q_1, T_A(Q_2) \rangle = \langle Q_1, AQ_2 - Q_2A \rangle = tr(Q_1^H A Q_2 - Q_1^H Q_2A).$$

Therefore  $(T_A)^* = T_{A^*}$ .

# Problem 20: HJE 3.44.

**Solution.** To prove the Fredholm alternative, we first show that if  $A\mathbf{x} = \mathbf{b}$  has no solution, then there is no  $\mathbf{y}$  in the null of  $A^H$  s.t.  $\langle \mathbf{y}, \mathbf{b} \rangle = 0$ . Assume that there is a solution to the equation and let  $\mathbf{y}$  be part of the null space as described above. Then:

$$\langle \mathbf{y}, \mathbf{b} \rangle = \langle \mathbf{y}, \mathbf{A} \mathbf{x} \rangle = tr(\mathbf{y}^H A \mathbf{x}) = \langle A^H \mathbf{y}, \mathbf{x} \rangle = \langle 0, \mathbf{x} \rangle = 0.$$

We next show that if  $\langle \mathbf{y}, \mathbf{b} \rangle \neq 0$ , then there is no solution to the equation.  $\mathbf{y}$  is in the null space of  $A^H$  which also means that  $\mathbf{y}$  is in  $R(A)^{\perp}$ . However, if there is a solution to the equation, then  $\mathbf{b}$  is in R(A). There is a contradiction since for  $\langle \mathbf{y}, \mathbf{b} \rangle$  to not equal 0,  $\mathbf{b}$  cannot be in R(A). There can be no solution to the equation. We have then proven the Fredholm alternative.

#### Problem 21: HJE 3.45.

**Solution.** We define a linear transformation  $L: M_n(\mathbb{R}) \to M_n(\mathbb{R})$ . as  $L(A) = A + A^T$ . The definition of Skew gives:  $Skew_n(\mathbb{R}) = \{A \in M_n(\mathbb{R}) | A^T = -A\}$ . For linear transformation L this is exactly equivalent to the null space because L(A) = 0 when  $A = -A^T$ .

Next, we show that  $Sym_n(\mathbb{R}) = R(L)$ . The definition of Sym gives:  $Sym_n(\mathbb{R}) = \{A \in M_n(\mathbb{R}) | A^T = A\}$ . Because  $(A + A^T)^T = A + A^T$  the kernel of L is part of  $Sym_n(\mathbb{R})$ . We also note that for any matrix A in  $Sym_n(\mathbb{R})$ :  $A = A^T$  so  $A = 0.5A^T + 0.5A$  so  $Sym_n(\mathbb{R})$  is also part of the kernel of L. Therefore  $Sym_n(\mathbb{R}) = R(L)$ .

Finally, we seek to prove that  $L = L^*$ . We note that  $tr(BA) = tr(AB) \implies tr(A^TB^T) = tr(AB) \implies tr(A^T(B+B^T)) = tr((A+A^T)B) \implies \langle A, L(B) \rangle = \langle L(A), B \rangle$ . Therefore  $L = L^*$ .

We already have that  $Sym_n(\mathbb{R})^{\perp} = R(L)^{\perp}$ . By the Fundamental Subspaces Theorem, this is then equal to  $N(L^*) = N(L)$  since  $L = L^*$ . Since  $N(L) = Skew_n(\mathbb{R})$ , we have that  $Sym_n(\mathbb{R})^{\perp} = Skew_n(\mathbb{R})$ .

## Problem 22: HJE 3.46.

#### Solution.

- (i.) Since  $\mathbf{x}$  is in the null space of  $A^H A$ :  $A^H A \mathbf{x} = 0 \implies A^H (A \mathbf{x}) = 0 \implies A \mathbf{x}$  is in the null space of  $A^H$ . By definition  $A \mathbf{x}$  is also in the kernel of A.
- (ii.) By definition (and from the result of part (i):  $N(A) \subseteq N(A^H A)$ . Now let  $\mathbf{x} \in N(A^H A)$ . Then  $\mathbf{x}^H A^H A \mathbf{x} = 0 \implies (A \mathbf{x})^H (A \mathbf{x}) = 0 \implies A \mathbf{x} = 0$ . Therefore  $N(A^H A) \subseteq N(A)$ . Then  $N(A^H A) = N(A)$ .

- (iii.) From part (ii) above,  $dimN(A) = dimN(A^HA) \implies n rank(A) = n rank(A^HA)$ . Therefore, A and  $A^HA$  have the same rank.
- (iv.) If A has linearly independent columns then N(A) = 0 and by part (ii),  $N(A) = N(A^H A)$ . Because the null space is 0,  $A^H A$  is invertible.

#### Problem 23: HJE 3.47.

#### Solution.

(i.) Let  $P = A(A^H A)^{-1}A^H$ . First we note that  $A^H A$  is a symmetric matrix. Therefore we can proceed to show the lemma that  $(A^H A)^{-1} = ((A^H A)^{-1})^H$ . Let  $Q = (A^H)A$ . By the properties of the matrix inverse,  $QQ^{-1} = I$ . Then:

$$I = I^{H}.$$

$$(QQ^{-1}) = (QQ^{-1})^{H}.$$

$$QQ^{-1} = (Q^{-1})^{H}Q^{H}.$$

And since  $Q = Q^H$ :

$$Q^{-1}Q = (Q^{-1})^{H}Q.$$

$$Q^{-1} = (Q^{-1})^{H}.$$

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

Having verified this, it is easy to calculate  $P^2 = A((A^HA)^{-1})^HA^HA((A^HA)^{-1})A^H = A(A^HA)^{-1}A^H = P$ . Therefore  $P^2 = P$  so the operator P is a projection.

- (ii.) Using the fact proved in part (i), we have  $P^H = A((A^HA)^{-1})^HA^H = A(A^HA)^{-1}A^H = P$ . Therefore  $P^H = P$ .
- (iii.) First we note that by the result of Exercise 2.14(i),  $rank(KL) \leq min(rank(L), rank(K))$  so we also have:

$$rank(P) \le min(rank(A), rank((A^H A)^{-1} A^H)) \le rank(A).$$

Then, let  $\mathbf{b} \in R(A)$ . This implies that  $\mathbf{b} = A\mathbf{x}$  for some  $\mathbf{x}$ . We then have that:  $P(\mathbf{b}) = A(A^HA)^{-1}A^HA\mathbf{x} = A\mathbf{x}$  so  $\mathbf{b}$  is also in the range of P. Therefore the range of A is a subset of the range of P so:

$$rank(A) \le rank(P)$$
.

Since  $rank(A) \le rank(P)$  and  $rank(P) \le rank(A)$ , rank(P) = rank(A) = n.

#### Problem 24: HJE 3.48.

# Solution.

(i.) P is linear if it preserves addition, preserves multiplication, and preserves 0. We first show that P preserves addition:

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

We next show that P preserves multiplication:

$$P(cA) = \frac{cA + (cA)^T}{2} = \frac{c(A + A^T)}{2} = cP(A).$$

Finally, P preserves 0 so it is linear:

$$P(0) = \frac{0+0}{2} = 0.$$

(ii.) We define  $P^2$  as applying the linear transformation P twice consecutively. Then:

$$P^{2} = \frac{1}{2} \left( \frac{A + A^{T}}{2} + \left( \frac{A + A^{T}}{2} \right)^{T} \right) = \frac{1}{2} \left( \frac{A}{2} + \frac{A^{T}}{2} + \frac{A^{T}}{2} + \frac{A}{2} \right) = \frac{A + A^{T}}{2} = P.$$

Therefore  $P^2 = P$ .

(iii.)

$$\begin{split} \langle A_1, P(A_2) \rangle &= \langle A_1, \frac{A_2 + A_2^T}{2} \rangle = \frac{1}{2} tr(A_1^T(A_2 + A_2^T)) \\ &= \frac{1}{2} tr(A_1^T A_2 + A_1^T A_2^T) = \frac{1}{2} tr(A_1^T A_2) + \frac{1}{2} tr(A_1^T A_2^T) \\ &= \frac{1}{2} tr(A_1^T A_2) + \frac{1}{2} tr(A_2 A_1) = \frac{1}{2} tr(A_1 A_2 + A_1^T A_2) \\ &= \langle P(A_1), A_2 \rangle \end{split}$$

Therefore  $P^* = P$ .

(iv.)  $Skew_n(R)$  is defined as  $\{A \in M_n(\mathbb{R}) | A^T = -A\}$ . When  $A^T = -A$ , then P(A) = 0 so this is equivalent to being in the null space of P.

(v.)  $Sym_n(R)$  is defined as  $\{A \in M_n(\mathbb{R}) | A^T = A\}$ . When  $A^T = A$ , then  $\frac{1}{2}A = \frac{1}{2}A^T \implies A = \frac{1}{2}(A + A^T)$ . so  $A \in R(P)$ .

(vi.)

$$\begin{split} \|A - P(A)\| &= \sqrt{(\langle A - P(A), A - P(A) \rangle)} \\ &= \sqrt{\langle A/2 - A^T/2, A/2 - A^T/2 \rangle} = \sqrt{tr((A^T - 2 - A/2)(A/2 - A^T/2))} \\ &= \sqrt{tr(A^T A/4 - A^2/4 + AA^T/4 - A^TA^T/4)} \\ &= \sqrt{\frac{tr(A^T A) - tr(A^2)}{2}} \end{split}$$

Problem 25: HJE 3.50.

**Solution.** If we believe that data points  $(x_i, y_i)_{i=1}^n$  lie roughly on an ellipse of form  $rx^2 + sy^2 = 1$ , we would solve the normal equation  $A\mathbf{x} = b$  where:

$$A = \begin{pmatrix} 1 & x_1^2 \\ 1 & x_2^2 \\ \dots & \dots \\ 1 & x_n^2 \end{pmatrix}$$
$$b = \begin{pmatrix} y_1 \\ y_2 \\ \dots \\ y_n \end{pmatrix}$$
$$\mathbf{x} = \begin{pmatrix} \frac{1}{s} \\ \frac{-r}{s} \end{pmatrix}$$

We would then use this equation and the data points to solve for the unknowns r and s.