## MATH 311-504 <br> Topics in Applied Mathematics

## Lecture 3-9:

Symmetric and orthogonal matrices.

Definition. An $n \times n$ matrix $A$ is called

- symmetric if $A^{T}=A$;
- orthogonal if $A A^{T}=A^{T} A=I$, that is, if
$A^{T}=A^{-1}$;
- normal if $A A^{T}=A^{T} A$.

Proposition For any $n \times n$ matrix $A$ and any column vectors $\mathbf{x}, \mathbf{y} \in \mathbb{R}^{n}, A \mathbf{x} \cdot \mathbf{y}=\mathbf{x} \cdot A^{T} \mathbf{y}$.

Theorem If $\mathbf{x}$ and $\mathbf{y}$ are eigenvectors of a symmetric matrix $A$ associated with different eigenvalues, then $\mathbf{x} \cdot \mathbf{y}=0$.

Theorem If $A$ is a normal matrix then
$\operatorname{Null}(A)=\operatorname{Null}\left(A^{T}\right)$ (that is, $A \mathbf{x}=\mathbf{0} \Longleftrightarrow A^{T} \mathbf{x}=\mathbf{0}$ ).
Proof: $A \mathbf{x}=\mathbf{0} \Longleftrightarrow A \mathbf{x} \cdot A \mathbf{x}=0 \Longleftrightarrow \mathbf{x} \cdot A^{\top} A \mathbf{x}=0$
$\Longleftrightarrow \mathbf{x} \cdot A A^{T} \mathbf{x}=0 \Longleftrightarrow A^{T} \mathbf{x} \cdot A^{T} \mathbf{x}=0 \Longleftrightarrow A^{T} \mathbf{x}=\mathbf{0}$.
Proposition If a matrix $A$ is normal, so are matrices $A-\lambda I, \lambda \in \mathbb{R}$.
Proof: Let $B=A-\lambda I$, where $\lambda \in \mathbb{R}$. Then $B^{T}=(A-\lambda I)^{T}=A^{T}-(\lambda I)^{T}=A^{T}-\lambda I$.
We have $B B^{T}=(A-\lambda I)\left(A^{T}-\lambda I\right)=A A^{T}-\lambda A-\lambda A^{T}+\lambda^{2} I$, $B^{T} B=\left(A^{T}-\lambda I\right)(A-\lambda I)=A^{T} A-\lambda A-\lambda A^{T}+\lambda^{2} I$.
Hence $A A^{T}=A^{T} A \quad \Longrightarrow B B^{T}=B^{T} B$.
Thus any normal matrix $A$ shares with $A^{T}$ all real eigenvalues and the corresponding eigenvectors. How about complex eigenvalues?

## Dot product of complex vectors

Dot product of real vectors
$\mathbf{x}=\left(x_{1}, \ldots, x_{n}\right), \mathbf{y}=\left(y_{1}, \ldots, y_{n}\right) \in \mathbb{R}^{n}$ :

$$
\mathbf{x} \cdot \mathbf{y}=x_{1} y_{1}+x_{2} y_{2}+\cdots+x_{n} y_{n} .
$$

Dot product of complex vectors
$\mathbf{x}=\left(x_{1}, \ldots, x_{n}\right), \mathbf{y}=\left(y_{1}, \ldots, y_{n}\right) \in \mathbb{C}^{n}$ :

$$
\mathbf{x} \cdot \mathbf{y}=x_{1} \overline{y_{1}}+x_{2} \overline{y_{2}}+\cdots+x_{n} \overline{y_{n}} .
$$

If $z=r+i t(r, t \in \mathbb{R})$ then $\bar{z}=r-i t$,
$z \bar{z}=r^{2}+t^{2}=|z|^{2}$.
Hence $\mathbf{x} \cdot \mathbf{x}=\left|x_{1}\right|^{2}+\left|x_{2}\right|^{2}+\cdots+\left|x_{n}\right|^{2} \geq 0$.
Also, $\mathbf{x} \cdot \mathbf{x}=0$ if and only if $\mathbf{x}=\mathbf{0}$.
Since $\overline{z+w}=\bar{z}+\bar{w}$ and $\overline{z w}=\bar{z} \bar{w}$, it follows that $\mathbf{y} \cdot \mathbf{x}=\overline{\mathbf{x} \cdot \mathbf{y}}$.

Definition. Let $V$ be a complex vector space. A function $\beta: V \times V \rightarrow \mathbb{C}$, denoted $\beta(\mathbf{x}, \mathbf{y})=\langle\mathbf{x}, \mathbf{y}\rangle$, is called an inner product on $V$ if
(i) $\langle\mathbf{x}, \mathbf{y}\rangle \geq 0,\langle\mathbf{x}, \mathbf{x}\rangle=0$ only for $\mathbf{x}=\mathbf{0}$ (positivity)
(ii) $\langle\mathbf{x}, \mathbf{y}\rangle=\overline{\langle\mathbf{y}, \mathbf{x}\rangle}$
(iii) $\langle r \mathbf{x}, \mathbf{y}\rangle=r\langle\mathbf{x}, \mathbf{y}\rangle$
(conjugate symmetry)
(iv) $\langle\mathbf{x}+\mathbf{y}, \mathbf{z}\rangle=\langle\mathbf{x}, \mathbf{z}\rangle+\langle\mathbf{y}, \mathbf{z}\rangle$
(homogeneity)
(additivity)
$\langle\mathbf{x}, \mathbf{y}\rangle$ is complex-linear as a function of $\mathbf{x}$.
The dependence on the second argument is called half-linearity: $\langle\mathbf{x}, \lambda \mathbf{y}+\mu \mathbf{z}\rangle=\bar{\lambda}\langle\mathbf{x}, \mathbf{y}\rangle+\bar{\mu}\langle\mathbf{x}, \mathbf{z}\rangle$.
Example. $\langle f, g\rangle=\int_{a}^{b} f(x) \overline{g(x)} d x$, $f, g \in C([a, b], \mathbb{C})$.

Proposition For any $n \times n$ matrix $B$ with complex entries and any column vectors $\mathbf{x}, \mathbf{y} \in \mathbb{C}^{n}$,

$$
B \mathbf{x} \cdot \mathbf{y}=\mathbf{x} \cdot \bar{B}^{T} \mathbf{y}
$$

If $B \bar{B}^{T}=\bar{B}^{T} B$ then $B \mathbf{x}=\mathbf{0} \Longleftrightarrow \bar{B}^{T} \mathbf{x}=\mathbf{0}$.
Theorem Suppose $A$ is a normal matrix. Then for any $\mathbf{x} \in \mathbb{C}^{n}$ and $\lambda \in \mathbb{C}$ one has

$$
A \mathbf{x}=\lambda \mathbf{x} \Longleftrightarrow A^{T} \mathbf{x}=\bar{\lambda} \mathbf{x}
$$

Also, $A \mathbf{x}=\lambda \mathbf{x} \Longleftrightarrow A^{T} \overline{\mathbf{x}}=\bar{\lambda} \overline{\mathbf{x}}$.
Corollary All eigenvalues of a symmetric matrix are real. Any eigenvalue $\lambda$ of an orthogonal matrix satisfies $\bar{\lambda}=\lambda^{-1} \Longleftrightarrow|\lambda|=1$.

Theorem If $\mathbf{x}$ and $\mathbf{y}$ are eigenvectors of a normal matrix $A$ associated with different eigenvalues, then $\mathbf{x} \cdot \mathbf{y}=0$.

Theorem Let $A$ be an $n \times n$ matrix with real entries. Then
(a) $A$ is normal $\Longleftrightarrow$ there exists an orthonormal basis for $\mathbb{C}^{n}$ consisting of eigenvectors of $A$; (b) $A$ is symmetric $\Longleftrightarrow$ there exists an orthonormal basis for $\mathbb{R}^{n}$ consisting of eigenvectors of $A$.

Example. $A=\left(\begin{array}{lll}1 & 0 & 1 \\ 0 & 3 & 0 \\ 1 & 0 & 1\end{array}\right)$.

- $A$ is symmetric.
- $A$ has three eigenvalues: 0,2 , and 3 .
- Associated eigenvectors are $\mathbf{v}_{1}=(-1,0,1)$,
$\mathbf{v}_{2}=(1,0,1)$, and $\mathbf{v}_{3}=(0,1,0)$.
- Vectors $\frac{1}{\sqrt{2}} \mathbf{v}_{1}, \frac{1}{\sqrt{2}} \mathbf{v}_{2}, \mathbf{v}_{3}$ form an orthonormal basis for $\mathbb{R}^{3}$.

Example. $\quad A_{\phi}=\left(\begin{array}{rr}\cos \phi & -\sin \phi \\ \sin \phi & \cos \phi\end{array}\right)$.

- $A_{\phi} A_{\psi}=A_{\phi+\psi}$
- $A_{\phi}^{-1}=A_{-\phi}=A_{\phi}^{T}$
- $A_{\phi}$ is orthogonal
- Columns of $A_{\phi}$ form an orthonormal basis.
- Rows of $A_{\phi}$ form an orthonormal basis.
- Eigenvalues: $\lambda_{1}=\cos \phi+i \sin \phi=e^{i \phi}$,
$\lambda_{2}=\cos \phi-i \sin \phi=e^{-i \phi}$.
- Associated eigenvectors: $\mathbf{v}_{1}=(1,-i)$, $\mathbf{v}_{2}=(1, i)$.
- Vectors $\frac{1}{\sqrt{2}} \mathbf{v}_{1}$ and $\frac{1}{\sqrt{2}} \mathbf{v}_{2}$ form an orthonormal basis for $\mathbb{C}^{2}$.


## Orthogonal matrices

Theorem Given an $n \times n$ matrix $A$, the following conditions are equivalent:
(i) $A$ is orthogonal: $A^{T}=A^{-1}$;
(ii) columns of $A$ form an orthonormal basis for $\mathbb{R}^{n}$;
(iii) rows of $A$ form an orthonormal basis for $\mathbb{R}^{n}$. Proof: Entries of the matrix $A^{T} A$ are the dot products of columns of $A$. Entries of $A A^{T}$ are the dot products of rows of $A$.

Thus an orthogonal matrix is the transition matrix from one orthonormal basis to another.

Consider a linear operator $L: \mathbb{R}^{n} \rightarrow \mathbb{R}^{n}, L(\mathbf{x})=A \mathbf{x}$, where $A$ is an $n \times n$ matrix.
Theorem The following conditions are equivalent:
(i) $|L(\mathbf{x})|=|\mathbf{x}|$ for all $\mathbf{x} \in \mathbb{R}^{n}$;
(ii) $L(\mathbf{x}) \cdot L(\mathbf{y})=\mathbf{x} \cdot \mathbf{y}$ for all $\mathbf{x}, \mathbf{y} \in \mathbb{R}^{n}$;
(iii) the matrix $A$ is orthogonal.
$\left[(\mathrm{ii}) \Longrightarrow(\mathrm{iii}): L\left(\mathbf{e}_{i}\right) \cdot L\left(\mathbf{e}_{j}\right)=\mathbf{e}_{i} \cdot \mathbf{e}_{j}=1\right.$ if $i=j$, and 0 otherwise. But $L\left(\mathbf{e}_{1}\right), \ldots, L\left(\mathbf{e}_{n}\right)$ are columns of A.]
Definition. A transformation $f: \mathbb{R}^{n} \rightarrow \mathbb{R}^{n}$ is called an isometry if it preserves distances between points: $|f(\mathbf{x})-f(\mathbf{y})|=|\mathbf{x}-\mathbf{y}|$.
Theorem Any isometry $f: \mathbb{R}^{n} \rightarrow \mathbb{R}^{n}$ is represented as $f(\mathbf{x})=A \mathbf{x}+\mathbf{x}_{0}$, where $\mathbf{x}_{0} \in \mathbb{R}^{n}$ and $A$ is an orthogonal matrix.

Consider a linear operator $L: \mathbb{R}^{n} \rightarrow \mathbb{R}^{n}, L(\mathbf{x})=A \mathbf{x}$, where $A$ is an $n \times n$ orthogonal matrix.
Theorem There exists an orthonormal basis for $\mathbb{R}^{n}$ such that the matrix of $L$ relative to this basis has a diagonal block structure

$$
\left(\begin{array}{cccc}
D_{ \pm 1} & O & \ldots & O \\
O & R_{1} & \ldots & O \\
\vdots & \vdots & \ddots & \vdots \\
O & O & \ldots & R_{k}
\end{array}\right)
$$

where $D_{ \pm 1}$ is a diagonal matrix whose diagonal entries are equal to 1 or -1 , and

$$
R_{j}=\left(\begin{array}{rr}
\cos \phi_{j} & -\sin \phi_{j} \\
\sin \phi_{j} & \cos \phi_{j}
\end{array}\right), \quad \phi_{j} \in \mathbb{R} .
$$

Classification of $2 \times 2$ orthogonal matrices:

$$
\left(\begin{array}{rr}
\cos \phi & -\sin \phi \\
\sin \phi & \cos \phi
\end{array}\right) \quad\left(\begin{array}{rr}
-1 & 0 \\
0 & 1
\end{array}\right)
$$

## rotation about the origin

reflection in a line

Determinant:
Eigenvalues: $\quad e^{i \phi}$ and $e^{-i \phi}$
-1 and 1

Classification of $3 \times 3$ orthogonal matrices:

$$
\begin{aligned}
& A=\left(\begin{array}{ccc}
1 & 0 & 0 \\
0 & \cos \phi & -\sin \phi \\
0 & \sin \phi & \cos \phi
\end{array}\right), \quad B=\left(\begin{array}{rrr}
-1 & 0 & 0 \\
0 & 1 & 0 \\
0 & 0 & 1
\end{array}\right), \\
& C=\left(\begin{array}{ccc}
-1 & 0 & 0 \\
0 & \cos \phi & -\sin \phi \\
0 & \sin \phi & \cos \phi
\end{array}\right) .
\end{aligned}
$$

$A=$ rotation about a line; $B=$ reflection in a plane; $C=$ rotation about a line combined with reflection in the orthogonal plane.
$\operatorname{det} A=1, \quad \operatorname{det} B=\operatorname{det} C=-1$.
$A$ has eigenvalues $1, e^{i \phi}, e^{-i \phi}$. $B$ has eigenvalues
$-1,1,1$. $C$ has eigenvalues $-1, e^{i \phi}, e^{-i \phi}$.

