

Mathematics for Machine Learning

— Linear Algebra

Basis, Rank, Linear Mappings & Affine Spaces

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Credits for the resource

- The slides are based on the textbooks:
 - *Marc Peter Deisenroth, A. Aldo Faisal, and Cheng Soon Ong: Mathematics for Machine Learning. Cambridge University Press. 2020.*
 - *Arnold J. Insel, Lawrence E. Spence, Stephen H. Friedberg: Linear Algebra, 4th Edition. Prentice Hall. 2013.*
 - *Howard Anton, Chris Rorres, Anton Kaul: Elementary Linear Algebra, 12th Edition. Wiley. 2019.*
- We could partially refer to the monograph:
Francesco Orabona: A Modern Introduction to Online Learning.
<https://arxiv.org/abs/1912.13213>

Outline

- 1 Why linear algebra?
- 2 Vector Space
- 3 Basis & Dimension & Rank
- 4 Linear Mappings
- 5 Affine Spaces

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Why linear algebra?

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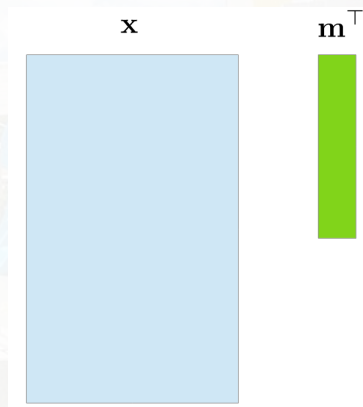
Why linear algebra?

- Crucial in the graduate school entrance examination.
- Matrix operations.
- Vectorization.

Vectorization Example (1/3)

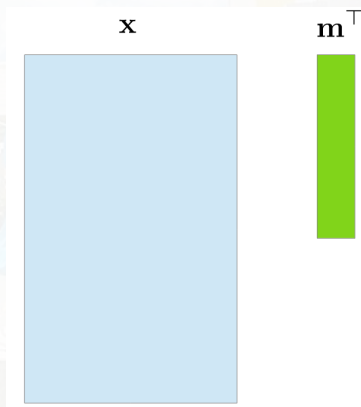
$$\begin{aligned}y_i &= \langle \mathbf{m}, \mathbf{x}_i \rangle \\ &= m_1 x_{i,1} + m_2 x_{i,2} + \dots + m_k x_{i,k}.\end{aligned}$$

```
m = np.random.rand(1,5)
x = np.random.rand(5000000,5)
#assume k=5
```



Vectorization Example (2/3)

```
start = time.time()
zer = []
for i in range(0,5000000):
    total = 0
    for j in range(0,5):
        total = total + x[i][j]*m[0][j]
    zer.append(total)
zer = np.array(zer)
end = time.time()
```



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```
In [8]: runfile('C:/Users/josep/_Project/
vectorization_matrix.py', wdir='C:/Users/josep/_Project')
Computation time = 13.515385389328003 seconds
```

Vectorization Example (3/3)

```
start = time.time()  
zer = np.matmul(x, m.T)  
end = time.time()
```

```
In [13]: runfile('C:/Users/josep/_Project/  
vectorization_matrix.py', wdir='C:/Users/josep/_Project')  
Computation time = 0.010425329208374023 seconds
```

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Group

Group

Consider a set \mathcal{G} and an operation $\otimes : \mathcal{G} \times \mathcal{G} \rightarrow \mathcal{G}$ defined on \mathcal{G} . Then $G : (\mathcal{G}, \otimes)$ is called a **group** if the following conditions hold:

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- ① $\forall x, y \in \mathcal{G}, x \otimes y \in \mathcal{G}$.
- ② $\forall x, y, z \in \mathcal{G}, (x \otimes y) \otimes z = x \otimes (y \otimes z)$.

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- 3 $\exists e \in \mathcal{G}$ such that $\forall x \in \mathcal{G}, x \otimes e = e \otimes x = x.$

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- If G is a group and $\forall x, y \in \mathcal{G}$ we have $x \otimes y = y \otimes x$, then G is an **Abelian** group.

Examples

- $(\mathbb{Z}, +)$: an Abelian group.
- $(\mathbb{N} \cup \{0\}, +)$ is NOT a group.
- (\mathbb{Z}, \cdot) is NOT a group.
- (\mathbb{R}, \cdot) is NOT a group.
- $(\mathbb{R} \setminus \{0\}, \cdot)$ is an Abelian group.
- $(\mathbb{R}^{m \times n}, +)$ is an Abelian group.

Vector Space

Vector Space

A real-valued vector space $V = (\mathcal{V}, +, \cdot)$ is a set \mathcal{V} with two operations:

$$+ : \mathcal{V} \times \mathcal{V} \rightarrow \mathcal{V}$$

$$\cdot : \mathbb{R} \times \mathcal{V} \rightarrow \mathcal{V}$$

where

- $(\mathcal{V}, +)$ is an Abelian group.
- Distributivity holds:
 - $\forall \lambda \in \mathbb{R}, \mathbf{x}, \mathbf{y} \in \mathcal{V}: \lambda \cdot (\mathbf{x} + \mathbf{y}) = \lambda \cdot \mathbf{x} + \lambda \cdot \mathbf{y}.$
 - $\forall \lambda, \psi \in \mathbb{R}, \mathbf{x} \in \mathcal{V}: (\lambda + \psi) \cdot \mathbf{x} = \lambda \cdot \mathbf{x} + \psi \cdot \mathbf{x}.$
- $\forall \lambda, \psi \in \mathbb{R}, \mathbf{x} \in \mathcal{V}: \lambda \cdot (\psi \cdot \mathbf{x}) = (\lambda\psi) \cdot \mathbf{x}.$
- $\forall \mathbf{x} \in \mathcal{V}: 1 \cdot \mathbf{x} = \mathbf{x}.$

★ Note: A vector multiplication is not defined.

Vector Subspaces

Vector Subspace

Let $V = (\mathcal{V}, +, \cdot)$ be a vector space and $\mathcal{U} \subset \mathcal{V}$ and $\mathcal{U} \neq \emptyset$. Then $U = (\mathcal{U}, +, \cdot)$ is called a vector **subspace** of V if U is a vector space with the operations $+$ and \cdot restricted to $\mathcal{U} \times \mathcal{U}$ and $\mathbb{R} \times \mathcal{U}$ respectively.

- Denote by $U \subseteq V$ a subspace U of V .

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- The intersection of arbitrarily many subspaces is a subspace.
- The solution of an **inhomogeneous system** of linear equations $A\mathbf{x} = \mathbf{b}$ for $\mathbf{b} \neq \mathbf{0}$ is NOT a subspace of \mathbb{R}^n .

Linear Combination

Linear Combination

Consider a vector space V and a finite number of vectors $\mathbf{x}_1, \dots, \mathbf{x}_k \in V$. Then, every $\mathbf{v} \in V$ of the form

$$\mathbf{v} = \lambda_1 \mathbf{x}_1 + \dots + \lambda_k \mathbf{x}_k = \sum_{i=1}^k \lambda_i \mathbf{x}_i \in V$$

with $\lambda_1, \dots, \lambda_k \in \mathbb{R}$ is a **linear combination** of the vectors $\mathbf{x}_1, \dots, \mathbf{x}_k$.

- **Question:** How to represent $\mathbf{0}$ as a linear combination of $\mathbf{x}_1, \dots, \mathbf{x}_k$?

Linearly Independent

Linear (In)dependence

Consider a vector space V with $k > 0$ vectors $\mathbf{x}_1, \dots, \mathbf{x}_k \in V$.

- If there is a nontrivial linear combination such that $\mathbf{0} = \sum_{i=1}^k \lambda_i \mathbf{x}_i$ with at least one $\lambda_i \neq 0$, then we say $\mathbf{x}_1, \dots, \mathbf{x}_k$ are **linearly dependent**.
- If only the trivial solution exists (i.e., $\lambda_1 = \lambda_2 = \dots = \lambda_k = 0$), then we say $\mathbf{x}_1, \dots, \mathbf{x}_k$ are **linearly independent**.

Recall some facts

- If at least one of vectors $\mathbf{x}_1, \dots, \mathbf{x}_k$ is $\mathbf{0}$ then they are linearly dependent.

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- Two identical vectors are linearly dependent.
- Write all vectors as rows (or columns) of a matrix and perform Gaussian elimination until the matrix is in row echelon form.

Remark (1/2)

Consider a vector space V with k linearly independent vectors $\mathbf{b}_1, \dots, \mathbf{b}_k$ and m linear combinations

$$\mathbf{x}_1 = \sum_{i=1}^k \lambda_{i,1} \mathbf{b}_i$$

$$\vdots$$

$$\mathbf{x}_m = \sum_{i=1}^k \lambda_{i,m} \mathbf{b}_i$$

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- Define $\mathbf{B} = [\mathbf{b}_1, \dots, \mathbf{b}_k]$ (i.e., a matrix), then

$$\mathbf{x}_j = \mathbf{B} \boldsymbol{\lambda}_j, \text{ for } \boldsymbol{\lambda}_j = \begin{bmatrix} \lambda_{1j} \\ \vdots \\ \lambda_{kj} \end{bmatrix}, j = 1, \dots, m.$$

Remark (2/2)

We want to test whether $\mathbf{x}_1, \dots, \mathbf{x}_m$ are linearly independent.

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- Why does the last equality hold?
- $\{\mathbf{x}_1, \dots, \mathbf{x}_m\}$ are linearly independent iff $\{\boldsymbol{\lambda}_1, \dots, \boldsymbol{\lambda}_m\}$ are linearly independent.
- **Note:** m linear combinations of k vectors $\mathbf{x}_1, \dots, \mathbf{x}_k$ are linearly dependent if $m > k$.

Example

Consider a set of linearly independent vectors $\mathbf{b}_1, \mathbf{b}_2, \mathbf{b}_3, \mathbf{b}_4 \in \mathbb{R}^n$ and

$$\begin{aligned}\mathbf{x}_1 &= \mathbf{b}_1 - 2\mathbf{b}_2 + \mathbf{b}_3 - \mathbf{b}_4 \\ \mathbf{x}_2 &= -4\mathbf{b}_1 - 2\mathbf{b}_2 + 4\mathbf{b}_4 \\ \mathbf{x}_3 &= 2\mathbf{b}_1 + 3\mathbf{b}_2 - \mathbf{b}_3 - 3\mathbf{b}_4 \\ \mathbf{x}_4 &= 17\mathbf{b}_1 - 10\mathbf{b}_2 + 11\mathbf{b}_3 + \mathbf{b}_4\end{aligned}$$

Question: Is $\{\mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3, \mathbf{x}_4\}$ linearly independent?

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$$\mathbf{A} = \begin{bmatrix} 1 & -2 & 1 & -1 \\ -4 & -2 & 0 & 4 \\ 2 & 3 & -1 & 3 \\ 17 & -10 & 11 & 1 \end{bmatrix}$$

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$$\mathbf{A} = \begin{bmatrix} 1 & -2 & 1 & -1 \\ -4 & -2 & 0 & 4 \\ 2 & 3 & -1 & 3 \\ 17 & -10 & 11 & 1 \end{bmatrix} \longrightarrow \begin{bmatrix} 1 & -2 & 1 & -1 \\ 0 & 1 & -\frac{2}{5} & 0 \\ 0 & 0 & 1 & 5 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

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Basis

Spanning/Generating

Consider a vector space $V = (\mathcal{V}, +, \cdot)$ and a set $\mathcal{A} = \{\mathbf{x}_1, \dots, \mathbf{x}_k\} \subseteq \mathcal{V}$.

If every vector $\mathbf{v} \in \mathcal{V}$ can be expressed as a linear combination of vectors in \mathcal{A} , then \mathcal{A} is called a **spanning set (or generating set)** of V .

- \mathcal{A} spans V ; $\text{span}(\mathcal{A}) = V$.

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Basis

Consider a vector space $V = (\mathcal{V}, +, \cdot)$ and a set $\mathcal{A} \subseteq \mathcal{V}$. Then if one of the following condition holds, we say that \mathcal{A} is a **basis** of V .

- \mathcal{A} is a minimal generating set of V .

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- \mathcal{A} is a minimal generating set of V .
No smaller set $\mathcal{A}' \subsetneq \mathcal{A} \subseteq \mathcal{V}$ that spans V .
- \mathcal{A} spans V and is also linearly independent.

Dimension

Dimension

The number of basis vectors of a vector space V is the *dimension* of V and denoted by $\dim(V)$.

- For $U \subset V$ a subspace of V , $\dim(U) \leq \dim(V)$

Example

Let $V = \mathbb{R}[x]$ be the vector space of all real-coefficient polynomials. Define

$$U = x\mathbb{R}[x] = \{xp(x) : p(x) \in \mathbb{R}[x]\},$$

the set of all polynomials whose constant term is 0.

Claim. $U \subsetneq V$ and $\dim(U) = \dim(V)$.

- U is a subspace of V : it is closed under addition and scalar multiplication by construction.
- U is proper: $1 \in V$ but $1 \notin U$ (no polynomial p satisfies $xp(x) = 1$).
- A standard basis of V is $\mathcal{B}_V = \{1, x, x^2, x^3, \dots\}$. Hence $\dim(V) = |\mathcal{B}_V| = \aleph_0$ (countably infinite).
- A basis of U is $\mathcal{B}_U = \{x, x^2, x^3, \dots\}$, so $\dim(U) = |\mathcal{B}_U| = \aleph_0$.

Therefore $U \subsetneq V$ but $\dim(U) = \dim(V) = \aleph_0$.

Exercise

$$\text{Given } \mathbf{x}_1 = \begin{bmatrix} 1 \\ 2 \\ -1 \\ -1 \\ -1 \end{bmatrix}, \mathbf{x}_2 = \begin{bmatrix} 2 \\ -1 \\ 1 \\ 2 \\ -2 \end{bmatrix}, \mathbf{x}_3 = \begin{bmatrix} 3 \\ -4 \\ 3 \\ 5 \\ -3 \end{bmatrix}, \mathbf{x}_4 = \begin{bmatrix} -1 \\ 8 \\ -5 \\ -6 \\ 1 \end{bmatrix}.$$

Find a basis of $\text{span}(\{\mathbf{x}_1, \dots, \mathbf{x}_4\})$.

Rank

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The number of linearly independent columns of a matrix $\mathbf{A} = \mathbb{R}^{m \times n}$.

Rank

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The number of linearly independent columns of a matrix $\mathbf{A} = \mathbb{R}^{m \times n}$.

- This equals the number of linearly independent rows of \mathbf{A} .
- Denote by $\text{rank}(\mathbf{A})$ the rank of \mathbf{A} .

Important Properties

- $\text{rank}(\mathbf{A}) = \text{rank}(\mathbf{A}^\top)$.
- For all $\mathbf{A} \in \mathbb{R}^{n \times n}$, \mathbf{A} is invertible if and only if $\text{rank}(\mathbf{A}) = n$.
- $\text{nullity}(\mathbf{A}) = \dim(\text{null}(\mathbf{A})) = n - \text{rank}(\mathbf{A})$, where $\text{null}(\mathbf{A})$ is the subspace of \mathbb{R}^n which solutions for $\mathbf{Ax} = \mathbf{0}$.
- If $\text{rank}(\mathbf{A}) = \min\{m, n\}$ for a matrix $\mathbf{A} \in \mathbb{R}^{m \times n}$, then we say \mathbf{A} has **full rank**.

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Linear Mappings/Linear Transformation

A mapping $\Phi : V \rightarrow W$ preserves the structure of the vector space if

- $\Phi(\mathbf{x} + \mathbf{y}) = \Phi(\mathbf{x}) + \Phi(\mathbf{y})$
- $\Phi(\lambda \mathbf{x}) = \lambda \Phi(\mathbf{x})$

for all $\mathbf{x}, \mathbf{y} \in V$ and $\lambda \in \mathbb{R}$.

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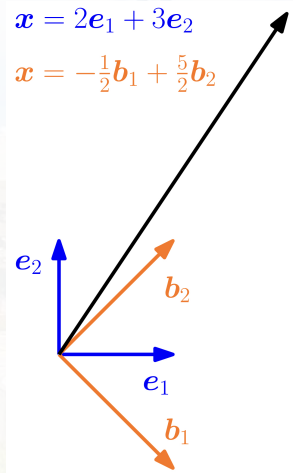
for all $\mathbf{x}, \mathbf{y} \in V$ and $\lambda \in \mathbb{R}$.

Linear Mapping

For two vector spaces V, W , a mapping $\Phi : V \rightarrow W$ is a **linear mapping** if

$$\forall \mathbf{x}, \mathbf{y} \in V, \forall \lambda, \psi \in \mathbb{R} : \Phi(\lambda\mathbf{x} + \psi\mathbf{y}) = \lambda\Phi(\mathbf{x}) + \psi\Phi(\mathbf{y}).$$

Different coordinate representation



Transformation Matrix

Transformation Matrix

Given vector spaces V, W with corresponding bases $B = (\mathbf{b}_1, \dots, \mathbf{b}_n)$ and $C = (\mathbf{c}_1, \dots, \mathbf{c}_m)$. Consider a linear mapping $\Phi : V \rightarrow W$. For $1 \leq j \leq n$,

$$\Phi(\mathbf{b}_j) = \alpha_{1j}\mathbf{c}_1 + \dots + \alpha_{mj}\mathbf{c}_m = \sum_{i=1}^m \alpha_{ij}\mathbf{c}_i$$

is the unique representation of $\Phi(\mathbf{b}_j)$ w.r.t. C (i.e., coordinate). Then, we call the $m \times n$ matrix \mathbf{A}_Φ , whose elements are $A_\Phi(i, j) = \alpha_{ij}$, the **transformation matrix** of Φ .

- If $\hat{\mathbf{x}}$ is the coordinate of $\mathbf{x} \in V$ w.r.t. B and $\hat{\mathbf{y}} = \Phi(\mathbf{x}) \in W$ w.r.t. C , then

$$\hat{\mathbf{y}} = \mathbf{A}_\Phi(\hat{\mathbf{x}}).$$

Example

Consider a linear mapping $\Phi : V \rightarrow W$ and ordered bases $B = (\mathbf{b}_1, \mathbf{b}_2, \mathbf{b}_3)$ of V and $C = (\mathbf{c}_1, \mathbf{c}_2, \mathbf{c}_3, \mathbf{c}_4)$ of W . Assume that

$$\Phi(\mathbf{b}_1) = \mathbf{c}_1 - \mathbf{c}_2 + 3\mathbf{c}_3 - \mathbf{c}_4$$

$$\Phi(\mathbf{b}_2) = 2\mathbf{c}_1 + \mathbf{c}_2 + 7\mathbf{c}_3 + 2\mathbf{c}_4$$

$$\Phi(\mathbf{b}_3) = 3\mathbf{c}_2 + \mathbf{c}_3 + 4\mathbf{c}_4.$$

The transformation matrix \mathbf{A}_Φ w.r.t. B and C satisfying $\Phi(\mathbf{b}_k) = \sum_{i=1}^4 \alpha_{ik} \mathbf{c}_i$ for $k = 1, 2, 3$ is

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$$\mathbf{A}_\Phi = [\alpha_1, \alpha_2, \alpha_3] = \begin{bmatrix} 1 & 2 & 0 \\ -1 & 1 & 3 \\ 3 & 7 & 1 \\ -1 & 2 & 4 \end{bmatrix}.$$

Basis Change (1/4)

- $[I]_B^{B'}$: a transformation matrix that maps coordinates w.r.t. B onto coordinates w.r.t. B' .

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 - $[I]_{B'}^B = \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$.
 - What about $[I]_B^{B'}$?

Basis Change (2/4)

Basis Change

Consider a transformation matrix

$$\mathbf{A} = \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix}$$

w.r.t. the standard basis (canonical basis) in \mathbb{R}^2 .

Basis Change (2/4)

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Consider a transformation matrix

$$\mathbf{A} = \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix}$$

w.r.t. the standard basis (canonical basis) in \mathbb{R}^2 . Define a new basis

$$B = \left(\begin{bmatrix} 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ -1 \end{bmatrix} \right)$$

Then, what about the transformation matrix $\tilde{\mathbf{A}}$ w.r.t. B ?

Basis Change (3/4)

Basis Change

Given

- a linear mapping $\Phi : V \rightarrow W$, ordered bases

$$B = (\mathbf{b}_1, \dots, \mathbf{b}_n), \tilde{B} = (\tilde{\mathbf{b}}_1, \dots, \tilde{\mathbf{b}}_n) \text{ of } V$$

$$C = (\mathbf{c}_1, \dots, \mathbf{c}_m), \tilde{C} = (\tilde{\mathbf{c}}_1, \dots, \tilde{\mathbf{c}}_m) \text{ of } W.$$

- a transformation matrix \mathbf{A}_Φ of Φ w.r.t. B and C .

Then, the corresponding transformation matrix $\tilde{\mathbf{A}}_\Phi$ w.r.t. \tilde{B} and \tilde{C} is

$$\tilde{\mathbf{A}}_\Phi = \mathbf{T}^{-1} \mathbf{A}_\Phi \mathbf{S}.$$

where $\mathbf{S} = [I]_{\tilde{B}}^B \in \mathbb{R}^{n \times n}$ and $\mathbf{T} = [I]_{\tilde{C}}^C \in \mathbb{R}^{m \times m}$.

Preview of the whole picture

$$\begin{array}{ccc}
 V & \xrightarrow{\Phi} & W \\
 \\
 B & \xrightarrow[\mathbf{A}_\Phi]{\Phi_{CB}} & C \\
 \uparrow [I]_{\tilde{B}}^B \mathbf{S} & & \uparrow [I]_{\tilde{C}}^C \mathbf{T} \\
 \tilde{B} & \xrightarrow[\Phi_{\tilde{C}\tilde{B}}]{\tilde{\mathbf{A}}_\Phi} & \tilde{C}
 \end{array}$$

Proof (1/2)

$$\tilde{\mathbf{b}}_j = s_{1j}\mathbf{b}_1 + \cdots s_{nj}\mathbf{b}_n = \sum_{i=1}^n s_{ij}\mathbf{b}_i, \quad j = 1, \dots, n.$$

$$\tilde{\mathbf{c}}_k = t_{1k}\mathbf{c}_1 + \cdots t_{m,k}\mathbf{c}_m = \sum_{\ell=1}^m t_{\ell k}\mathbf{c}_\ell, \quad k = 1, \dots, m.$$

Let $\mathbf{S} = ((s_{ij})) = [I]_{\tilde{\mathbf{B}}}^{\mathbf{B}} \in \mathbb{R}^{n \times n}$ and $\mathbf{T} = ((t_{\ell k})) = [I]_{\tilde{\mathbf{C}}}^{\mathbf{C}} \in \mathbb{R}^{m \times m}$.

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- Applying the mapping Φ , we get that for all $j = 1, \dots, n$,

$$\Phi(\tilde{\mathbf{b}}_j) = \sum_{k=1}^m \underbrace{\tilde{a}_{kj}\tilde{\mathbf{c}}_k}_{\in W}$$

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Let $\mathbf{S} = ((s_{ij})) = [I]_{\tilde{\mathbf{B}}}^{\mathbf{B}} \in \mathbb{R}^{n \times n}$ and $\mathbf{T} = ((t_{\ell k})) = [I]_{\tilde{\mathbf{C}}}^{\mathbf{C}} \in \mathbb{R}^{m \times m}$.

- Applying the mapping Φ , we get that for all $j = 1, \dots, n$,

$$\Phi(\tilde{\mathbf{b}}_j) = \sum_{k=1}^m \underbrace{\tilde{a}_{kj}}_{\in W} \tilde{\mathbf{c}}_k = \sum_{k=1}^m \tilde{a}_{kj} \sum_{\ell=1}^m t_{\ell k} \mathbf{c}_\ell = \sum_{\ell=1}^m \left(\sum_{k=1}^m t_{\ell k} \tilde{a}_{kj} \right) \mathbf{c}_\ell.$$

- Alternatively,

$$\begin{aligned} \Phi(\tilde{\mathbf{b}}_j) &= \Phi \left(\sum_{i=1}^n s_{ij} \mathbf{b}_i \right) = \sum_{i=1}^n s_{ij} \Phi(\mathbf{b}_i) = \sum_{i=1}^n s_{ij} \sum_{\ell=1}^m a_{\ell i} \mathbf{c}_\ell \\ &= \sum_{\ell=1}^m \left(\sum_{i=1}^n a_{\ell i} s_{ij} \right) \mathbf{c}_\ell \end{aligned}$$

Proof (2/2)

Hence,

$$\sum_{k=1}^m t_{\ell k} \tilde{a}_{kj} = \sum_{i=1}^n a_{\ell i} s_{ij}, \text{ for each } j$$

and it means that

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Hence,

$$\sum_{k=1}^m t_{\ell k} \tilde{a}_{kj} = \sum_{i=1}^n a_{\ell i} s_{ij}, \text{ for each } j$$

and it means that

$$\mathbf{T} \tilde{\mathbf{A}}_{\Phi} = \mathbf{A}_{\Phi} \mathbf{S} \in \mathbb{R}^{m \times n},$$

such that

$$\tilde{\mathbf{A}}_{\Phi} = \mathbf{T}^{-1} \mathbf{A}_{\Phi} \mathbf{S}.$$

Basis Change (4/4)

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With

- a basis change in V (i.e., $B \rightarrow \tilde{B}$) and
- a basis change in W (i.e., $C \rightarrow \tilde{C}$),

the transformation matrix \mathbf{A}_Φ of a linear mapping $\Phi : V \rightarrow W$ is replaced by an equivalent matrix $\tilde{\mathbf{A}}_\Phi$ with

$$\tilde{\mathbf{A}}_\Phi = \mathbf{T}^{-1} \mathbf{A}_\Phi \mathbf{S}.$$

$$\begin{array}{ccc}
 V & \xrightarrow{\Phi} & W \\
 B & \xrightarrow[\mathbf{A}_\Phi]{\Phi_{CB}} & C \\
 \uparrow [I]_{\tilde{B}}^B \quad \mathbf{S} & & \uparrow \mathbf{T} \quad [I]_{\tilde{C}}^C \\
 \tilde{B} & \xrightarrow[\Phi_{\tilde{C}\tilde{B}}]{\tilde{\mathbf{A}}_\Phi} & \tilde{C}
 \end{array}$$

$$\begin{array}{ccc}
 V & \xrightarrow{\Phi} & W \\
 \\
 B & \xrightarrow[\mathbf{A}_\Phi]{\Phi_{CB}} & C \\
 \uparrow \scriptstyle [I]_{\tilde{B}}^B \quad \mathbf{S} & & \downarrow \scriptstyle T^{-1} \quad [I]_{\tilde{C}}^C = [I]_{\tilde{C}}^C{}^{-1} \\
 \tilde{B} & \xrightarrow[\Phi_{\tilde{C}\tilde{B}}]{\tilde{\mathbf{A}}_\Phi} & \tilde{C}
 \end{array}$$

Example

Consider a linear mapping $\Phi : \mathbb{R}^3 \rightarrow \mathbb{R}^4$ with transformation matrix

$$\mathbf{A}_\Phi = \begin{bmatrix} 1 & 2 & 0 \\ -1 & 1 & 3 \\ 3 & 7 & 1 \\ -1 & 2 & 4 \end{bmatrix}$$

w.r.t. the standard bases

$$B = \left(\begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \right), \quad C = \left(\begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix} \right).$$

We seek the transformation matrix $\tilde{\mathbf{A}}_\Phi$ of Φ w.r.t. the new bases

$$\tilde{B} = \left(\begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix} \right), \quad \tilde{C} = \left(\begin{bmatrix} 1 \\ 1 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 \\ 0 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 \\ 0 \\ 0 \\ 1 \end{bmatrix} \right).$$

$$S =$$

$$T =$$

$$\mathbf{S} = \begin{bmatrix} 1 & 0 & 1 \\ 1 & 1 & 0 \\ 0 & 1 & 1 \end{bmatrix}, \quad \mathbf{T} = \begin{bmatrix} 1 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 \\ 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}.$$

Then,

$$\tilde{\mathbf{A}}_{\Phi} = \mathbf{T}^{-1} \mathbf{A}_{\Phi} \mathbf{S} = \dots$$

$$\mathbf{S} = \begin{bmatrix} 1 & 0 & 1 \\ 1 & 1 & 0 \\ 0 & 1 & 1 \end{bmatrix}, \quad \mathbf{T} = \begin{bmatrix} 1 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 \\ 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}.$$

Then,

$$\tilde{\mathbf{A}}_{\Phi} = \mathbf{T}^{-1} \mathbf{A}_{\Phi} \mathbf{S} = \cdots = \begin{bmatrix} -4 & -4 & -2 \\ 6 & 0 & 0 \\ 4 & 8 & 4 \\ 1 & 6 & 3 \end{bmatrix}.$$

Image and Kernel

Image & Kernel

For $\Phi : V \rightarrow W$, we define

$$\ker(\Phi) := \Phi^{-1}(\mathbf{0}_W) = \{\mathbf{v} \in V \mid \Phi(\mathbf{v}) = \mathbf{0}_W\}$$

and

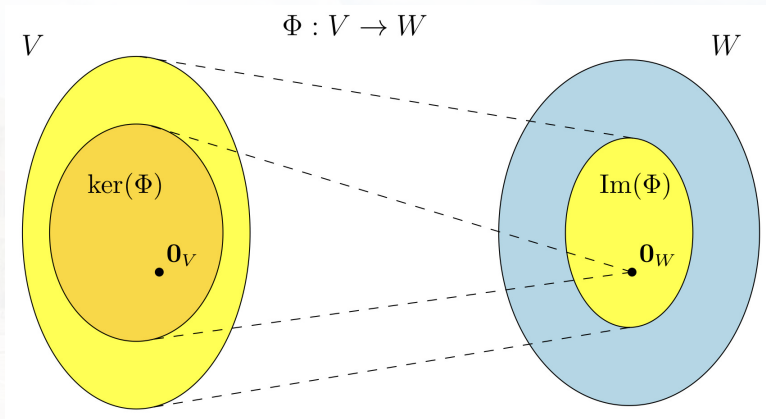
$$\text{Image}(\Phi) := \Phi(V) = \{\mathbf{w} \in W \mid \exists \mathbf{v} \in V \text{ s.t. } \Phi(\mathbf{v}) = \mathbf{w}\}.$$

- V : domain of Φ
- W : codomain of Φ

Remark

For vector spaces V and W and a linear mapping $\Phi : V \rightarrow W$:

- $\Phi(\mathbf{0}_V) = \mathbf{0}_W$ so $\mathbf{0} \in \ker(\Phi)$.
- $\text{Image}(\Phi) \subseteq W$ is a subspace of W
- $\ker(\Phi) \subseteq V$ is a subspace of V .
- Φ is injective (i.e., one-to-one) if and only if $\ker(\Phi) = \{\mathbf{0}\}$.
- $\text{Image}(\Phi) = \{\mathbf{A}\mathbf{x} \mid \mathbf{x} \in \mathbb{R}^n\} = \{\sum_{i=1}^n x_i \mathbf{a}_i \mid x_1, \dots, x_n \in \mathbb{R}\} = \text{span}(\mathbf{a}_1, \dots, \mathbf{a}_n) \subseteq \mathbb{R}^m$.
- $\text{rank}(\Phi) = \dim(\text{Image}(\Phi))$.
- ★ $\dim(\ker(\Phi)) + \dim(\text{Image}(\Phi)) = \dim(V)$.
 - $\text{null}(\mathbf{A}) + \text{rank}(\mathbf{A}) = \text{number of columns of } \mathbf{A}$.
- If $\dim(V) = \dim(W)$, then Φ is injective, surjective and bijective ($\because \text{Image}(\Phi) \subseteq W$).



Example

Consider the mapping $\Phi : \mathbb{R}^4 \rightarrow \mathbb{R}^2$,

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} \mapsto \begin{bmatrix} 1 & 2 & -1 & 0 \\ 1 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} = \begin{bmatrix} x_1 + 2x_2 - x_3 \\ x_1 + x_4 \end{bmatrix}$$

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$$\begin{aligned} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} &\mapsto \begin{bmatrix} 1 & 2 & -1 & 0 \\ 1 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} = \begin{bmatrix} x_1 + 2x_2 - x_3 \\ x_1 + x_4 \end{bmatrix} \\ &= x_1 \begin{bmatrix} 1 \\ 1 \end{bmatrix} + x_2 \begin{bmatrix} 2 \\ 0 \end{bmatrix} + x_3 \begin{bmatrix} -1 \\ 0 \end{bmatrix} + x_4 \begin{bmatrix} 0 \\ 1 \end{bmatrix} \end{aligned}$$

$\text{Image}(\Phi) =$

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$$= x_1 \begin{bmatrix} 1 \\ 1 \end{bmatrix} + x_2 \begin{bmatrix} 2 \\ 0 \end{bmatrix} + x_3 \begin{bmatrix} -1 \\ 0 \end{bmatrix} + x_4 \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

$$\text{Image}(\Phi) = \text{span} \left(\left\{ \begin{bmatrix} 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 2 \\ 0 \end{bmatrix}, \begin{bmatrix} -1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right\} \right)$$

Example (contd.)

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

Example (contd.)

$$\begin{bmatrix} 1 & 2 & -1 & 0 \\ 1 & 0 & 0 & 1 \end{bmatrix} \longrightarrow \cdots \longrightarrow$$

Example (contd.)

$$\begin{bmatrix} 1 & 2 & -1 & 0 \\ 1 & 0 & 0 & 1 \end{bmatrix} \rightarrow \cdots \rightarrow \begin{bmatrix} 1 & 0 & 0 & 1 \\ 0 & 1 & -\frac{1}{2} & -\frac{1}{2} \end{bmatrix}.$$

Example (contd.)

$$\begin{bmatrix} 1 & 2 & -1 & 0 \\ 1 & 0 & 0 & 1 \end{bmatrix} \longrightarrow \cdots \longrightarrow \begin{bmatrix} 1 & 0 & 0 & 1 \\ 0 & 1 & -\frac{1}{2} & -\frac{1}{2} \end{bmatrix}.$$

Thus,

$$\ker(\Phi) =$$

Example (contd.)

$$\begin{bmatrix} 1 & 2 & -1 & 0 \\ 1 & 0 & 0 & 1 \end{bmatrix} \longrightarrow \cdots \longrightarrow \begin{bmatrix} 1 & 0 & 0 & 1 \\ 0 & 1 & -\frac{1}{2} & -\frac{1}{2} \end{bmatrix}.$$

Thus,

$$\ker(\Phi) = \text{span} \left\{ \begin{bmatrix} 0 \\ \frac{1}{2} \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} -1 \\ \frac{1}{2} \\ 0 \\ 1 \end{bmatrix} \right\}.$$

Outline

- 1 Why linear algebra?
- 2 Vector Space
- 3 Basis & Dimension & Rank
- 4 Linear Mappings
- 5 Affine Spaces**

Affine Spaces

- Spaces that are offset from the origin.
- They are NO LONGER vector (sub)spaces.

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Affine Subspace

Let V be a vector space, $\mathbf{x}_0 \in V$, and $U \subseteq V$ be a subspace. Then,

$$\begin{aligned} L &= \mathbf{x}_0 + U := \{\mathbf{x}_0 + \mathbf{u} \mid \mathbf{u} \in U\} \\ &= \{\mathbf{v} \in V \mid \exists \mathbf{u} \in U : \mathbf{v} = \mathbf{x}_0 + \mathbf{u}\} \subseteq V \end{aligned}$$

is called **affine subspace** (or linear manifold) of V .

- U : **direction space**.
- \mathbf{x}_0 : **support point**.

Remark

- An affine subspace excludes $\mathbf{0}$ if $\mathbf{x}_0 \notin U$.
- Examples: points, lines, and planes in \mathbb{R}^3 which do not go through the origin.

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- An affine subspace excludes $\mathbf{0}$ if $\mathbf{x}_0 \notin U$.
- Examples: points, lines, and planes in \mathbb{R}^3 which do not go through the origin.
- One-dimensional affine subspaces:

$$\mathbf{y} = \mathbf{x}_0 + \lambda \mathbf{b}_1$$

for $\lambda \in \mathbb{R}$ and $U = \text{span}(\mathbf{b}_1)$ is a one-dimensional subspace of \mathbb{R}^n .

- Two-dimensional affine subspaces:

$$\mathbf{y} = \mathbf{x}_0 + \lambda_1 \mathbf{b}_1 + \lambda_2 \mathbf{b}_2$$

for $\lambda_1, \lambda_2 \in \mathbb{R}$ and $U = \text{span}(\{\mathbf{b}_1, \mathbf{b}_2\})$ is a two-dimensional subspace of \mathbb{R}^n .

•
⋮

Affine Mappings

Affine Mappings

Given two vector spaces V, W , a linear mapping $\Phi : V \rightarrow W$, and $\mathbf{a} \in W$, the mapping $\phi : V \rightarrow W$ with

$$\phi(\mathbf{x}) = \mathbf{a} + \Phi(\mathbf{x})$$

is called an **affine mapping** from V to W . The vector \mathbf{a} is called the **translation vector** of ϕ .

Discussions