

# Review: Linear Algebra

CMPT 882

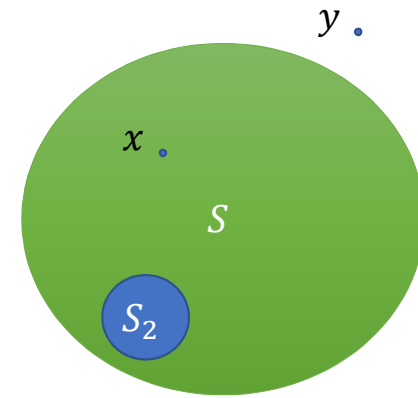
Jan. 7, 2018

# Outline

- Notation
- Linear maps
- Norms
- Diagonalization and Jordan form
- Functions of matrices

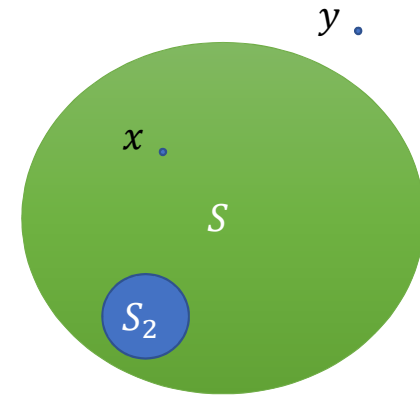
# Notation

- Sets of numbers:  $\mathbb{Z}, \mathbb{R}, \mathbb{R}^n, \mathbb{R}^{n \times m}, \mathbb{R}_+, \mathbb{C}^n$
- Membership and Quantifiers:  $\in, \notin, \forall, \exists, \exists!$ 
  - $x \in S, y \notin S$



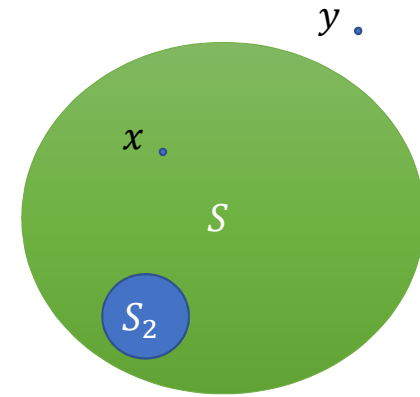
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  - $x \in S, y \notin S$
  - $\forall x \in \mathbb{R}, \exists y \in \mathbb{R}$  such that  $x + y = 0$



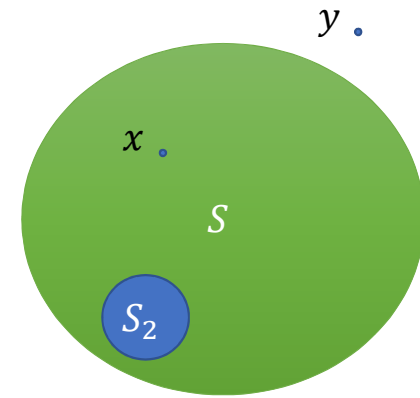
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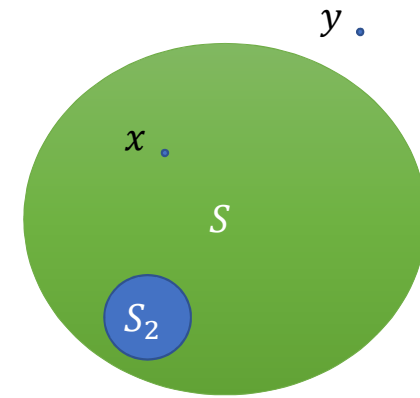
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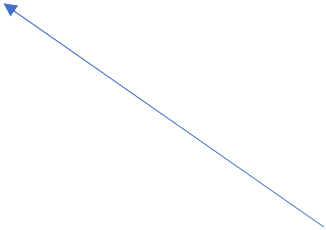


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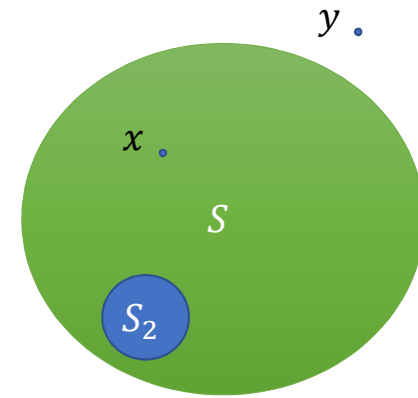


This is false



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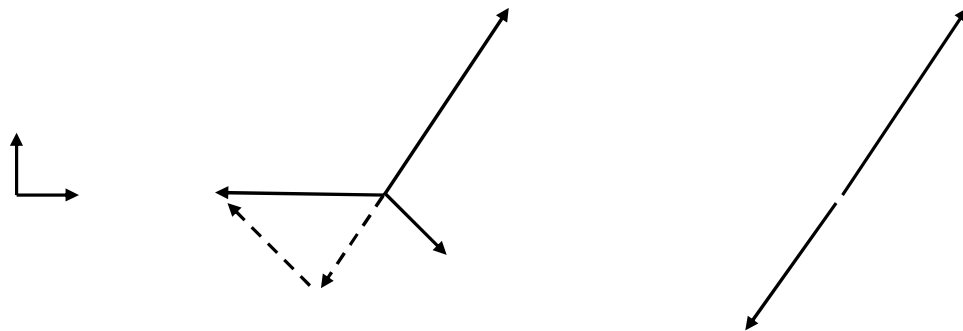
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- Implications and negation:  $\Rightarrow, \Leftarrow, \Leftrightarrow, \neg$ 
  - $z \in S_2 \Rightarrow z \in S, y \notin S \Leftrightarrow \neg(y \in S)$
  - $p \Rightarrow q$  and  $p \Leftarrow q$  means  $p \Leftrightarrow q$





# Basis

- Let  $v_1, v_2, \dots, v_p$  be vectors in  $\mathbb{R}^n$ 
  - They are **linearly independent** if and only if
$$\alpha_1 v_1 + \alpha_2 v_2 + \dots + \alpha_p v_p = 0 \Rightarrow \alpha_1 = \alpha_2 = \dots = \alpha_p = 0$$

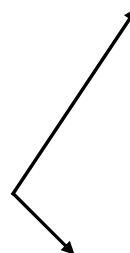


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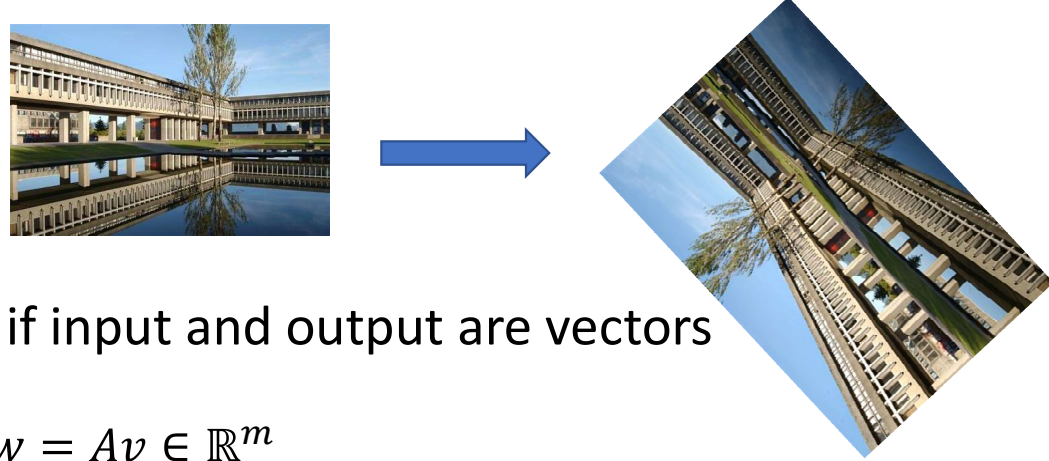
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- A set of vectors  $B = \{b_1, b_2, \dots, b_n\}$  is a **basis** of  $\mathbb{R}^n$  if and only if
  - $\forall v \in \mathbb{R}^n, \exists \alpha_1, \alpha_2, \dots, \alpha_n \in \mathbb{R}$  such that  $v = \alpha_1 b_1 + \alpha_2 b_2 + \dots + \alpha_n b_n$
  - $\{b_1, b_2, \dots, b_n\}$  is a linearly independent set of vectors

- Bases of  $\mathbb{R}^2$ :

- $\left\{ \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right\}, \left\{ \begin{bmatrix} 2 \\ 3 \end{bmatrix}, \begin{bmatrix} 1 \\ -1 \end{bmatrix} \right\}$

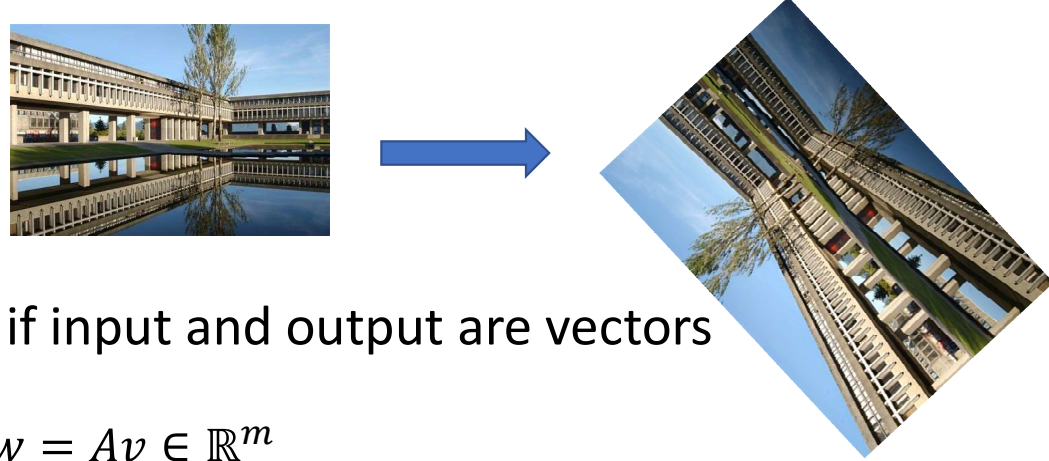


# Linear Maps



- Represented by a matrix  $A \in \mathbb{R}^{m \times n}$ , if input and output are vectors
  - $\mathcal{A}: v \rightarrow Av$
  - Operates on a vector  $v \in \mathbb{R}^n$ ; outputs  $w = Av \in \mathbb{R}^m$
- Linearity:  $\mathcal{A}(a_1 v_1 + a_2 v_2) = a_1 \mathcal{A}(v_1) + a_2 \mathcal{A}(v_2)$ 
  - for all scalars  $a_1, a_2 \in \mathbb{R}$ , vectors  $v_1, v_2 \in \mathbb{R}^n$

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  - for all scalars  $a_1, a_2 \in \mathbb{R}$ , vectors  $v_1, v_2 \in \mathbb{R}^n$
- Range space:  $R(\mathcal{A}) = \{w \mid w = \mathcal{A}(v), v \in \mathbb{R}^n\} \subseteq \mathbb{R}^m$ 
  - Also known as the image of  $\mathcal{A}$
- Null space:  $N(\mathcal{A}) = \{v \mid \mathcal{A}v = 0\} \subseteq \mathbb{R}^n$ 
  - Also known as the kernel of  $\mathcal{A}$

# Linear Maps

- Example:  $A = \begin{bmatrix} 1 & 4 & 2 \\ 1 & 4 & 2 \end{bmatrix}$ 
  - $R(A) = \text{span} \left( \begin{bmatrix} 1 \\ 1 \end{bmatrix} \right) = \text{all vectors in the form } \begin{bmatrix} t \\ t \end{bmatrix}, t \in \mathbb{R}$ 
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- Matlab:
  - `A=sym([1 4 2; 1 4 2]);`
  - `colspace(A)`
  - `null(A)`

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  - We use  $\mathcal{A}$  to denote the map in this case
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  - Maps quadratic functions to quadratic functions
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- Is the above map linear?
  - Let  $v_1 = a_1s^2 + b_1s + c_1, v_2 = a_2s^2 + b_2s + c_2$
  - Check whether  $\mathcal{A}(\alpha_1 v_1 + \alpha_2 v_2) = \alpha_1 \mathcal{A}(v_1) + \alpha_2 \mathcal{A}(v_2)$

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- Therefore, the map is linear

# Linear Map Properties

- Matrix inverse
  - System of equations,  $Ax = b, A \in \mathbb{R}^{n \times n}$
  - Solution:  $x = A^{-1}b$ , if a solution exists
  - However, try not to do this in Matlab. Instead, use  $x=A \backslash b$
  - If  $A = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$ , then  $A^{-1} = \frac{1}{ad-bc} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix}$
- $A$  is singular if it does not have an inverse
  - Columns of  $A$  are not linear independent  $\Leftrightarrow A$  is singular
- Non-commutative in general
  - $\mathcal{A}(\mathcal{B}(x)) \neq \mathcal{B}(\mathcal{A}(x))$

# Linear Map Properties

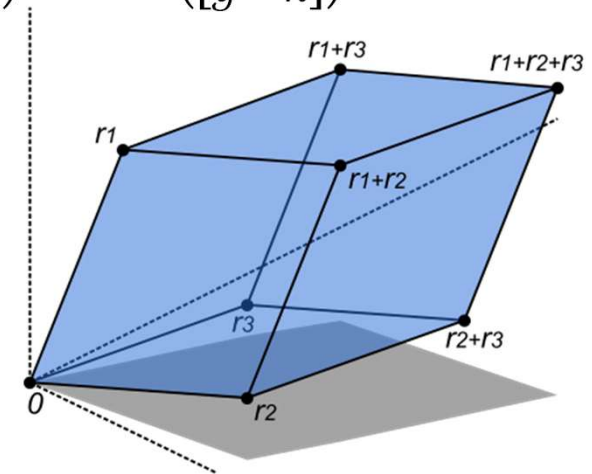
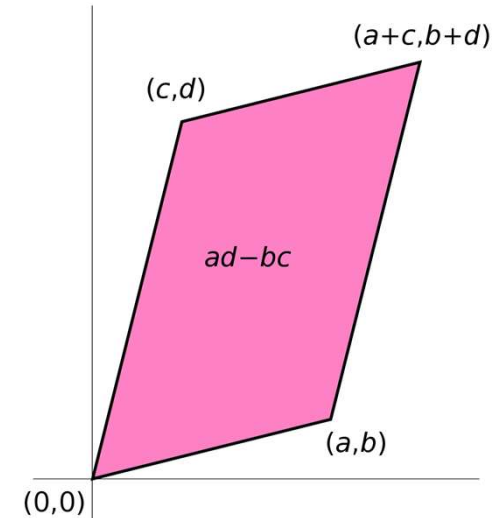
- Matrix determinant

- If  $A = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$ , then  $\det A = ad - bc$

- If  $A = \begin{bmatrix} a & b & c \\ d & e & f \\ g & h & i \end{bmatrix}$ , then  $\det A = a \det \begin{pmatrix} e & f \\ h & i \end{pmatrix} - b \det \begin{pmatrix} d & f \\ g & i \end{pmatrix} + c \det \begin{pmatrix} d & e \\ g & h \end{pmatrix}$

- Can be defined recursively

- $\det A = 0 \Leftrightarrow A$  is singular



# Linear Map Properties

- Let  $A$  be a linear map from  $\mathcal{U} \rightarrow \mathcal{V}$ , and  $b \in \mathcal{V}$ , then
  - $Au = b$  has at least one solution  $\Leftrightarrow b \in R(A)$
  - If  $b \in R(A)$ , then
    - $Au = b$  has a unique solution  $\Leftrightarrow N(A) = \{\theta_u\}$
    - Let  $x_0$  be such that  $Ax_0 = b$ . Then,  $Ax = b \Leftrightarrow x - x_0 \in N(A)$

# Norms

- A norm is a map  $\|\cdot\|: \mathcal{V} \rightarrow \mathbb{R}_+$  satisfying
  - $\forall v_1, v_2 \in \mathcal{V}, \|v_1 + v_2\| \leq \|v_1\| + \|v_2\|$  (triangle inequality)
  - $\forall \alpha \in \mathbb{R}, v \in \mathcal{V}, \|\alpha v\| = |\alpha| \|v\|$
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- Examples in  $\mathbb{R}^n$ 
  - $\|x\|_1 = \sum_{i=1}^n |x_i|$  (“1-norm”, or “ $l_1$  norm”)
  - $\|x\|_2 = \left(\sum_{i=1}^n x_i^2\right)^{\frac{1}{2}}$  (“2-norm”, or “ $l_2$  norm”)
  - $\|x\|_p = \left(\sum_{i=1}^n x_i^p\right)^{\frac{1}{p}}$  (“ $p$ -norm”, or “ $l_p$  norm”)
  - $\|x\|_{\infty} = \max_i |x_i|$  (“ $\infty$ -norm”, or “ $l_{\infty}$  norm”)

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  - $\forall v \in \mathcal{V}, \|v\| = 0 \Leftrightarrow v = \theta_{\mathcal{V}}$
- Examples in  $\mathbb{R}^{m \times n}$ 
  - $\|A\|_a = \sum_{i=1}^m \sum_{j=1}^n |a_{ij}|$
  - $\|A\|_F = \left( \sum_{i=1}^m \sum_{j=1}^n a_{ij}^2 \right)^{\frac{1}{2}}$  (“Frobenius norm”)
  - $\|A\|_b = \max_{i,j} |a_{ij}|$

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  - $\forall v \in \mathcal{V}, \|v\| = 0 \Leftrightarrow v = \theta_{\mathcal{V}}$
- Examples for continuous functions  $f: [t_0, t_1] \rightarrow \mathbb{R}^n$ 
  - $\|f\|_1 = \int_{t_0}^{t_1} \|f(t)\| dt$ , where  $\|f(t)\|$  is any of the vector norms from before
  - $\|f\|_2 = \left( \int_{t_0}^{t_1} \|f(t)\|^2 dt \right)^{\frac{1}{2}}$  (“2-norm”, or “ $l_2$  norm”)
  - $\|f\|_{\infty} = \max\{\|f(t)\|, t \in [t_0, t_1]\}$  (“ $\infty$ -norm”, or “ $l_{\infty}$  norm”)



# Induced Norms

- Let  $A$  be a linear operator. Then, the induced norm of  $\mathcal{A}$  is defined as

$$\|A\|_{p,i} = \sup_{x \neq 0} \frac{\|Ax\|_p}{\|x\|_p}$$

- Properties

- $\|A\|_{1,i} = \max_j \sum_{i=1}^m |a_{ij}|$  (maximum column sum)
- $\|A\|_{2,i} = \max_j \text{eig}(A^\top A)^{\frac{1}{2}}$  (maximum singular value)
- $\|A\|_{\infty,i} = \max_i \sum_{j=1}^n |a_{ij}|$  (maximum row sum)

# Eigenvalues and Eigenvectors

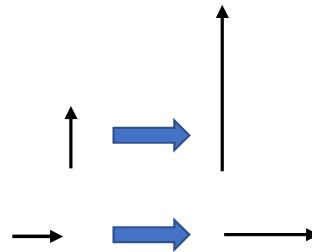
- Eigenvalues:

- If there is some vector  $e$  and scalar  $\lambda$  such that  $Ae = \lambda e$ , then  $e$  is called the eigenvector corresponding to eigenvalue  $\lambda$  of the matrix  $A$

- Example:  $A = \begin{bmatrix} 3 & 0 \\ 0 & 2 \end{bmatrix}$

- $\begin{bmatrix} 3 & 0 \\ 0 & 2 \end{bmatrix} \begin{bmatrix} 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 3 \\ 0 \end{bmatrix} = 3 \begin{bmatrix} 1 \\ 0 \end{bmatrix}$

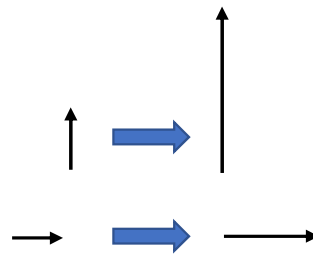
- $\begin{bmatrix} 3 & 0 \\ 0 & 2 \end{bmatrix} \begin{bmatrix} 0 \\ 1 \end{bmatrix} = \begin{bmatrix} 0 \\ 2 \end{bmatrix} = 2 \begin{bmatrix} 0 \\ 1 \end{bmatrix}$



- When a matrix is applied to eigenvectors, the effect is simple!

# Eigenvalues and Eigenvectors

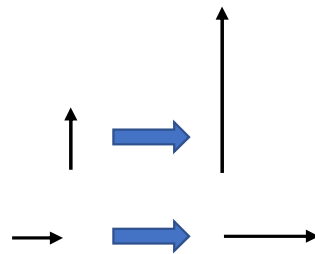
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- What if the matrix is applied to another vector?



$$\begin{bmatrix} 3 & 0 \\ 0 & 2 \end{bmatrix} \begin{bmatrix} 1 \\ 2 \end{bmatrix} = \begin{bmatrix} 3 & 0 \\ 0 & 2 \end{bmatrix} \left( \begin{bmatrix} 1 \\ 0 \end{bmatrix} + 2 \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right)$$

# Eigenvalues and Eigenvectors

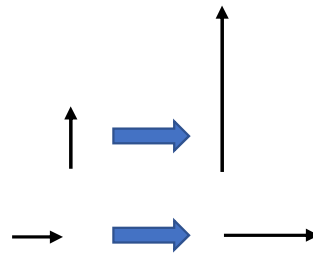
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# Eigenvalues and Eigenvectors

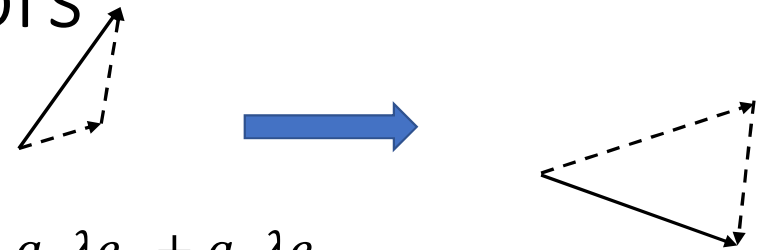
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- Looks silly, but we can apply the same idea for more complex matrices

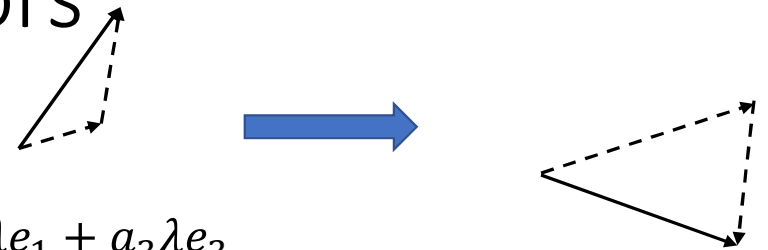
# Eigenvalues and Eigenvectors



- Geometric interpretation:

- $Ax = A(a_1 e_1 + a_2 e_2) = a_1 A e_1 + a_2 A e_2 = a_1 \lambda e_1 + a_2 \lambda e_2$
- Negative eigenvalues  $\rightarrow$  reflection
- Complex eigenvalues  $\rightarrow$  rotation

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- Geometric interpretation:
  - $Ax = A(a_1e_1 + a_2e_2) = a_1Ae_1 + a_2Ae_2 = a_1\lambda e_1 + a_2\lambda e_2$
  - Negative eigenvalues  $\rightarrow$  reflection
  - Complex eigenvalues  $\rightarrow$  rotation
- Property:  $\det A$  = the product of eigenvalues
  - Recall  $\det A = 0 \Leftrightarrow A$  is singular
  - If  $\det A = 0$ , then there must be an eigenvalue that's 0
  - $Ae = 0$ , so  $e \in N(A)$
  - Any vector in the direction of  $e$  gets scaled by a factor of 0
  - Example:  $A = \begin{bmatrix} 1 & 2 \\ 1 & 2 \end{bmatrix}$

# Eigenvalues and Eigenvectors

- Define  $T^{-1} = [e_1 \quad e_2 \quad \cdots \quad e_n]$ 
  - Then,  $AT^{-1} = T^{-1}\Lambda$ , where  $\Lambda = \begin{bmatrix} \lambda_1 & & & \\ & \lambda_2 & & \\ & & \ddots & \\ & & & \lambda_n \end{bmatrix}$
  - So,  $A = T^{-1}\Lambda T$ . This is a **similarity transform**



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- So,  $A = T^{-1}\Lambda T$ . This is a **similarity transform**.
- Define  $z = Tx$ , and we have  $Ax = T^{-1}\Lambda Tx = T^{-1}\Lambda z$ 
  - In the coordinate system obtained from applying transformation  $T$ , the map  $A$  is diagonal
  - To obtain the result of applying  $A$  in the original coordinate system, transform back with  $T^{-1}$

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Solve for  $\lambda$  in  $\det(A - \lambda I) = 0$

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$$2 - \lambda = \pm 3$$

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- Matlab: `eig(A)`

# Generalized Eigenvalues and Eigenvectors

- Not all matrices are diagonalizable

$$Ae_1 = \lambda e_1$$

$$Ae_2 = \lambda e_2$$

$$Ae_3 = \lambda e_3$$



# Generalized Eigenvalues and Eigenvectors

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$$\begin{array}{ll} Ae_1 = \lambda e_1 & Av_1 = \lambda v_1 + e_1 \\ Ae_2 = \lambda e_2 & Av_2 = \lambda v_2 + e_2 \\ Ae_3 = \lambda e_3 & \end{array}$$

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$$J = TAT^{-1} = \begin{bmatrix} \lambda & 1 & 0 & & & \\ 0 & \lambda & 1 & & & \\ 0 & 0 & \lambda & & & \\ & & & \lambda & 1 & \\ & & & 0 & \lambda & \\ & & & & & \lambda \end{bmatrix}$$

$$T^{-1} = [e_1 \quad v_1 \quad w_1 \quad e_2 \quad v_2 \quad e_3]$$

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$$T^{-1} = [e_1 \quad v_1 \quad w_1 \quad e_2 \quad v_2 \quad e_3]$$

- This is the matrix structure for one eigenvalue
  - There may be more than one such blocks in general
- 
- All matrices can be put into **Jordan form**

# Functions of Matrices

- Consider a polynomial of a matrix,  $f(A) = A^k$ 
  - $A^k = (T^{-1}JT)^k = (T^{-1}JT)(T^{-1}JT)(T^{-1}JT)\dots(T^{-1}JT) = T^{-1}J^kT$
  - Adjacent  $T$  matrices and inverse cancel!
- This motivates general functions of matrices, like  $f(A) = \sin A$ , defined through Taylor series
  - $\sin A = A - \frac{A^3}{3!} + \frac{A^5}{5!} - \frac{A^7}{7!} + \dots$

# Functions of Matrices

- Suppose  $J = \begin{bmatrix} \lambda & 1 & & \\ & \lambda & \ddots & \\ & & \ddots & 1 \\ & & & \lambda \end{bmatrix}$   $\begin{matrix} \xleftarrow{n} \\ \xrightarrow{n} \end{matrix}$   $\begin{matrix} \uparrow n \\ \downarrow n \end{matrix}$
- Then,  $f(J) = \begin{bmatrix} f(\lambda) & f'(\lambda) & \cdots & \frac{f^{(n-1)}(\lambda)}{(n-1)!} \\ & f(\lambda) & \ddots & \vdots \\ & & \ddots & f'(\lambda) \\ & & & f(\lambda) \end{bmatrix}$
- And  $f(A) = T^{-1}f(J)T$ , where  $A = T^{-1}JT$ 
  - Therefore, we also have that the eigenvalues of  $f(A)$  are  $\{f(\lambda)\}$ , where  $\{\lambda\}$  are eigenvalues of  $A$

# Linear Maps

- How about  $\mathcal{A}: as^2 + bs + c \rightarrow \int_0^s (bt + a)dt$ ?