

7.7

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7.7 Which quadric surface does the equation $7x^2 + 7y^2 - 2z^2 + 20yz - 20zx - 2xy - 36 = 0$ describe? Explain by reducing the quadratic form involved to a diagonal form. Express x, y, z in terms of the new coordinates u, v, w .

$$Q(x, y, z) = \begin{bmatrix} x & y & z \end{bmatrix} \begin{bmatrix} 7 & -1 & -10 \\ -1 & 7 & 10 \\ -10 & 10 & -2 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix}$$

$$\text{Let } A = \begin{bmatrix} 7 & -1 & -10 \\ -1 & 7 & 10 \\ -10 & 10 & -2 \end{bmatrix}$$

$$\begin{aligned} \text{Then, } P_A(t) &= -t^3 + 12t^2 + 180t - 1296 \\ &= -(t-18)(t-6)(t+12). \end{aligned}$$

Each eigenvalue has geo-mult = 1.

$$\cdot \lambda = -12: \quad \mathcal{N}(A + 12I) = \text{span} \left\{ \frac{1}{\sqrt{6}} \begin{bmatrix} 1 \\ -1 \\ 2 \end{bmatrix} \right\}$$

orthonormal basis

(Do the calculations.
Solve $(A + 12I)x = 0$. Convert $A + 12I$ into REF and solve.)

$$\cdot \lambda = 6: \quad \mathcal{N}(A - 6I) = \text{span} \left\{ \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix} \right\}$$

$$\cdot \lambda = 18: \quad \mathcal{N}(A - 18I) = \text{span} \left\{ \frac{1}{\sqrt{3}} \begin{bmatrix} -1 \\ 1 \\ 1 \end{bmatrix} \right\}$$

$$\text{D1. } \quad \text{11.} = \Gamma \quad y, z \quad y\sqrt{2} \quad -y, z$$

Define $U := \begin{bmatrix} 1/\sqrt{6} & 1/\sqrt{2} & -1/\sqrt{3} \\ -1/\sqrt{6} & 1/\sqrt{2} & 1/\sqrt{3} \\ 2/\sqrt{6} & 0 & 1/\sqrt{3} \end{bmatrix}$.

Note that U is orthogonal. Thus, $U^T = U^{-1}$ and

$$U^T A U = D := \begin{bmatrix} -12 & & \\ & 6 & \\ & & 18 \end{bmatrix}.$$

Thus, $A = U D U^T$ and hence,

$$\begin{aligned} Q(x, y, z) &= [x \ y \ z] A \begin{bmatrix} x \\ y \\ z \end{bmatrix} \\ &= [x \ y \ z] U D U^T \begin{bmatrix} x \\ y \\ z \end{bmatrix} \\ &= \left(U^T \begin{bmatrix} x \\ y \\ z \end{bmatrix} \right)^T D \left(U^T \begin{bmatrix} x \\ y \\ z \end{bmatrix} \right). \end{aligned}$$

Define $\begin{bmatrix} u \\ v \\ w \end{bmatrix} := U^T \begin{bmatrix} x \\ y \\ z \end{bmatrix}$.

Then,

$$\begin{aligned} Q(x, y, z) &= [u \ v \ w] D \begin{bmatrix} u \\ v \\ w \end{bmatrix} \\ &= -12u^2 + 6v^2 + 18w^2. \end{aligned}$$

The surface becomes

$$-12u^2 + 6v^2 + 18w^2 - 36 = 0$$

or

$$\boxed{-\frac{u^2}{3} + \frac{v^2}{6} + \frac{w^2}{2} = 1}$$

where $\begin{bmatrix} u \\ v \\ w \end{bmatrix} = U^T \begin{bmatrix} x \\ y \\ z \end{bmatrix}$.

There are two positives and one negative. Thus, it is a 1-sheeted hyperboloid.

7.8 Let Y be a subspace of $\mathbb{K}^{n \times 1}$. Show that $(Y^\perp)^\perp = Y$.

• Claim 1. $Y \subseteq (Y^\perp)^\perp$.

Proof. Let $y \in Y$.
Let $\tilde{y} \in Y^\perp$ be arbitrary.

Then, $\langle y, \tilde{y} \rangle = 0$, by definition of Y^\perp .

Thus, $\langle y, \tilde{y} \rangle = 0 \quad \forall \tilde{y} \in Y^\perp$.

Thus, $y \in (Y^\perp)^\perp$. ◻

• Claim 2. $\dim(Y) = \dim((Y^\perp)^\perp)$.

Proof. Recall $\mathbb{K}^n = Y \oplus Y^\perp$.

Define $P: \mathbb{K}^n \rightarrow Y$ to be the orthogonal projection.

Then, $\mathcal{N}(P) = Y^\perp$ and $\mathcal{I}(P) = Y$.

$\therefore \dim(V) = \text{rank}(P) + \text{nullity}(P) = \dim(Y) + \dim(Y^\perp)$

Thus, $\dim(V) = \dim(Y) + \dim(Y^\perp)$ ⁽¹⁾ for any subspace $Y \subseteq V$.

Since Y^\perp is again a subspace, we have

$\dim(V) = \dim(Y^\perp) + \dim((Y^\perp)^\perp)$ ⁽²⁾

(1) and (2) give $\dim(Y) = \dim((Y^\perp)^\perp)$. \square

• Claim 3. $Y = (Y^\perp)^\perp$.

Proof. $Y \subseteq (Y^\perp)^\perp$ is proven and $\dim(Y) = \dim((Y^\perp)^\perp)$.
Thus, $Y = (Y^\perp)^\perp$. \square

If $W \subseteq V \subseteq \mathbb{K}^{n \times 1}$ are subspaces and $\dim(W) = \dim(V)$,
then $W = V$.
Proof. Let B be a basis of W .
Then, $|B| = \dim(W) = \dim(V)$. Since B is
lin. indep and has "correct" cardinality, it is a
basis of V .

Here, it is important that Y was a subspace
to begin with. Otherwise we can only guarantee
 $Y \subseteq (Y^\perp)^\perp$.

(And also that $\mathbb{K}^{n \times 1}$ is finite dimensional.)

Aliter (Wagar): $Y \subseteq (Y^\perp)^\perp$ is as before.

Claim: $(Y^\perp)^\perp \subseteq Y$.

Proof. Let $x \in (Y^\perp)^\perp$.

Since Y is a subspace, the projection theorem tells
us that

$$x = y + \tilde{y} \quad \text{for some } y \in Y, \tilde{y} \in Y^\perp.$$

$$\text{Thus, } \underbrace{\langle x, \tilde{y} \rangle}_1 = \underbrace{\langle y, \tilde{y} \rangle}_0 + \langle \tilde{y}, \tilde{y} \rangle.$$

$$\text{Thus, } \langle x, \tilde{y} \rangle = \langle y, \tilde{y} \rangle + \langle \tilde{y}, \tilde{y} \rangle.$$

$$\begin{array}{ccc} | & & | \\ \downarrow & & \downarrow \\ 0 & & 0 \\ \text{since } & & \text{since} \\ x \in (Y^\perp)^\perp & & \tilde{y} \in Y^\perp \end{array}$$

$$\therefore \|\tilde{y}\|^2 = 0 \quad \text{or} \quad \tilde{y} = 0.$$

$$\text{Thus, } x = y \in Y. \quad \square$$

7.9

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7.9 Let A be a self-adjoint matrix. If $\langle Ax, x \rangle = 0$ for all $x \in \mathbb{K}^{n \times 1}$, then show that $A = O$. Deduce that if $\|A^*x\| = \|Ax\|$ for all $x \in \mathbb{K}^{n \times 1}$, then A is a normal matrix, and if $\|Ax\| = \|x\|$ for all $x \in \mathbb{K}^{n \times 1}$, then A is a unitary matrix.

① Since A is self-adjoint, $\exists D \in \mathbb{K}^{n \times n}$ and invertible $U \in \mathbb{K}^{n \times n}$
 s.t. \downarrow diagonal
 $U^{-1} A U = D.$

(Since A is self-adjoint, the above is true even if $\mathbb{K} = \mathbb{R}.$)

Claim. $D = O.$

Proof Let λ be a diagonal entry of $D.$

Then, λ is an eigenvalue of $A.$

Let $0 \neq u \in \mathbb{K}^{n \times 1}$ be an eigenvector corresponding to $\lambda.$

Then,

$$\bar{\lambda} \|u\|^2 = \bar{\lambda} \langle u, u \rangle = \langle \bar{\lambda} u, u \rangle = \langle Au, u \rangle = 0.$$

$$\text{Thus, } \bar{\lambda} = 0 \text{ or } \lambda = 0.$$

$$\therefore D = O. \quad \square$$

Thus, $A = U D U^{-1} = O,$ as desired. \square

(All we needed was that A is diagonalisable.)

② $\|Ax\| = \|A^*x\| \quad \forall x \in \mathbb{K}^{n \times 1}. \quad \underline{\text{IS}}: A \text{ is normal.}$

Define $B = AA^* - A^*A$.

Then, $B^* = B$. (check!)

$$\begin{aligned}\text{Note } \langle Bx, x \rangle &= \langle (AA^* - A^*A)x, x \rangle \\ &= \langle AA^*x, x \rangle + (-1) \langle A^*Ax, x \rangle \\ &= \langle A^*x, A^*x \rangle - \langle Ax, Ax \rangle \\ &= \|A^*x\|^2 - \|Ax\|^2 = 0.\end{aligned}$$

By ①, $B = 0$. $\therefore A^*A = AA^*$. \square

② Given: $\|Ax\| = \|x\| \quad \forall x \in \mathbb{K}^{n \times 1}$.

TS: A is unitary.

Proof. $B = A^*A - I$. Then, $B^* = B$.

$$\begin{aligned}\langle Bx, x \rangle &= \langle A^*Ax - x, x \rangle \\ &= \langle A^*Ax, x \rangle - \langle x, x \rangle \\ &= \langle Ax, Ax \rangle - \langle x, x \rangle \\ &= \|Ax\|^2 - \|x\|^2 = 0.\end{aligned}$$

By ①, $B = 0$ or $A^*A = I$. \square

7.10

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7.10 Let E be a nonempty subset of $\mathbb{K}^{n \times 1}$.(i) If E is not closed, then show that there is $x \in \mathbb{K}^{n \times 1}$ such that no best approximation to x exists from E .(ii) If E is convex, then show that for every $x \in \mathbb{K}^{n \times 1}$, there is at most one best approximation to x from E .(i) E is not closed

\Leftrightarrow There is a sequence (x_n) in E such that (x_n) converges to $x \in \mathbb{K}^{n \times 1} \setminus E$.

IS: $\exists x \in \mathbb{K}^{n \times 1}$ s.t. there is no best approx to x from E .

Proof. Take $x \in \mathbb{K}^{n \times 1} \setminus E$ s.t. $\exists (x_n)$ in E which converges to x .
(By defⁿ of E not being closed.)

For sake of contradiction, assume $a \in E$ is a best approximation. Then $a \neq x$ since $x \notin E$ and hence

$$\varepsilon := \frac{\|x - a\|}{2} > 0.$$

By defⁿ of convergence, $\exists N \in \mathbb{N}$ s.t.

$$\|x_n - x\| < \varepsilon \quad \forall n \geq N.$$

Thus, $\|x_N - x\| < \|x - a\|$. This contradicts the fact that a is a best approximation.

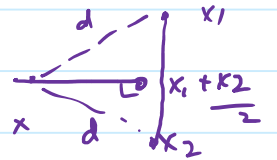
Thus, we are done. \square

(ii) Recall:

$E \subset \mathbb{R}^{n \times n}$ is convex if

$$\forall x, y \in E \text{ and } \forall t \in [0, 1]: tx + (1-t)y \in E.$$

Suppose $x \in \mathbb{R}^{n \times n}$ has two distinct best approximations $x_1, x_2 \in E$.



$$v_1 := x - x_1, \quad v_2 := x - x_2.$$

$$\text{Let } \bar{x} = \frac{x_1 + x_2}{2}. \quad \text{Note } \|v_1\| = \|v_2\| =: d \text{ (say).}$$

$$\|x - \bar{x}\| = \left\| x - \left(\frac{x_1 + x_2}{2} \right) \right\| = \frac{1}{2} \|v_1 + v_2\|.$$

$$\|v_1 + v_2\|^2 = 2\|v_1\|^2 + 2\|v_2\|^2 - \|v_1 - v_2\|^2 \quad (\text{Parallelogram rule})$$

$$= 4d^2 - \|v_1 - v_2\|^2 < 4d^2 \quad \left. \begin{array}{l} \text{since } v_1 \neq v_2 \end{array} \right\}$$

$$\Rightarrow \|v_1 + v_2\| < 2d \quad \text{or} \quad \frac{1}{2} \|v_1 + v_2\| < d.$$

$$\|x - \bar{x}\|$$

$$\|x - \bar{x}\| < \|x - x_1\|.$$

But $\bar{x} \in E$ since E is convex. This contradicts that x_1 was a best approximation of x from E .

7.11

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7.11 Find $x := [x_1, x_2]^T \in \mathbb{R}^{2 \times 1}$ such that the straight line $t = x_1 + x_2 s$ fits the data points $(-1, 2)$, $(0, 0)$, $(1, -3)$ and $(2, -5)$ best in the 'least squares' sense.

$$A := \begin{bmatrix} 1 & -1 \\ 1 & 0 \\ 1 & 1 \\ 1 & 2 \end{bmatrix} \quad \text{and} \quad b := \begin{bmatrix} 2 \\ 0 \\ -3 \\ -5 \end{bmatrix}.$$

Let $x = [x_1, x_2]^T$. Want to minimise $\|Ax - b\|$.

Thus, we the best approximation a of b from $\mathcal{C}(A)$.

Then, we find $x \in \mathbb{R}^{2 \times 1}$ s.t. $Ax = a$.

Step 1. Getting an orthonormal basis for $\mathcal{C}(A)$.
(o.n.b.)

Applying GSDP on columns.

$$y_1 := [1 \quad 1 \quad 1 \quad 1]^T.$$

$$\begin{aligned} y_2 &:= [-1 \quad 0 \quad 1 \quad 2] - \frac{2}{4} [1 \quad 1 \quad 1 \quad 1]^T \\ &= [-3/2 \quad -1/2 \quad 1/2 \quad 3/2] \end{aligned}$$

$$\therefore u_1 = \frac{1}{2} [1 \quad 1 \quad 1 \quad 1]^T$$

$$\text{and } u_2 = \frac{1}{\sqrt{20}} [-3 \quad -1 \quad 1 \quad 3]^T.$$

$\therefore \{u_1, u_2\}$ is an o.n.b. for $\mathcal{C}(A)$.

Step 2. Finding the best approximation.

$$\text{This is } a = \langle u_1, b \rangle u_1 + \langle u_2, b \rangle u_2$$

$$\begin{aligned}
&= (-3)u_1 + \frac{-24}{\sqrt{20}} u_2 \\
&= -\frac{3}{2} [1 \ 1 \ 1 \ 1]^T - \frac{6}{20} [-3 \ -1 \ 1 \ 3]^T \\
&= \left[\frac{21}{10} \quad -\frac{3}{10} \quad -\frac{27}{10} \quad -\frac{51}{10} \right]^T.
\end{aligned}$$

Thus, $d = \frac{3}{10} [7 \ -1 \ 9 \ -17]^T$ is

the best approximation of b from $\mathcal{C}(A)$.

Step 3 Getting $x = [x_1 \ x_2]^T$ such that $Ax = d$.

$$\left[\begin{array}{cc|c} 1 & -1 & 21/10 \\ 1 & 0 & -3/10 \\ 1 & 1 & -27/10 \\ 1 & 2 & -51/10 \end{array} \right]$$

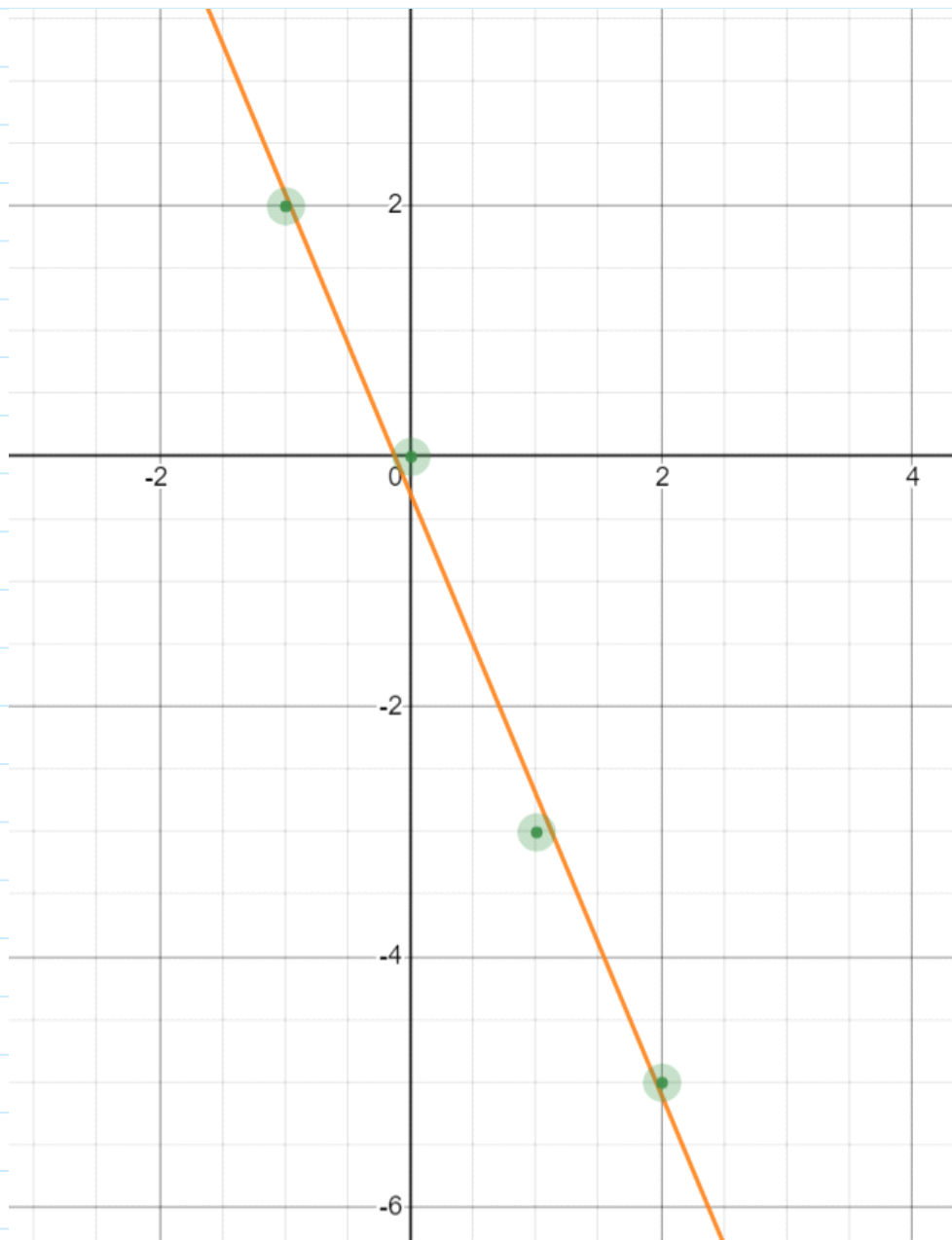
(Note that we already know this system is consistent since $d \in \mathcal{C}(A)$.)

Second equation gives $x_1 = -3/10$.

First equation gives $x_1 - x_2 = \frac{21}{10}$

and hence, $x_2 = x_1 - \frac{21}{10} = -\frac{24}{10}$.

Thus, the desired line is $t = -\frac{3}{10} - \frac{24}{10} s$
 $= -\frac{3}{10} - \frac{12}{5} s$.



7.12

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7.12. Let $Q(x_1, \dots, x_n) := \sum_{j=1}^n \sum_{k=1}^n \alpha_{jk} x_k \bar{x}_j$, where $\alpha_{jk} \in \mathbb{C}$, be a **complex quadratic form**. If the complex quadratic form $Q(x_1, \dots, x_n)$ takes values in \mathbb{R} for all $[x_1 \ \dots \ x_n]^T \in \mathbb{C}^{n \times 1}$, then show that there is a unique self-adjoint matrix \mathbf{A} such that

$$Q(x_1, \dots, x_n) = \mathbf{x}^* \mathbf{A} \mathbf{x} \quad \text{for all } \mathbf{x} := [x_1 \ \dots \ x_n]^T \in \mathbb{C}^{n \times 1}.$$

• $Q(x_1, \dots, x_n) = \mathbf{x}^* \mathbf{A} \mathbf{x}$, where

$$\mathbf{A} := \begin{bmatrix} \alpha_{11} & \dots & \alpha_{1n} \\ \vdots & \ddots & \vdots \\ \alpha_{n1} & \dots & \alpha_{nn} \end{bmatrix}.$$

• Claim. $\mathbf{A} = \mathbf{A}^*$.

Proof. Write $\mathbf{A} = \mathbf{B} + i\mathbf{C}$ where $\mathbf{B}, \mathbf{C} \in \mathbb{C}^{n \times n}$ are self-adjoint.

$$\left[\mathbf{B} = \frac{1}{2}(\mathbf{A} + \mathbf{A}^*), \quad \mathbf{C} = \frac{1}{2i}(\mathbf{A} - \mathbf{A}^*) \right]$$

$$\langle \mathbf{A}x, x \rangle = \langle \mathbf{B}x, x \rangle - i \langle \mathbf{C}x, x \rangle \quad \forall x \in \mathbb{C}^{n \times 1}.$$

Since \mathbf{B}, \mathbf{C} are self-adjoint, we get

$$\langle \mathbf{B}x, x \rangle, \langle \mathbf{C}x, x \rangle \in \mathbb{R} \quad \forall x \in \mathbb{C}^{n \times 1} \quad (*)$$

Since $\langle \mathbf{A}x, x \rangle \in \mathbb{R} \quad \forall x \in \mathbb{C}^{n \times 1}$, (given)

we get $\langle \mathbf{C}x, x \rangle = 0 \quad \forall x \in \mathbb{C}^{n \times 1}.$

Thus, $C = 0$. (By 7.9)

$\therefore A = B$ and B is self-adjoint.

Thus, A is self-adjoint. \square

Proof of (*) IS: $\langle Bx, x \rangle \in \mathbb{R} \quad \forall x \in \mathbb{C}^{n \times 1}$.

Since $B = B^*$, \exists an orthonormal eigen basis $\{u_1, \dots, u_n\}$ where the corresp. λ_i are real.

Now, given $x \in \mathbb{C}^{n \times 1}$, write
$$x = a_1 u_1 + \dots + a_n u_n = \sum_{i=1}^n a_i u_i. \quad (a_i \in \mathbb{C})$$

Then, $\langle Bx, x \rangle = \left\langle \sum_{i=1}^n \lambda_i a_i u_i, \sum_{i=1}^n a_i u_i \right\rangle$

$$= \sum_{i=1}^n \overline{\lambda_i} |a_i|^2 \quad \lambda_i \in \mathbb{R}$$

$$= \sum_{i=1}^n \lambda_i |a_i|^2 \in \mathbb{R}.$$

$\lambda_i, |a_i| \in \mathbb{R}$

• Uniqueness of A .

Suppose A' is self-adjoint s.t. $x^* A x = x^* A' x \quad \forall x \in \mathbb{C}^{n \times 1}$.

Put $B = A - A'$. This is also self-adjoint and

$$x^* B x = 0 \quad \forall x \in \mathbb{C}^{n \times 1}.$$

$$\downarrow$$
$$\langle Bx, x \rangle$$

Conclude as before.

7.13

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7.13. Let $\mathbf{A} \in \mathbb{C}^{n \times n}$ be normal, and let μ_1, \dots, μ_k be the distinct eigenvalues of \mathbf{A} . Let $Y_j := \mathcal{N}(\mathbf{A} - \mu_j \mathbf{I})$ for $j = 1, \dots, k$. Show that $\mathbb{C}^{n \times 1} = Y_1 \oplus \dots \oplus Y_k$, which means show that every $\mathbf{x} \in \mathbb{C}^{n \times 1}$ can be written as $\mathbf{x} = \mathbf{y}_1 + \dots + \mathbf{y}_k$ for unique $\mathbf{y}_j \in Y_j$, $1 \leq j \leq k$. Also, if P_j is the orthogonal projection of $\mathbb{C}^{n \times 1}$ onto Y_j (defined by $P_j(\mathbf{x}) := \mathbf{y}_j$), then show that $P_1 + \dots + P_k = I$, $P_i P_j = O$ if $i \neq j$ and $\mathbf{A}\mathbf{x} = \mu_1 P_1(\mathbf{x}) + \dots + \mu_k P_k(\mathbf{x})$ for all $\mathbf{x} \in \mathbb{C}^{n \times 1}$.

Let $g_j = \text{geo-mult. of } \mu_j$.

Then, we have an orthonormal eigen basis:

$$B = \left\{ \underbrace{u_1^{(1)}, \dots, u_1^{(g_1)}}_{\text{orthonormal eigenbasis of } Y_1}, \underbrace{u_2^{(1)}, \dots, u_2^{(g_2)}}_{\text{of } Y_2}, \dots, \underbrace{u_k^{(1)}, \dots, u_k^{(g_k)}}_{\text{of } Y_k} \right\}.$$

① Given $\mathbf{x} \in \mathbb{C}^{n \times 1}$, define

$$\begin{aligned} \mathbf{y}_1 &= \langle u_1^{(1)}, \mathbf{x} \rangle u_1^{(1)} + \dots + \langle u_1^{(g_1)}, \mathbf{x} \rangle u_1^{(g_1)} \\ &\vdots \\ \mathbf{y}_k &= \langle u_k^{(1)}, \mathbf{x} \rangle u_k^{(1)} + \dots + \langle u_k^{(g_k)}, \mathbf{x} \rangle u_k^{(g_k)}. \end{aligned}$$

Since B is an o.n.b., we have

$$\mathbf{x} = \sum_{u \in B} \langle u, \mathbf{x} \rangle u$$

$$\mathbf{x} = \mathbf{y}_1 + \dots + \mathbf{y}_k. \quad \text{--- (i)}$$

Thus, each \mathbf{x} can be written as a sum of vectors in Y_i .

Uniqueness: Suppose $\mathbf{y}_1' \in Y_1, \dots, \mathbf{y}_k' \in Y_k$ were s.t.

$$x = y_1' + \dots + y_k'$$

$$y_1 + \dots + y_k$$

Then, $(y_1 - y_1') + \dots + (y_k - y_k') = 0.$

\swarrow \searrow
 eigenvectors \leftrightarrow \leftrightarrow \leftrightarrow
 corresp. to distinct
 eigenvalues

$$\therefore y_1 - y_1' = \dots = y_k - y_k' = 0$$

$$\therefore y_i = y_i' \quad \forall i. \quad \text{This proves uniqueness.} \quad \square$$

② By eq (1), we have $I = P_1 + \dots + P_k$ since

$$I(x) = x = y_1 + \dots + y_k = P_1(x) + \dots + P_k(x). \quad \square$$

$$P_i P_j = 0 \quad \forall i \neq j$$

Let $x \in \mathbb{C}^{n \times 1}$. Then, $P_j(x) \in Y_j$.

Let $y_j = P_j(x)$.

$$\therefore P_j(x) = 0 + \dots + 0 + y_j + 0 + \dots + 0$$

Since $i \neq j$, $P_i(P_j(x)) = 0$.

Since x was arbitrary, $P_i P_j = 0$.

Given $x \in \mathbb{C}^{n \times h}$, write $x = \sum_{i=1}^m y_i$ for $y_i \in Y_i$.

$$\begin{aligned} \text{Then, } Ax &= \sum_{i=1}^m Ay_i = \sum_{i=1}^m \mu_i y_i \\ &= \sum_{i=1}^m \mu_i P_i(x). \end{aligned}$$

$$\therefore Ax = \sum \mu_i P_i(x).$$

□