

i) Case 1 A or B is singular.

If A or B is singular,  $\det(A) \text{ or } \det(B) = 0$

$$\Rightarrow \det(C) = \det(A)\det(B) = 0$$

$\Rightarrow C$  is also singular.

For a singular matrix, the minimum singular value is 0.

So,

If A or B is singular  $\Rightarrow a_m = 0$  or  $b_m = 0$   
~~or~~ and  $c_m = 0$ .

$$\Rightarrow \min(a, b_m, a_m b_1) = 0$$

$$c_m = 0$$

$$a_m b_m = 0$$

So,  $\min(a, b_m, a_m b_1) \geq c_m \geq a_m b_m$  is trivially true  
 $0 \geq 0 \geq 0$ .

$$\Rightarrow \max(a, b_m, a_m b_1) = 0$$

(TP = To prove)  $\Rightarrow$  TP  $a, b, \geq c, \geq 0 \Rightarrow$  TP  $a, b, \geq c,$

since  $c, \geq 0$  is trivially true.

Proof :  $\|C\|_2 = \|AB\|_2$

Let  $A = U_1 \Sigma_1 V_1^*$ ,  $B = U_2 \Sigma_2 V_2^*$ ,  $C = U_3 \Sigma_3 V_3^*$

Also,  $\|UAVV^*\|_2 = \|A\|$  where  $U, V$  are unitary.

$$\Rightarrow \|U_3 \Sigma_3 V_3^*\|_2 = \|U_1 \Sigma_1 V_1^* U_2 \Sigma_2 V_2^*\|_2$$

$$\Rightarrow \|\Sigma_3\|_2 = \|\Sigma_1 V_1^* U_2 \Sigma_2\|_2$$

$$\Rightarrow \|\xi_3\|_2 \leq \|\xi_1 v_1^* \| \|v_2 \xi_2\|$$

$$\Rightarrow \|\xi_3\|_2 \leq \|\xi_1\| \|v_2 \xi_2\|$$

$$\Rightarrow c_1 \leq a_1 b_1$$

Hence proved.

Case 2 A and B are invertible.

i) TP  $a_1 b_1 \geq c_1 \Rightarrow$  Same proof as in case 1

ii) TP  $c_m \geq a_m b_m$

Proof:  $C = AB \Rightarrow C^{-1} = B^{-1} A^{-1}$

$$\Rightarrow \|C^{-1}\|_2 = \|B^{-1} A^{-1}\|_2$$

$$\Rightarrow \|C^{-1}\|_2 \leq \|B^{-1}\|_2 \|A^{-1}\|_2$$

$$\Rightarrow \frac{1}{c_m} \leq \frac{1}{b_m} \times \frac{1}{a_m}$$

$$\Rightarrow a_m b_m \leq c_m$$

Hence proved.

iii) TP  $c_1 \geq \max(a_1 b_m, a_m b_1)$

Part 1

$$a_m \leq \frac{\|Ax\|}{\|x\|} \quad \forall x$$

Let  $x = By$  ( $B$  is invertible  $\Rightarrow$  one-one)

$$\Rightarrow a_m \|x\| \leq \|Ax\| \Rightarrow a_m \|By\| \leq \|ABy\| \quad \forall y$$

$$\Rightarrow a_m \frac{\|By\|}{\|y\|} \leq \frac{\|ABy\|}{\|y\|} \quad \forall y$$

$$\Rightarrow a_m b_1 \leq c_1$$

~~.....~~

### Part 2

$$\frac{1}{c_1} \leq \frac{\|(AB)^{-1}y\|}{\|y\|} \quad \forall y$$

$$\Rightarrow \frac{1}{c_1} \times \|y\| \leq \|(B^{-1}A^{-1}y)\| \quad \forall y$$

$$\Rightarrow \frac{1}{c_1} \times \|Ax\| \leq \|B^{-1}x\| \quad \forall x \quad [\text{Let } \cancel{y} = Ax]$$

$$\Rightarrow \frac{1}{c_1} \times \frac{\|Ax\|}{\|x\|} \leq \frac{\|B^{-1}x\|}{\|x\|} \quad \forall x$$

$$\Rightarrow \frac{1}{c_1} \times a_1 \leq \frac{1}{b_m}$$

$$\Rightarrow c_1 \geq a_1 b_m.$$

$$\text{Hence } c_1 \geq \max(a_1 b_m, a_m b_1)$$

$$\text{iv) TP } c_m \leq \min(a_1 b_m, a_m b_1)$$

### Part 1

$$\frac{1}{b_1} \leq \frac{\|B^{-1}x\|}{\|x\|} \quad \forall x$$

$$\Rightarrow \frac{1}{b_1} \times \|x\| \leq \|B^{-1}x\| \quad \forall x$$

$$\text{Let } x = A^{-1}y.$$

$$\Rightarrow \frac{1}{b_1} \times \frac{\|A^{-1}y\|}{\|y\|} \leq \frac{\|(AB)^{-1}y\|}{\|y\|} \quad \forall y.$$

$$\Rightarrow \frac{1}{b_1} \times \frac{1}{a_m} \leq \frac{1}{c_m}$$

$$\Rightarrow c_m \leq a_m b_1$$

## Part 2

$$c_m \leq \frac{\|ABy\|}{\|y\|} \quad \forall y$$

$$\Rightarrow c_m \|y\| \leq \|ABy\| \quad \forall y$$

Let  $y = B^{-1}x$ ,

$$\Rightarrow c_m \frac{\|B^{-1}x\|}{\|x\|} \leq \frac{\|Ax\|}{\|x\|} \quad \forall x$$

$$\Rightarrow c_m \times \frac{1}{b_m} \leq a_1$$

$$\Rightarrow c_m \leq a_1 b_m$$

$$\text{Hence } c_1 \leq \max(a_1 b_m, a_m b_1) //$$

2) Let  $\{v \in \mathbb{C}^n : v^*v = 0 \text{ for all } v \in S\} = T'$

TP  $T' \subseteq T$  and  $T \subseteq T'$

Part 1  $[T' \subseteq T \text{ i.e. } \vec{x} \in T' \rightarrow \vec{x} \in T]$

Let  $\vec{x} \in T'$ . Then  $\vec{x} \in \mathbb{C}^n$



$$\Rightarrow \exists s_i \in S, t_i \in T \text{ s.t. } \vec{x} = \vec{s}_i + \vec{t}_i$$

We know that  $\vec{x}^* \vec{v} = 0, \forall \vec{v} \in S$

$$\Rightarrow (\vec{s}_i + \vec{t}_i)^* \vec{v} = 0 \quad \forall \vec{v} \in S$$

but  $\vec{t}_i^* \vec{v} = 0$  bcoz  $\vec{v} \in S$  and  $\vec{t}_i \in T$  and  $S \perp T$ .

$$\Rightarrow \vec{s}_i^* \vec{v} = 0 \quad \forall \vec{v} \in S$$

$$\Rightarrow \vec{s}_i = 0 //$$

$$\Rightarrow \vec{x} = \vec{t}_i$$

$$\Rightarrow \vec{x} \in T // \text{ proved.}$$

Part 2  $[T \subseteq T' \text{ i.e. } \vec{x} \in T \rightarrow \vec{x} \in T']$

Let  $\vec{x} \in T$ .

We know that  $S \perp T \Rightarrow \vec{x}^* \vec{v} = 0 \quad \forall \vec{v} \in S$

$$\Rightarrow \vec{x} \in T' // \text{ proved.}$$

Hence  $T = T' //$

$$3) \text{ a) } \|x_i\|_2 = \|y_i\|_2 \Rightarrow x_i^* x_i = y_i^* y_i \quad \text{---} \forall i \quad - \textcircled{1}$$

$$\|x_i - x_j\|_2 = \|y_i - y_j\|_2 \Rightarrow (x_i - x_j)^* (x_i - x_j) = (y_i - y_j)^* (y_i - y_j)$$

$$\begin{aligned} & \Rightarrow x_i^* x_i - x_j^* x_i - x_i^* x_j + x_j^* x_j \\ & = y_i^* y_i - y_j^* y_i - y_i^* y_j + y_j^* y_j \end{aligned}$$

But since  $x_i^* x_i = y_i^* y_i$

$$\begin{aligned} & \Rightarrow x_i^* x_i - x_j^* x_i - x_i^* x_j + x_j^* x_j \\ & = y_i^* y_i - y_j^* y_i - y_i^* y_j + y_j^* y_j \end{aligned}$$

But since  $x_i^* x_j = x_j^* x_i$  and  $y_i^* y_j = y_j^* y_i$   
since  $x_i, x_j, y_i, y_j \in \mathbb{R}^n$

$$\Rightarrow \sum x_i^* x_j = \sum y_i^* y_j$$

$$\textcircled{2} \Rightarrow x_i^* x_j = y_i^* y_j \quad \forall i, j, i \neq j$$

\textcircled{1} and \textcircled{2} imply that  $\cancel{x^* x = y^* y}$

Let  $X = \hat{Q}_1 \hat{R}_1$  and  $Y = \hat{Q}_2 \hat{R}_2$  be their reduced QR factorizations (with positive diagonal elements  $\bullet$  in both  $\hat{R}_1$  and  $\hat{R}_2$ )

$$x^* x = y^* y$$

$$\Rightarrow \hat{R}_1^* \hat{Q}_1^* \hat{Q}_1 \hat{R}_1 = \hat{R}_2^* \hat{Q}_2^* \hat{Q}_2 \hat{R}_2$$

$$\Rightarrow \hat{R}_1^* \hat{R}_1 = \hat{R}_2^* \hat{R}_2$$

$$[\hat{Q}_1^* \hat{Q}_1^\bullet = I \text{ and } \hat{Q}_2^* \hat{Q}_2^\bullet = I]$$

Then, there exists a matrix  $D \in \mathbb{C}^{n \times n}$  s.t.

$$\hat{R}_1^* \hat{R}_1 = D = \hat{R}_2^* \hat{R}_2$$

- $D = \hat{R}_1^* \hat{R}_1$  is a Cholesky factorization with positive diagonal elements in  $\hat{R}_1$ ,
- similarly for  $D = \hat{R}_2^* \hat{R}_2$

But we know that ~~for a given matrix, there~~  
Cholesky factorization for a matrix is unique.

$$\text{So, } \hat{R}_1 = \hat{R}_2 // \text{ Hence proved.}$$

b) Let  $X = \hat{Q}_1 \hat{R}_1, Y = \hat{Q}_2 \hat{R}_2$

$$\Rightarrow \hat{Q}_1^* X = \hat{Q}_1^* \hat{Q}_1 \hat{R}_1 \quad \text{and} \quad \hat{Q}_2^* Y = \hat{Q}_2^* \hat{Q}_2 \hat{R}_2$$

$$\Rightarrow \hat{Q}_1^* X = \hat{R}_1 = \hat{Q}_2^* Y$$

$$\Rightarrow \hat{Q}_2 \hat{Q}_1^* X = \hat{Q}_2 \hat{Q}_2^* Y \Rightarrow \boxed{\hat{Q}_2 \hat{Q}_1^* X = Y}$$

$$\Rightarrow \hat{Q}_2 \hat{Q}_1^* x_i = y_i \quad \forall i$$

$$\boxed{Q = \hat{Q}_2 \hat{Q}_1^*}$$

Alg o

- Compute reduced QR factorization of  $X = \hat{Q}_1 \hat{R}_1$ ,
- Compute reduced QR factorization of  $Y = \hat{Q}_2 \hat{R}_2$
- Return  $\hat{Q}_2 \hat{Q}_1^*$

$$\begin{aligned}
 4) a) FA &= A - 2 \frac{vv^*}{v^*v} \times A \\
 &= A - \frac{2}{v^*v} \times v \times (v^* A) \\
 &= A - v \left[ \frac{2}{v^*v} (v^* A) \right]
 \end{aligned}$$

Hence,

$$w = \left[ \frac{-2}{v^*v} (v^* A) \right]^* = \left[ \frac{-2}{v^*v} (A^* v) \right] \rightarrow \begin{matrix} \text{an} \\ \text{nx1} \\ \text{vector} \end{matrix}$$

scalar  
 $\in \mathbb{R}$

Note:  $v^* A$  is compatible since  $\dim(v^*) = 1 \times \underline{n}$ ,  
 $\dim(A) = \underline{m} \times n$

As a result,  $\dim(w) = n \times 1 \rightarrow \text{vector.}$

i) The dominating operation is the matrix multiplication  $FA$ . [Computing  $F$  takes  $\sim 3m^2$  flops].

$\hookrightarrow FA$  has  $m \times n$  entries.

$$\dim(F) = m \times m, \dim(A) = m \times n.$$

For each entry in  $FA$ , we need to do

=  $m$  multiplications +  $m-1$  additions

=  $2m-1$  flops

For all entries =  $(2m-1) \times m \times n$

$$= 2m^2n - mn$$

$$\sim 2m^2n \text{ flops} //$$

Ans:  $2m^2n$  flops

ii) Computing  $w \Rightarrow$  computing  $A^*v \sim (2m-1)n$  flops  
computing  $\frac{-2}{v^*v}$  on  $2m$  flops  
Scalar multiplication  
of  $\frac{-2}{v^*v}$  with  $A^*v = \sim n$  flops  

---

 $\sim 2mn$  flops

Computing  $vw^* \Rightarrow mn$  multiplications  
 $\sim mn$  flops

Computing  $A + vw^* \Rightarrow mn$  additions  
 $\sim mn$  flops

Total  $\sim \underline{4mn}$  flops ..

b) Given  $\frac{\|\tilde{v} - v\|_2}{\|v\|_2} = O(\epsilon_m)$

TP  $\|\tilde{F} - F\|_2 = O(\epsilon_m)$

We knew that r.f.e.  $\leq (k(v) + o(1)) \boxed{\text{r.b.e.}}$

$$\Rightarrow \frac{\|\tilde{F} - F\|_2}{\|F\|_2} \leq (k(v) + o(1)) \frac{\|\tilde{v} - v\|_2}{\|v\|_2}$$

①  $\Rightarrow \|\tilde{F} - F\|_2 \leq \|F\|_2 (k(v) + o(1)) O(\epsilon_m)$

To find:  $k(v)$ .

[Assume  $\|\cdot\| = \|\cdot\|_2$ ]

$$k(v) = \sup_{\delta v} \frac{\|SF\|_2}{\|F\|_2} / \frac{\|\delta v\|_2}{\|v\|_2}$$

$$= \boxed{\frac{\|v\|_2}{\|F\|_2}} \sup_{\delta v} \frac{\|SF\|_2}{\|\delta v\|_2}$$

$$= \frac{\|v\|_2}{\|F\|_2} \sup_{\delta v} \left\| \left( I - \frac{2(v + \delta v)(v + \delta v)^*}{(v + \delta v)^*(v + \delta v)} \right) - \left( I - \frac{2vv^*}{v^*v} \right) \right\| \frac{\|\delta v\|_2}{\|\delta v\|_2}$$

$$= \frac{2\|v\|_2}{\|F\|_2} \sup_{\delta v} \left\| \frac{(v + \delta v)(v + \delta v)^*}{\|v + \delta v\|^2} - \frac{vv^*}{\|v\|^2} \right\| \frac{\|\delta v\|_2}{\|\delta v\|_2}$$

(Approximating  $\|v + \delta v\| \rightarrow \|v\|$ )

$$= \boxed{2} \frac{\|v\|_2}{\|F\|_2} \sup_{\delta v} \left\| \frac{(v + \delta v)(v + \delta v)^*}{\|v\|^2} - \frac{vv^*}{\|v\|^2} \right\| \frac{\|\delta v\|_2}{\|\delta v\|_2}$$

$$= \boxed{2} \cdot \frac{\|v\|_2}{\|F\|_2} \cdot \frac{1}{\|v\|^2} \sup_{\delta v} \frac{\|(v + \delta v)(v + \delta v)^* - vv^*\|}{\|\delta v\|_2}$$

$$= \frac{2}{\|v\|\|F\|} \sup_{sv} \| \cancel{sv.v^* + vsv^*} + svsv^* \| / \|sv\|$$

Ignoring  $svsv^*$  because it is negligible,

$$= \frac{2}{\|v\|\|F\|} \sup_{sv} \|sv.v^* + vsv^*\| / \|sv\|$$

$$\leq \frac{2}{\|v\|\|F\|} \sup_{sv} \frac{\|sv.v^*\| + \|vsv^*\|}{\|sv\|}$$

[Note:  $\|A\|_2 = \|A^*\|_2$  (~~can be proved using SVD~~)]

$$\leq \frac{2}{\|v\|\|F\|} \sup_{sv} \frac{\|sv\|/\|v\|}{\|sv\|} + \frac{\|v\|/\|sv\|}{\|sv\|}$$

$$\leq \frac{2}{\|v\|\|F\|} \times 2\|v\|$$

$$K(v) \leq \frac{4}{\|F\|}$$

Substituting in ①,

$$\Rightarrow \|\tilde{F} - F\|_2 \leq \|F\| \left( \frac{4}{\|F\|} + o(1) \right) o(\epsilon_m)$$

$$\Rightarrow \|\tilde{F} - F\|_2 \leq [4 + \|F\|o(1)] o(\epsilon_m)$$

(The  $o(1)$  term tends to 0 as  $\epsilon_m \rightarrow 0$ ). So,

$$\Rightarrow \|\tilde{F} - F\|_2 = o(\epsilon_m) //$$

Let  $\| \cdot \| = \| \cdot \|_2$

Part 2

Let  $E$  be an  $m \times n$  matrix with  $E_{ij}$  terms s.t.  
 $|E_{ij}| \leq \epsilon_m$  and  $\| E \|_2 = O(\epsilon_m)$ . Then

$$f_1(\tilde{F}A) = \tilde{F}A(I+E)$$

$$\text{Let } \tilde{F} = F + \frac{\Delta F}{\| F \|} \text{ with } \|\frac{\Delta F}{\| F \|}\| = O(\epsilon_m)$$

$$\begin{aligned} \text{Then, } \tilde{F}A(I+E) &= (F+\Delta F)A(I+E) \\ &= (F+\Delta F)A + (F+\Delta F)AE \\ &= FA + \Delta FA + FAE + \Delta FAE. \end{aligned}$$

$$\Rightarrow FA = \Delta FA + FAE + \Delta FAE$$

Since  $F$  is unitary  $FF^* = F^*F = I$ . and  $\| F \| = \| F^* \| = 1$

$$\Rightarrow SA = F^*\Delta FA + AE + F^*\Delta FAE$$

$$\begin{aligned} \Rightarrow \frac{\| SA \|}{\| A \|} &= \frac{\| F^*\Delta FA + AE + F^*\Delta FAE \|}{\| A \|} \\ &\leq \frac{\| F^* \| \| \Delta F \| \| A \|}{\| A \|} + \frac{\| A \| \| E \|}{\| A \|} + \frac{\| F^* \| \| \Delta F \| \| A \| \| E \|}{\| A \|} \\ &\leq \| \Delta F \| + \| E \| + \| \Delta F \| \| E \| \\ &\leq O(\epsilon_m) + O(\epsilon_m) + O(\epsilon_m^2) \end{aligned}$$

Hence,

$$\frac{\| SA \|}{\| A \|} = O(\epsilon_m) \|$$

5) a) The  $\vec{y} \in \text{range}(A)$  which minimizes  $\|b - \vec{y}\|_2$  is the  ~~$\vec{y}$~~   $\vec{y}$  s.t.  $(\vec{b} - \vec{y}) \perp \text{range}(A)$ ,

$$\Rightarrow A^*(b - \vec{y}) = 0$$

$$\Rightarrow \boxed{A^*\vec{y} = A^*b}$$

$$\Rightarrow (U\Sigma V^*)^* \vec{y} = (U\Sigma V^*)^* b$$

$$\Rightarrow V\Sigma^* U^* \vec{y} = V\Sigma^* U^* b$$

$$\Rightarrow \Sigma^* U^* \vec{y} = \Sigma^* U^* b \quad [V \text{ is invertible}]$$

$$\Rightarrow \Sigma [U^* \vec{y} - U^* b] = 0$$

~~$\Sigma$~~   $\Sigma$  is not a zero matrix. There has to be at least one singular value for any matrix.

$$\Rightarrow U^* \vec{y} = U^* b$$

$$\Rightarrow \boxed{\vec{y} = UU^* b}$$

Ans:  $\boxed{\vec{y} = UU^* b}$

b) The  $Ax$  which minimizes  $\|Ax - b\|_2$  is,

$$Ax = UV^*b$$

$$\Rightarrow U\Sigma V^*x = UV^*b$$

$$\Rightarrow \Sigma V^*x = U^*b \quad [U^*U = UV^* = I]$$

Let  $\vec{z} = V^*x$ ,

$$\Rightarrow \Sigma z = U^*b$$

$$\Rightarrow \begin{bmatrix} \sigma_1 & & \\ & \ddots & \\ & & \sigma_r & \\ \hline & & 0 & \\ & & & \ddots & \\ & & & & 0 \end{bmatrix} \begin{bmatrix} z_1 \\ | \\ z_n \end{bmatrix} = \begin{bmatrix} U_1^*b \\ | \\ U_n^*b \end{bmatrix}$$

where  $\sigma_i$  = singular values

$z_i$  = entries of  $\vec{z}$

$U_i^*$  = rows of  $U^*$

$$\Rightarrow \sigma_1 z_1 = U_1^*b \quad \Rightarrow \quad z_1 = \frac{U_1^*b}{\sigma_1}$$

$$\sigma_r z_r = U_r^*b \quad \Rightarrow \quad z_r = \frac{U_r^*b}{\sigma_r}$$

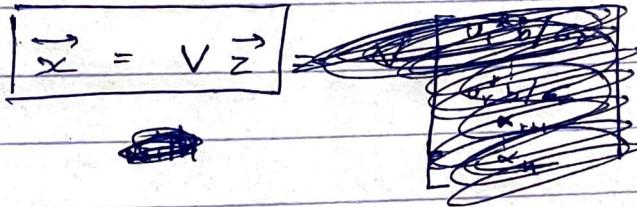
$$\Rightarrow \boxed{\begin{aligned} z_i &= \frac{U_i^*b}{\sigma_i}, \quad i = 1 \dots r \\ z_i &= \text{arbitrary}, \quad i = r+1 \dots n \end{aligned}}$$

- ①

Since  $\vec{z} = V^* \vec{x} \Rightarrow \vec{x} = V \vec{z}$   $[V^* V = V V^* = I]$

Hence,

$$\boxed{\vec{x} = V \vec{z}}$$



The above  $\vec{x}$  with the entries of  $\vec{z}$  given in ① minimizes  $\|b - Ax\|_2$

The  $\vec{x}$  with  $\min \|x\|_2$  is

$$\vec{x} = V \vec{z} \text{ s.t. } z_i = u_i^* b / \sigma_i, i=1 \dots r$$

$$z_i = 0, i=r+1 \dots n$$

6) a) Let the coefficients of  $p$  be  $\begin{bmatrix} a_0 \\ a_1 \\ \vdots \\ a_n \end{bmatrix}$

$q$  be  $\begin{bmatrix} b_0 \\ \vdots \\ b_n \end{bmatrix}$

$$(p, q) = \int_{-1}^1 (\bar{a}_0 + \bar{a}_1 x + \dots + \bar{a}_n x^n)(b_0 + \dots + b_n x^n)$$

$$= \int_{-1}^1 \sum_{i=0}^n \sum_{j=0}^n \bar{a}_i b_j x^{i+j}$$

$$= \left[ \sum_{i=0}^n \sum_{j=0}^n \frac{\bar{a}_i b_j x^{i+j+1}}{i+j+1} \right]_{-1}^1$$

$$= \sum_{i=0}^n \sum_{j=0}^n \bar{a}_i b_j \times \frac{2}{i+j+1} \times [(i+j+1) \bmod 2]$$

↓  
even ~~odd~~ degree  
~~powers cancel out~~

Let  $G_i = \left[ \begin{array}{c|c|c|c} 1 & 1 & \dots & 1 \\ g_{i0} & g_{i1} & \dots & g_{in} \\ \hline 1 & 1 & \dots & 1 \end{array} \right]$

where  $g_{ij}$  are the columns of  $G_i$  and  $g_{ii} = (i, i)^{th}$  entry of  $G_i$

$$[p]^* G_i [q] = [\bar{a}_0 \bar{a}_1 \dots \bar{a}_n] \left[ \begin{array}{c|c|c|c} g_{i0} & g_{i1} & \dots & g_{in} \end{array} \right] \begin{bmatrix} b_0 \\ \vdots \\ b_n \end{bmatrix}$$

$$= [p]^* g_0 [p]^* g_1 \dots [p]^* g_n \begin{bmatrix} b_0 \\ \vdots \\ b_n \end{bmatrix}$$

$$= \sum_{i=0}^n \sum_{j=0}^n \bar{a}_i b_j g_{ij}$$

$$[p]^* G_i [q] = (p, q)$$

$$\sum_{i=0}^n \sum_{j=0}^n \bar{a}_i b_j g_{ij} = \sum_{i=0}^n \sum_{j=0}^n \bar{a}_i b_j \times \left[ \frac{2 [(i+j+1) \bmod 2]}{i+j+1} \right]$$

By comparing the two, we see that

$$g_{ij} = \frac{2 [(i+j+1) \bmod 2]}{i+j+1}$$

This describes the matrix  $G$

Also,  $G^* = G$  because

$$g_{ij} = \bar{g}_{ji} = \frac{2 [(i+j+1) \bmod 2]}{i+j+1}$$

→ real valued.

Hence  $G$  exists.

b) We know that  $P_{pq} = \vec{p}(\vec{p}^* q)$  and  $P_{\perp p} = I - P_p P_p^*$

~~Similarly for polynomials ( $\mathbb{Q}[x]$  set  $P_n$  is also a vector space),~~

~~$P_p + (P_p)^*$~~

~~$P_p P_p^* + (P_p^*)^* P_p$~~

b) Projection of  $q$  onto the  $\langle p \rangle \Rightarrow \frac{p(p^* q)}{(p^* p)} = p(x) \frac{(p, q)}{(p, p)}$

(Algebraic Defn)

$$\Rightarrow p(x) \left[ \frac{\int_1^1 \overline{p(x)} q(x) dx}{\left[ \int_1^1 \overline{p(x)} p(x) dx \right]} \right] //$$

Matrix form  $\rightarrow \frac{\tilde{P} (p, q)}{(p, p)} = [p] \cdot \frac{[p]^* G [q]}{[p]^* G [p]}$

$$= \left( \frac{[p][p]^* G}{[p]^* G [p]} \right) [q]$$

$$\text{Matrix} = \frac{[p][p]^* G}{[p]^* G [p]}$$

Similarly,

Projection of  $q$  orthogonal to  $\langle p \rangle = q(x) - p(x) \left[ \frac{\int_1^1 \overline{p(x)} q(x) dx}{\int_1^1 \overline{p(x)} p(x) dx} \right] p(x)$

$$\text{Matrix form} = I - \frac{[p][p]^* G}{[op]^* G [p]} //$$