

# Appendix C: Complex Numbers

- $z = a + bi$

- $i = \sqrt{-1}$

- $\text{Im}(z) = b$

- $\text{Re}(z) = a$

$$i^0 = 1$$

$$i = \sqrt{-1}$$

- $i^2 = -1$

- $i^3 = i \cdot i^2 = -i$

- $|z| = \text{modulus of } z = \sqrt{a^2 + b^2}$

- $\bar{z} = \text{complex conjugate} = a - bi$

- $z\bar{z} = |z|^2$

↳ polar form

$$z = r(\cos \theta + i \sin \theta) \quad z = re^{i\theta}$$

- principal argument:

$$\text{if } -\pi < \theta < \pi$$

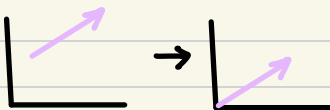
to find, add  $2\pi + \theta$   
until  $\theta$  is in range

- $z^n = r(\cos n\theta + i \sin n\theta)^n \quad \text{or } r^n e^{in\theta}$

# Chapter 1 Vectors

## Standard position

has an origin at  $O_1O$

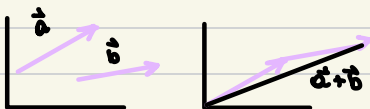


## dot product ( $\cdot$ )

$$\vec{u} = \begin{pmatrix} u_1 \\ u_2 \\ u_3 \end{pmatrix} \quad \vec{v} = \begin{pmatrix} v_1 \\ v_2 \\ v_3 \end{pmatrix}$$

$$\vec{u} \cdot \vec{v} = u_1 v_1 + u_2 v_2 + u_3 v_3$$

## Vector addition



## Cross product

$$\vec{u} = \begin{pmatrix} u_1 \\ u_2 \\ u_3 \end{pmatrix} \quad \vec{v} = \begin{pmatrix} v_1 \\ v_2 \\ v_3 \end{pmatrix}$$

$$\vec{u} \times \vec{v} = \begin{pmatrix} u_2 v_3 - v_2 u_3 \\ -(u_1 v_3 - v_1 u_3) \\ u_1 v_2 - v_1 u_2 \end{pmatrix}$$

## length/norm ( $\|\vec{v}\|$ )

$$\|\vec{v}\| = \sqrt{\vec{v} \cdot \vec{v}} = \sqrt{v_1 v_1 + v_2 v_2 + v_3 v_3}$$

$$\hookrightarrow \|c\vec{v}\| = |c| \|\vec{v}\|$$

## normalizing vectors

$$\frac{1}{\|\vec{v}\|} \vec{v}$$

## projection of $\vec{v}$ onto $\vec{u}$

$$\text{proj}_{\vec{u}}(\vec{v}) = \frac{\vec{v} \cdot \vec{u}}{\vec{u} \cdot \vec{u}} \vec{u}$$

## the Cauchy inequality

$$|\vec{u} \cdot \vec{v}| \leq \|\vec{u}\| \cdot \|\vec{v}\|$$

## the triangle inequality

$$\|\vec{u} + \vec{v}\| \leq \|\vec{u}\| + \|\vec{v}\|$$

## distance

$$d(\vec{u}, \vec{v}) = \|\vec{u} - \vec{v}\|$$

# Chapter 2: systems of linear equations

## Solving linear equations

$$\begin{aligned}x - y - z &= 2 \\ 3x - 3y + 2z &= 16 \\ 2x - y + z &= 9\end{aligned}$$

augmented coefficient matrix

$$\left[ \begin{array}{ccc|c} 1 & -1 & -1 & 2 \\ 3 & -3 & 2 & 16 \\ 2 & -1 & 1 & 9 \end{array} \right] \xrightarrow{\substack{R_3 - 2R_1 \\ R_2 - 3R_1}}$$

$$\left[ \begin{array}{ccc|c} 1 & -1 & -1 & 2 \\ 0 & 0 & 5 & 10 \\ 0 & 1 & -1 & 5 \end{array} \right] \xrightarrow{\frac{R_2}{5} \leftrightarrow R_3}$$

row echelon form

$$\left[ \begin{array}{ccc|c} 1 & -1 & -1 & 2 \\ 0 & 1 & -1 & 2 \\ 0 & 0 & 1 & 2 \end{array} \right] \xrightarrow{\substack{R_2 - R_1 \\ R_1 + R_2 \\ R_1 + R_3}}$$

reduced row echelon

$$\left[ \begin{array}{ccc|c} 1 & 0 & 0 & 3 \\ 0 & 1 & 0 & -1 \\ 0 & 0 & 1 & 2 \end{array} \right] \quad \begin{aligned}x &= 3 \\ y &= -1 \\ z &= 2\end{aligned}$$

## homogenous system

$$\left[ \begin{array}{ccc|c} 1 & 2 & 3 & 0 \\ 4 & 5 & 6 & 0 \\ 7 & 8 & 9 & 0 \end{array} \right]$$

homogenous systems always have a solution (either the trivial solution or infinite many solutions)

## matrix solutions

pivot: leading entry

free variable: a column with no pivots

consistent systems: a system w solutions

unique solution: matrix with no free var.

## linear combination

when a vector  $\vec{w}$  is written in terms of other vectors (eg  $\vec{w} = 2\vec{v} + 3\vec{y}$ )

## Spanning set

Let  $S$  be the set of vectors  $\{\vec{v}_1, \vec{v}_2, \dots, \vec{v}_n\}$   
 $\text{Span}(S)$  is the set of all linear combinations of  $S$

If  $\text{Span}(S) = \mathbb{R}^n$  then  $S$  is a spanning set of  $\mathbb{R}^n$

## linearly dependent

a set of vectors  $\{\vec{v}_1, \dots, \vec{v}_n\}$  is linearly dependent if there is at least one non trivial scalar such that  $c_1\vec{v}_1 + \dots + c_n\vec{v}_n = \vec{0}$

# Chapter 3 Matrices

## matrix multiplication

$$\begin{matrix} A & \times & B & = & AB \\ m \times n & & n \times m & & m \times m \end{matrix}$$

$$\begin{bmatrix} a & b & c \\ d & e & f \end{bmatrix} \begin{bmatrix} u & v \\ w & x \\ y & z \end{bmatrix} = \begin{bmatrix} au+bw+cy & av+bv+cz \\ du+ew+fy & dv+ex+fz \end{bmatrix}$$

## transpose

if  $A$  is an  $m \times n$  matrix

$A^T$  will be the  $n \times m$  matrix

$$A = \begin{bmatrix} a & b \\ c & d \end{bmatrix} \quad A^T = \begin{bmatrix} a & c \\ b & d \end{bmatrix}$$

## Symmetric matrices

square matrix is symmetric if  $A^T = A$

## the inverse of a matrix

A matrix  $A$  is invertible if and only if  $A$  has the  $\vec{0}$ ,

if there exists a matrix  $B$  such that  $AB = I_n$  and  $BA = I_n$

$$\hookrightarrow [A | I] \rightarrow [I | A^{-1}]$$

## elementary matrix

any matrix that can be obtained by performing elementary row operations to the Identity matrix

$\hookrightarrow$  how to express a matrix  $A$  as

a product of elementary matrices

if  $A$  reduces to  $I_n$ , let each row operation be 1 to  $n$ . Perform row operations 1 to  $n$  to the  $I_n$  and name it  $E_1, \dots, E_n$ .  $A = (E_1)^{-1} \dots (E_n)^{-1}$

## row equivalent matrices

$A$  and  $B$  are R.E. when  $A + \text{row op} = B$

## Subspace

any collection of vectors  $W$  is a Subspace of  $\mathbb{R}^n$  if

$W$  is closed under scalar multiplication

$\hookrightarrow$  spans are always a subspace of  $\mathbb{R}^n$

## basis

a basis for a subspace  $W$  is a subspace that spans  $W$  and is linearly indep.

## possible basis for a matrix $A$

• row ( $A$ )    • col ( $A$ )

## Dimension

the # of vectors in any basis for a subspace

## rank

number of pivots -  $\text{rank}(A^T) = \text{rank}(A)$

## nullity

the dimension of the nullspace of  $A$

$$\text{rank}(A) + \text{nullity}(A) = 0$$

## Linear transformation

a transformation  $T(\vec{v}) = \begin{bmatrix} x+y \\ x-y \end{bmatrix}$  is linear ( $\Rightarrow$ )

1.  $T(\vec{u} + \vec{v}) = T(\vec{u}) + T(\vec{v})$  for all  $\vec{u}, \vec{v}$  in  $\mathbb{R}^n$

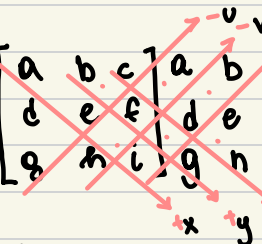
2.  $T(c\vec{v}) = cT(\vec{v})$  for all  $\vec{v}$  in  $\mathbb{R}^n$  and all scalars  $c$

# Chapter 4 Eigenvalues and Eigenvectors

## Determinants

- $\begin{vmatrix} a & b \\ c & d \end{vmatrix} = ad - bc$

- $\begin{vmatrix} a & b & c \\ d & e & f \\ g & h & i \end{vmatrix} = (-1)^{i+j} \begin{vmatrix} a & b \\ d & e \end{vmatrix} + (-1)^{i+k} \begin{vmatrix} a & c \\ d & f \end{vmatrix} + (-1)^{i+l} \begin{vmatrix} b & c \\ g & h \end{vmatrix}$

- $A = \begin{bmatrix} a & b & c \\ d & e & f \\ g & h & i \end{bmatrix}$   
  
 $\det A = x + y + z - u - v - w$

- a square matrix is invertible if and only if  $\det A \neq 0$   
 $\det A = \det A^T$   
 $\det(AB) = (\det A)(\det B)$

- Let  $A$  be an  $n \times n$  matrix, if  $A\vec{x} = \lambda\vec{x}$  then the scalar  $\lambda$  is an eigenvalue the vector  $\vec{x}$  is called an eigenvector

## eigenspace

A collection of all eigenvectors and  $\vec{0}$  that correspond to an eigenvalue  $(E_\lambda) \cdot \text{span}[\text{eigenvector}]$

## how to find eigenvalues for matrix A

$\det(A - \lambda I) = 0$ ; characteristic polynomial  
 the solutions of the polynomial are the eigenvalues of  $A$

## how to find eigenvectors for $\lambda$

Solve  $[A | \lambda I]$ , the set of vectors will be the eigenvectors

## Algebraic multiplicity

how many times  $\lambda$  shows as a root

## Geometric multiplicity

the dim of an eigenspace

## Similar Matrices

$A$  is similar to  $B$  ( $A \sim B$ ) if there is an invertible matrix  $P$  such that  $P^{-1}AP = B$

↳ if  $A \sim B$  then

- $\det A = \det B$
- $A^m \sim B^m$
- $A$  and  $B$  have same characteristic poly

## Diagonalization

A matrix is diagonalizable if there is a diagonal matrix  $D$  and an invertible matrix  $P$  such that

$$P^{-1}AP = D$$

$$A \sim P D P^{-1}$$

↳ to find  $P$ :

find eigenvalues of  $A$  and eigenvectors for each eigenvalue.

$$P = [\vec{v}_1, \dots, \vec{v}_n]$$

# Chapter 5 Orthogonality

## orthogonal Set

a set is orthogonal if all pairs of vectors in the set are orthogonal  
aka  $v_i \cdot v_j = 0$  for  $i \neq j$   $i, j = 1, 2, \dots, k$

## orthogonal basis

a basis of subspace  $W$  that is orthogonal

## theorem 5.2

if  $\beta$  is an orthogonal basis for a subspace  $W$ . When  $\vec{w}$  is a vector in  $W$ , then there are unique scalars such that

$$\vec{w} = c_1 \vec{v}_1 + \dots + c_k \vec{v}_k, \text{ then}$$
$$c_i = \frac{\vec{w} \cdot \vec{v}_i}{\vec{v}_i \cdot \vec{v}_i} \text{ for } i = 1, \dots, k$$

$$\text{then } [\vec{w}]_{\beta} = \begin{bmatrix} c_1 \\ \vdots \\ c_k \end{bmatrix}$$

## Orthonormal Set

a set is orthonormal if it is orthogonal and its vectors are unit  
this is:  $v_i \cdot v_j = 0$  and  $v_i \cdot v_i = 1$   
for  $i \neq j$  and  $i = 1, \dots, k$

↳ normalize the vectors of an

Orthogonal set

## orthogonal matrices

a matrix whose columns form an orthonormal set

- if a matrix is orthogonal then  $Q^{-1} = Q^T$

## orthogonal complement

the set of all vectors that are orthogonal to subspace  $W$  ( $W^{\perp}$ )  
 $W^{\perp} = \{ \vec{v} \text{ in } \mathbb{R}^n : \vec{v} \cdot \vec{w} = 0 \text{ for all } \vec{w} \text{ in } W \}$

- $(\text{col}(A))^{\perp} = \text{null}(A^T)$

## Orthogonal projections

Let  $\{\vec{u}_1, \dots, \vec{u}_k\}$  be a basis for subspace  $W$  then the proj of  $\vec{v}$  onto  $W$   
 $\text{proj}_W(\vec{v}) = \frac{\vec{u}_1 \cdot \vec{v}}{\vec{u}_1 \cdot \vec{u}_1} \vec{u}_1 + \dots + \frac{\vec{u}_k \cdot \vec{v}}{\vec{u}_k \cdot \vec{u}_k} \vec{u}_k$

and  $\text{perp}_W(\vec{v}) = \vec{v} - \text{proj}_W(\vec{v})$

## the orthogonal decomposition theorem

there are unique vectors  $\vec{w}$  in subspace  $W$  and  $\vec{w}^{\perp}$  in  $W^{\perp}$  such that

$$\vec{v} = \vec{w} + \vec{w}^{\perp}$$

$$\vec{w} = \text{proj}_W(\vec{v})$$

$$\vec{w}^{\perp} = \text{perp}_W(\vec{v})$$

- $\dim W + \dim W^{\perp} = n$

## Gram - Schmidt Process

a process to orthogonalize a basis for subspace  $W$ .

Let  $\{\vec{x}_1, \dots, \vec{x}_k\}$  be a basis for subspace  $W$

- $\vec{v}_1 = \vec{x}_1$
- $\vec{v}_2 = \vec{x}_2 - \text{proj}_{\vec{v}_1}(\vec{x}_2)$
- $\vec{v}_3 = \vec{x}_3 - \text{proj}_{\vec{v}_1}(\vec{x}_3) - \text{proj}_{\vec{v}_2}(\vec{x}_3)$
- ...

then  $\{\vec{v}_1, \vec{v}_2, \vec{v}_3, \dots, \vec{v}_n\}$  will be an orthogonal basis for  $W$

## QR Factorization

Let  $A$  be an  $m \times n$  matrix with linearly dependent columns. Then  $A$  can be factored as  $A = QR$  where  $Q$  is an  $m \times n$  matrix with orthonormal columns and  $R$  is an invertible upper triangular matrix.

- ① find a basis for  $A$
- ② use GS to find an orth. basis
- ③ normalize basis
- ④  $R = Q^T A$

## Orthogonally diagonalize matrices

A square matrix  $A$  is orthogonally diagonalizable if there exists an orthogonal matrix  $Q$  and a diagonal matrix  $D$  such that  $Q^T A Q = D$

•  $A$  is symmetric if and only if it is orthogonally diagonalizable

• if  $A$  is a symmetric matrix then any two eigenvectors corresponding to distinct eigenvalues of  $A$  are orthogonal

- ① find char. polynomial and  $\lambda$ s
- ② find corresponding eigenvectors
- ③ normalize eigenvectors
- ④  $Q =$  matrix of normalized eig. vec.