## LINEAR ALGEBRA FOR DATASCIENCE

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DS 3
Data Science Summer School

IIIIII Hertie School
Data Science Lab

## Lecturer

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- Scientific Assistant at Zuse Institute Berlin
- Passionate about Artificial Intelligence
- I love to travel and lift weights


# Why Data Science? 

## Typical problems in Data Science

- Image Segmentation

- Object Classifcation




## Typical problems in Data Science

■ 3D Shape Analysis, e.g. Shape Retrieval


- Optical Character Recognition
"qnnivm"


## Web, ads and recommendations



> Google AdSense

## Prerequisites for Data Science

Mathematical background in

- Linear Algebra (Today)
- Calculus (August 17)
- Statistics and Probability Theory (August 18)


## Outline

- Basic Notation
- Matrix Multiplication
- Vector-Vector Products
- Matrix-Vector Products
- Matrix-Matrix Products
- Operations and Properties
- The Identity Matrix and Diagonal Matrices
- The Transpose
- Symmetric Matrices
- The Trace
- Norms
- Linear Independence and Rank
- The Inverse
- Orthogonal Matrices
- Range and Nullspace of a Matrix
- The Determinant

■ Quadratic Forms and Positiv Semidefinite Matrices

- Eigenvalues and Eigenvectors
- Eigenvalues and Eigenvectors of Symmetric Matrices


## Why Linear Algebra?

- Linear Algebra to compactly represent and operate on sets of linear equations
- E.g., system of equations

$$
\begin{aligned}
4 x_{1}-5 x_{2} & =-13 \\
-2 x_{1}+3 x_{2} & =9
\end{aligned}
$$

- Matrix notation

$$
A x=b
$$

with

$$
A=\left[\begin{array}{cc}
4 & -5 \\
-2 & 3
\end{array}\right], \quad b=\left[\begin{array}{c}
-13 \\
9
\end{array}\right]
$$

## Basic Concepts and Notation

- $A \in \mathbb{R}^{m \times n}$ a matrix with $m$ rows and $n$ columns
- $x \in \mathbb{R}^{n}$ a vector of $n$ entries
$\hookrightarrow$ column vector - matrix with $n$ rows and 1 column
$\hookrightarrow$ row vector $x^{T}$
- $i^{\text {th }}$ element of $x$ is $x_{i}$

$$
x=\left[\begin{array}{c}
x_{1} \\
x_{2} \\
\vdots \\
x_{n}
\end{array}\right]
$$

- Purpose of vector is to visually represent a piece of data


## Matrix Elements

- Entry of $A$ in $i^{\text {th }}$ row and $j^{\text {th }}$ column is $a_{i j}$ (or $A_{i j}, A_{i, j}$ )

$$
A=\left[\begin{array}{cccc}
a_{11} & a_{12} & \ldots & a_{1 n} \\
a_{21} & a_{22} & \ldots & a_{2 n} \\
\vdots & \vdots & \ddots & \vdots \\
a_{m 1} & a_{m 2} & \ldots & a_{m n}
\end{array}\right]
$$

- $j^{\text {th }}$ column of $A$ is $a_{j}$ or $A_{:, j}$

$$
A=\left[\begin{array}{cccc}
\mid & \mid & & \mid \\
a_{1} & a_{2} & \ldots & a_{n} \\
\mid & \mid & & \mid
\end{array}\right]
$$

- $i^{t h}$ row of $A$ is $a_{i}^{T}$ or $A_{i,}$ :

$$
A=\left[\begin{array}{ccc}
- & a_{1}^{T} & - \\
- & a_{2}^{T} & - \\
& \vdots & \\
- & a_{n}^{T} & -
\end{array}\right]
$$

## Application: Machine Learning

1-layer network $f=W x$


2 -layer network $f=W_{2} \max \left(0, W_{1} x\right)$


## Matrix Multiplication

- Product of two matrices $A \in \mathbb{R}^{m \times n}$ and $B \in \mathbb{R}^{n \times p}$ is the matrix

$$
C=A B \in \mathbb{R}^{m \times p}
$$

where

$$
C_{i j}=\sum_{k=1}^{n} A_{i k} B_{k j}
$$

## Vector-Vector Products

- Inner (dot) product of two vectors $x, y \in \mathbb{R}^{n}$ is a real number given by

$$
x^{T} y \in \mathbb{R}=\left[\begin{array}{llll}
x_{1} & x_{2} & \ldots & x_{n}
\end{array}\right]\left[\begin{array}{c}
y_{1} \\
y_{2} \\
\vdots \\
y_{n}
\end{array}\right]=\sum_{i=1}^{n} x_{i} y_{i}
$$

$\hookrightarrow$ special case of matrix multiplication
$\hookrightarrow$ note $x^{T} y=y^{T} x$

- Outer product of two vectors $x \in \mathbb{R}^{m}, y \in \mathbb{R}^{n}$ is a matrix whose entries are given by $\left(x y^{T}\right)_{i j}=x_{i} y_{j}$

$$
x y^{T} \in \mathbb{R}^{m \times n}=\left[\begin{array}{c}
x_{1} \\
x_{2} \\
\vdots \\
x_{m}
\end{array}\right]\left[\begin{array}{llll}
y_{1} & y_{2} & \ldots & y_{n}
\end{array}\right]=\left[\begin{array}{cccc}
x_{1} y_{1} & x_{1} y_{2} & \ldots & x_{1} y_{n} \\
x_{2} y_{1} & x_{2} y_{2} & \ldots & x_{2} y_{n} \\
\vdots & \vdots & \ddots & \vdots \\
x_{m} y_{1} & x_{m} y_{2} & \ldots & x_{m} y_{n}
\end{array}\right]
$$

## Matrix-Vector Products

- Product of a matrix $A \in \mathbb{R}^{m \times n}$ and a vector $x \in \mathbb{R}^{n}$ is a vector $y=A x \in \mathbb{R}^{m}$
- If we write A by rows

$$
y=A x=\left[\begin{array}{ccc}
- & a_{1}^{T} & - \\
- & a_{2}^{T} & - \\
& \vdots & \\
- & a_{m}^{T} & -
\end{array}\right] x=\left[\begin{array}{c}
a_{1}^{T} x \\
a_{2}^{T} x \\
\vdots \\
a_{m}^{T} x
\end{array}\right]
$$

- If we write $A$ by columns

$$
y=A x=\left[\begin{array}{cccc}
\mid & \mid & & \mid \\
a_{1} & a_{2} & \cdots & a_{n} \\
\mid & \mid & & \mid
\end{array}\right]\left[\begin{array}{c}
x_{1} \\
x_{2} \\
\vdots \\
x_{n}
\end{array}\right]=\left[a_{1}\right] x_{1}+\left[a_{2}\right] x_{2}+\cdots+\left[a_{n}\right] x_{n}
$$

$\hookrightarrow y$ is a linear combination of the columns of $A$

## Matrix-Matrix Products

- Matrix-matrix as a set of vector-vector products

$$
C=A B=\left[\begin{array}{ccc}
- & a_{1}^{T} & - \\
- & a_{2}^{T} & - \\
\vdots & \\
- & a_{m}^{T} & -
\end{array}\right]\left[\begin{array}{cccc}
\mid & \mid & & \mid \\
b_{1} & b_{2} & \cdots & b_{p} \\
\mid & \mid & & \mid
\end{array}\right]=\left[\begin{array}{cccc}
a_{1}^{T} b_{1} & a_{1}^{T} b_{2} & \cdots & a_{1}^{T} b_{p} \\
a_{2}^{T} b_{1} & a_{2}^{T} b_{2} & \cdots & a_{2}^{T} b_{p} \\
\vdots & \vdots & \ddots & \vdots \\
a_{m}^{T} b_{1} & a_{m}^{T} b_{2} & \cdots & a_{m}^{T} b_{p}
\end{array}\right]
$$

$\hookrightarrow(i, j)^{t h}$ entry of $C$ equals inner product of $i^{t h}$ row of $A$ and $j^{t h}$ column of $B$

- Represent $A$ by columns, $B$ by rows

$$
C=A B=\left[\begin{array}{cccc}
\mid & \mid & & \mid \\
a_{1} & a_{2} & \cdots & a_{n} \\
\mid & \mid & & \mid
\end{array}\right]\left[\begin{array}{ccc}
- & b_{1}^{T} & - \\
- & b_{2}^{T} & - \\
& \vdots & \\
- & b_{n}^{T} & -
\end{array}\right]=\sum_{i=1}^{n} a_{i} b_{i}^{T}
$$

$\hookrightarrow A B$ is equal to the sum, over all $i$, of the outer product of the $i^{t h}$ column of $A$ and $i^{t h}$ row of $B$

## Matrix-Matrix Products

- Matrix-matrix multiplication as a set of matrix-vector products

$$
C=A B=A\left[\begin{array}{cccc}
\mid & \mid & & \mid \\
b_{1} & b_{2} & \cdots & b_{p} \\
\mid & \mid & & \mid
\end{array}\right]=\left[\begin{array}{cccc}
\mid & \mid & & \mid \\
A b_{1} & A b_{2} & \cdots & A b_{p} \\
\mid & \mid & & \mid
\end{array}\right]
$$

$\hookrightarrow i^{t h}$ column of $C$ is given by the matrix-vector product with the vector on the right, $c_{i}=A b_{i}$

- Represent $A$ by rows, view rows of $C$ as matrix-vector product between rows of $A$ and C

$$
C=A B=\left[\begin{array}{ccc}
- & a_{1}^{T} & - \\
- & a_{2}^{T} & - \\
& \vdots & \\
- & a_{m}^{T} & -
\end{array}\right] B=\left[\begin{array}{ccc}
- & a_{1}^{T} B & - \\
- & a_{2}^{T} B & - \\
& \vdots & \\
- & a_{m}^{T} B & -
\end{array}\right]
$$

$\hookrightarrow i^{\text {th }}$ row of $C$ is given by the matrix-vector product with the vector on the left, $c_{i}^{T}=a_{i}^{T} B$

## Matrix multiplication properties

- Matrix multiplication is associative

$$
(A B) C=A(B C)
$$

## Proof

$$
\begin{aligned}
((A B) C)_{i j} & =\sum_{k=1}^{p}(A B)_{i k} C_{k j}=\sum_{k=1}^{p}\left(\sum_{l=1}^{n} A_{i l} B_{l k}\right) C_{k j} \\
& =\sum_{k=1}^{p}\left(\sum_{l=1}^{n} A_{i l} B_{l k} C_{k j}\right)=\sum_{l=1}^{n}\left(\sum_{k=1}^{p} A_{i l} B_{l k} C_{k j}\right) \\
& =\sum_{l=1}^{n} A_{i l}\left(\sum_{k=1}^{p} B_{l k} C_{k j}\right)=\sum_{l=1}^{n} A_{i l}(B C)_{l j}=(A(B C))_{i j}
\end{aligned}
$$

- Matrix multiplication is distributive

$$
A(B+C)=A B+A C
$$

- Matrix multiplication is, in general, not commutative $A B \neq B A$ $\hookrightarrow$ If $A \in \mathbb{R}^{m \times n}, B \in \mathbb{R}^{n \times q}$, then $B A$ does not exist if $m$ and $q$ are not equal !


## Identity Matrix and Diagonal Matrices

- Identity matrix $I \in \mathbb{R}^{n \times n}$ defined as

$$
I_{i j}= \begin{cases}1, & i=j \\ 0, & i \neq j\end{cases}
$$

- $A I=A=I A$
- Diagonal matrix $D=\operatorname{diag}\left(d_{1}, d_{2}, \ldots, d_{n}\right)$

$$
D_{i j}= \begin{cases}d_{i}, & i=j \\ 0, & i \neq j\end{cases}
$$

- $I=\operatorname{diag}(1,1, \ldots, 1)$


## The Transpose

- Transpose of a matrix $A \in \mathbb{R}^{m \times n}$ is $A^{T} \in \mathbb{R}^{n \times m}$ where

$$
\left(A^{T}\right)_{i j}=A_{j i}
$$

Properties

- $\left(A^{T}\right)^{T}=A$
- $(A B)^{T}=B^{T} A^{T}$
- $(A+B)^{T}=A^{T}+B^{T}$


## Symmetric Matrices

- $A \in \mathbb{R}^{n \times n}$ is symmetric if $A=A^{T}$
- $A \in \mathbb{R}^{n \times n}$ is anti-symmetric if $A=-A^{T}$

Properties

- $A+A^{T}$ is symmetric, $A-A^{T}$ is anti-symmetric
- $A=\frac{1}{2}\left(A+A^{T}\right)+\frac{1}{2}\left(A-A^{T}\right)$
- $\mathbb{S}^{n}$ - set of symmetric matrices of size $n$


## The Trace

- Trace of $A \in \mathbb{R}^{n \times n}$

$$
\operatorname{tr} A=\sum_{i=1}^{n} A_{i i}
$$

Properties

- $A \in \mathbb{R}^{n \times n}, \operatorname{tr} A=\operatorname{tr} A^{T}$
- $A, B \in \mathbb{R}^{n \times n}, \operatorname{tr}(A+B)=\operatorname{tr} A+\operatorname{tr} B$
- $A \in \mathbb{R}^{n \times n}, t \in \mathbb{R}, \operatorname{tr}(t A)=t \operatorname{tr} A$
- $A, B$ such that $A B$ is square, $\operatorname{tr} A B=\operatorname{tr} B A$


## Proof

$$
\begin{aligned}
\operatorname{tr} A B & =\sum_{i=1}^{m}(A B)_{i i}=\sum_{i=1}^{m}\left(\sum_{j=1}^{n} A_{i j} B_{j i}\right) \\
& =\sum_{i=1}^{m} \sum_{j=1}^{n} A_{i j} B_{j i}=\sum_{j=1}^{n} \sum_{i=1}^{m} B_{j i} A_{i j} \\
& =\sum_{j=1}^{n}\left(\sum_{i=1}^{m} B_{j i} A_{i j}\right)=\sum_{j=1}^{n}(B A)_{j j}=\operatorname{tr} B A
\end{aligned}
$$

- $A, B, C$ such that $A B C$ is square, $\operatorname{tr} A B C=\operatorname{tr} B C A=\operatorname{tr} C A B$


## Norms

- Norm is any function $f: \mathbb{R}^{n} \rightarrow \mathbb{R}$ satisfying

I $\forall x \in \mathbb{R}^{n}, f(x) \geq 0$ (non-negativity)
$2 \quad f(x)=0$ if and only if $x=0$ (definiteness)
$3 x \in \mathbb{R}^{n}, t \in \mathbb{R}, f(t x)=|t| f(x)$ (homogeneity)
$4 \forall x, y \in \mathbb{R}^{n}, f(x+y) \leq f(x)+f(y)$ (triangle inequality)

- $\ell_{p}$ norm $\|x\|_{p}=\left(\sum_{i=1}^{n}\left|x_{i}\right|^{p}\right)^{1 / p}$
- $\ell_{2}$ (Euclidean) norm measures the 'length' of the vector

$$
\|x\|_{2}=\sqrt{\sum_{i=1}^{n} x_{i}^{2}}
$$

- $\ell_{1}$ norm

$$
\|x\|_{1}=\sum_{i=1}^{n}\left|x_{i}\right|
$$

- $\ell_{\infty}$ norm

$$
\|x\|_{\infty}=\max _{i}\left|x_{i}\right|
$$

- Frobenius norm $\|A\|_{F}=\sqrt{\sum_{i=1}^{m} \sum_{j=1}^{n} A_{i j}^{2}}=\sqrt{\operatorname{tr}\left(A^{T} A\right)}$


## Norm Exercise

## Exercise

Show that the length of $A x$ equals the length of $A^{T} x$ if $A A^{T}=A^{T} A$.

## Solution

## Norm Exercise

## Exercise

Show that the length of $A x$ equals the length of $A^{T} x$ if $A A^{T}=A^{T} A$.

## Solution

$$
\begin{aligned}
\|A x\|^{2} & =(A x)^{T}(A x) \\
& =x^{T} A^{T} A x \\
& =x^{T} A A^{T} x \\
& =\left(A^{T} x\right)^{T}\left(A^{T} x\right) \\
& =\left\|A^{T} x\right\|^{2}
\end{aligned}
$$

## Linear (In)dependence

- Set $\left\{x_{1}, x_{2}, \ldots, x_{n}\right\} \subset \mathbb{R}^{m}$ is (linearly) independent if no vector can be represented as linear combination of remaining vectors
■ Set $\left\{x_{1}, x_{2}, \ldots, x_{n}\right\} \subset \mathbb{R}^{m}$ is (linearly) dependent if one vector can be represented as a linear combination of the remaining vectors

$$
x_{n}=\sum_{i=1}^{n-1} \alpha_{i} x_{i}, \quad \alpha_{1}, \ldots, \alpha_{n-1} \in \mathbb{R}
$$

- E.g. $x_{1}=\left[\begin{array}{l}1 \\ 2 \\ 3\end{array}\right], \quad x_{1}=\left[\begin{array}{l}4 \\ 1 \\ 5\end{array}\right], \quad \mathrm{x}_{1}=\left[\begin{array}{c}2 \\ -3 \\ -1\end{array}\right]$ linearly dependent $\left(x_{3}=-2 x_{1}+x_{2}\right)$


## Rank

- Column rank of $A \in \mathbb{R}^{m \times n}$ is the size of largest subset of columns of $A$ that consitute a linearly independent set
- Row rank of $A \in \mathbb{R}^{m \times n}$ is the size of largest subset of rows of $A$ that consitute a linearly independent set
- For any $A \in \mathbb{R}^{m \times n}$ the column rank of $A$ equals the row rank of $A-\operatorname{rank}(A)$

Properties

- For $A \in \mathbb{R}^{m \times n}, \operatorname{rank}(A) \leq \min (m, n)$
- $A$ is full rank if $\operatorname{rank}(A)=\min (m, n)$
- $A \in \mathbb{R}^{m \times n}, \operatorname{rank}(A)=\operatorname{rank}\left(A^{T}\right)$
- $A \in \mathbb{R}^{m \times n}, B \in \mathbb{R}^{n \times p}, \operatorname{rank}(A B) \leq \min (\operatorname{rank}(A), \operatorname{rank}(B))$
- $A, B \in \mathbb{R}^{m \times n}, \operatorname{rank}(A+B) \leq \operatorname{rank}(A)+\operatorname{rank}(B)$


## The Inverse

- Inverse of $A \in \mathbb{R}^{n \times n}, A^{-1}$, is the unique matrix

$$
A^{-1} A=I=A A^{-1}
$$

- Note not all matrices have inverses (e.g., non-square matrices)
- A is invertible (non-singular) if $A^{-1}$ exists and non-invertible (singular) otherwise
- $A$ has an inverse $A^{-1}$ if $A$ is of full rank

Properties for $A, B \in \mathbb{R}^{n \times n}$

- $\left(A^{-1}\right)^{-1}=A$
- $(A B)^{-1}=B^{-1} A^{-1}$
- $\left(A^{-1}\right)^{T}=\left(A^{T}\right)^{-1}$, often denoted by $A^{-T}$


## Inverse Usage

Consider $A x=b$ where $A \in \mathbb{R}^{n \times n}$ and $x, b \in \mathbb{R}^{n}$. If $A$ is non-singular (invertible), then $x=A^{-1} b$

- What if $A \in \mathbb{R}^{m \times n}$ is not a square matrix ?


## The Determinant

■ Determinant of $A \in \mathbb{R}^{n \times n},|A|$ or $\operatorname{det} A$, is a function det $: \mathbb{R}^{n \times n} \rightarrow \mathbb{R}$

- $A_{\backslash i, \backslash j} \in \mathbb{R}^{(n-1) \times(n-1)}$ is the matrix resulting from deleting $i^{\text {th }}$ row and $j^{\text {th }}$ column from A
- Recursive formula

$$
\begin{aligned}
|A| & =\sum_{i=1}^{n}(-1)^{i+j} a_{i j}\left|A_{\backslash i, \backslash j}\right| \quad \text { for any } j \in 1, \ldots, n \\
& =\sum_{j=1}^{n}(-1)^{i+j} a_{i j}\left|A_{\backslash i, \backslash j}\right| \quad \text { for any } i \in 1, \ldots, n
\end{aligned}
$$

with initial $|A|=a_{11}$ for $A \in \mathbb{R}^{1 \times 1}$

- $\left|\left[a_{11}\right]\right|=a_{11}$
- $\left|\left[\begin{array}{ll}a_{11} & a_{12} \\ a_{21} & a_{22}\end{array}\right]\right|=a_{11} a_{22}-a_{12} a_{21}$
- $\left|\left[\begin{array}{lll}a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33}\end{array}\right]\right|=a_{11}\left|\left[\begin{array}{ll}a_{22} & a_{23} \\ a_{32} & a_{33}\end{array}\right]\right|-a_{12}\left|\left[\begin{array}{ll}a_{21} & a_{23} \\ a_{31} & a_{33}\end{array}\right]\right|+a_{13}\left|\left[\begin{array}{ll}a_{21} & a_{22} \\ a_{31} & a_{32}\end{array}\right]\right|$


## Determinant Properties

- $|I|=1$
- $\left|\left[\begin{array}{ccc}- & t a_{1}^{T} & - \\ - & a_{2}^{T} & - \\ & \vdots & \\ - & a_{m}^{T} & -\end{array}\right]\right|=t|A|$
- $\left|\left[\begin{array}{ccc}- & a_{2}^{T} & - \\ - & a_{1}^{T} & - \\ & \vdots & \\ - & a_{m}^{T} & -\end{array}\right]\right|=-|A|$
- Describes how much a sampled area changes in scale with linear transformations

- $A \in \mathbb{R}^{n \times n},|A|=\left|A^{T}\right|$
- $A, B \in \mathbb{R}^{n \times n},|A B|=|A||B|$
- $A \in \mathbb{R}^{n \times n},|A|=0$ if and only if $A$ is singular (non-invertible)
- $A \in \mathbb{R}^{n \times n}$ and $A$ non-singular, $\left|A^{-1}\right|=1 /|A|$


## Determinant Properties

- Shears and rotations do not affect determinant

- Linearly dependent transformations result in determinant 0
- In $2 D$ space is compressed into one dimension
- In $3 D$ space is compressed into two dimensions



## Determinant Exercise

## Exercise

If $A \in \mathbb{R}^{n \times n}$ has determinant $\frac{1}{2}$, find $|2 A|,|-A|,\left|A^{2}\right|,\left|A^{-1}\right|$

Solution


## Determinant Exercise

## Exercise

If $A \in \mathbb{R}^{n \times n}$ has determinant $\frac{1}{2}$, find $|2 A|,|-A|,\left|A^{2}\right|,\left|A^{-1}\right|$

## Solution

- $|2 A|=2^{n}|A|=2^{n-1}$
- $|-A|=(-1)^{n}|A|=(-1)^{n} / 2$
- $\left|A^{2}\right|=|A||A|=1 / 4$
- $\left|A^{-1}\right|=\frac{1}{|A|}=2($ as $|A| \neq 0)$


## Determinant Exercise

## Exercise

Find the determinants of

$$
A=\left[\begin{array}{l}
1 \\
4 \\
2
\end{array}\right]\left[\begin{array}{lll}
2 & -1 & 2
\end{array}\right], \quad U=\left[\begin{array}{llll}
4 & 4 & 8 & 8 \\
0 & 1 & 2 & 2 \\
0 & 0 & 2 & 6 \\
0 & 0 & 0 & 2
\end{array}\right], \quad \mathrm{U}^{T} \text { and } \mathrm{U}^{-1}
$$

## Solution



## Determinant Exercise

## Exercise

Find the determinants of

$$
A=\left[\begin{array}{l}
1 \\
4 \\
2
\end{array}\right]\left[\begin{array}{lll}
2 & -1 & 2
\end{array}\right], \quad U=\left[\begin{array}{llll}
4 & 4 & 8 & 8 \\
0 & 1 & 2 & 2 \\
0 & 0 & 2 & 6 \\
0 & 0 & 0 & 2
\end{array}\right], \quad \mathrm{U}^{T} \text { and } \mathrm{U}^{-1}
$$

## Solution

- $|A|=\left|\left[\begin{array}{l}1 \\ 4 \\ 2\end{array}\right]\left[\begin{array}{lll}2 & -1 & 2\end{array}\right]\right|=\left|\left[\begin{array}{lll}2 & -1 & 2 \\ 8 & -4 & 8 \\ 4 & -2 & 4\end{array}\right]\right|=2(-16+16)+1(32-32)+2(-16+16)=0$
- $|U|=4 \times 1 \times 2 \times 2=16=\left|U^{T}\right|, \quad$ as $U$ is an upper diagonal matrix
- $U^{-1}=\frac{1}{|U|}=\frac{1}{16}$


## Eigenvalues and Eigenvectors

- $\lambda \in \mathbb{C}$ is an eigenvalue and $x \in \mathbb{C}^{n}$ is the corresponding eigenvector of $A \in \mathbb{R}^{n \times n}$ if

$$
A x=\lambda x, \quad x \neq 0
$$

- ( $\lambda, x)$ is an eigenvalue-eigenvector pair of $A$ if

$$
(\lambda I-A) x=0, \quad x \neq 0
$$

- Equation has a non-zero solution to $x$ if and only if $(\lambda I-A)$ is singular

$$
|(\lambda I-A)|=0
$$

- Polynomial in $\lambda$ of order $n$

$$
p\left(\lambda_{i}\right)=\lambda_{i}^{n}+c_{n-1} \lambda_{i}^{n-1}+\ldots+c_{1} \lambda_{i}+c_{0}
$$

- Roots of characteristic polynomial $\lambda_{1}, \lambda_{2}, \ldots, \lambda_{n}$ are the eigenvalues of $A$
- Eigenvector corresponding to eigenvalue $\lambda_{i}$

$$
\left(\lambda_{i} I-A\right) x=0
$$

## Properties of Eigenvalues and Eigenvectors

- For any eigenvector $x \in \mathbb{C}^{n}$ and a scalar $t \in \mathbb{C}, A(c x)=c A x=x \lambda x=\lambda(c x)$, so $c x$ is also an eigenvector
- The eigenvector associated with $\lambda$ is normalized to have length 1
- $\operatorname{tr} A=\sum_{i=1}^{n} \lambda_{i}$
- $|A|=\prod_{i=1}^{n} \lambda_{i}$
- Rank of $A$ equals the number of non-zero eigenvalues of $A$
- If $A$ non-singular then $1 / \lambda_{i}$ is an eigenvalue of $A^{-1}$ with associated eigenvector $x_{i}$

$$
A^{-1} x_{i}=\left(1 / \lambda_{i}\right) x_{i}
$$

- Eigenvalues of diagonal matrix $D=\operatorname{diag}\left(d_{1}, \ldots, d_{n}\right)$ are the diagonal entries $d_{1}, \ldots, d_{n}$


## Eigendecomposition

- Write eigenvector equations simultaneously

$$
A X=X \Lambda
$$

- Columns of $X \in \mathbb{R}^{n \times n}$ are eigenvectors of $A$
- $\Lambda$ is a diagonal matrix whose entries are eigenvalues of $A$

$$
X \in \mathbb{R}^{n \times n}=\left[\begin{array}{cccc}
\mid & \mid & & \mid \\
x_{1} & x_{2} & \cdots & x_{n} \\
\mid & \mid & & \mid
\end{array}\right], \quad \Lambda=\operatorname{diag}\left(\lambda_{1}, \ldots, \lambda_{n}\right)
$$

- If eigenvectors of $A$ are linearly independent, then matrix $X$ is invertible

$$
A=X \Lambda X^{-1}
$$

- A matrix written in such a form is diagonalizable
- $A \in \mathbb{S}^{n}$
- All eigenvalues of $A$ are real
- Eigenvectors of $A$ are orthonormal ( $X$ is orthogonal, denoted by $U$ )
- $A=U \Lambda U^{T}$


## Eigendecomposition Exercise

## Exercise

Find eigenvalues and eigenvectors of $A=\left[\begin{array}{lll}3 & 4 & 2 \\ 0 & 1 & 2 \\ 0 & 0 & 0\end{array}\right]$ and $B=\left[\begin{array}{lll}0 & 0 & 2 \\ 0 & 2 & 0 \\ 2 & 0 & 0\end{array}\right]$, their traces and their determinants

## Solution

```
葍 }|A|=
-\operatorname{tr}(A)-1
```


## Eigendecomposition Exercise

## Exercise

Find eigenvalues and eigenvectors of $A=\left[\begin{array}{lll}3 & 4 & 2 \\ 0 & 1 & 2 \\ 0 & 0 & 0\end{array}\right]$ and $B=\left[\begin{array}{lll}0 & 0 & 2 \\ 0 & 2 & 0 \\ 2 & 0 & 0\end{array}\right]$, their traces and their determinants

## Solution

- $|A|=0$
- $\operatorname{tr}(A)=4$
- 

$$
\begin{aligned}
& |A-\lambda I|=0 \\
& \left|\left[\begin{array}{ccc}
3-\lambda & 4 & 2 \\
0 & 1-\lambda & 2 \\
0 & 0 & -\lambda
\end{array}\right]\right|=0 \\
& (3-\lambda)\left(\lambda^{2}-\lambda\right)=0
\end{aligned}
$$

Eigenvalues are $\lambda=\{0,1,3\}$ and their corresponding eigenvectors $\left[\begin{array}{c}2 \\ -2 \\ 1\end{array}\right],\left[\begin{array}{c}-2 \\ 1 \\ 0\end{array}\right],\left[\begin{array}{l}1 \\ 0 \\ 0\end{array}\right]$

## Eigendecomposition Exercise

## Solution

- $|B|=-8$ (recall product of eigenvalues)
- $\operatorname{tr}(B)=2$ (recall sum of eigenvalues)

$$
\begin{aligned}
|B-\lambda I| & =0 \\
\left|\left[\begin{array}{ccc}
-\lambda & 0 & 2 \\
0 & 2-\lambda & 0 \\
2 & 0 & -\lambda
\end{array}\right]\right| & =0 \\
(-\lambda)(2-\lambda)(-\lambda)-4(2-\lambda) & =0 \\
\left(\lambda^{2}-4\right)(2-\lambda)=0 &
\end{aligned}
$$

Eigenvalues are $\lambda=\{-2,2,2\}$

- To find eigenvectors

$$
\left[\begin{array}{lll}
0 & 0 & 2 \\
0 & 2 & 0 \\
2 & 0 & 0
\end{array}\right]\left[\begin{array}{c}
-1 \\
0 \\
1
\end{array}\right]=-2\left[\begin{array}{c}
-1 \\
0 \\
1
\end{array}\right],\left[\begin{array}{lll}
0 & 0 & 2 \\
0 & 2 & 0 \\
2 & 0 & 0
\end{array}\right]\left[\begin{array}{l}
1 \\
0 \\
1
\end{array}\right]=2\left[\begin{array}{l}
1 \\
0 \\
1
\end{array}\right],\left[\begin{array}{lll}
0 & 0 & 2 \\
0 & 2 & 0 \\
2 & 0 & 0
\end{array}\right]\left[\begin{array}{l}
0 \\
1 \\
0
\end{array}\right]=2\left[\begin{array}{l}
0 \\
1 \\
0
\end{array}\right]
$$

- Note the relations are also valid for normalized eigenvectors


## Systems of Equations and Inverse Matrices

- Basic use of linear algebra is to solve systems of equations

$$
\begin{aligned}
4 x+2 y+4 z & =44 \\
5 x+3 y+7 z & =56 \\
9 x+3 y+6 z & =72
\end{aligned}
$$

Solutions
1 Solve it manually with algebraic operations to isolate three variables
2 Express the problem in terms of matrices and let a computer solve it
Solve $A X=B$ where

$$
A=\left[\begin{array}{lll}
4 & 2 & 4 \\
5 & 3 & 7 \\
9 & 3 & 6
\end{array}\right], \quad B=\left[\begin{array}{l}
44 \\
56 \\
72
\end{array}\right], \quad X=\left[\begin{array}{l}
x \\
y \\
z
\end{array}\right]
$$

1 Solve by hand using Gaussian elimination
$\boxed{2}$ Use a computer to find inverse matrix $A^{-1}$

## Eigendecomposition Exercise

## Exercise

Using the characteristic polynomial, find the relationship between trace, determinants and eigenvalues of any square matrix

## Solution


whose eigenvalues are $\lambda_{1}, \ldots, \lambda_{n}$

- Characteristic polynomial $p(\lambda)=\mid \lambda I$ -
$\square$ $\left(\lambda-\lambda_{n}\right)$ (Eigenvalues of $A$ are zeros of $\left.p(\lambda)\right)$
- Express determinant as product of eigenvalues


## Eigendecomposition Exercise

## Exercise

Using the characteristic polynomial, find the relationship between trace, determinants and eigenvalues of any square matrix

## Solution

- Let $A=\left[\begin{array}{ccc}a_{11} & \cdots & a_{1 n} \\ \vdots & \ddots & \vdots \\ a_{n 1} & \cdots & a_{n n}\end{array}\right]$ whose eigenvalues are $\lambda_{1}, \ldots, \lambda_{n}$
- Characteristic polynomial $p(\lambda)=|\lambda I-A|=\lambda_{n}+c_{n-1} \lambda^{n-1}+\cdots+c_{1} \lambda+c_{0}$
- Also $p(\lambda)=\left(\lambda-\lambda_{1}\right) \cdots\left(\lambda-\lambda_{n}\right)$ (Eigenvalues of $A$ are zeros of $\left.p(\lambda)\right)$
- Express determinant as product of eigenvalues

$$
\begin{aligned}
& \text { 凹 } p(0)=\left(0-\lambda_{1}\right) \cdots\left(0-\lambda_{n}\right)=(-1)^{n} \lambda_{1} \cdots \lambda_{n} \\
& \text { ■ } p(0)=|0 I-A|=|-A|=(-1)^{n}|A| \\
& \hookrightarrow c_{0}=(-1)^{n} \lambda_{1} \cdots \lambda_{n}=(-1)^{n}|A| \Longrightarrow|A|=\lambda_{1} \cdots \lambda_{n}
\end{aligned}
$$

## Eigendecomposition Exercise

## Solution

- Express trace as sum of eigenvalues

1 Expand $p(\lambda)=\left(\lambda-\lambda_{1}\right) \cdots\left(\lambda-\lambda_{n}\right)$ to get $\lambda^{n-1}$ term

$$
-\lambda_{1} \lambda^{n-1}-\cdots-\lambda \lambda^{n-1}=-\left(\lambda_{1}+\cdots+\lambda_{n}\right) \lambda^{n-1} \Longrightarrow c_{n-1}=-\left(\lambda_{1}+\cdots+\lambda_{n}\right)
$$

2 Expand $|\lambda I-A|=\left|\left[\begin{array}{cccc}\lambda-a_{11} & -a_{12} & \cdots & -a_{1 n} \\ -a_{21} & \lambda-a_{22} & \cdots & -a_{2 n} \\ \vdots & \vdots & \ddots & \vdots \\ -a_{n 1} & -a_{n 2} & \cdots & \lambda-a_{n n}\end{array}\right]\right|$
$\hookrightarrow p(\lambda)=\left(\lambda-a_{11}\right) \cdots\left(\lambda-a_{n n}\right)+q(\lambda)$
$\hookrightarrow q(\lambda)$ has degree at most $n-2$, hence no $\lambda^{n-1}$ term
$\hookrightarrow \lambda^{n-1}$ term must be from $\left(\lambda-a_{11}\right) \cdots\left(\lambda-a_{n n}\right)$
$\hookrightarrow-\left(a_{11}+\cdots+a_{n n}\right) \lambda^{n-1}$
$\hookrightarrow c_{n-1}=-\left(\lambda_{1}+\lambda_{n}\right)=-\left(a_{11}+\cdots+a_{n n}\right) \Longrightarrow \operatorname{tr}(A)=\lambda_{1}+\cdots+\lambda_{n}$

## Eigendecomposition Exercise

## Exercise

Diagonalize unitary matrix $V=\frac{1}{\sqrt{3}}\left[\begin{array}{cc}1 & 1-i \\ 1+i & -1\end{array}\right]$ to reach $V=U \Lambda U^{T}$

## Solution



## Eigendecomposition Exercise

## Exercise

Diagonalize unitary matrix $V=\frac{1}{\sqrt{3}}\left[\begin{array}{cc}1 & 1-i \\ 1+i & -1\end{array}\right]$ to reach $V=U \Lambda U^{T}$

## Solution

$$
\begin{aligned}
|V-\lambda I| & =0 \\
(1-\sqrt{3} \lambda)(-1-\sqrt{3} \lambda)-\left(1+i-i-i^{2}\right) & =0 \\
3 \lambda^{2} & =3
\end{aligned}
$$

- Eigenvalues are $\lambda=\{1,-1\}$, hence $\Lambda=\left[\begin{array}{cc}-1 & 0 \\ 0 & 1\end{array}\right]$
- Corresponding eigenvectors $\left[\begin{array}{c}-0.366+0.366 i \\ 1\end{array}\right],\left[\begin{array}{c}1.366-1.366 i \\ 1\end{array}\right]$
- Normalize eigenvectors to get $U=\left[\begin{array}{cc}\frac{-0.366+0.366 i}{1.1^{26}} & \frac{1.366-1.366 i}{1.126} \\ \frac{2.1^{75}}{2.175}\end{array}\right]$


## Eigendecomposition Exercise

## Homework

Suppose $T$ is a $3 \times 3$ upper triangular matrix with entries $t_{i j}$. Compare entries of $T^{T} T$ and $T T^{T}$. Show that if they are equal, then $T$ must be diagonal.

## Singular Value Decomposition (SVD)

- Generalization of eigendecomposition to $m \times n$ matrices
- $A=U \Lambda V^{T}$
- $U$ is $m \times m$ unitary matrix, whose column vectors are left-singular vectors
- $\Lambda$ is $m \times n$ rectangular diagonal matrix, whose values $\sigma_{i}$ are singular values

■ $V$ is $n \times n$ unitary matrix, whose column vectors are right-singular vectors

- Singular values of $m \times n$ matrix $A$ are equal to positive square roots of non-zero eignelvalues of $n \times n$ matrix $A^{T} A$ (and $A A^{T}$ )
- Eigenvectors of $A A^{T}$ are columns of $U$
- Eigenvectors of $A^{T} A$ are columns of $V$


## SVD Exercise

## Exercise

Find singular values and singular vectors of $A=\left[\begin{array}{ll}1 & 4 \\ 2 & 8\end{array}\right]$

## Solution

- $A^{T} A=\left[\begin{array}{ll}1 & 2 \\ 4 & 8\end{array}\right]\left[\begin{array}{ll}1 & 4 \\ 2 & 8\end{array}\right]=\left[\begin{array}{cc}5 & 20 \\ 20 & 80\end{array}\right]$

$$
\begin{aligned}
\left|\left[\begin{array}{cc}
5-\lambda & 20 \\
20 & 80-\lambda
\end{array}\right]\right| & =0 \\
(5-\lambda)(80-\lambda)-400 & =0
\end{aligned}
$$

$\hookrightarrow \lambda=\{0,85\}$ hence singular values are $\{0, \sqrt{85}\}$ and eigenvectors $\left[\begin{array}{l}1 \\ 4\end{array}\right],\left[\begin{array}{c}-4 \\ 1\end{array}\right]$

- $A A^{T}=\left[\begin{array}{ll}1 & 4 \\ 2 & 8\end{array}\right]\left[\begin{array}{ll}1 & 2 \\ 4 & 8\end{array}\right]=\left[\begin{array}{ll}17 & 34 \\ 34 & 68\end{array}\right]$
- Similarly for $A A^{T}$ we have $\lambda=\{85,0\}$ and eigenvectors $\left[\begin{array}{l}1 \\ 2\end{array}\right],\left[\begin{array}{c}-2 \\ 1\end{array}\right]$
$\hookrightarrow \Sigma=\left[\begin{array}{cc}\sqrt{85} & 0 \\ 0 & 0\end{array}\right], \quad U=\left[\begin{array}{cc}\frac{1}{\sqrt{5}} & -\frac{2}{\sqrt{5}} \\ \frac{2}{\sqrt{5}} & \frac{1}{\sqrt{5}}\end{array}\right], \quad V=\left[\begin{array}{cc}\frac{1}{\sqrt{17}} & -\frac{4}{\sqrt{17}} \\ \frac{4}{\sqrt{17}} & \frac{1}{\sqrt{17}}\end{array}\right]$


## SVD Exercise

## Exercise

Explain how $U \Sigma V^{T}$ expresses $A$ as a sum or $r$ rank-1 matrices $A=\sigma_{1} u_{1} v_{1}^{T}+\cdots+\sigma_{r} u_{r} v_{r}^{T}$

## Solution

- $A=U \Sigma V^{T}$
- $\epsilon_{i}=\operatorname{diag}\left(0, \ldots, \sigma_{i}, \ldots, 0\right)$
- $\Sigma=\sum_{i} \epsilon_{i}$ and $\epsilon_{i} \neq 0$ if and only if $i \in\{1, \cdots, k\}$

$$
\begin{aligned}
A=U \Sigma V^{T} & =U\left(\Sigma_{i} \epsilon_{i}\right) V^{T} \\
& =\sum_{i=1}^{k} U \epsilon_{i} V^{T}
\end{aligned}
$$

## SVD Exercise

## Exercise

If $A$ changes to $4 A$ what is the change in SVD? What is the SVD for $A^{T}$ and for $A^{-1}$ ?

## Solution



- $\Sigma^{-1}=\operatorname{diag}\left(1 / \sigma_{1}, \cdots, 1 / \sigma_{n}\right)$
$\pm U V$ orthogonal $\Longrightarrow I H H^{T}=I^{T} U=I$ and $V V^{T}=V^{T} V=I$


## SVD Exercise

## Exercise

If $A$ changes to $4 A$ what is the change in SVD? What is the SVD for $A^{T}$ and for $A^{-1}$ ?

## Solution

- $4 A=U(4 \Sigma) V^{T}$, singular values of $4 A$ are 4 times that of $A$

$$
\begin{aligned}
A^{T} & =\left(U \Sigma V^{T}\right)^{T} \\
& =\left(V^{T}\right)^{T} \Sigma^{T} U^{T} \\
& =V \Sigma^{T} U^{T}
\end{aligned}
$$

$$
\begin{aligned}
A^{-1} & =\left(U \Sigma V^{T}\right)^{-1} \\
& =\left(V^{T}\right)^{-1} \Sigma^{-1} U^{-1} \\
& =V \Sigma^{-1} U^{T}
\end{aligned}
$$

- $\Sigma^{-1}=\operatorname{diag}\left(1 / \sigma_{1}, \cdots, 1 / \sigma_{n}\right)$
- $U, V$ orthogonal $\Longrightarrow U U^{T}=U^{T} U=I$ and $V V^{T}=V^{T} V=I$
- Double check $A^{-1} A=I$


## Pseudoinverse

- Regression model in Machine Learning requires the computation of (Moore-Penrose) pseudoinverse

$$
A^{\dagger}=\left(U \Lambda V^{T}\right)^{\dagger}=V D^{\dagger} U^{T}
$$

- $D^{\dagger}$ is pseudo-inverse of $D$

$$
\sigma_{i}^{\dagger}= \begin{cases}1 / \sigma_{i}, & \text { if } \sigma_{i} \neq 0 \\ 0, & \text { otherwise }\end{cases}
$$

## Pseudoinverse Exercise

## Exercise

Find SVD and pseudoinverse of $A=\left[\begin{array}{llll}1 & 1 & 1 & 1\end{array}\right], \quad B=\left[\begin{array}{lll}0 & 1 & 0 \\ 1 & 0 & 0\end{array}\right]$, and $C=\left[\begin{array}{ll}1 & 1 \\ 0 & 0\end{array}\right]$

## Solution



- Solving $\left|A^{T} A-\lambda I\right|=0$ and $\left|A A^{T}-\lambda I\right|=0$ we find $\lambda=\{4,0,0,0\}$
- Corresponding eigenvectors



## Pseudoinverse Exercise

## Exercise

Find SVD and pseudoinverse of $A=\left[\begin{array}{llll}1 & 1 & 1 & 1\end{array}\right], \quad B=\left[\begin{array}{lll}0 & 1 & 0 \\ 1 & 0 & 0\end{array}\right]$, and $C=\left[\begin{array}{ll}1 & 1 \\ 0 & 0\end{array}\right]$

## Solution

- $A^{T} A=\left[\begin{array}{l}1 \\ 1 \\ 1 \\ 1\end{array}\right]\left[\begin{array}{llll}1 & 1 & 1 & 1\end{array}\right]=\left[\begin{array}{llll}1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1\end{array}\right]$
- $A A^{T}=[4]$
- Solving $\left|A^{T} A-\lambda I\right|=0$ and $\left|A A^{T}-\lambda I\right|=0$ we find $\lambda=\{4,0,0,0\}$
- Corresponding eigenvectors

$$
\left[\begin{array}{l}
1 \\
1 \\
1 \\
1
\end{array}\right],\left[\begin{array}{c}
-1 \\
0 \\
0 \\
1
\end{array}\right],\left[\begin{array}{c}
-1 \\
0 \\
1 \\
0
\end{array}\right],\left[\begin{array}{c}
-1 \\
1 \\
0 \\
0
\end{array}\right]
$$

$\hookrightarrow \Sigma=\left[\begin{array}{llll}2 & 0 & 0 & 0\end{array}\right], \quad U=[4], \quad V=\left[\begin{array}{cccc}\frac{1}{2} & -\frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} \\ \frac{1}{2} & 0 & 0 & \frac{1}{\sqrt{2}} \\ \frac{1}{2} & 0 & \frac{1}{\sqrt{2}} & 0 \\ \frac{1}{2} & \frac{1}{\sqrt{2}} & 0 & 0\end{array}\right]$

## Pseudoinverse Exercise

## Solution

- Pseudoinverse $A^{\dagger}=V \Sigma^{\dagger} U^{T}$
- $A^{\dagger}=\left[\begin{array}{cccc}\frac{1}{2} & -\frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} \\ \frac{1}{2} & 0 & 0 & \frac{1}{\sqrt{2}} \\ \frac{1}{2} & 0 & \frac{1}{\sqrt{2}} & 0 \\ \frac{1}{2} & \frac{1}{\sqrt{2}} & 0 & 0\end{array}\right]\left[\begin{array}{l}\frac{1}{2} \\ 0 \\ 0 \\ 0\end{array}\right][4]=\left[\begin{array}{l}1 \\ 1 \\ 1 \\ 1\end{array}\right]$
- $B^{T} B=\left[\begin{array}{ll}0 & 1 \\ 1 & 0 \\ 0 & 0\end{array}\right]\left[\begin{array}{lll}0 & 1 & 0 \\ 1 & 0 & 0\end{array}\right]=\left[\begin{array}{lll}1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0\end{array}\right]$
- $B B^{T}=\left[\begin{array}{lll}0 & 1 & 0 \\ 1 & 0 & 0\end{array}\right]\left[\begin{array}{ll}0 & 1 \\ 1 & 0 \\ 0 & 0\end{array}\right]=\left[\begin{array}{ll}1 & 0 \\ 0 & 1\end{array}\right]$
- Solving $\left|B^{T} B-\lambda I\right|=0$ we find $\lambda=\{1,1,0\}$


## Pseudoinverse Exercise

## Solution

- Corresponding eigenvectors $\left[\begin{array}{l}1 \\ 0 \\ 0\end{array}\right],\left[\begin{array}{l}0 \\ 1 \\ 0\end{array}\right],\left[\begin{array}{l}0 \\ 0 \\ 1\end{array}\right]$
$\hookrightarrow \Sigma=\left[\begin{array}{lll}1 & 0 & 0 \\ 0 & 1 & 0\end{array}\right], \quad V=\left[\begin{array}{lll}1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1\end{array}\right], \quad U=\left[\begin{array}{ll}1 & 0 \\ 0 & 1\end{array}\right]$
- $B^{\dagger}=V \Sigma^{\dagger} U^{T}=\left[\begin{array}{lll}1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1\end{array}\right]\left[\begin{array}{ll}1 & 0 \\ 0 & 1 \\ 0 & 0\end{array}\right]\left[\begin{array}{ll}0 & 1 \\ 1 & 0\end{array}\right]=\left[\begin{array}{ll}0 & 1 \\ 1 & 0 \\ 0 & 0\end{array}\right]$
- $C^{T} C=\left[\begin{array}{ll}1 & 0 \\ 1 & 0\end{array}\right]\left[\begin{array}{ll}1 & 1 \\ 0 & 0\end{array}\right]=\left[\begin{array}{ll}1 & 1 \\ 1 & 1\end{array}\right]$
- $C C^{T}=\left[\begin{array}{ll}1 & 1 \\ 0 & 0\end{array}\right]\left[\begin{array}{ll}1 & 0 \\ 1 & 0\end{array}\right]=\left[\begin{array}{ll}2 & 0 \\ 0 & 0\end{array}\right]$


## Pseudoinverse Exercise

## Solution

- Solving $\left|C^{T} C-\lambda I\right|=0$ we find $\lambda=\{2,0\}$, corresponding eigenvectors $\left[\begin{array}{l}1 \\ 1\end{array}\right],\left[\begin{array}{c}-1 \\ 1\end{array}\right]$
- Solving $\left|C C^{T}-\lambda I\right|=0$ we find $\lambda=\{2,0\}$, corresponding eigenvectors $\left[\begin{array}{l}1 \\ 0\end{array}\right],\left[\begin{array}{l}0 \\ 1\end{array}\right]$

$$
\hookrightarrow \Sigma=\left[\begin{array}{cc}
\sqrt{2} & 0 \\
0 & 0
\end{array}\right], \quad U=\left[\begin{array}{ll}
1 & 0 \\
0 & 1
\end{array}\right], \quad\left[\begin{array}{cc}
\frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} \\
\frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}}
\end{array}\right]
$$

- $C^{\dagger}=V \Sigma^{\dagger} U^{T}=\left[\begin{array}{cc}\frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}}\end{array}\right]\left[\begin{array}{cc}\frac{1}{\sqrt{2}} & 0 \\ 0 & 0\end{array}\right]\left[\begin{array}{ll}1 & 0 \\ 0 & 1\end{array}\right]=\left[\begin{array}{cc}\frac{1}{2} & 0 \\ \frac{1}{2} & 0\end{array}\right]$


## THANK YOU!

Slides available at:
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