# Problem Set 2- Inner Product Spaces

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## Problem 3.1

In problem 3.1 and 3.2 the inner product spaces are defined on real numbers. Hence  $\langle x,y\rangle=\langle y,x\rangle$ 

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

We note we are on a real inner product space so we can write:

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

$$= \frac{1}{4}(4\langle x, y \rangle)$$

$$= \langle x, y \rangle$$

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

# Problem 3.2

$$\begin{split} \langle x,y\rangle &= \tfrac{1}{4}(||x+y||^2 - ||x-y||^2 + i||x-iy||^2 - i||x+iy||^2) \\ \text{Using the proof from above we can write this as:} \\ &= \mathcal{R}\langle x,y\rangle + \tfrac{1}{4}i(\langle x-iy,x-iy\rangle - \langle x+iy,x+iy\rangle) \\ &= \mathcal{R}\langle x,y\rangle + \tfrac{1}{4}4(\mathcal{I}\langle x,y\rangle) \\ &= \langle x,y\rangle \end{split}$$

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i. 
$$cos(\theta) = \frac{\langle x, y \rangle}{||x|| ||y||}$$

Subbing in we have:

$$= \frac{\int_0^1 x^6 dx}{\sqrt{\int_0^1 x^2 dx} \sqrt{\int_0^1 x^1 0 dx}}$$
$$= \frac{1/7}{\sqrt{1/33}}$$

Therefore the angle is  $=\cos^{-1}\left(\frac{1/7}{\sqrt{1/33}}\right)$  degrees.

ii. 
$$cos(\theta) = \frac{\int_0^1 x^6 dx}{\sqrt{\int_0^1 x^4 dx} \sqrt{\int_0^1 x^8 dx}}$$
$$= \frac{1/7}{\sqrt{1/45}}$$

Therefore the angle is  $=\cos^{-1}\left(\frac{1/7}{\sqrt{1/45}}\right)$  degrees.

#### Problem 3.8

- i. A set is orthonormal if the inner products of the set satisfy:
  - $\langle x_i, x_j \rangle = 1$  if i = j
  - $\langle x_i, x_i \rangle = 0$  if  $i \neq j$

Checking the first condition:

Firstly for cos(t), cos(t)

$$\langle \cos(t), \cos(t) \rangle = \frac{1}{\pi} \int_{-\pi}^{\pi} \cos^2(t) dt$$
$$= \frac{1}{\pi} \left[ \frac{x}{2} + \frac{\sin(2x)}{4} \right]_{-\pi}^{\pi}$$

$$=\frac{1}{\pi}(\pi)$$

$$=1$$

We can also see that this result will hold for  $\cos(2t)$ ,  $\cos(2t)$  as well. (The evaluated sin functions in the integral will still be zero).

Now checking sin(t), sin(t), and by virtue of the argument above, sin(2t), sin(2t) as well.

$$\langle sin(t), sin(t) \rangle = \frac{1}{\pi} \int_{-\pi}^{\pi} sin^2(t)dt$$
$$= \frac{1}{\pi} \left[ \frac{x}{2} - \frac{1}{4} sin(2x) \right]_{-\pi}^{\pi}$$

Now we need to check the cross terms, and verify that their inner product is zero.

=1

$$\langle cos(t), sin(t) \rangle = \frac{1}{\pi} [sin^2(t)]_{-\pi}^{\pi}$$

$$= 0$$

And we note that this also holds for the combinations of  $\cos(2t)$ ,  $\sin(t)$  and also  $\cos(t)$ ,  $\sin(2t)$ .

$$\langle cos(t), cos(2t) \rangle = \frac{1}{\pi} \left[ \frac{sin(t)}{2} + \frac{sin(3t)}{6} \right]_{-\pi}^{\pi}$$

$$= 0$$

$$\langle sin(t), sin(2t) \rangle = \frac{1}{\pi} \left[ \frac{sin(t)^3}{1.5} \right]_{-\pi}^{\pi}$$

= 0

Therefore the set is orthonormal

ii. 
$$||t||^2 = \frac{1}{\pi} \int_{-\pi}^{\pi} t^2 dt$$
  
 $= \left[ \frac{t^3}{3} \right]_{-\pi}^{\pi}$   
 $= \left[ \frac{\pi^3}{3} + \frac{\pi^3}{3} \right]$   
 $= 2\frac{\pi^3}{3}$ 

Therefore  $||t|| = (\frac{2\pi^3}{3})^{0.5}$ 

iii. Because we are dealing with an orthonormal sets we can write:

$$Proj_x(cos(3t)) = \Sigma_i \langle S_i, cos3t \rangle s_i$$

$$= \langle cos(t), cos(3t) \rangle cos(t) + \langle cos(2t), cos(3t) \rangle cos(2t) + \langle sin(t), cost(3t) \rangle sin(t) + \langle sin(2t), cos(3t) \rangle sin(2t)$$

After substituting in the integrals we get

=0

i.e.  $\cos(3t)$  is orthogonal to all the elements in S, as its projection matrix is a zero matrix.

iv. 
$$Proj_x(t) = \sum_i \langle S_i, t \rangle s_i$$
  
 $= \langle cos(t), t \rangle cos(t) + \langle cos(2t), t \rangle cos(2t) + \langle sin(t), t \rangle sin(t) + \langle sin(2t), t \rangle sin(2t)$   
 $= 0 + 0 + 2sin(t) - sin(2t)$   
 $= 2sin(t) - sin(2t)$ 

#### Problem 3.9

We use the fact that for an orthonormal transformation, if for the corresponding transformation matrix Q, if  $Q^TQ = I$  then the transformation is orthonormal.

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

So,

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

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

i. First we show that if Q is orthonormal then  $QQ^H=I$ .

If Q is an orthonormal matrix, then it preserves the inner product of two vectors. i.e.

$$\langle m, n \rangle = \langle Qm, Qn \rangle$$

Which we can rewrite as:

$$m^H n = (Qm)^H (Qn)$$

$$m^H n = m^H (Q^H Q) n$$

Therefore, since this has to hold for all m and n:

$$Q^HQ = I$$

Now we can show that if  $QQ^H = I$ , then Q is orthonormal.

If 
$$QQ^H = I$$

Then:

$$\langle Qm, Qn \rangle = (Qm)^H (Qn)$$

$$= m^H Q^H Q n$$

$$= \langle m, n \rangle$$

ii. 
$$||Qx|| = \sqrt{\langle Qx, Qx \rangle}$$

By the definition of what a orthonrmal matrix is (it preserves the inner product), we can write:

$$= \sqrt{\langle x, x \rangle}$$

$$= ||x||$$

iii. If Q is orthonormal we can write:

$$QQ^H = I$$

i.e.

$$Q^H = Q^{-1}$$

 $Q^H$  is clearly orthonormal because  $(Q^H)^H=Q$ , therefore so is  $Q^{-1}$ .

iv. If Q is orthonormal we know that  $G = Q^H Q = I$ 

For some element of G, we can write that:

$$G_{i,j} = \langle q_i, q_j \rangle$$

Where  $q_i$  is the i'th column of Q.

By the definition of orthornomality, we know that:

$$\langle q_i, q_j \rangle = 1, if, i = j$$

and

$$\langle q_i, q_j \rangle = 0, if, i \neq j$$

So we can see that when i = j we are on the diagonal of Q, so clearly  $\langle q_i, q_j \rangle = 1$  if i = j. And similarly, everywhere else  $i \neq j$ , and have zero entries, so  $\langle q_i, q_j \rangle = 0$  if  $i \neq j$ .

v. We can find a counterexample to show that not all matrices with determinant equal to 1 are orthonormal.

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

We can see that: det(D) = 1 But, if we test for orthonormality,

$$DD^H = \begin{bmatrix} n^2 & 0\\ 0 & (\frac{1}{n})^2 \end{bmatrix} \neq I$$

vi. Checking if the product of the two matrices is an orthonormal matrix:

$$(Q_1Q_2)(Q_1Q_2)^H = Q_1Q_2Q_2^HQ_1^H$$

Then using the fact that  $Q_1$  and  $Q_2$  are orthonormal we can write:

$$Q_1 Q_2 Q_2^H Q_1^H = Q_1 Q_1^H = I$$

So the product of the matrices is orthonormal.

## Problem 3.11

Suppose, WLOG, that for 2 < n < N,  $\{x_i\}_{i=1}^{m-1}$ , linearly independent. That also means that  $\{q_i\}_{i=1}^{m-1}$  are linearly independent (Showing this is very trivial!) However, if  $\{x_i\}_{i=1}^m$  are linearly dependent, then  $x_m \in Span(\{x_i\}_{i=1}^{m-1})$ , and  $q_m = 0$ . This is contradictory to the assumption that  $\{q_1, ..., q_N\}$  are linearly dependent.

#### Problem 3.16

i. Let  $A \in \mathbb{M}_{mxn}$  where  $\operatorname{rank}(A) = \leq n$ . Then there exist orthonormal  $Q \in \mathbb{M}_{nxn}$  and upper triangular  $R \in \mathbb{M}_{mxn}$  such that A = QR. Since  $\tilde{Q} = -Q$  is still orthonormal  $(-Q(-Q)^H = -Q(-Q^H) = QQ^H = I$  and similarly one shows  $(-Q)^H(-Q) = I$ ) and  $\tilde{R} = -R$  is still upper triangular,  $A = QR = \tilde{Q}\tilde{R}$ . Therefore QR-decomposition is not unique.

ii. Now take a reduced QR-decomposition  $A = \hat{Q}\hat{R}$ , where  $\hat{Q} \in \mathbb{M}_{nxn}$  is orthonormal and  $\hat{R} \in \mathbb{M}_{nxn}$  is upper triangular. Since A has full column rank,  $\hat{R}$  has full rank and is therefore nonsingular. Then,

$$A^{H}Ax = A^{H}b \implies$$

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

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

and premultiplying both LHS and RHS of the last equation by  $\hat{R}^{-1}$  gives  $\hat{R}x = \hat{Q}^H b$ .

#### Problem 3.17

$$A^H A X = A^H b \leftrightarrow (\hat{Q} \hat{R})^H (\hat{Q} \hat{R}) x = (\hat{Q} \hat{R})^H b \leftrightarrow \hat{R}^H (\hat{Q}^H \hat{Q}) \hat{R} x = \hat{R}^H \hat{Q}^H b \leftrightarrow \hat{R}^H \hat{R} x = \hat{R}^H \hat{Q}^H b$$

Note that  $\hat{R}^H$  is invertible. Thus,  $\hat{R}^H x = \hat{Q}^H b$ .

#### Problem 3.23

Let z = x - y. Then, by triangle inequality, the following is satisfied:

$$\|z + y\| \le \|z\| + \|y\| \leftrightarrow \|x\| \le \|x - y\| + \|y\| \leftrightarrow \|x\| - \|y\| \le \|x - y\|$$

In the same way,  $||y|| - ||x|| \le ||x - y||$ .

## Problem 3.24

i. 
$$||f||_{L^1} = \int_a^b |f(t)|dt > 0$$
 for  $f(t) \neq 0$ 

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

$$||f + g||_{L^1} = \int_a^b |f(t) + g(t)| dt \le \int_a^b |f(t)| + |g(t)| dt \le \int_a^b |f(t)| dt + \int_a^b |g(t)| dt = ||f|| + ||g||$$

ii. 
$$||f||_{L^2} = (\int_a^b |f(t)|^2 dt)^{1/2} > 0$$
 for  $f(t) \neq 0$ 

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

$$\begin{split} \|f+g\|_{L^2} &= (\int_a^b |f(t)+g(t)|^2 dt)^{1/2} \leq (\int_a^b |f(t)|^2 + |g(t)|^2 dt)^{1/2} \leq = (\|f\|^2 + \|g\|^2)^{1/2} \leq \sqrt{\|f\|^2} + \sqrt{\|g\|^2} = \|f\| + \|g\| \end{split}$$

iii. 
$$||f||_{L^{\infty}} = \sup_{x \in [a,b]} |f(x)| > 0$$
 for  $f(t) \neq 0$ 

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

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

*Proof.* Let  $a \sim b$  if  $\exists m, M > 0$  and  $m \leq M$  for vector space X s.t  $m||x||_a \leq ||x||_b \leq M||x||_a \ \forall x \in X$ 

i. Reflexivity

If 
$$m = M = 1$$
, then  $m||x||_a \le ||x||_a \le M||x||_a$ 

ii. Symmetry

Suppose  $a \sim b$ . Then,  $m||x||_a \leq ||x||_b \leq M||x||_a$ . This leads to the following inequalities;  $\frac{1}{M}||x||_b \leq ||x||_a \leq \frac{1}{m}||x||_b$ . So, as long as m = M, the symmetry property can be satisfied!

iii. Transitivity

Suppose  $a \sim b$  and  $b \sim c$ 

Then,  $m||x||_a \le ||x||_b \le M||x||_a$  and  $m^*||x||_b \le ||x||_c \le M^*||x||_b$ 

Then, this leads to:  $m\|x\|_a \leq \|x\|_b \leq \frac{1}{m^*} \|x\|_c \leq \frac{M}{m^*} \|x\|_b \leq \frac{M^2}{m^*} \|x\|_a \to m\|x\|_a \leq \frac{1}{m^*} \|x\|_c \leq \frac{M^2}{m^*} \|x\|_a$ 

Thus,  $a \sim c$ 

Take  $x \in \mathbb{R}^n$  Notice that

$$\sum_{i=1}^{n} |x_i|^2 \le \left(\sum_{i=1}^{n} |x_i|^2 + 2\sum_{i \ne j} |x_i| |x_j|\right) = \left(\sum_{i=1}^{n} |x_i|\right)^2$$

and that

$$\sum_{i=1}^{n} |x_i| \cdot 1 \le \left(\sum_{i=1}^{n} |x_i|^2\right)^{1/2} \left(\sum_{i=1}^{n} 1^2\right)^{1/2} = \sqrt{n} \left(\sum_{i=1}^{n} |x_i|^2\right)^{1/2}$$

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

Also notice that

$$\max_{i} |x_{i}| = \left(\max_{i} |x_{i}|^{2}\right)^{1/2} \le \left(\sum_{i=1}^{n} |x_{i}|^{2}\right)^{1/2} =$$

and

$$\sum_{i=1}^{n} |x_i|^2 \le n \cdot \max_i |x_i|^2$$

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

## Problem 3.28

Notice that (applying the results of the previous exercise)

$$\sup_{x \neq 0} \frac{||Ax||_1}{||x||_1} \le \sup_{x \neq 0} \frac{||Ax||_1}{||x||_1} \le \sqrt{n} \sup_{x \neq 0} \frac{||Ax||_2}{||x||_2},$$

and

$$\sup_{x \neq 0} \frac{||Ax||_1}{||x||_1} \ge \sup_{x \neq 0} \frac{||Ax||_2}{||x||_1} \ge \frac{1}{\sqrt{n}} \sup_{x \neq 0} \frac{||Ax||_2}{||x||_2}$$

imply that  $\frac{1}{\sqrt{n}}||A||_2 \leq ||A||_1 \leq ||A||_2$ . Notice that

$$\sup_{x \neq 0} \frac{||Ax||_2}{||x||_2} \le \sup_{x \neq 0} \frac{\sqrt{n}||Ax||_{\infty}}{||x||_{\infty}},$$

and

$$\sup_{x \neq 0} \frac{||Ax||_2}{||x||_2} \ge \sup_{x \neq 0} \frac{||Ax||_{\infty}}{\sqrt{n}||x||_{\infty}}.$$

- i.  $||Q||_p := \sup_{x \neq 0} \frac{||Qx||_p}{||x||_p} = \sup_{x \neq 0} \frac{||x||_p}{||x||_p} = \sup_{x \neq 0} 1 = 1$  (By orthonormal transformation).
- ii. Now let  $R_x : \mathbb{M}_n(\mathbb{F}) \to \mathbb{F}^n, A \mapsto Ax$  for every  $x \in \mathbb{F}^n$ .

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

## Problem 3.30

$$\|AB\|_S = \|SABS^{-1}\| = \|SAS^{-1}SBS^{-1}\| \le \|SAS^{-1}\| \|SBS^{-1}\| = \|A\|_S \|B\|_S$$

$$\|A\|_S\|x\| = \|SAS^{-1}\|\|x\| = (\sup_{x \neq 0} \frac{\|SAS^{-1}x\|}{\|x\|})\|x\| \ge \|S\|\|A\|\|S^{-1}\|\|x\| = \|A\|\|x\| \ge \|Ax\|$$

## Problem 3.37

Note that according to the Riesz Representation theorem,  $L[q] = \langle q, q \rangle = \int_0^1 q^2(x) dx = q'(1)$ . Let  $q(x) := a + bx + cx^2$ . Then,

$$L[1] = 0 = \langle q, 1 \rangle = \int_0^1 q(x)dx = a + \frac{1}{2}b + \frac{1}{3}c$$

$$L[x] = 1 = \langle q, x \rangle = \int_0^1 x q(x) dx = \frac{1}{2}a + \frac{1}{3}b + \frac{1}{4}c$$

$$L[x^2] = 2 = \langle q, x^2 \rangle = \int_0^1 x^2 q(x) dx = \frac{1}{3}a + \frac{1}{4}b + \frac{1}{5}c$$

If we solve this 3 equations with three unknowns (a, b, c), then  $q(x) = 24 - 168x + 180x^2$ 

The matrix representation of differential operator is

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

The adjoint matrix is the following:

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

#### Problem 3.39

i. By definition of adjoint and linearity of inner products,

$$<(S+T)^*w, v>_V = < w, (S+T)v>_W =$$
 $< w, Sv + Tv>_W = < w, Sv>_W + < w, Tv>_W =$ 
 $< S^*w, v>_V + < T^*w, v>_V = < S^*w + T^*w, v>_V.$ 

Then 
$$(S+T)^*=S^*+T^*$$
. Also, 
$$<(\alpha T)^*w,v>_V=< w,(\alpha T)v>_W=$$
 
$$< w,\alpha Tv>_W=\alpha< w,Tv>=$$
 
$$\alpha< T^*w,v>=<\bar{\alpha}T^*w,v>,$$

thus  $(\alpha T)^* = \bar{\alpha} T$ .

ii. By the definition of adjoint of S and the properties of inner products we have that

$$< w, Sv>_W = < S^*w, v>_V = \overline{< v, S^*w>_V} = \overline{< S^{**}v, w>_W} = < w, S^{**}v>_W$$

for all  $v \in V$  and  $w \in W$ . Therefore S = S \* \*.

iii. By the definition of adjoint we have

$$<(ST)^*v', v>_V = < v', (ST)v>_V = < v', S(Tv)>_V = < S^*v', Tv>_V = < T*S*v', v>_V,$$

thereby proving that  $(ST)^* = T^*S^*$ .

iv. Using (iii) we have  $T^*(T^*)^{-1} = (TT^{-1})^* = I^* = I$ .

## Problem 3.40

i. Let  $B, C \in \mathbb{M}_n(\mathbb{F})$ . By definition of Frobenious inner product

$$\langle B, AC \rangle_F = \operatorname{tr}(B^H AC) = \operatorname{tr}((A^H B)^H C) = \langle A^H B, C \rangle_F.$$

ii. By definition of Frobenious norm and the properties of the trace we have

$$< A_2, A_3 A_1 >_F = \operatorname{tr}(A_2^H A_3 A_1) = \operatorname{tr}(A_1 A_2^H A_3) = \operatorname{tr}((A_2 A_1^H)^H A_3) = < A_2 A_1^H, A_3 >_F = < A_2 A_1^*, A_3 >$$

iii. Given  $B, C \in \mathbb{M}_n(\mathbb{F})$ , we have  $\langle B, AC - CA \rangle = \langle B, AC \rangle - \langle B, CA \rangle$ . Applying (ii) to the second term we get  $\langle B, CA \rangle = \langle BA^*, C \rangle$ . On the other hand,

$$< B, AC > = \operatorname{tr}(B^H AC) = \operatorname{tr}((A^H B)^H C) = < A^H B, C > = < A^* B, C >$$
 .

Putting all together we obtain that  $T_A^* = T_{A^*}$ .

Suppose there exists an  $x \in \mathbb{F}^n$  such that Ax = b. Then, for every  $y \in \mathcal{N}(A^H)$ ,

$$< y, b > = < y, Ax > = < A^{H}y, x > = < 0, x > = 0.$$

Now suppose that there exists a  $y \in \mathcal{N}(A^H)$  such that  $\langle y, b \rangle \neq 0$ . Then  $b \notin \mathcal{N}(A^H)^{\perp} = \mathcal{R}(A)$ . Therefore for no  $x \in \mathbb{F}^n$ , Ax = b.

## Problem 3.45

Let  $A \in \operatorname{Sym}_n(\mathbb{R})$  and  $B \in \operatorname{Skew}_n(\mathbb{R})$ . Then

$$\langle B, A \rangle = \text{Tr}(B^T A) = \text{Tr}(AB^T) = \text{Tr}(A^T (-B)) = -\langle A, B \rangle.$$

We conclude that  $\langle A, B \rangle = 0$  and  $\operatorname{Skew}_n(\mathbb{R}) \subset \operatorname{Sym}_n(\mathbb{R})^{\perp}$ . Now suppose  $B \in \operatorname{Sym}_n(\mathbb{R})^{\perp}$ . As for any other matrix,  $B + B^T \in \operatorname{Sym}_n(\mathbb{R})$ . Thus,

$$0 = \langle B + B^T, B \rangle = \text{Tr}((B + B^T)B) = \text{Tr}(BB + B^TB) = \text{Tr}(BB) + \text{Tr}(B^TB),$$

which implies  $< B^T, B> = <-B, B>$  and so  $B^T=-B$ . Therefore  $\mathrm{Sym}_n(\mathbb{R})^\perp=\mathrm{Skew}_n(\mathbb{R})$ .

## Problem 3.46

- i. If  $x \in \mathcal{N}(A^H A)$ ,  $0 = (A^H A)x = A^H (Ax)$  and  $Ax \in \mathcal{N}(A^H)$ . Also, Ax is in the range of A by definition.
- ii. Suppose  $x \in \mathcal{N}(A)$ . Then Ax = 0. Premultiplying by  $A^H$  both sides of the equation we obtain  $A^HAx = A^H0 = 0$  and so  $x \in \mathcal{N}(A^HA)$ . On the other hand, suppose  $x \in \mathcal{N}(A^HA)$ . Then  $||Ax|| = x^HA^HAx = x^H0 = 0$ , so that Ax = 0 and  $x \in \mathcal{N}(A)$
- iii. By the rank-nullity theorem we have  $n = \text{Rank}(A) + \text{Dim}\mathcal{N}(A)$  and  $n = \text{Rank}(A^H A) + \text{Dim}\mathcal{N}(A^H A)$ . Then by (ii) it follows that  $\text{Rank}(A) = \text{Rank}(A^H A)$ .

iv. By (iii) and the assumption on A we have that  $n = \text{Rank}(A) = \text{Rank}(A^H A)$ . Since  $A^H A \in \mathbb{M}_n$ , it is nonsingular.

#### Problem 3.47

i. Notice that

$$P^{2} = (A(A^{H}A)^{-1}A^{H})(A(A^{H}A)^{-1}A^{H}) = A(A^{H}A)^{-1}A^{H}A(A^{H}A)^{-1}A^{H} = A(A^{H}A)^{-1}A^{H} = P.$$

ii. Notice that

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

iii. A has rank n, therefore P has at most rank n. Take y in the range of A. Then there exists an  $x \in \mathbb{F}^n$  such that y = Ax. Then

$$Py = A(A^{H}A)A^{H}y = A(A^{H}A)^{-1}A^{H}Ax = Ax = y$$

shows that y is also in the range of P. Therefore  $\operatorname{Rank}(P) \geq \operatorname{Rank}(A)$  and so P has rank p

#### Problem 3.48

i. Let  $A, B \in \mathbb{M}_n(\mathbb{R})$  and  $x \in \mathbb{R}$ . Then

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

Thus P is a linear transformation.

ii. Now notice that

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

iii. By definition of adjoint we have  $\langle P^*(A), B \rangle = \langle A, P(B) \rangle$ . Then, notice that

$$< A, P(B) > = < A, (B + B^{T})/2 > = < A, B/2 > + < A, B^{T}/2 > =$$

$$\operatorname{Tr}(A^{T}B/2) + \operatorname{Tr}(A^{T}B^{T}/2) = \operatorname{Tr}(A^{T}/2B) + \operatorname{Tr}(BA/2) =$$

$$\operatorname{Tr}(A^{T}/2B) + \operatorname{Tr}(A/2B) = < (A + A^{T})/2, B > = < P(A), B > .$$

Thus  $P = P^*$ .

- iv. Suppose  $A \in \mathcal{N}(P)$ . Then  $0 = P(A) = (A + A^T)/2$  implies  $A^T = -A$ , thus  $\mathcal{N}(P) \subset \text{Skew}(\mathbb{R})$ . Now suppose  $A \in \text{Skew}(\mathbb{R})$ . Then  $A^T = -A$  and so  $P(A) = (A + A^T)/2 = 0$ . Thus  $\text{Skew}(\mathbb{R}) \subset \mathcal{N}(P)$ .
- v. Let  $A \in \mathbb{M}_n(\mathbb{R})$ . Then  $P(A) = (A + A^T)/2 = (A^T + A)/2 = P(A)^T$  and so  $\mathcal{R}(P) = \operatorname{Sym}(\mathbb{R})$ . Now let  $A = \operatorname{Sym}(\mathbb{R})$ . Thus  $A = A^T$  and  $P(A) = (A + A^T)/2 = (A + A)/2 = A$  and so  $A \in \mathcal{R}(P)$ . This shows that  $\mathcal{R}(P) = \operatorname{Sym}(\mathbb{R})$ .
- vi. Notice that

$$||A - P(A)||_F^2 = \langle A - P(A), A - P(A) \rangle = \langle A - \frac{A + A^T}{2}, A - \frac{A + A^T}{2} \rangle =$$

$$\langle \frac{A - A^T}{2}, \frac{A - A^T}{2} \rangle = \operatorname{Tr}\left(\left(\frac{A - A^T}{2}\right)^T \frac{A - A^T}{2}\right) =$$

$$\operatorname{Tr}\left(\frac{A^T - A}{2} \frac{A - A^T}{2}\right) = \operatorname{Tr}\left(\frac{A^T A - A^2 - (A^T)^2 + AA^T}{4}\right) =$$

$$\operatorname{Tr}\left(\frac{A^T A - A^2 - A^2 + A^T A}{4}\right) = \operatorname{Tr}\left(\frac{A^T A - A^2}{2}\right) = \frac{\operatorname{Tr}(A^T A) - \operatorname{Tr}(A^2)}{2}.$$

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

#### Problem 3.50

We want to estimate  $y^2 = 1/s + rx^2/s$  via OLS. We rewrite the model in the form Ax = b where  $b_i = y_i^2$ ,  $A_i = (1 \ x_i)$  and  $x = (\beta_1 \ \beta_2)^T$  where  $\beta_1 = 1/s$  and  $\beta_2 = r/s$ .

Then the normal equations are  $A^{H}A\hat{x} = A^{H}b$ , where

$$A^{H}A\hat{x} = \begin{bmatrix} \sum_{i} 1 & \sum_{i} x_{i}^{2} \\ \sum_{i} x_{i}^{2} & \sum_{i} x_{i}^{4} \end{bmatrix} \begin{bmatrix} \hat{\beta}_{1} \\ \hat{\beta}_{2} \end{bmatrix} = \begin{bmatrix} n\hat{\beta}_{1} - \hat{\beta}_{2} \sum_{i} x_{i}^{2} \\ \hat{\beta}_{1} \sum_{i} x_{i}^{2} - \hat{\beta}_{2} \sum_{i} x_{i}^{4} \end{bmatrix}$$

 $\quad \text{and} \quad$ 

$$A^H b = \begin{bmatrix} \sum_i y_i^2 \\ \sum_i x_i^2 y_i^2 \end{bmatrix}.$$