

# MATHS CRASH COURSE

## LINEAR ALGEBRA

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## General information

- ▶ Our goal is to have a common language and understanding of the relevant content.
- ▶ The crash course shall provide you an opportunity to identify knowledge gaps.
- ▶ If something is too fast, feel free to pause the video.

- ① Vector Spaces
- ② Linear mappings
- ③ Matrices
- ④ Matrix identities

# Vector Spaces

## Content

- ▶ Vector spaces and subspaces
- ▶ Linear (in-)dependence
- ▶ Bases and dimensions
- ▶ Inner products
- ▶ Orthogonality and -normality

**Definition:** Vector space

A triple  $(V, +, \cdot)$  is called a *vector space over  $\mathbb{F}$*  or a *real vector space* for  $\mathbb{F} = \mathbb{R}$ , if  $V \neq \emptyset$ ,  $(\mathbb{F}, +_{\mathbb{F}}, \cdot_{\mathbb{F}})$  is a field and the mappings  $+: V \times V \rightarrow V$  as well as  $\cdot: \mathbb{F} \times V \rightarrow V$  are such that the following properties regarding *vector addition* and *scalar multiplication* hold true:

## Vector addition

$$\forall u, v, w \in V : (u + v) + w = u + (v + w)$$

associativity

$$\forall u, v \in V : u + v = v + u$$

commutativity

$$\exists \mathbf{0}_V \in V : \forall v \in V : \mathbf{0}_V + v = v$$

identity element

$$\forall v \in V : \exists w \in V : v + w = \mathbf{0}_V$$

inverse elements

**Definition:** Vector space

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**Scalar multiplication**

$$\forall \lambda \in \mathbb{F}, u, v \in V : \lambda \cdot (u + v) = \lambda \cdot u + \lambda \cdot v \quad \text{distributivity 1}$$

$$\forall \lambda, \mu \in \mathbb{F}, v \in V : (\lambda +_{\mathbb{F}} \mu) \cdot v = \lambda \cdot v + \mu \cdot v \quad \text{distributivity 2}$$

$$\forall v \in V : 1 \cdot v = v \quad \text{identity element}$$

$$\forall \lambda, \mu \in \mathbb{F}, v \in V : \lambda \cdot_{\mathbb{F}} \mu \cdot v = \lambda \cdot (\mu \cdot v) \quad \text{multiplicative compatibility}$$

## Convention

The set  $V$  by itself may be called a vector space if  $+$  and  $\cdot$  are irrelevant or trivial.

## Examples of real vector spaces

- ▶ Set of  $n$ -dimensional vectors  $\mathbb{R}^n$  with  $+$  and  $\cdot$  defined element-wise
- ▶ Set of square matrices  $\mathbb{R}^{n \times n}$  with  $+$  and  $\cdot$  defined element-wise
- ▶ Set of real continuous functions on closed interval  $I \subseteq \mathbb{R}$ :  
 $C(I) := \{f : I \rightarrow \mathbb{R} \mid f \text{ continuous}\}$  with  $+$  and  $\cdot$  defined element-wise

## Definition: Subspaces

Let  $(V, +, \cdot)$  be a vector space over  $\mathbb{F}$  and  $U \subseteq V$ . If  $(U, +|_{U \times U}, \cdot|_{\mathbb{F} \times U})$  is also a vector space, it is called a *subspace* of  $V$ . This is denoted as  $U \leq V$ .



## Definition: Span and linear combination

Let  $U \subseteq V$  be a subset of a vector space  $V$  over  $\mathbb{F}$ . Then the *span* of  $U$  is defined as

$$\text{span}(U) := \left\{ \sum_{i=1}^k \lambda_i v_i \mid k \in \mathbb{N}, \forall i \in \{1, \dots, k\} : \lambda_i \in \mathbb{F}, v_i \in U \right\}$$

A combination of elements of  $U$  as  $\sum_{i=1}^k \lambda_i v_i$  is called a *linear combination*.

## Proposition: A span is a vector space

Let  $V$  be a vector space and  $U \subseteq V$ . Then  $\text{span}(U) \leq V$ .

## Definition: Linear (in-)dependence

Let  $V$  be a vector space. A finite set of vectors  $\{v_1, \dots, v_k\} \subseteq V$  is called *linear dependent*, if there is a set of scalars  $\{\lambda_1, \dots, \lambda_k\} \subseteq \mathbb{F}$  with  $\lambda_i \neq 0$  for some  $i \in \{1, \dots, k\}$  and

$$\sum_{i=1}^k \lambda_i v_i = 0$$

If there is no such set of scalars, the set of vectors is called *linear independent*.

## Examples

- ▶ The set  $\{(\frac{1}{0}), (\frac{0}{1}), (\frac{1}{1})\} \subseteq \mathbb{R}^2$  is linear dependent as  $(\frac{1}{0}) + (\frac{0}{1}) - (\frac{1}{1}) = (\frac{0}{0}) = 0_{\mathbb{R}^2}$
- ▶ The set  $\{(\frac{1}{0}), (\frac{0}{1})\} \subseteq \mathbb{R}^2$  is linear independent

## Definition: Basis

A linear independent set  $B \subseteq V$  with  $\text{span}(B) = V$  is called a *basis* for  $V$ .

## Definition: Unit basis

Let  $V = \mathbb{R}^n$  for some  $n \in \mathbb{N}$ , then the set  $B := \{(\delta_j^i)_{i=1}^n\}_{j=1}^n$  yields a basis for  $V$ . It is called *the unit basis*. Its elements are usually denoted as  $e_j := (\delta_j^i)_{i=1}^n \in \mathbb{R}^n$ , where  $\delta_j^i$  is the Kronecker delta, equal to 1 if  $i = j$  and else equal to 0.

## Definition: Vector space dimension

Let  $V$  be a vector space with basis  $B$ . We call the cardinality of  $B$  the *dimension* of  $V$  and denote it as  $\dim(V) := |B|$ .

## Definition: Inner product

Let  $(V, +, \cdot)$  be a vector space over  $\mathbb{F} \in \{\mathbb{R}, \mathbb{C}\}$ , then a mapping  $\langle \cdot, \cdot \rangle : V \times V \rightarrow \mathbb{F}$  is called an *inner product* or *scalar product*, if the following conditions hold:

## Requirements for inner products

$$\forall u, v \in V : \langle u, v \rangle = \overline{\langle v, u \rangle}$$

(conjugate) symmetry

$$\forall \lambda, \mu \in \mathbb{F}, u, v, w \in V : \langle \lambda u + \mu v, w \rangle = \lambda \langle u, w \rangle + \mu \langle v, w \rangle$$

linearity in first argument

$$\forall v \in V \setminus \{0_V\} : \langle v, v \rangle > 0$$

positive definiteness

## Definition: Inner product space

A vector space having a inner product is called an *inner product space*.

## Example

The dot product defined as  $\langle u, v \rangle := \sum_{i=1}^n u_i v_i$  is an inner product for  $\mathbb{R}^n$  yielding  $(\mathbb{R}^n, +, \cdot, \langle \cdot, \cdot \rangle)$  an inner product space.

## Definition: Orthogonal basis

Let  $B$  be a basis for an inner product space  $V$ , then  $B$  is called *orthogonal* if for all  $u \neq v \in B$  the equality  $\langle u, v \rangle = 0$  holds true.

## Definition: Induced norm

Let  $V$  be an inner product space over  $\mathbb{F} \in \{\mathbb{R}, \mathbb{C}\}$ . The mapping  $\|\cdot\| : V \rightarrow \mathbb{R}_0^+$  defined as  $\|v\| := \sqrt{\langle v, v \rangle}$  is called the *induced norm* for  $V$ .

## Definition: Orthonormal basis

Let  $B$  be a orthogonal basis for an inner product space  $V$ . If for all  $v \in B$  the equality  $\|v\| = 1$  holds,  $B$  is called an *orthonormal* basis.

## Linear mappings

## Content

- ▶ Definition of linear mappings
- ▶ Range and kernel
- ▶ Rank-nullity theorem



## Definition: Linear mapping

Let  $V, W$  be vector spaces over a field  $\mathbb{F}$  and  $L : V \rightarrow W$  be a mapping.  $L$  is called a *linear mapping* or *linear*, if

$$\forall \lambda \in \mathbb{F}, v, w \in V : L(\lambda \cdot v + w) = \lambda \cdot L(v) + L(w)$$

## Proposition: Linear mappings are uniquely defined by their definition on a basis

Let  $V, W$  be vector spaces and  $B$  be a basis for  $V$ . If  $L_1, L_2 : V \rightarrow W$  are linear with  $L_1(v) = L_2(v)$  for all  $v \in B$ , then  $L_1(v) = L_2(v)$  for all  $v \in V$ .

## Definition: Range

Let  $L : V \rightarrow W$  be a linear mapping between vector spaces  $V, W$ . Then the *image* or *range* of  $L$  is defined as

$$\text{Im}(L) := L[V] = \{w \in W \mid \exists v \in V : L(v) = w\}$$

## Definition: Kernel

Let  $L : V \rightarrow W$  be as above. Then the *kernel* or *null space* of  $L$  is defined as

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

## Proposition: The kernel and range of linear mappings are subspaces

For vector spaces  $V, W$  and  $L : V \rightarrow W$  linear it is  $\text{Im}(L) \leq W$  and  $\ker L \leq V$ .

## Reminder

A mapping  $f : X \rightarrow Y$  is called *injective*, if for each  $y \in f[X] = \{y \in Y \mid \exists x \in X : f(x) = y\}$  there is **exactly one**  $x \in X$  with  $f(x) = y$ . Short:

$$f(x_1) = f(x_2) \Rightarrow x_1 = x_2$$

## Proposition: Relation to kernel

A linear mapping  $L : V \rightarrow W$  is injective iff (short for if and only if) its kernel is trivial, meaning  $\ker(L) = \{\mathbf{0}_V\}$ .

## **Theorem:** Rank-nullity theorem

Let  $L : V \rightarrow W$  be a linear mapping between two vector spaces  $V$  and  $W$ . Then the following identity holds:

$$\dim(\text{Im}(L)) + \dim(\ker(L)) = \dim(V)$$

## **Definition:** Rank and nullity

The dimension of the image of  $L$  is also called *rank* and the dimension of the kernel *nullity*.

## **Corollary**

Injective linear mappings  $L : V \rightarrow W$  are surjective (and thus bijective), if  $\dim(V) = \dim(W)$ .

# Matrices

## Content

- ▶ Identification of linear mappings with matrices
- ▶ Matrix operations
- ▶ Determinant, inverse matrices and the general linear group
- ▶ Eigenvector decomposition

## Observation

Let  $V, W$  be finite dimensional real vector spaces with basis  $B_V := \{v_1, \dots, v_n\}$ ,  $B_W := \{w_1, \dots, w_m\}$  respectively and  $L : V \rightarrow W$  be linear.

► For all  $v_i \in B_V$  there are  $\mu_{ji} \in \mathbb{R}$  such that  $L(v_i) = \sum_{j=1}^m \mu_{ji} w_j$ .

## Matrix representation of linear mappings

As  $L$  is fully described by its operation on  $B_V$  and each  $L(v_i)$  can be written as a unique [!] linear combination of  $B_W$ ,  $L$  is (for given  $B_V$  and  $B_W$ ) uniquely defined by the  $\mu_{ji}$  as above. These are usually arranged in a matrix  $M_{B_W}^{B_V}(L) \in \mathbb{R}^{m \times n}$  which can be identified with the linear mapping:

$$L \simeq M_{B_W}^{B_V}(L) := \begin{pmatrix} \mu_{11} & \cdots & \mu_{1n} \\ \vdots & \ddots & \vdots \\ \mu_{m1} & \cdots & \mu_{mn} \end{pmatrix}$$

## Convention for further slides

For simplicity, we will focus on  $B_V$  and  $B_W$  being unit bases and drop explicit mentioning of the used bases.

## Definition: Matrix-vector multiplication

Let  $V, W$  be finite dimensional real vector spaces and  $L : V \rightarrow W$  be linear with matrix representation  $M(L) \in \mathbb{R}^{m \times n}$ . The *matrix-vector multiplication*  $\cdot : \mathbb{R}^{m \times n} \times \mathbb{R}^n \rightarrow \mathbb{R}^m$  is defined via the evaluation of  $L$  at  $v$  as

$$M(L) \cdot v := L(v) = \left( \sum_{i=1}^n \mu_{ji} v_i \right)_{j=1}^m$$



## Definition: Matrix-matrix multiplication

Let  $V_1, V_2, V_3$  be finite dimensional real vector spaces with dimensions  $n_1, n_2, n_3 \in \mathbb{N}$  respectively and  $L_1 : V_1 \rightarrow V_2, L_2 : V_2 \rightarrow V_3$  be linear mappings. For  $M(L_1) \in \mathbb{R}^{n_2 \times n_1}, M(L_2) \in \mathbb{R}^{n_3 \times n_2}$  we can define the *matrix-matrix multiplication*  $\cdot : \mathbb{R}^{n_3 \times n_2} \times \mathbb{R}^{n_2 \times n_1} \rightarrow \mathbb{R}^{n_3 \times n_1}$  via the composition of  $L_2$  and  $L_1$ :

$$M(L_2) \cdot M(L_1) := M(L_2 \circ L_1)$$

## Matrix-matrix multiplication mnemonic

The product  $A \cdot B$  can be calculated as dot products of the rows of  $A$  and columns of  $B$ :

$$\mathbb{R}^{n_2 \times n_3} \ni B = \begin{pmatrix} b_{11} & \cdots & b_{1n_3} \\ \vdots & \ddots & \vdots \\ b_{n_2 1} & \cdots & b_{n_2 n_3} \end{pmatrix}$$

$$\mathbb{R}^{n_1 \times n_2} \ni A = \begin{pmatrix} a_{11} & \cdots & a_{1n_2} \\ \vdots & \ddots & \vdots \\ a_{n_1 1} & \cdots & a_{n_1 n_2} \end{pmatrix} \begin{pmatrix} \sum_{i=1}^{n_2} a_{1i} b_{i1} & \cdots & \sum_{i=1}^{n_2} a_{1i} b_{in_3} \\ \vdots & \ddots & \vdots \\ \sum_{i=1}^{n_2} a_{n_1 i} b_{i1} & \cdots & \sum_{i=1}^{n_2} a_{n_1 i} b_{in_3} \end{pmatrix} = A \cdot B \in \mathbb{R}^{n_1 \times n_3}$$

## Definition: Transpose

Let  $A := (a_{ij})_{i,j=1}^{i=n,j=m} \in \mathbb{R}^{n \times m}$  be a matrix, then  $A^T := (a_{ji})_{i,j=1}^{i=m,j=n} \in \mathbb{R}^{m \times n}$  is called the *transpose* of  $A$ .

## Definition: Symmetric matrices

If for  $A \in \mathbb{R}^{n \times n}$  the equality  $A^T = A$  holds,  $A$  is called *symmetric*.

## Definition: Orthogonal matrices

Let  $V$  be an  $n$ -dimensional inner product space and  $A \in \mathbb{R}^{n \times n}$ . Then  $A$  is called *orthogonal* if  $A^{-1} = A^T$ .

**Definition:** Square matrix

A matrix  $A \in \mathbb{R}^{n \times m}$  is called *square matrix* if  $n = m$ .

**Definition:** Unit matrix

For  $n \in \mathbb{N}$ , the matrix  $\mathbb{I}_n := \left( \delta_i^j \right)_{i,j=1}^n$  is called the *identity matrix of rank  $n$* .

## Definition: Inverse matrix

Let  $A \in \mathbb{R}^{n \times n}$  be a square matrix. If there is a matrix  $B \in \mathbb{R}^{n \times n}$  with  $A \cdot B = B \cdot A = \mathbb{I}_n$ ,  $A$  is called *invertible* and  $B =: A^{-1}$  is called the *inverse of  $A$* .

## Proposition: Existence of inverse

A square matrix  $A \in \mathbb{R}^{n \times n}$  is invertible if and only if and only if it has full rank, meaning

$$\dim(\text{Im}(v \mapsto A \cdot v)) = n$$

Equivalently it is invertible if its nullity is 0, meaning

$$\dim(\ker(v \mapsto A \cdot v)) = 0$$

This also means the mapping  $v \mapsto A \cdot v$  is bijective for invertible matrices.

## Definition: Determinant

For a square matrix  $A \in \mathbb{R}^{n \times n}$ , the *determinant of A* is defined via the Leibniz-formula as

$$\det(A) := \sum_{\sigma \in S_n} \text{sgn}(\sigma) \prod_{i=1}^n a_{\sigma(i),i}$$

Here  $S_n$  is the group of permutations of  $\{1, \dots, n\}$  and  $\text{sgn}(\sigma)$  is the sign of  $\sigma$ , which equals  $+1$  if the number of inversions the permutation composes of is even and  $-1$  if it is odd.

## Proposition: Link to invertibility

A square matrix  $A \in \mathbb{R}^{n \times n}$  is invertible if and only if its determinant is non-zero.

Equivalently, if  $\det(A) = 0$ , then  $\dim(\ker(A)) > 0$ .

**Definition: Group**

Let  $G \neq \emptyset$  and  $* : G \times G \rightarrow G$ . Then  $(G, *)$  is called a *group*, if:

$$\forall a, b, c : (a * b) * c = a * (b * c) \quad \text{associativity}$$

$$\exists e \in G : \forall a \in G : e * a = a * e = a \quad \text{existence of neutral element}$$

$$\forall a \in G : \exists b \in G : a * b = e \wedge b * a = e \quad \text{existence of inverse elements}$$

**Proposition and definition: General linear group**

The set of invertible matrices  $GL_n := \{A \in \mathbb{R}^{n \times n} \mid \det(A) \neq 0\}$  together with the matrix-matrix multiplication forms a group. It is called the *general linear group* and its neutral element is  $\mathbb{I}_n$ .

## Definition: Diagonalizable

A square matrix  $A \in \mathbb{R}^{n \times n}$  is called *diagonalizable*, if there is an invertible matrix  $P \in GL_n$  such that  $D := P^{-1}AP$  is a diagonal matrix. This means the elements of  $D$  are only non-zero on the main diagonal as such:

$$D = \begin{pmatrix} d_{11} & 0 & \cdots & 0 & 0 \\ 0 & d_{22} & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & d_{n-1,n-1} & 0 \\ 0 & 0 & \cdots & 0 & d_{nn} \end{pmatrix}$$



## Definition: Eigenvectors and -values

Let  $A \in \mathbb{R}^{n \times n}$  be a square matrix. If  $A \cdot v = \lambda v$  for  $\lambda \in \mathbb{R}$  and  $v \in \mathbb{R}^n \setminus \{0\}$  holds,  $\lambda$  is called an *eigenvalue* for  $A$  and  $v$  is called an *eigenvector with eigenvalue*  $\lambda$ .

## Definition: Eigenvalue-problem

To find eigenvectors and values for a square matrix, one can find non-trivial solutions ( $v \neq 0$ ) of the following linear equation system, the *eigenvalue problem*:

$$(A - \lambda \mathbb{I}_n) \cdot v = 0$$

Non-trivial solutions exist for  $\lambda$  such that  $\dim(\ker(A - \lambda \mathbb{I}_n)) > 0$ , which is the case iff  $p_A(\lambda) := \det(A - \lambda \mathbb{I}_n) = 0$ . The mapping  $p_A : \mathbb{R} \rightarrow \mathbb{R}$  is called the *characteristic polynomial* of  $A$ .

## Theorem: Eigenvector decomposition

If for a matrix  $A$  a set of linearly independent eigenvectors  $\{v_1, \dots, v_n\} \subseteq \mathbb{R}^n$  with corresponding eigenvalues  $\{\lambda_1, \dots, \lambda_n\}$  exists, then the matrix is diagonalizable using  $P := (v_1 \dots v_n) \in \mathbb{R}^{n \times n}$  and  $\Lambda := \left( \delta_i^j \lambda_i \right)_{i,j=1}^n \in \mathbb{R}^{n \times n}$  as

$$P^{-1}AP = \Lambda$$

## Notes

- ▶ To prove the identity, observe that  $Av_i = \lambda_i v_i$  holds for all  $i \in \{1, \dots, n\}$  yielding  $AP = P\Lambda$ .
- ▶ Outlook: For non-square matrices the *singular value decomposition* (short *SVD*) yields a similar identity.

## Definition: Positive (semi-)definite

Let  $A \in \mathbb{R}^{n \times n}$  be symmetric. Then  $A$  is called *positive definite* if

$$\forall v \in \mathbb{R}^n \setminus \{\mathbf{0}_{\mathbb{R}^n}\} : \quad v^T A v > 0$$

If only  $v^T A v \geq 0$  holds,  $A$  is called *positive semi-definite* instead.

## Remarks

- ▶ If  $A$  is positive semi-definite, it is diagonalizable and all its eigenvalues are non-negative.
- ▶ If  $A$  is positive definite, it is diagonalizable and all its eigenvalues are positive.

## Matrix identities

## Content

- ▶ Transpose matrices
- ▶ Inverse matrices
- ▶ Determinant of matrices

## Identities regarding transpose

Let  $A, B \in \mathbb{R}^{n \times m}$  and  $c \in \mathbb{R}$ , then

$$(A + B)^T = A^T + B^T$$

$$(AB)^T = B^T A^T$$

$$(cA)^T = cA^T$$

$$p_{A^T}(\lambda) = p_A(\lambda)$$

If  $A$  is additionally invertible, we have

$$(A^{-1})^T = (A^T)^{-1}$$

thus conventionally we write  $A^{-T} := (A^{-1})^T$ .

## Identities regarding inverse

Let  $A, B \in GL_n(\mathbb{R})$  and  $c \in \mathbb{R} \setminus \{0\}$ , then

$A + B$  is not necessarily invertible! (e.g.  $B = -A$ )

$$(AB)^{-1} = B^{-1}A^{-1}$$

$$(cA)^{-1} = c^{-1}A^{-1}$$

$\lambda \neq 0$  eigenvalue of  $A \Rightarrow \lambda^{-1}$  eigenvalue of  $A^{-1}$

## Identities regarding determinant

Let  $A, B \in \mathbb{R}^{n \times n}$  and  $c \in \mathbb{R} \setminus \{0\}$ , as well as  $A$  invertible if needed, then

$$\det(cA) = c^n \det(A)$$

$$\det(AB) = \det(A) \det(B)$$

$$\det(A^T) = \det(A)$$

$$\det(A^{-1}) = \det(A)^{-1}$$

$$\det(A) = \prod_{i=1}^n \lambda_i$$

where  $\lambda_i$  are the eigenvalues of  $A$ , if needed repeated to occur as often as their algebraic multiplicity.



## We recapped

- ▶ definitions regarding vector spaces,
- ▶ definitions regarding linear mappings,
  - ▶ as well as the rank-nullity theorem
- ▶ and content on matrices as representations of linear mappings:
  - ▶ matrix operations,
  - ▶ the general linear group
  - ▶ and eigenvector decomposition.
- ▶ Additionally, some identities regarding to matrices.

# Thank You!

## Feel free to ask questions in the forums!