

Chapter 7: Eigenvalues & eigenvectors

Section 7.1 Definition and examples

Definition If $A \in \mathbb{R}^{n \times n}$, then $\underline{x} \in \mathbb{R}^n$ is an eigenvector of A , with eigenvalue λ if $A\underline{x} = \lambda \underline{x}$ (and $\underline{x} \neq \underline{0}$)

Example If $A = \begin{pmatrix} 1 & 2 \\ -1 & 4 \end{pmatrix}$, $u = \begin{pmatrix} 1 \\ 1 \end{pmatrix}$, $w = \begin{pmatrix} 1 \\ 2 \end{pmatrix}$

$$\text{then } Au = \begin{pmatrix} 3 \\ 3 \end{pmatrix} = 3u$$

$$\& Aw = \begin{pmatrix} 4 \\ 2 \end{pmatrix} = 2w$$

so $\underline{u}, \underline{w}$ are eigenvectors of A .

Indeed $\{\underline{u}, \underline{w}\}$ is a basis of \mathbb{R}^2 consisting of eigenvectors of A .

Writing the linear transformation $L: \underline{x} \mapsto A\underline{x}$

with respect to the basis $B = \{\underline{u}, \underline{w}\}$, the matrix

$$[L]_B^B = \begin{pmatrix} 3 & 0 \\ 0 & 2 \end{pmatrix} \cdot \begin{cases} L(u) = 3\underline{u} + 0\underline{w} \\ L(w) = 0\underline{u} + 2\underline{w} \end{cases}$$

How to find eigenvalues & eigenvectors?

If $A\underline{x} = \lambda \underline{x}$

then $A\underline{x} - \lambda \underline{1} = 0$

so $(A - \lambda I) \underline{x} = 0$
 $\xrightarrow{n \times n \text{ matrix}}$

i.e. $\underline{x} \in N(A - \lambda I)$

If \underline{x} is an eigenvector then $\underline{x} \neq 0$,

so $N(A - \lambda I)$ is non-zero

$\Leftrightarrow \underbrace{\det(A - \lambda I)}_{\text{polynomial of degree } n} = 0.$

called the characteristic polynomial of A .

So the eigenvalues of A are exactly

the roots of the characteristic polynomial.

To summarize:

Theorem 7.4 The following are equivalent:

- (a) λ is an eigenvalue of A
- (b) $(A - \lambda I)x = 0$ has a non-zero solution
- (c) $N(A - \lambda I) \neq \{0\}$.
- (d) $A - \lambda I$ is singular
- (e) $\det(A - \lambda I) = 0$.

Terminology 7.5 $N(A - \lambda I)$ is called the eigenspace of A corresponding to λ .

Example 7.6 $A = \begin{pmatrix} -7 & -6 \\ 9 & 8 \end{pmatrix}$

$$\Rightarrow A - \lambda I = \begin{pmatrix} -7 - \lambda & -6 \\ 9 & 8 - \lambda \end{pmatrix}$$

$$\begin{aligned}\Rightarrow \det(A - \lambda I) &= (-7 - \lambda)(8 - \lambda) - 9(-6) \\ &= \lambda^2 - \lambda - 56 + 54 \\ &= \lambda^2 - \lambda - 2 \\ &= (\lambda - 2)(\lambda + 1)\end{aligned}$$

So the characteristic equation is
 $(\lambda - 2)(\lambda + 1) = 0$.

\Rightarrow the eigenvalues are $\lambda = 2$
and $\lambda = -1$.

Case $\lambda = 2$: $A - \lambda I = \begin{pmatrix} -9 & -6 \\ 9 & 6 \end{pmatrix}$ is singular.

$(A - \lambda I)x = 0$ if & only if
 $9x_1 + 6x_2 = 0$

So the eigenspace = $\left\{ \alpha \begin{pmatrix} 2 \\ -3 \end{pmatrix} \mid \alpha \in \mathbb{R} \right\}$

& $\begin{pmatrix} 2 \\ -3 \end{pmatrix}$ is an eigenvector for eigenvalue 2.

[$\alpha \begin{pmatrix} 2 \\ -3 \end{pmatrix}$ is also an eigenvector, when $\alpha \neq 0$.]

Case $\lambda = -1$: $A - \lambda I = \begin{pmatrix} -6 & -6 \\ 9 & 9 \end{pmatrix}$

$(A - \lambda I)x = 0$ if & only if
 $x_1 + x_2 = 0$

\Rightarrow eigenspace = $\left\{ \alpha \begin{pmatrix} 1 \\ -1 \end{pmatrix} : \alpha \in \mathbb{R} \right\}$.

Example 7.8 Find the eigenvalues of

$$A = \begin{pmatrix} 1 & 2 & 3 \\ 0 & 4 & 5 \\ 0 & 0 & 6 \end{pmatrix}.$$

$$A - \lambda I = \begin{pmatrix} (1-\lambda) & 2 & 3 \\ 0 & (4-\lambda) & 5 \\ 0 & 0 & (6-\lambda) \end{pmatrix}$$

$$\Rightarrow \det(A - \lambda I) = (1-\lambda)(4-\lambda)(6-\lambda)$$

\Rightarrow eigenvalues of A are $1, 4, 6$.

More generally:

Theorem 7.9 The eigenvalues of a triangular matrix are the diagonal entries.

Theorem 7.10 (Change of basis for linear transformations)

If A and B are two $n \times n$ matrices, and $B = S^{-1}AS$ for some (invertible) S , then ~~that~~ the characteristic polynomial of A is equal to the characteristic polynomial of B .

Hence the eigenvalues of A are equal to the eigenvalues of B .

Proof Char. poly. of A is $\det(A - \lambda I)$ & char. poly. of B is $\det(B - \lambda I)$.

$$\begin{aligned} \text{Now } \cancel{\det(B - \lambda I)} &= S^{-1}AS - \lambda I \\ &= S^{-1}AS - \cancel{S^{-1}\lambda I} S \\ &= S^{-1}(A - \lambda I)S. \end{aligned}$$

$$\Rightarrow \det(B - \lambda I) = \det(S^{-1}(A - \lambda I)S)$$

$$= \det(S^{-1}) \det(A - \lambda I) \det S$$

$$= \det(A - \lambda I)$$

Since $\det S^{-1} = (\det S)^{-1}$.

$$\left. \begin{aligned} &= \det(A - \lambda I) \cdot \underbrace{\det S^{-1} \cdot \det S}_{= 1} \\ &= \det(A - \lambda I) \cdot \underbrace{\det(S^{-1}S)}_{= 1}. \end{aligned} \right)$$

Done.

Section 7.2: Diagonalisation

"Diagonalisation" is a shorthand for
"finding a basis consisting of eigenvectors" -

We saw in the example at the beginning of
this chapter that the matrix of a linear
transformation with respect to a basis of eigenvectors
is diagonal.

Diagonal matrices are very easy to calculate with.

Example 7.11 If $D = \begin{pmatrix} 2 & 0 \\ 0 & 3 \end{pmatrix}$

$$\text{then } D^2 = DD = \begin{pmatrix} 2^2 & 0 \\ 0 & 3^2 \end{pmatrix}$$

and more generally

$$D^k = D D^{k-1} = \begin{pmatrix} 2^k & 0 \\ 0 & 3^k \end{pmatrix}.$$

Definition 7.12

- Two $n \times n$ matrices A, B are called similar if there is an invertible matrix P such that

$$P^{-1}AP = B.$$

[in effect, they are the matrices of the same linear transformation, written with respect to (possibly) different bases.]

- An $n \times n$ matrix A is called diagonalisable if it is similar to a diagonal matrix.

Consequence If $P^{-1}AP = B$ then

$$\begin{aligned}B^2 &= (P^{-1}AP)(P^{-1}AP) \\&= P^{-1}A(PP^{-1})AP = P^{-1}AIAAP = P^{-1}AAP \\&= P^{-1}A^2P\end{aligned}$$

and more generally

$$\begin{aligned}B^k &= (P^{-1}AP)(P^{-1}AP)\dots(P^{-1}AP) \\&= P^{-1}A^kP\end{aligned}$$

In particular if D is diagonal and $A = PDP^{-1}$ then $\overset{\text{hard to calculate}}{\overbrace{A^k}} = P D^k P^{-1} \overset{\text{easy to calculate}}{\uparrow}$.

Note If D is diagonal ($n \times n$)
then the coordinate vectors $\begin{pmatrix} 0 \\ i \\ 0 \end{pmatrix}$ are

eigenvectors of D

Example $D = \begin{pmatrix} 2 & 0 \\ 0 & 3 \end{pmatrix}$

$$\Rightarrow D\begin{pmatrix} 1 \\ 0 \end{pmatrix} = \begin{pmatrix} 2 & 0 \\ 0 & 3 \end{pmatrix} \begin{pmatrix} 1 \\ 0 \end{pmatrix} = \begin{pmatrix} 2 \\ 0 \end{pmatrix} = 2\begin{pmatrix} 1 \\ 0 \end{pmatrix}.$$

$$D\begin{pmatrix} 0 \\ 1 \end{pmatrix} = \begin{pmatrix} 0 \\ 3 \end{pmatrix} = 3\begin{pmatrix} 0 \\ 1 \end{pmatrix}.$$

So the key to diagonalising matrices is
finding the eigenvectors.

Helpful result 7.13

If v_1, \dots, v_r are eigenvectors of A , with distinct eigenvalues $\lambda_1, \dots, \lambda_r$, ($\lambda_i \neq \lambda_j$ if $i \neq j$)

then v_1, \dots, v_r are linearly independent.

(So they span an r -dimensional subspace of \mathbb{R}^n .)

Proof If $c_1 v_1 + c_2 v_2 + \dots + c_r v_r = 0$
we need to show all $c_i = 0$.

$$\text{Now } A(c_1 v_1 + \dots + c_r v_r) = A 0 = 0.$$

$$\Rightarrow \lambda_1 c_1 v_1 + \lambda_2 c_2 v_2 + \dots + \lambda_r c_r v_r = 0.$$

$$\text{Also } \lambda_1 c_1 v_1 + \lambda_1 c_2 v_2 + \dots + \lambda_1 c_r v_r = 0.$$

$$\Rightarrow (\lambda_2 - \lambda_1) c_2 v_2 + \dots + (\lambda_r - \lambda_1) c_r v_r = 0.$$

We can keep going, eliminating one vector at a time, until we're left with

$$\underbrace{(\lambda_{r-1} - \lambda_{r-2}) \dots (\lambda_r - \lambda_1)}_{\neq 0} c_r v_r = 0$$

$$\Rightarrow c_r = 0 \quad \text{since } v_r \neq 0$$

$$\& (\lambda_{r-1} - \lambda_{r-2}) \dots (\lambda_{r-1} - \lambda_1) c_{r-1} v_{r-1} \\ + \cancel{(\dots) c_r v_r} = 0$$

$$\Rightarrow c_{r-1} = 0 \quad \& \text{so on.}$$

$$\Rightarrow c_r = c_{r-1} = \dots = c_2 = c_1 = 0. \quad \underline{\text{Done.}}$$

Main result 7.14

- An $n \times n$ matrix A is diagonalisable if and only if A has n linearly independent eigenvectors
- In more detail, $P^{-1}AP = D$, with D diagonal, if and only if the columns of P are n linearly independent eigenvectors of A .
The diagonal entries of D are the corresponding eigenvalues.

Proof Suppose $D = \begin{pmatrix} \lambda_1 & 0 & \cdots & 0 \\ 0 & \ddots & & \\ 0 & & \ddots & 0 \\ 0 & 0 & \cdots & \lambda_n \end{pmatrix}$
 $\& P = \begin{pmatrix} v_1 & v_2 & \cdots & v_n \end{pmatrix}$ as (column vectors v_1, \dots, v_n).

$$\text{Then } PD = \begin{pmatrix} v_1 & \cdots & v_n \end{pmatrix} \begin{pmatrix} \lambda_1 & 0 & \cdots & 0 \\ 0 & \ddots & & \\ 0 & & \ddots & 0 \\ 0 & 0 & \cdots & \lambda_n \end{pmatrix} = \\ = (\lambda_1 v_1, \lambda_2 v_2, \dots, \lambda_n v_n)$$

If v_1, \dots, v_n are eigenvectors of A with eigenvalues $\lambda_1, \dots, \lambda_n$

$$AP = A \begin{pmatrix} v_1 & v_2 & \cdots & v_n \end{pmatrix} = (\lambda_1 v_1, \lambda_2 v_2, \dots, \lambda_n v_n)$$

$$\Rightarrow AP = PD$$

Moreover P is invertible if & only if v_1, \dots, v_n

are linearly independent.

- If the columns of P are linearly independent eigenvectors of A with eigenvalues $\lambda_1, \dots, \lambda_n$

then $AP = \boxed{AP} (\lambda v_1, \dots, \lambda_n v_n)$

$$= P \begin{pmatrix} \lambda_1 & & 0 \\ & \ddots & \\ 0 & & \lambda_n \end{pmatrix}$$

~~$P^{-1}AP = \lambda v_1, \dots, \lambda_n v_n$~~ & P is invertible

$$\Rightarrow A = APP^{-1} = P \begin{pmatrix} \lambda_1 & & 0 \\ & \ddots & \\ 0 & & \lambda_n \end{pmatrix} P^{-1}.$$

$\Rightarrow A$ is diagonalisable.

- Conversely if A is diagonalisable, say

$$A = PDP^{-1} \text{ with } D = \begin{pmatrix} \lambda_1 & & \\ & \ddots & \\ & & \lambda_n \end{pmatrix}$$

then $AP = PD$

$$\text{i.e. } A(v_1, \dots, v_n) = (\lambda_1 v_1, \lambda_2 v_2, \dots, \lambda_n v_n)$$

$$\Rightarrow Av_1 = \lambda_1 v_1, \dots, Av_n = \lambda_n v_n$$

v_1, \dots, v_n are eigenvectors of A .
with eigenvalues $\lambda_1, \dots, \lambda_n$

Also v_1, \dots, v_n are linearly independent
since P is invertible.

Done.

Example 7.15 Diagonalise, if possible:

$$A = \begin{pmatrix} -7 & 3 & -3 \\ -9 & 5 & -3 \\ 9 & -3 & 5 \end{pmatrix}$$

Solution Step 1 $\det(A - \lambda I) =$

$$\begin{vmatrix} -7-\lambda & 3 & -3 \\ -9 & 5-\lambda & -3 \\ 9 & -3 & 5-\lambda \end{vmatrix} = \dots$$

$$= -\lambda^3 + 3\lambda^2 - 4$$

$$= -(\lambda+1)(\lambda^2 - 4\lambda + 4)$$

$$= -(\lambda+1)(\lambda-2)^2$$

\Rightarrow eigenvalues are -1 and 2 .

Step 2 Find $N(A + I)$ and $N(A - 2I)$
(i.e. the eigenspaces corresponding to
the eigenvalues -1 and 2)

$$\begin{pmatrix} -6 & 3 & -3 \\ -9 & 6 & -3 \\ 9 & -3 & 6 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix} \text{ if & only if }$$

$$\begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} \in \text{Span} \left\{ \begin{pmatrix} -1 \\ -1 \\ 1 \end{pmatrix} \right\}$$

$$\text{& similarly } N(A - 2I) = \text{Span} \left\{ \begin{pmatrix} 1 \\ 3 \\ 0 \end{pmatrix}, \begin{pmatrix} -1 \\ 0 \\ 3 \end{pmatrix} \right\}.$$

Step 3
So if $P = \begin{pmatrix} -1 & 1 & -1 \\ -1 & 3 & 0 \\ 1 & 0 & 3 \end{pmatrix}$

then $P^{-1}AP = \begin{pmatrix} -1 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 2 \end{pmatrix}$

Example 7.16 If $A = \begin{pmatrix} -6 & 3 & -2 \\ -7 & 5 & -1 \\ 8 & -3 & 4 \end{pmatrix}$

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$$\text{then } \det(A - \lambda I) = -(\lambda + 1)(\lambda - 2)^2$$

\Rightarrow eigenvalues are -1 and 2 .

$$N(A + I) = \text{Span} \left\{ \begin{pmatrix} -1 \\ -1 \\ 1 \end{pmatrix} \right\}$$

$$N(A - 2I) = \text{Span} \left\{ \begin{pmatrix} 1 \\ 2 \\ -1 \end{pmatrix} \right\}$$

So in this case there are not enough eigenvectors to span the whole space,
& therefore A is not diagonalisable.

More generally (7.17) If $A \in \mathbb{R}^{n \times n}$
and $\lambda_1, \dots, \lambda_k$ are the distinct eigenvalues of A , then

A is diagonalisable

if & only if

$$\dim N(A - \lambda_1 I) + \dots + \dim N(A - \lambda_k I) = n.$$

Special case 7.18 If $A \in \mathbb{R}^{n \times n}$ has
 n distinct eigenvalues, then
A is diagonalisable.

Proof Each eigenvalue $\lambda_1, \dots, \lambda_n$
comes with at least one non-zero
eigenvector v_1, \dots, v_n .

(7.13) $\Rightarrow v_1, \dots, v_n$ are linearly independent.
 \Rightarrow they form a basis \mathbb{R}^n
 $\Rightarrow A$ is diagonalisable. Done.

Section 7:3 : Complex vector spaces

Everything we've done in Chapters 1-5 & 7
(BUT NOT Chapter 6) applies equally well
if we extend the real scalars to
complex scalars everywhere.

Example $A = \begin{pmatrix} 0 & -1 \\ 1 & 0 \end{pmatrix}$

$$\det(A - \lambda I) = \begin{vmatrix} -\lambda & -1 \\ 1 & -\lambda \end{vmatrix} = \lambda^2 + 1$$

So A has no real eigenvalues or eigenvectors,
but if we allow complex numbers then

$$\lambda^2 + 1 = 0 \Leftrightarrow \lambda = \pm i$$

So we have two complex eigenvalues.

$$\lambda = i \quad N(A - iI) = N\left(\begin{pmatrix} -i & -1 \\ 1 & -i \end{pmatrix}\right)$$

= set of solutions $\begin{pmatrix} x_1 \\ x_2 \end{pmatrix}$ to

$$\begin{pmatrix} -i & -1 \\ 1 & -i \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$$

$$-ix_1 - x_2 = 0 \quad \leftarrow \cancel{x_1 = 0}$$

$$x_1 - ix_2 = 0$$

Solutions: $x_2 = \alpha$, $x_1 = i\alpha$, so $\begin{pmatrix} i \\ 1 \end{pmatrix}$ is
an eigenvector.

$$\text{Also } \begin{pmatrix} i \\ i \end{pmatrix} = \begin{pmatrix} 0 \\ i \end{pmatrix} + i \begin{pmatrix} 1 \\ 0 \end{pmatrix}$$

Similarly if $\lambda = -i$, we get an eigenvector
 $\begin{pmatrix} -i \\ i \end{pmatrix}$ or $i \begin{pmatrix} -i \\ i \end{pmatrix} = \begin{pmatrix} 1 \\ i \end{pmatrix}$.

Section 7.4 : Diagonalising Symmetric matrices

There is a substantial theory of (real) symmetric matrices, which are important in applications to physics.

It turns out they can always be diagonalised. Moreover, the transition matrix P that does the diagonalisation can be chosen in a very special way — to be an orthogonal matrix, so that $P^{-1} = P^T$.

Let's do an example first:

Example 7.31 $A = \begin{pmatrix} 0 & 2 & -1 \\ 2 & 3 & -2 \\ -1 & -2 & 0 \end{pmatrix}$

Step 1 $\det(A - \lambda I) = -\lambda^3 + 3\lambda^2 + 9\lambda + 5$
 $= (\lambda + 1)^2(5 - \lambda)$

so the eigenvalues of A are -1 and 5 .

Step 2 $N(A + I)$ has a basis $\left\{ \begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix}, \begin{pmatrix} -2 \\ 1 \\ 0 \end{pmatrix} \right\}$
 $N(A - 5I)$ has a basis $\left\{ \begin{pmatrix} -1 \\ -2 \\ 1 \end{pmatrix} \right\}$.

Step 3 Use Gram-Schmidt to get an
orthogonal basis for $N(A + I)$:

$$v_1 = \begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix}$$

$$v_2 = \begin{pmatrix} -2 \\ 1 \\ 0 \end{pmatrix} - \frac{\begin{pmatrix} -2 \\ 1 \\ 0 \end{pmatrix} \cdot \begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix}}{\begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix} \cdot \begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix}} \begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix}$$
$$= \begin{pmatrix} -2 \\ 1 \\ 0 \end{pmatrix} + \begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix} = \begin{pmatrix} -1 \\ 1 \\ 1 \end{pmatrix}.$$

Step 4 Normalize the basis vectors to have norm 1:

$$u_1 = \frac{1}{\sqrt{2}} v_1 = \begin{pmatrix} \frac{1}{\sqrt{2}} \\ 0 \\ \frac{1}{\sqrt{2}} \end{pmatrix}$$

$$u_2 = \frac{1}{\sqrt{3}} v_2 = \begin{pmatrix} -\frac{1}{\sqrt{3}} \\ \frac{1}{\sqrt{3}} \\ \frac{1}{\sqrt{3}} \end{pmatrix}$$

$$\& \underline{u}_3 = \frac{1}{\sqrt{6}} \begin{pmatrix} -1 \\ -2 \\ 1 \end{pmatrix}$$

Step 5 The transition matrix $P = (\underline{u}_1 \ \underline{u}_2 \ \underline{u}_3)$

$$= \begin{pmatrix} \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{3}} & -\frac{1}{\sqrt{6}} \\ 0 & \frac{1}{\sqrt{3}} & -\frac{2}{\sqrt{6}} \\ \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{3}} & \frac{1}{\sqrt{6}} \end{pmatrix}$$

Then P is orthogonal ($P^{-1} = P^T$)

& $P^T A P = P^T A P$ is diagonal:

$$\begin{pmatrix} -1 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & 5 \end{pmatrix}$$

with the eigenvalues on the diagonal.



- Now let's try and sort out why all this works.

There are two main questions we have to answer:

① Why are the eigenvectors (for distinct eigenvalues) orthogonal to each other?

② Why are there enough eigenvectors to span the whole of \mathbb{R}^n ?

Q.1 uses Chapter 6

Q.2 uses complex vectors.

Lemma 7.27 If $A \in \mathbb{R}^{n \times n}$ is symmetric (that is, $A^T = A$), and $\underline{x}, \underline{y} \in \mathbb{R}^n$, then

$$(A\underline{x}) \cdot \underline{y} = \underline{x} \cdot (A\underline{y})$$

Proof

$$\begin{aligned} (A\underline{x}) \cdot \underline{y} &= (A\underline{x})^T \underline{y} \\ &= \underline{x}^T A^T \underline{y} \\ &= \underline{x}^T (A\underline{y}) \\ &= \underline{x} \cdot (A\underline{y}) \quad \underline{\text{Done.}} \end{aligned}$$

Consequence If $\underline{x}, \underline{y}$ are eigenvectors of A (symmetric) with eigenvalues $\lambda \neq \mu$,

then $(A\underline{x}) \cdot \underline{y} = (\lambda \underline{x}) \cdot \underline{y} = \lambda (\underline{x} \cdot \underline{y})$

and $\underline{x} \cdot (A\underline{y}) = \underline{x} \cdot (\mu \underline{y}) = \mu (\underline{x} \cdot \underline{y})$

$$\Rightarrow (\lambda - \mu) \underline{x} \cdot \underline{y} = 0$$

$$\Rightarrow \underline{x} \cdot \underline{y} = 0 \quad (\text{since } \lambda - \mu \neq 0).$$

This answers Q. 1.

If A is a symmetric $n \times n$ real matrix,
we know that A

The fundamental theorem of algebra

Every (complex) polynomial (of degree n)
has at least one complex root.

Say α is a root.

Then $(x - \alpha)$ is a factor of the polynomial.

\Rightarrow by induction a polynomial of degree n
factorises into n linear factors over \mathbb{C} .

(real or complex)

Consequence Every matrix has at
least one complex eigenvalue.

Lemma 7.29 Every symmetric matrix

$A \in \mathbb{R}^{n \times n}$ has at least one real eigenvalue, with corresponding real eigenvector $\underline{v} \in \mathbb{R}^n$.

Proof By the fundamental theorem of algebra,

($a, b \in \mathbb{R}$)
 A has a complex eigenvalue $a + ib$ with
 a corresponding complex eigenvector $\underline{v} + i\underline{w}$
 (with $\underline{v}, \underline{w} \in \mathbb{R}^n$).

This means $A(\underline{v} + i\underline{w}) = (a + ib)(\underline{v} + i\underline{w})$

$$\Rightarrow A\underline{v} + iA\underline{w} = (a\underline{v} - b\underline{w}) + i(b\underline{v} + a\underline{w})$$

So equating real and imaginary parts

$$A\underline{v} = a\underline{v} - b\underline{w}$$

$$A\underline{w} = b\underline{v} + a\underline{w}$$

$$\Rightarrow (A\underline{v}) \cdot \underline{w} = a\underline{v} \cdot \underline{w} - b\underline{w} \cdot \underline{w}$$

$$= \underline{v} \cdot (A\underline{w}) = b\underline{v} \cdot \underline{v} + a\underline{v} \cdot \underline{w}$$

$$\Rightarrow -b\underline{w} \cdot \underline{w} = b\underline{v} \cdot \underline{v}$$

$$\Rightarrow b(\underline{v} \cdot \underline{v} + \underline{w} \cdot \underline{w}) = 0$$

But $\underline{v} \cdot \underline{v} + \underline{w} \cdot \underline{w} \neq 0$

$$\Rightarrow b = 0$$

\Rightarrow the eigenvalue $a+ib = a$ is real.

Done.

Actually, the proof shows more:

Consequence Every eigenvalue of a
Symmetric real matrix $A \in \mathbb{R}^{n \times n}$ is real.

Now we need to show that the eigenvectors span the whole space.

If not we can use Gram-Schmidt to get an orthogonal set of eigenvectors $\underline{v}_1, \dots, \underline{v}_k$, which span the same

space as all the eigenvectors.
(Call this space H .) (Want to show $H = \mathbb{R}^n$.)

If we have run out of eigenvectors at this stage, then we know there are no eigenvectors in H^\perp .

(We want to show $H^\perp = \{0\}$.)

Lemma If $\underline{x} \in H^\perp$ then $A\underline{x} \in H^\perp$

Proof $\underline{x} \in H^\perp \Rightarrow \underline{x} \cdot \underline{v}_i = 0 \text{ for } i = 0, \dots, k$

$$\begin{aligned} \Rightarrow A\underline{x} \cdot \underline{v}_i &= \underline{x} \cdot (A\underline{v}_i) = \underline{x} \cdot \lambda_i \underline{v}_i \\ &= \lambda_i (\underline{x} \cdot \underline{v}_i) = 0 \text{ for all } i \end{aligned}$$

$$\Rightarrow A\underline{x} \in H^\perp.$$

Done.

Now let $\underline{\omega}_1, \dots, \underline{\omega}_r$ be an basis for H^\perp
 & let B be the matrix of the
 linear $\xrightarrow{\text{transformation}}$ $\underline{x} \mapsto A\underline{x}$
 with respect to the basis $\underline{\omega}_1, \dots, \underline{\omega}_r$.

Claim B is symmetric

Proof $b_{ij} = \text{coefficient of } \underline{\omega}_j \text{ in } A\underline{\omega}_i$

$$\begin{aligned} &= (A\underline{\omega}_i) \cdot \underline{\omega}_j \\ &= \underline{\omega}_i \cdot (A\underline{\omega}_j) \\ &= b_{ji} \quad \text{Dae.} \end{aligned}$$

Hence B has an eigenvector $\in H^\perp$

Contradiction.

This answers Q. 2