3. Matrices

- notation and terminology
- matrix operations
- linear and affine functions
- complexity
Matrix

a rectangular array of numbers, for example

\[
A = \begin{bmatrix}
0 & 1 & -2.3 & 0.1 \\
1.3 & 4 & -0.1 & 0 \\
4.1 & -1 & 0 & 1.7
\end{bmatrix}
\]

• numbers in array are the elements (entries, coefficients, components)

• \(A_{ij}\) is the \(i, j\) element of \(A\); \(i\) is its row index, \(j\) the column index

• size (dimensions) of the matrix is specified as (\#rows) \(\times\) (\#columns)
  for example, \(A\) is a \(3 \times 4\) matrix

• set of \(m \times n\) matrices with real elements is written \(\mathbb{R}^{m \times n}\)

• set of \(m \times n\) matrices with complex elements is written \(\mathbb{C}^{m \times n}\)
Other conventions

- many authors use parentheses as delimiters:

\[
A = \begin{pmatrix}
0 & 1 & -2.3 & 0.1 \\
1.3 & 4 & -0.1 & 0 \\
4.1 & -1 & 0 & 1.7
\end{pmatrix}
\]

- often \( a_{ij} \) is used to denote the \( i, j \) element of \( A \)
Matrix shapes

Scalar: we don’t distinguish between a $1 \times 1$ matrix and a scalar

Vector: we don’t distinguish between an $n \times 1$ matrix and an $n$-vector

Row and column vectors

- a $1 \times n$ matrix is called a row vector
- an $n \times 1$ matrix is called a column vector (or just vector)

Tall, wide, square matrices: an $m \times n$ matrix is

- tall if $m > n$
- wide if $m < n$
- square if $m = n$
Block matrix

- a block matrix is a rectangular array of matrices
- elements in the array are the blocks or submatrices of the block matrix

Example

\[
A = \begin{bmatrix}
B & C \\
D & E
\end{bmatrix}
\]

is a $2 \times 2$ block matrix; if the blocks are

\[
B = \begin{bmatrix}
2 \\
1
\end{bmatrix}, \quad
C = \begin{bmatrix}
0 & 2 & 3 \\
5 & 4 & 7
\end{bmatrix}, \quad
D = \begin{bmatrix}
1
\end{bmatrix}, \quad
E = \begin{bmatrix}
-1 & 6 & 0
\end{bmatrix}
\]

then

\[
A = \begin{bmatrix}
2 & 0 & 2 & 3 \\
1 & 5 & 4 & 7 \\
1 & -1 & 6 & 0
\end{bmatrix}
\]

Note: dimensions of the blocks must be compatible!
Rows and columns

A matrix can be viewed as a block matrix with row/column vector blocks

• $m \times n$ matrix $A$ as $1 \times n$ block matrix

$$A = \begin{bmatrix} a_1 & a_2 & \cdots & a_n \end{bmatrix}$$

each $a_j$ is an $m$-vector (the $j$th column of $A$)

• $m \times n$ matrix $A$ as $m \times 1$ block matrix

$$A = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_m \end{bmatrix}$$

each $b_i$ is a $1 \times n$ row vector (the $i$th row of $A$)
Special matrices

Zero matrix

• matrix with $A_{ij} = 0$ for all $i, j$
• notation: 0 (usually) or $0_{m \times n}$ (if dimension is not clear from context)

Identity matrix

• square matrix with $A_{ij} = 1$ if $i = j$ and $A_{ij} = 0$ if $i \neq j$
• notation: $I$ (usually) or $I_n$ (if dimension is not clear from context)
• columns of $I_n$ are unit vectors $e_1, e_2, \ldots, e_n$; for example,

$$I_3 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} e_1 \\ e_2 \\ e_3 \end{bmatrix}$$
Symmetric and Hermitian matrices

**Symmetric matrix:** square with $A_{ij} = A_{ji}$

\[
\begin{bmatrix}
4 & 3 & -2 \\
3 & -1 & 5 \\
-2 & 5 & 0
\end{bmatrix},
\begin{bmatrix}
4 + 3j & 3 - 2j & 0 \\
3 - 2j & -j & -2j \\
0 & -2j & 3
\end{bmatrix}
\]

**Hermitian matrix:** square with $A_{ij} = \bar{A}_{ji}$ (complex conjugate of $A_{ij}$)

\[
\begin{bmatrix}
4 & 3 - 2j & -1 + j \\
3 + 2j & -1 & 2j \\
-1 - j & -2j & 3
\end{bmatrix}
\]

note: diagonal elements are real (since $A_{ii} = \bar{A}_{ii}$)
Structured matrices

matrices with special patterns or structure arise in many applications

- diagonal matrix: square with $A_{ij} = 0$ for $i \neq j$
  \[
  \begin{bmatrix}
  -1 & 0 & 0 \\
  0 & 2 & 0 \\
  0 & 0 & -5
  \end{bmatrix},
  \begin{bmatrix}
  -1 & 0 & 0 \\
  0 & 0 & 0 \\
  0 & 0 & -5
  \end{bmatrix}
  \]

- lower triangular matrix: square with $A_{ij} = 0$ for $i < j$
  \[
  \begin{bmatrix}
  4 & 0 & 0 \\
  3 & -1 & 0 \\
  -1 & 5 & -2
  \end{bmatrix},
  \begin{bmatrix}
  4 & 0 & 0 \\
  0 & -1 & 0 \\
  -1 & 0 & -2
  \end{bmatrix}
  \]

- upper triangular matrix: square with $A_{ij} = 0$ for $i > j$

Sparse matrices

A matrix is *sparse* if most (almost all) of its elements are zero.

- Sparse matrix storage formats and algorithms exploit sparsity.
- Efficiency depends on the number of nonzeros and their positions.
- Positions of nonzeros are visualized in a ‘spy plot’.

**Example**

- 2,987,012 rows and columns
- 26,621,983 nonzeros

(Freescale/FullChip matrix from Univ. of Florida Sparse Matrix Collection)
Outline

- notation and terminology
- matrix operations
- linear and affine functions
- complexity
Scalar-matrix multiplication and addition

Scalar-matrix multiplication:

scalar-matrix product of $m \times n$ matrix $A$ with scalar $\beta$

$$\beta A = \begin{bmatrix}
\beta A_{11} & \beta A_{12} & \cdots & \beta A_{1n} \\
\beta A_{21} & \beta A_{22} & \cdots & \beta A_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
\beta A_{m1} & \beta A_{m2} & \cdots & \beta A_{mn}
\end{bmatrix}$$

$A$ and $\beta$ can be real or complex

**Addition:** sum of two $m \times n$ matrices $A$ and $B$ (real or complex)

$$A + B = \begin{bmatrix}
A_{11} + B_{11} & A_{12} + B_{12} & \cdots & A_{1n} + B_{1n} \\
A_{21} + B_{21} & A_{22} + B_{22} & \cdots & A_{2n} + B_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
A_{m1} + B_{m1} & A_{m2} + B_{m2} & \cdots & A_{mn} + B_{mn}
\end{bmatrix}$$
Transpose

the *transpose* of an $m \times n$ matrix $A$ is the $n \times m$ matrix

$$A^T = \begin{bmatrix}
A_{11} & A_{21} & \cdots & A_{m1} \\
A_{12} & A_{22} & \cdots & A_{m2} \\
\vdots & \vdots & \ddots & \vdots \\
A_{1n} & A_{2n} & \cdots & A_{mn}
\end{bmatrix}$$

- $(A^T)^T = A$
- a symmetric matrix satisfies $A = A^T$
- $A$ may be complex, but transpose of complex matrices is rarely needed
- transpose of matrix-scalar product and matrix sum

$$(\beta A)^T = \beta A^T, \quad (A + B)^T = A^T + B^T$$
Conjugate transpose

the *conjugate transpose* of an $m \times n$ matrix $A$ is the $n \times m$ matrix

$$A^H = \begin{bmatrix}
\bar{A}_{11} & \bar{A}_{21} & \cdots & \bar{A}_{m1} \\
\bar{A}_{12} & \bar{A}_{22} & \cdots & \bar{A}_{m2} \\
\vdots & \vdots & \ddots & \vdots \\
\bar{A}_{1n} & \bar{A}_{2n} & \cdots & \bar{A}_{mn}
\end{bmatrix}$$

($\bar{A}_{ij}$ is complex conjugate of $A_{ij}$)

- $A^H = A^T$ if $A$ is a real matrix
- a Hermitian matrix satisfies $A = A^H$
- conjugate transpose of matrix-scalar product and matrix sum

$$(\beta A)^H = \bar{\beta} A^H, \quad (A + B)^H = A^H + B^H$$
Matrix-matrix product

product of $m \times n$ matrix $A$ and $n \times p$ matrix $B$ ($A$, $B$ are real or complex)

$$C = AB$$

is the $m \times p$ matrix with $i, j$ element

$$C_{ij} = A_{i1}B_{1j} + A_{i2}B_{2j} + \cdots + A_{in}B_{nj}$$

dimensions must be compatible:

$$\#\text{columns in } A = \#\text{rows in } B$$
Exercise: paths in directed graph

directed graph with $n = 5$ vertices

matrix representation

$$A = \begin{bmatrix}
0 & 1 & 0 & 0 & 1 \\
1 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 1 & 1 \\
1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0
\end{bmatrix}$$

$A_{ij} = 1$ indicates an edge $j \to i$

Question: give a graph interpretation of $A^2 = AA$, $A^3 = AAA$, ...

$$A^2 = \begin{bmatrix}
1 & 0 & 1 & 1 & 0 \\
0 & 1 & 0 & 1 & 2 \\
1 & 0 & 0 & 1 & 0 \\
0 & 1 & 0 & 0 & 1 \\
1 & 0 & 0 & 1 & 0
\end{bmatrix}, \quad A^3 = \begin{bmatrix}
1 & 1 & 0 & 1 & 2 \\
2 & 0 & 1 & 2 & 0 \\
1 & 1 & 0 & 0 & 1 \\
1 & 0 & 1 & 1 & 0 \\
0 & 1 & 0 & 0 & 1
\end{bmatrix}, \quad \ldots$$
Properties of matrix-matrix product

- **associative:** \((AB)C = A(BC)\) so we write \(ABC\)

- **associative with scalar-matrix multiplication:** \((\gamma A)B = \gamma(AB) = \gamma AB\)

- **distributes with sum:**

  \[
  A(B + C) = AB + AC, \quad (A + B)C = AC + BC
  \]

- **transpose and conjugate transpose of product:**

  \[
  (AB)^T = B^T A^T, \quad (AB)^H = B^H A^H
  \]

- **not commutative:** \(AB \neq BA\) in general; for example,

  \[
  \begin{bmatrix}
  -1 & 0 \\
  0 & 1
  \end{bmatrix}
  \begin{bmatrix}
  0 & 1 \\
  1 & 0
  \end{bmatrix}
  \neq
  \begin{bmatrix}
  0 & 1 \\
  1 & 0
  \end{bmatrix}
  \begin{bmatrix}
  -1 & 0 \\
  0 & 1
  \end{bmatrix}
  \]

  there are exceptions, e.g., \(AI = IA\) for square \(A\)
Notation for vector inner product

- inner product of \( a, b \in \mathbb{R}^n \) (see page 1-17):

\[
b^T a = b_1 a_1 + b_2 a_2 + \cdots + b_n a_n = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_n \end{bmatrix}^T \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{bmatrix}
\]

product of the transpose of the column vector \( b \) and the column vector \( a \)

- inner product of \( a, b \in \mathbb{C}^n \) (see page 1-24):

\[
b^H a = \bar{b}_1 a_1 + \bar{b}_2 a_2 + \cdots + \bar{b}_n a_n = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_n \end{bmatrix}^H \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{bmatrix}
\]

product of conjugate transpose of the column vector \( b \) and the column vector \( a \)
Matrix-matrix product and block matrices

block-matrices can be multiplied as regular matrices

**Example:** product of two $2 \times 2$ block matrices

\[
\begin{bmatrix}
A & B \\
C & D
\end{bmatrix}
\begin{bmatrix}
W & Y \\
X & Z
\end{bmatrix}
= \begin{bmatrix}
AW + BX & AY + BZ \\
CW + DX & CY + DZ
\end{bmatrix}
\]

if the dimensions of the blocks are compatible
Outline

• notation and terminology

• matrix operations

• linear and affine functions

• complexity
Matrix-vector product

product of $m \times n$ matrix $A$ with $n$-vector (or $n \times 1$ matrix) $x$

$$Ax = \begin{bmatrix} A_{11}x_1 + A_{12}x_2 + \cdots + A_{1n}x_n \\ A_{21}x_1 + A_{22}x_2 + \cdots + A_{2n}x_n \\ \vdots \\ A_{m1}x_1 + A_{m2}x_2 + \cdots + A_{mn}x_n \end{bmatrix}$$

- dimensions must be compatible: number of columns of $A$ equals the size of $x$
- $Ax$ is a linear combination of the columns of $A$:

$$Ax = \begin{bmatrix} a_1 & a_2 & \cdots & a_n \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} = x_1a_1 + x_2a_2 + \cdots + x_na_n$$

each $a_i$ is an $m$-vector ($i$th column of $A$)
Linear function

A function $f : \mathbb{R}^n \rightarrow \mathbb{R}^m$ is linear if superposition holds:

$$f(\alpha x + \beta y) = \alpha f(x) + \beta f(y)$$

for all $n$-vectors $x, y$ and all scalars $\alpha, \beta$

**Extension:** If $f$ is linear, superposition holds for any linear combination:

$$f(\alpha_1 u_1 + \alpha_2 u_2 + \cdots + \alpha_p u_p) = \alpha_1 f(u_1) + \alpha_2 f(u_2) + \cdots + \alpha_p f(u_p)$$

for all scalars, $\alpha_1, \ldots, \alpha_p$ and all $n$-vectors $u_1, \ldots, u_p$
Matrix-vector product function

for fixed $A \in \mathbb{R}^{m \times n}$, define a function $f : \mathbb{R}^n \rightarrow \mathbb{R}^m$ as

$$f(x) = Ax$$

- any function of this type is linear: $A(\alpha x + \beta y) = \alpha(Ax) + \beta(Ay)$
- every linear function can be written as a matrix-vector product function:

$$f(x) = f(x_1 e_1 + x_2 e_2 + \cdots + x_n e_n)$$

$$= x_1 f(e_1) + x_2 f(e_2) + \cdots + x_n f(e_n)$$

$$= \begin{bmatrix} f(e_1) & \cdots & f(e_n) \end{bmatrix} \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix}$$

hence, $f(x) = Ax$ with $A = \begin{bmatrix} f(e_1) & f(e_2) & \cdots & f(e_n) \end{bmatrix}$
Input-output (operator) interpretation

think of a function $f : \mathbb{R}^n \rightarrow \mathbb{R}^m$ in terms of its effect on $x$

$$x \xrightarrow{} A \xrightarrow{} y = f(x) = Ax$$

- signal processing/control interpretation: $n$ inputs $x_i$, $m$ outputs $y_i$
- $f$ is linear if we can represent its action on $x$ as a product $f(x) = Ax$
Examples ($f : \mathbb{R}^3 \rightarrow \mathbb{R}^3$)

- $f$ reverses the order of the components of $x$
  
  a linear function: $f(x) = Ax$ with

  $$A = \begin{bmatrix} 0 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 0 \end{bmatrix}$$

- $f$ sorts the components of $x$ in decreasing order: not linear

- $f$ scales $x_1$ by a given number $d_1$, $x_2$ by $d_2$, $x_3$ by $d_3$
  
  a linear function: $f(x) = Ax$ with

  $$A = \begin{bmatrix} d_1 & 0 & 0 \\ 0 & d_2 & 0 \\ 0 & 0 & d_3 \end{bmatrix}$$

- $f$ replaces each $x_i$ by its absolute value $|x_i|$: not linear
Operator interpretation of matrix-matrix product

explains why in general $AB \neq BA$

Example

$$A = \begin{bmatrix} -1 & 0 \\ 0 & 1 \end{bmatrix}, \quad B = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$$

• $f(x) = ABx$ reverses order of elements; then changes sign of first element

• $f(x) = BAx$ changes sign of 1st element; then reverses order
Reverser and circular shift

Reverser matrix

\[
A = \begin{bmatrix}
0 & 0 & \cdots & 0 & 1 \\
0 & 0 & \cdots & 1 & 0 \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
0 & 1 & \cdots & 0 & 0 \\
1 & 0 & \cdots & 0 & 0
\end{bmatrix}, \quad Ax = \begin{bmatrix}
x_n \\
x_{n-1} \\
\vdots \\
x_2 \\
x_1
\end{bmatrix}
\]

Circular shift matrix

\[
A = \begin{bmatrix}
0 & 0 & \cdots & 0 & 1 \\
1 & 0 & \cdots & 0 & 0 \\
0 & 1 & \cdots & 0 & 0 \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
0 & 0 & \cdots & 1 & 0
\end{bmatrix}, \quad Ax = \begin{bmatrix}
x_n \\
x_1 \\
x_2 \\
\vdots \\
x_{n-1}
\end{bmatrix}
\]
Permutation

Permutation matrix

• a square 0-1 matrix with one element 1 per row and one element 1 per column
• equivalently, an identity matrix with columns reordered
• equivalently, an identity matrix with rows reordered

\( Ax \) is a permutation of the elements of \( x \)

Example

\[
A = \begin{bmatrix}
0 & 1 & 0 & 0 \\
0 & 0 & 0 & 1 \\
1 & 0 & 0 & 0 \\
0 & 0 & 1 & 0
\end{bmatrix}, \quad Ax = \begin{bmatrix}
x_2 \\
x_4 \\
x_1 \\
x_3
\end{bmatrix}
\]
Rotation in a plane

\[ A = \begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix} \]

\( Ax \) is \( x \) rotated counterclockwise over an angle \( \theta \)
Projection on line and reflection

- projection on line through \(a\) (see page 2-12):

  \[
y = \frac{a^T x}{\|a\|^2} a = Ax \quad \text{with} \quad A = \frac{1}{\|a\|^2} aa^T
  \]

- reflection with respect to line through \(a\)

  \[
z = x + 2(y - x) = Bx, \quad \text{with} \quad B = \frac{2}{\|a\|^2} aa^T - I
  \]
Node-arc incidence matrix

- directed graph (network) with \( m \) vertices, \( n \) arcs (directed edges)
- incidence matrix is \( m \times n \) matrix \( A \) with

\[
A_{ij} = \begin{cases} 
1 & \text{if arc } j \text{ enters node } i \\
-1 & \text{if arc } j \text{ leaves node } i \\
0 & \text{otherwise}
\end{cases}
\]

\[
A = \begin{bmatrix}
-1 & -1 & 0 & 1 & 0 \\
1 & 0 & -1 & 0 & 0 \\
0 & 0 & 1 & -1 & -1 \\
0 & 1 & 0 & 0 & 1
\end{bmatrix}
\]
Kirchhoff’s current law

\[ n\text{-vector } x = (x_1, x_2, \ldots, x_n) \text{ with } x_j \text{ the current through arc } j \]

\[(Ax)_i = \sum_{\text{arc } j \text{ enters } \node i} x_j - \sum_{\text{arc } j \text{ leaves } \node i} x_j \]

\[= \text{ total current arriving at node } i \]

\[
A = \begin{bmatrix}
-x_1 - x_2 + x_4 \\
x_1 - x_3 \\
x_3 - x_4 - x_5 \\
x_2 + x_5
\end{bmatrix}
\]
Kirchhoff’s voltage law

\( m \)-vector \( y = (y_1, y_2, \ldots, y_m) \) with \( y_i \) the potential at node \( i \)

\[
(A^T y)_j = y_k - y_l \quad \text{if edge } j \text{ goes from node } l \text{ to } k
\]

\( \quad = \text{ negative of voltage across arc } j \)

\[
A^T y = \begin{bmatrix}
y_2 - y_1 \\
y_4 - y_1 \\
y_3 - y_2 \\
y_1 - y_3 \\
y_4 - y_3 \\
\end{bmatrix}
\]
**Convolution**

The *convolution* of an $n$-vector $a$ and an $m$-vector $b$ is the $(n + m - 1)$-vector $c$

\[
c_k = \sum_{\text{all } i \text{ and } j \text{ with } i + j = k + 1} a_i b_j
\]

notation: $c = a \ast b$

**Example:** $n = 4$, $m = 3$

\[
\begin{align*}
c_1 &= a_1 b_1 \\
c_2 &= a_1 b_2 + a_2 b_1 \\
c_3 &= a_1 b_3 + a_2 b_2 + a_3 b_1 \\
c_4 &= a_2 b_3 + a_3 b_2 + a_4 b_1 \\
c_5 &= a_3 b_3 + a_4 b_2 \\
c_6 &= a_4 b_3
\end{align*}
\]
Properties

Interpretation: if $a$ and $b$ are the coefficients of polynomials

\[ p(x) = a_1 + a_2x + \cdots + a_nx^{n-1}, \quad q(x) = b_1 + b_2x + \cdots + b_mx^{m-1} \]

then $c = a \ast b$ gives the coefficients of the product polynomial

\[ p(x)q(x) = c_1 + c_2x + c_3x^2 + \cdots + c_{n+m-1}x^{n+m-2} \]

Properties

- symmetric: $a \ast b = b \ast a$
- associative: $(a \ast b) \ast c = a \ast (b \ast c)$
- if $a \ast b = 0$ then $a = 0$ or $b = 0$

these properties follow directly from the polynomial product interpretation
Example: moving average of a time series

- $n$-vector $x$ represents a time series
- the 3-period moving average of the time series is the time series

$$y_k = \frac{1}{3}(x_k + x_{k-1} + x_{k-2}), \quad k = 1, 2, \ldots, n + 2$$

(with $x_k$ interpreted as zero for $k < 1$ and $k > n$)
- this can be expressed as a convolution $y = a \ast x$ with $a = (1/3, 1/3, 1/3)$
Convolution and Toeplitz matrices

• \( c = a \ast b \) is a linear function of \( b \) if we fix \( a \)

• \( c = a \ast b \) is a linear function of \( a \) if we fix \( b \)

Example: convolution \( c = a \ast b \) of a 4-vector \( a \) and a 3-vector \( b \)

\[
\begin{bmatrix}
  c_1 \\
  c_2 \\
  c_3 \\
  c_4 \\
  c_5 \\
  c_6
\end{bmatrix} = \begin{bmatrix}
  a_1 & 0 & 0 \\
  a_2 & a_1 & 0 \\
  a_3 & a_2 & a_1 \\
  a_4 & a_3 & a_2 \\
  0 & a_4 & a_3 \\
  0 & 0 & a_4
\end{bmatrix} \begin{bmatrix}
  b_1 \\
  b_2 \\
  b_3
\end{bmatrix} = \begin{bmatrix}
  b_1 & 0 & 0 & 0 \\
  b_2 & b_1 & 0 & 0 \\
  b_3 & b_2 & b_1 & 0 \\
  0 & b_3 & b_2 & b_1 \\
  0 & 0 & b_3 & b_2 \\
  0 & 0 & 0 & b_3
\end{bmatrix} \begin{bmatrix}
  a_1 \\
  a_2 \\
  a_3 \\
  a_4
\end{bmatrix}
\]

the matrices in these matrix-vector products are called Toeplitz matrices
Vandermonde matrix

- polynomial of degree $n - 1$ or less with coefficients $x_1, x_2, \ldots, x_n$:

$$p(t) = x_1 + x_2 t + x_3 t^2 + \cdots + x_n t^{n-1}$$

- values of $p(t)$ at $m$ points $t_1, \ldots, t_m$:

$$\begin{bmatrix} p(t_1) \\ p(t_2) \\ \vdots \\ p(t_m) \end{bmatrix} = \begin{bmatrix} 1 & t_1 & \cdots & t_1^{n-1} \\ 1 & t_2 & \cdots & t_2^{n-1} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & t_m & \cdots & t_m^{n-1} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} = Ax$$

the matrix $A$ is called a Vandermonde matrix

- $f(x) = Ax$ maps coefficients of polynomial to function values
Discrete Fourier transform

the DFT maps a complex $n$-vector $(x_1, x_2, \ldots, x_n)$ to the complex $n$-vector

$$
\begin{bmatrix}
y_1 \\
y_2 \\
y_3 \\
\vdots \\
y_n
\end{bmatrix} =
\begin{bmatrix}
1 & 1 & 1 & \cdots & 1 \\
1 & \omega^{-1} & \omega^{-2} & \cdots & \omega^{-(n-1)} \\
1 & \omega^{-2} & \omega^{-4} & \cdots & \omega^{-2(n-1)} \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
1 & \omega^{-(n-1)} & \omega^{-2(n-1)} & \cdots & \omega^{-(n-1)(n-1)}
\end{bmatrix}
\begin{bmatrix}
x_1 \\
x_2 \\
x_3 \\
\vdots \\
x_n
\end{bmatrix}
= Wx
$$

where $\omega = e^{2\pi j/n}$ (and $j = \sqrt{-1}$)

- DFT matrix $W \in \mathbb{C}^{n \times n}$ has $k, l$ element $W_{kl} = \omega^{-(k-1)(l-1)}$
- a Vandermonde matrix with $m = n$ and

$$
t_1 = 1, \quad t_2 = \omega^{-1}, \quad t_3 = \omega^{-2}, \quad \ldots, \quad t_n = \omega^{-(n-1)}
$$
Affine function

A function $f : \mathbb{R}^n \to \mathbb{R}^m$ is **affine** if it satisfies

$$f(\alpha x + \beta y) = \alpha f(x) + \beta f(y)$$

for all $n$-vectors $x, y$ and all scalars $\alpha, \beta$ with $\alpha + \beta = 1$

**Extension:** If $f$ is affine, then

$$f(\alpha_1 u_1 + \alpha_2 u_2 + \cdots + \alpha_m u_m) = \alpha_1 f(u_1) + \alpha_2 f(u_2) + \cdots + \alpha_m f(u_m)$$

for all $n$-vectors $u_1, \ldots, u_m$ and all scalars $\alpha_1, \ldots, \alpha_m$ with

$$\alpha_1 + \alpha_2 + \cdots + \alpha_m = 1$$
Affine functions and matrix-vector product

for fixed $A \in \mathbb{R}^{m \times n}$, $b \in \mathbb{R}^{m}$, define a function $f : \mathbb{R}^{n} \rightarrow \mathbb{R}^{m}$ by

$$f(x) = Ax + b$$

i.e., a matrix-vector product plus a constant

- any function of this type is affine: if $\alpha + \beta = 1$ then

$$A(\alpha x + \beta y) + b = \alpha(Ax + b) + \beta(Ax + b)$$

- every affine function can be written as $f(x) = Ax + b$ with:

$$A = \begin{bmatrix} f(e_1) - f(0) & f(e_2) - f(0) & \cdots & f(e_n) - f(0) \end{bmatrix}$$

and $b = f(0)$
Affine approximation

first-order Taylor approximation of differentiable \( f : \mathbb{R}^n \to \mathbb{R}^m \) around \( z \):

\[
\hat{f}_i(x) = f_i(z) + \frac{\partial f_i}{\partial x_1}(z)(x_1 - z_1) + \cdots + \frac{\partial f_i}{\partial x_n}(z)(x_n - z_n), \quad i = 1, \ldots, m
\]

in matrix-vector notation: \( \hat{f}(x) = f(z) + Df(z)(x - z) \) where

\[
Df(z) = \begin{bmatrix}
\frac{\partial f_1}{\partial x_1}(z) & \frac{\partial f_1}{\partial x_2}(z) & \cdots & \frac{\partial f_1}{\partial x_n}(z) \\
\frac{\partial f_2}{\partial x_1}(z) & \frac{\partial f_2}{\partial x_2}(z) & \cdots & \frac{\partial f_2}{\partial x_n}(z) \\
\vdots & \vdots & \ddots & \vdots \\
\frac{\partial f_m}{\partial x_1}(z) & \frac{\partial f_m}{\partial x_2}(z) & \cdots & \frac{\partial f_m}{\partial x_n}(z)
\end{bmatrix} = \begin{bmatrix}
\nabla f_1(z)^T \\
\nabla f_2(z)^T \\
\vdots \\
\nabla f_m(z)^T
\end{bmatrix}
\]

- \( Df(z) \) is called the \textit{derivative matrix} or \textit{Jacobian matrix} of \( f \) at \( z \)
- \( \hat{f} \) is a local affine approximation of \( f \) around \( z \)
Example

\[ f(x) = \begin{bmatrix} f_1(x) \\ f_2(x) \end{bmatrix} = \begin{bmatrix} e^{2x_1 + x_2} - x_1 \\ x_1^2 - x_2 \end{bmatrix} \]

• derivative matrix

\[ Df(x) = \begin{bmatrix} 2e^{2x_1 + x_2} - 1 & e^{2x_1 + x_2} \\ 2x_1 & -1 \end{bmatrix} \]

• first order approximation of \( f \) around \( z = 0 \):

\[ \hat{f}(x) = \begin{bmatrix} \hat{f}_1(x) \\ \hat{f}_2(x) \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \end{bmatrix} + \begin{bmatrix} 1 & 1 \\ 0 & -1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \]
Outline

- notation and terminology
- matrix operations
- linear and affine functions
- complexity
Matrix-vector product

matrix-vector multiplication of $m \times n$ matrix $A$ and $n$-vector $x$:

$$y = Ax$$

requires $(2n - 1)m$ flops

- $m$ elements in $y$; each element requires an inner product of length $n$
- approximately $2mn$ for large $n$

**Special cases**: flop count is lower for structured matrices

- $A$ diagonal: $n$ flops
- $A$ lower triangular: $n^2$ flops
- $A$ sparse: #flops $\ll 2mn$
Matrix-matrix product

product of \( m \times n \) matrix \( A \) and \( n \times p \) matrix \( B \):

\[
C = AB
\]

requires \( mp(2n - 1) \) flops

- \( mp \) elements in \( C \); each element requires an inner product of length \( n \)
- approximately \( 2mnp \) for large \( n \)
Exercises

1. evaluate $y = ABx$ two ways ($A$ and $B$ are $n \times n$, $x$ is a vector)

- $y = (AB)x$ (first make product $C = AB$, then multiply $C$ with $x$)
- $y = A(Bx)$ (first make product $y = Bx$, then multiply $A$ with $y$)

both methods give the same answer, but which method is faster?

2. evaluate $y = (I + uv^T)x$ where $u, v, x$ are $n$-vectors

- $A = I + uv^T$ followed by $y = Ax$
  
  in MATLAB: $y = (\text{eye}(n) + u*v') * x$

- $w = (v^T x)u$ followed by $y = x + w$
  
  in MATLAB: $y = x + (v'*x) * u$