Linear Algebra I - 線形代数学 I

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Overview notes

G30 Program, Nagoya University (Fall 2022)

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Lecture notes and exercises are available at: https://www.henrikbachmann.com/la1_2022.html

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These notes serve as a compact overview of the definitions, propositions, lemmas, corollaries, and theorems given in the lectures. It will be updated regularly (This is Version 1 from October 4, 2022). The proofs, examples, and explanations are provided in the handwritten notes/lectures. The reference book for this course is [B], and we will cover parts of Chapters 1,2,3 and 5 during this semester. (Chapter 4 will be part of Linear Algebra II)

If you find any typos in this note, please let me know!

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References

[B] O. Bretscher: *Linear Algebra with Applications*, 4th edition, Pearson 2009.

1 Linear systems

By $\mathbb{R}$ we will denote the set of real numbers. $\mathbb{R}$ contains all numbers you usually considered in high school, such as $1, -1, 0, 2, 3, \frac{3}{8}, \pi, \sqrt{2}, e, \ldots$. There are rigorous definitions of the real numbers, which would be part of a pure mathematics lecture[1]. But in this course, we just assume that they exist and that everyone is familiar with them.

Definition 1.1. *i) For real numbers $a_1, a_2, \ldots, a_n, b \in \mathbb{R}$ an equation of the form*

$$a_1 x_1 + \cdots + a_n x_n = b$$

is called a **linear equation***.*

ii) A finite collection of linear equations is called a **linear system***.*

iii) A **solution of a linear system** *is a simultaneous solution for all of its equations.*

Definition 1.2. *The following operations on a linear system are called* **elementary row operations***.*

(R1) Add a multiple of an equation to another.

(R2) Multiply an equation with a non-zero number.

(R3) Change the order of the equations.

Proposition 1.3. *Applying an elementary row operation to a linear system does not change the set of all solutions of this linear system.*

2 Matrices & Vectors

Definition 2.1. *i) A $m \times n$-***matrix** *is given by an array (m rows, n columns) of numbers $a_{ij} \in \mathbb{R}$*

$$A = \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{pmatrix} = (a_{ij})_{\substack{1 \le i \le m \\ 1 \le j \le n}} .$$

Notation: We often just write $A = (a_{ij})$ if the size of A, i.e. m and n, are known from context. By $\mathbb{R}^{m \times n}$ we denote the set all of all $m \times n$-matrices.

ii) A (column-) **vector** *of size n is a $n \times 1$-matrix*

$$v = \begin{pmatrix} v_1 \\ \vdots \\ v_n \end{pmatrix}$$

and the set of all vectors of size n is denoted by $\mathbb{R}^n = \mathbb{R}^{n \times 1}$.

[1] See for example `https://en.wikipedia.org/wiki/Construction_of_the_real_numbers` for an overview of the "construction" of real numbers.

Definition 2.2. *For matrices $A = (a_{ij}), B = (b_{ij}) \in \mathbb{R}^{m\times n}$ and a real number $\lambda \in \mathbb{R}$ we define*

$$\begin{aligned} A + B &= (a_{ij} + b_{ij}) \in \mathbb{R}^{m\times n} && \textit{(Sum of two matrices)},\\ \lambda A &= (\lambda a_{ij}) \in \mathbb{R}^{m\times n} && \textit{(Scalar multiplication)}. \end{aligned}$$

In the case $\lambda = -1$ we write $(-1)A = -A$ and $A - B$ means $A + (-1)B$.

The matrices A and B need to be of the same size, otherwise the sum $A + B$ is not defined. A special case of the addition of matrices is given by the addition of vectors. For $u, v \in \mathbb{R}^n$ and $\lambda \in \mathbb{R}$ we have

$$u = \begin{pmatrix} u_1 \\ \vdots \\ u_n \end{pmatrix}, v = \begin{pmatrix} v_1 \\ \vdots \\ v_n \end{pmatrix}, \quad u + v = \begin{pmatrix} u_1 + v_1 \\ \vdots \\ u_n + v_n \end{pmatrix}, \quad \lambda v = \begin{pmatrix} \lambda v_1 \\ \vdots \\ \lambda v_n \end{pmatrix}.$$

Definition 2.3. *The product of a matrix $A = (a_{ij}) \in \mathbb{R}^{m\times n}$ and a vector $v \in \mathbb{R}^n$ is defined by*

$$Av = \begin{pmatrix} a_{11} & \dots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \dots & a_{mn} \end{pmatrix} \begin{pmatrix} v_1 \\ \vdots \\ v_n \end{pmatrix} = \begin{pmatrix} a_{11}v_1 + a_{12}v_2 + \dots + a_{1n}v_n \\ a_{21}v_1 + a_{22}v_2 + \dots + a_{2n}v_n \\ \vdots \\ a_{m1}v_1 + a_{m2}v_2 + \dots + a_{mn}v_n \end{pmatrix} \in \mathbb{R}^m.$$

We have: ($m\times n$-matrix) $\cdot$ (vector of size n) = (vector of size m).

Proposition 2.4. *We have for $A \in \mathbb{R}^{m\times n}$, $x, y \in \mathbb{R}^n$ and $\lambda \in \mathbb{R}$*

i) $A(x + y) = Ax + Ay$,

ii) $A(\lambda x) = \lambda(Ax)$.

Definition 2.5. *For a matrix $A = (a_{ij}) \in \mathbb{R}^{m\times n}$ and a vector $b \in \mathbb{R}^m$ the matrix*

$$(A \mid b) = \left(\begin{array}{ccc|c} a_{11} & \dots & a_{1n} & b_1 \\ \vdots & \ddots & \vdots & \vdots \\ a_{m1} & \dots & a_{mn} & b_m \end{array}\right) \in \mathbb{R}^{m\times(n+1)}$$

is called the **augmented matrix** *of the linear system $Ax = b$.*

The augmented matrix $(A \mid b)$ is just the matrix A where we append the vector b as a column. The line $\mid$ is a useful notation to distinguish between the left- and right-hand side of the corresponding linear system but it has no mathematical meaning. We will view $(A \mid b)$ as a usual matrix with m rows and $n + 1$ columns.

Definition 2.6. *The following operations on a matrix are called* **elementary row operations**.

(R1) Add a multiple of one row to another row.

(R2) Multiply a row with a non-zero number.

(R3) Interchange two rows.

Applying a row operation to a linear system (Definition 1.2) corresponds to the same row operation (Definition 2.6) on the corresponding augmented matrix of this linear system.

Definition 2.7. *Two matrices A and B are called* **row equivalent***, if B can be obtained from A by elementary row operations. In this case we write*

$$A \sim B\,.$$

Notice that if $A \sim B$, then also $B \sim A$, i.e. A can be obtained from B by elementary row operations.

Proposition 2.8. *Let $A, B \in \mathbb{R}^{m\times n}$ and $b, c \in \mathbb{R}^m$. If $(A \mid b) \sim (B \mid c)$ then the linear systems $Ax = b$ and $Bx = c$ have the same solutions.*

Definition 2.9. *A matrix $A = (a_{ij}) \in \mathbb{R}^{m\times n}$ is on* **row-reduced echelon form** *if*

i) The first non-zero element on each row (if any) is equal to 1.

ii) If there is a leading 1 in a row, then all rows above contain a leading 1 further to the left.

iii) If a_{ij} is the first non-zero element in row i, then there are no other non-zero elements in the j-th column.

The first non-zero element in a row of a matrix in row-reduced echelon form is called **pivot element***.*

Theorem 2.10. *Every matrix A is row equivalent to a unique matrix B on row-reduced echelon form and we write*

$$B = \mathrm{rref}(A)\,.$$

Definition 2.11. *Let $A \in \mathbb{R}^{m\times n}$ be a matrix. The* **rank** $\mathrm{rk}(A)$ *of A is the number of pivot elements in* $\mathrm{rref}(A)$.

3 Sets & Functions

Definition 3.1. *Let X and Y be two sets.*

i) A **function** *$f : X \to Y$ is a rule, assigning to each element $x \in X$ an element $f(x) \in Y$. This is also denoted by*

$$\begin{aligned} f : X &\longrightarrow Y \\ x &\longmapsto f(x)\,. \end{aligned}$$

ii) For $f : X \to Y$ the set X is called the **domain of** *f and Y is called the* **codomain of** *f.*

A function is also sometimes called a **map**. These two names (for the exact same mathematical object) are used interchangeably in the literature.

Definition 3.2. *For a function $f : X \to Y$ the* **image of** *f is defined by*

$$\mathrm{im}(f) = \{y \in Y \mid \exists x \in X : y = f(x)\}\,.$$

Another notation is $\mathrm{im}(f) = f(X)$. The image is a subset of Y, i.e. $\mathrm{im}(f) \subset Y$.

Definition 3.3. *A function $f : X \to Y$ is called*

i) **injective** *if $f(x_1) \neq f(x_2)$ whenever $x_1 \neq x_2$. ($x_1, x_2 \in X$)*

ii) **surjective** *if $\mathrm{im}(f) = Y$.*

iii) **bijective** *if it is injective and surjective.*

4 Linear maps

Definition 4.1. *A function $F : \mathbb{R}^n \to \mathbb{R}^m$ is a* **linear map** *if for all $u, v \in \mathbb{R}^n$, $\lambda \in \mathbb{R}$ we have*

i) $F(u + v) = F(u) + F(v)$,

ii) $F(\lambda u) = \lambda F(u)$.

Theorem 4.2. *Let $F : \mathbb{R}^n \to \mathbb{R}^m$ be a linear map. Then there exists a unique matrix $[F] \in \mathbb{R}^{m\times n}$, such that for all $x \in \mathbb{R}^n$ we have*

$$F(x) = [F]x\,.$$

Here the left-hand side is the evaluation of the function F at x and the right-hand side is the multiplication of the matrix $[F]$ with the vector x.

Definition 4.3. *The matrix $[F]$ in Theorem 4.2 is called* **the matrix of F**.

5 Linear maps in geometry

Definition 5.1. *Let* $u = \begin{pmatrix} u_1 \\ \vdots \\ u_n \end{pmatrix}, v = \begin{pmatrix} v_1 \\ \vdots \\ v_n \end{pmatrix} \in \mathbb{R}^n$.

i) The **dot product** *of u and v is defined by*

$$u \bullet v = u_1 v_1 + \cdots + u_n v_n\,.$$

ii) u and v are called **orthogonal** *if $u \bullet v = 0$.*

iii) The **norm** *of u is defined by*

$$\|u\| = \sqrt{u \bullet u} = \sqrt{u_1^2 + \cdots + u_n^2}\,.$$

Proposition 5.2. *The dot product satisfies the following properties for all $u, v, w \in \mathbb{R}^n$ and $\lambda \in \mathbb{R}$:*

i) $u \bullet v = v \bullet u$,

ii) $u \bullet (v + w) = u \bullet v + u \bullet w$,

iii) $u \bullet (\lambda v) = \lambda(u \bullet v)$.

Definition 5.3. *Let $u \in \mathbb{R}^n$ with $u \neq 0$. We define the* **orthogonal projection** P_u *onto the line spanned by* u *as*

$$\begin{aligned} P_u : \mathbb{R}^n &\longrightarrow \mathbb{R}^n \\ x &\longmapsto \frac{u \bullet x}{u \bullet u} u \,. \end{aligned}$$

Proposition 5.4. $P_u : \mathbb{R}^n \to \mathbb{R}^n$ *is a linear map.*

Definition 5.5. *Let $u \in \mathbb{R}^n$ with $u \neq 0$. We define the* **reflection** ρ_u *along the line spanned by* u *as*

$$\begin{aligned} \rho_u : \mathbb{R}^n &\longrightarrow \mathbb{R}^n \\ x &\longmapsto 2\frac{u \bullet x}{u \bullet u} u - x \,. \end{aligned}$$

Proposition 5.6. $\rho_u : \mathbb{R}^n \longrightarrow \mathbb{R}^n$ *is a linear map.*

Definition 5.7. *For $\varphi \in \mathbb{R}$ the counterclockwise* **rotation by an angle** φ *(in $\mathbb{R}^2$) is given by*

$$\begin{aligned} \mathrm{rot}_\varphi : \mathbb{R}^2 &\longrightarrow \mathbb{R}^2 \\ x &\longmapsto \begin{pmatrix} \cos(\varphi) & -\sin(\varphi) \\ \sin(\varphi) & \cos(\varphi) \end{pmatrix} x \,. \end{aligned}$$

6 Composition of linear maps & Matrix multiplication

Theorem 6.1. *If $F : \mathbb{R}^n \to \mathbb{R}^m$ and $G : \mathbb{R}^m \to \mathbb{R}^l$ are linear, then $GF : \mathbb{R}^n \to \mathbb{R}^l$ is linear.*

Definition 6.2. *Let $A \in \mathbb{R}^{l \times m}$ and $B \in \mathbb{R}^{m \times n}$, where B has the columns $v_1, \ldots, v_n \in \mathbb{R}^m$, i.e.*

$$B = \begin{pmatrix} | & & | \\ v_1 & \ldots & v_n \\ | & & | \end{pmatrix} .$$

Then the **product of** A **and** B *is the $l \times n$-matrix with columns $Av_1, \ldots, Av_n \in \mathbb{R}^l$, i.e.*

$$A \cdot B = \begin{pmatrix} | & & | \\ Av_1 & \ldots & Av_n \\ | & & | \end{pmatrix} \in \mathbb{R}^{l \times n} .$$

Theorem 6.3. *Let $F : \mathbb{R}^n \to \mathbb{R}^m$ and $G : \mathbb{R}^m \to \mathbb{R}^l$ be linear maps. Then the matrix of GF is given by the product of the matrices of G and F, i.e.*

$$[GF] = [G] \cdot [F] .$$

Proposition 6.4. *For all $A \in \mathbb{R}^{l \times m}, B, D \in \mathbb{R}^{m \times n}, C \in \mathbb{R}^{n \times p}$ and $\lambda \in \mathbb{R}$ we have*

i) $A \cdot I_m = I_l \cdot A = A$, *where I_m denotes the $m \times m$-identity matrix.*

ii) $(A \cdot B) \cdot C = A \cdot (B \cdot C)$.

iii) $A \cdot (B + D) = A \cdot B + A \cdot D$.

iv) $(B + D) \cdot C = B \cdot C + D \cdot C$.

v) $\lambda(A \cdot B) = (\lambda A) \cdot B = A \cdot (\lambda B)$.

7 The inverse of a linear map

The rank of a linear map $F : \mathbb{R}^n \to \mathbb{R}^m$ is defined by the rank of its matrix, i.e. $\mathrm{rk}(F) := \mathrm{rk}([F])$.

Theorem 7.1. *A linear map $F : \mathbb{R}^n \to \mathbb{R}^m$ is invertible if and only if $m = n = \mathrm{rk}(F)$.*

Proposition 7.2. *If a linear map $F : \mathbb{R}^n \to \mathbb{R}^n$ is invertible, then its inverse F^{-1} is also linear.*

Definition 7.3. *If $A \in \mathbb{R}^{n\times n}$ is the matrix of an invertible linear map $F : \mathbb{R}^n \to \mathbb{R}^n$ (i.e. $A = [F]$), then we define the* **inverse of** *A by $A^{-1} := [F^{-1}]$.*

Theorem 7.4. *The inverse of $A \in \mathbb{R}^{n\times n}$ exists (A is invertible) if and only if $\mathrm{rref}(A) = I_n$.*

Proposition 7.5. *If $A, B \in \mathbb{R}^{n\times n}$ are invertible we have*

i) $AA^{-1} = A^{-1}A = I_n$,

ii) $(BA)^{-1} = A^{-1}B^{-1}$.

(Definition 7.6 and Theorem 7.7 are just a remark and they are not so important for the rest of this course. They will appear again in detail in Linear Algebra II)

Definition 7.6. *For $\lambda \in \mathbb{R}$ with $\lambda \neq 0$ and $1 \leq i, j \leq n$ we define the* **elementary matrices** *$R_i^{\lambda,j}, R_i^{\lambda}, R_{i,j} \in \mathbb{R}^{n\times n}$ by*

$$R_i^{\lambda,j} = \begin{pmatrix} 1 & & & & & & \\ & \ddots & & & & & \\ & & 1 & & & & \\ & & & \ddots & & & \\ & & \lambda & & 1 & & \\ & & & & & \ddots & \\ & & & & & & 1 \end{pmatrix}, \quad R_i^{\lambda} = \begin{pmatrix} 1 & & & & & \\ & \ddots & & & & \\ & & 1 & & & \\ & & & \lambda & & \\ & & & & 1 & \\ & & & & & \ddots & \\ & & & & & & 1 \end{pmatrix}, \quad R_{i,j} = \begin{pmatrix} 1 & & & & & & \\ & \ddots & & & & & \\ & & 0 & & 1 & & \\ & & & \ddots & & & \\ & & 1 & & 0 & & \\ & & & & & \ddots & \\ & & & & & & 1 \end{pmatrix}.$$

Here the λ in $R_i^{\lambda,j}$ is in the i-th row and j-th column, in R_i^{λ} it is in the i-th row, and in $R_{i,j}$ the 0 are on the diagonal in the i-th row and j-th column.

Multiplying with an elementary matrix from the left corresponds to the elementary row operations (Definition 2.6)

(R1) Multiyplying with $R_i^{\lambda,j}$: Add λ-times row j to row i.

(R2) Multiyplying with R_i^{λ}: Multiply row j by λ. ($\lambda \neq 0$)

(R3) Multiyplying with $R_{i,j}$: Change row i and j.

Theorem 7.7. *Every invertible matrix is a product of elementary matrices.*

8 Subspaces, Kernel & Image

Definition 8.1. *A subset $U \subset \mathbb{R}^n$ is a* **subspace** *of $\mathbb{R}^n$ if*

i) $0 \in U$,

ii) for all $u, v \in U$ we have $u + v \in U$,

iii) for all $u \in U$ and $\lambda \in \mathbb{R}$ we have $\lambda u \in U$.

Definition 8.2. *For a linear map $F : \mathbb{R}^n \to \mathbb{R}^m$ the* **kernel of** *F is defined by*

$$\ker(F) = \{x \in \mathbb{R}^n \mid F(x) = 0\} .$$

Proposition 8.3. *For any linear map $F : \mathbb{R}^n \to \mathbb{R}^m$ we have the following:*

i) The kernel $\ker(F)$ is a subspace of $\mathbb{R}^n$.

ii) The image $\mathrm{im}(F)$ is a subspace of $\mathbb{R}^m$.

Definition 8.4. *i) A* **linear combination** *of vectors $v_1, \dots, v_n \in \mathbb{R}^m$ is a vector of the form*

$$u = \lambda_1 v_1 + \lambda_2 v_2 + \cdots + \lambda_n v_n \in \mathbb{R}^m$$

for some numbers $\lambda_1, \dots, \lambda_n \in \mathbb{R}$.

ii) The **span** *of $v_1, \dots, v_n \in \mathbb{R}^m$ is the set of all linear combinations*

$$\mathrm{span}\{v_1, \dots, v_n\} = \{\lambda_1 v_1 + \cdots + \lambda_n v_n \in \mathbb{R}^m \mid \lambda_1, \dots, \lambda_n \in \mathbb{R}\} .$$

Proposition 8.5. *For $v_1, \dots, v_n \in \mathbb{R}^m$ we have the following.*

i) $\mathrm{span}\{v_1, \dots, v_n\}$ is a subspace of $\mathbb{R}^m$.

ii) If $U \subset \mathbb{R}^m$ is a subspace and $v_1, \dots, v_n \in U$ then $\mathrm{span}\{v_1, \dots, v_n\} \subset U$.

Proposition 8.6. *A linear map $F : \mathbb{R}^n \to \mathbb{R}^m$ is injective if and only if $\ker(F) = \{0\}$.*

Theorem 8.7. *Let $F : \mathbb{R}^n \to \mathbb{R}^m$ be a linear map.*

i) We have the following equivalent statements for F being injective:

$$F \text{ is injective} \iff \ker(F) = \{0\} \iff \mathrm{rk}([F]) = n .$$

ii) We have the following equivalent statements for F being surjective:

$$F \text{ is surjective} \iff \mathrm{im}(F) = \mathbb{R}^m \iff \mathrm{rk}([F]) = m .$$

iii) If $\underline{m = n}$ then the following statements are equivalent:

$$F \text{ is bijective} \iff F \text{ is injective} \iff F \text{ is surjective} .$$

9 Linear independence

Lemma 9.1. *Let* $v_1, \dots, v_l \in \mathbb{R}^m$*. If* $v_l \in \operatorname{span}\{v_1, \dots, v_{l-1}\}$ *then*

$$\operatorname{span}\{v_1, \dots, v_l\} = \operatorname{span}\{v_1, \dots, v_{l-1}\}\,.$$

Definition 9.2. *i) Vectors* $v_1, \dots, v_l \in \mathbb{R}^m$ *are called* **linearly independent** *if the equation*

$$\lambda_1 v_1 + \cdots + \lambda_l v_l = 0 \tag{9.1}$$

with $\lambda_1, \dots, \lambda_l \in \mathbb{R}$ *just has the* <u>*unique*</u> *solution* $\lambda_1 = \cdots = \lambda_l = 0$*.*

ii) If there exist another solution of (9.1)*, i.e. where at least for one* $j = 1, \dots, l$ *we have* $\lambda_j \neq 0$*, then the vectors* $v_1, \dots, v_l$ *are called* **linearly dependent***.*

Theorem 9.3. *Let* $v_1, \dots, v_l \in \mathbb{R}^m$*. The following statements are equivalent:*

i) $v_1, \dots, v_l$ *are linearly dependent.*

ii) There exists a $j = 1, \dots, l$*, such that* v_j *is a linear combination of the other vectors.*

iii) There exists a $j = 1, \dots, l$ *with*

$$\operatorname{span}\{v_1, \dots, v_{j-1}, v_{j+1}, \dots, v_l\} = \operatorname{span}\{v_1, \dots, v_l\}\,.$$

Lemma 9.4. *Let* $V \subset \mathbb{R}^n$ *be a subspace,* $v_1, \dots, v_l \in V$ *linearly independent and* $V = \operatorname{span}\{w_1, \dots, w_m\}$ *for some* $w_1, \dots, w_m \in \mathbb{R}^n$*. Then we have* $l \leq m$*.*

Lemma 9.5. *If* $v_1, \dots, v_l \in \mathbb{R}^n$ *are linearly independent and* $w \in \mathbb{R}^n$ *with* $w \notin \operatorname{span}\{v_1, \dots, v_l\}$ *then* $v_1, \dots, v_l, w$ *are linearly independent.*

10 Bases & dimensions

Definition 10.1. *Let* $V \subset \mathbb{R}^n$ *be a subspace. Vectors* $v_1, \dots, v_l \in V$ *form a* **basis of V** *if*

i) $V = \operatorname{span}\{v_1, \dots, v_l\}$*,*

ii) $v_1, \dots, v_l$ *are linearly independent.*

In this case we also say that $\{v_1, \dots, v_l\}$ *is a basis of* V*.*

Later we will also be interested in the order of the v_j and write a basis as a tuple $(v_1, \dots, v_l)$.

Theorem 10.2. *For any subspace* $V \subset \mathbb{R}^n$ *we have the following:*

i) V *has a basis.*

ii) All bases of V *have the same number of elements.*

iii) *If* $v_1, \dots, v_l \in V$ *are linearly independent then there exist* $u_{l+1}, \dots, u_t \in V$*, such that* $\{v_1, \dots, v_l, u_{l+1}, \dots, u_t\}$ *is a basis of* V*.*

iv) *If* $V = \operatorname{span}\{w_1, \dots, w_m\}$ *then there exists a subset* $\{u_1, \dots, u_t\} \subset \{w_1, \dots, w_m\}$ *such that* $\{u_1, \dots, u_t\}$ *is a basis of* V*.*

Definition 10.3. *Let* $V \subset \mathbb{R}^n$ *be a subspace. The* **dimension of V***, denoted by* $\dim(V)$*, is the number of elements in a basis of* V*.*

Corollary 10.4. *Let* $V \subset \mathbb{R}^n$ *be a subspace with* $\dim(V) = m$ *and* $v_1, \dots, v_m \in V$*. Then the following statements are equivalent:*

i) $v_1, \dots, v_m$ *are linearly independent.*

ii) $V = \operatorname{span}\{v_1, \dots, v_m\}$*.*

iii) $\{v_1, \dots, v_m\}$ *is a basis of* V*.*

Theorem 10.5. *For a linear map* $F : \mathbb{R}^n \to \mathbb{R}^m$ *we have*

$$n = \dim(\ker(F)) + \dim(\operatorname{im}(F)) \,.$$

11 Coordinates

From now on we will consider ordered bases, which means that we will write $(b_1, \dots, b_n)$ (a tuple) for a basis instead of $\{b_1, \dots, b_n\}$ (a set). The difference is, that we care about the order now. For example, the two sets $\{b_1, b_2\} = \{b_2, b_1\}$ are the same, but $(b_1, b_2) \neq (b_2, b_1)$.

Definition 11.1. *Let* $B = (b_1, \dots, b_m)$ *be a basis of a subspace* $V \subset \mathbb{R}^n$*. We define the* **coordinate map** *by*

$$\begin{aligned} c_B : \mathbb{R}^m &\longrightarrow \mathbb{R}^n \\ \begin{pmatrix} \lambda_1 \\ \vdots \\ \lambda_m \end{pmatrix} &\longmapsto \lambda_1 b_1 + \cdots + \lambda_m b_m \,. \end{aligned}$$

Theorem 11.2. *Let* $B = (b_1, \dots, b_m)$ *be a basis of a subspace* $V \subset \mathbb{R}^n$*.*

i) *The coordinate map* $c_B : \mathbb{R}^m \longrightarrow V$ *is bijective.*

ii) *For all* $x \in V$ *there exist unique* $\lambda_1, \dots, \lambda_m \in \mathbb{R}$ *such that*

$$x = \lambda_1 b_1 + \cdots + \lambda_m b_m \,.$$

Definition 11.3. *Let* $B = (b_1, \dots, b_m)$ *be a basis of a subspace* $V \subset \mathbb{R}^n$ *and* $x \in V$ *with*

$$x = \lambda_1 b_1 + \cdots + \lambda_m b_m \,.$$

i) The numbers $\lambda_1, \dots, \lambda_m \in \mathbb{R}$ *are the* **coordinates of** x **(in the basis** B**)**.

ii) The **coordinate vector** *of* x *(with respect to* B*) is given by*

$$[x]_B = c_B^{-1}(x) = \begin{pmatrix} \lambda_1 \\ \vdots \\ \lambda_m \end{pmatrix} .$$

Proposition 11.4. *Let* $B = (b_1, \dots, b_m)$ *be a basis of a subspace* $V \subset \mathbb{R}^n$, $x, y \in V$ *and* $\mu \in \mathbb{R}$. *Then*

i) $[x + y]_B = [x]_B + [y]_B$,

ii) $[\mu x]_B = \mu [x]_B$,

iii) $[0]_B = 0$.

Definition 11.5. *Let* $B = (b_1, \dots, b_n)$ *be a basis of* $\mathbb{R}^n$. *The* **change-of-basis matrix** *associated with* B *is*

$$S_B = [c_B] = \begin{pmatrix} | & & | \\ b_1 & \dots & b_n \\ | & & | \end{pmatrix} .$$

Definition 11.6. *Let* $F : \mathbb{R}^n \to \mathbb{R}^m$ *be a linear map,* B_1 *be a basis of* $\mathbb{R}^n$ *and* B_2 *be a basis of* $\mathbb{R}^m$. *The* **matrix of** F **with respect to** B_1 **and** B_2 *is the matrix*

$$[F]_{B_1}^{B_2} := [c_{B_2}^{-1} \circ F \circ c_{B_1}] .$$

In the case $n = m$ *and* $B_1 = B_2$ *we just write* $[F]_{B_1} := [F]_{B_1}^{B_1}$.

Proposition 11.7. *Let* $F : \mathbb{R}^n \to \mathbb{R}^m$ *be a linear map,* B_1 *be a basis of* $\mathbb{R}^n$ *and* B_2 *be a basis of* $\mathbb{R}^m$.

i) We have

$$[F]_{B_1}^{B_2} = S_{B_2}^{-1} [F] S_{B_1} .$$

ii) If $B_1 = (b_1, \dots, b_n)$ *then*

$$[F]_{B_1}^{B_2} = \begin{pmatrix} | & & | \\ [F(b_1)]_{B_2} & \dots & [F(b_n)]_{B_2} \\ | & & | \end{pmatrix} .$$

12 Orthonormal bases & Gram-Schmidt algorithm

Definition 12.1. *i) A vector* $u \in \mathbb{R}^n$ *is called a* **unit vector** *if* $\|u\| = 1$. *(i.e.* $u \bullet u = 1$*)*

ii) Every vector $u \in \mathbb{R}^n$ *with* $u \neq 0$ *can be normalized by*

$$\widehat{u} = \frac{1}{\|u\|} u .$$

The vector $\hat{u}$ *is a unit vector and shows in the same direction as* u.

iii) Vectors $u_1, \dots, u_l \in \mathbb{R}^n$ *are called* **orthonormal** *if for* $1 \leq i, j \leq l$

$$u_i \bullet u_j = \begin{cases} 1 & , \text{if } i = j \\ 0 & , \text{if } i \neq j \end{cases} .$$

Definition 12.2. *A basis* $B = (b_1, \dots, b_m)$ *of a subspace* U *is called an* **orthonormal basis (ONB)** *of* U *if* $b_1, \dots, b_m$ *are orthonormal.*

Proposition 12.3. *i) If* $v_1, \dots, v_m \in \mathbb{R}^n$ *are orthonormal (ON), then they are linearly independent.*

ii) Let $B = (v_1, \dots, v_m)$ *be an ONB of* $V \subset \mathbb{R}^n$ *and* $u \in V$*. Then*

$$[u]_B = \begin{pmatrix} u \bullet v_1 \\ \vdots \\ u \bullet v_m \end{pmatrix} \in \mathbb{R}^m ,$$

i.e. $u = \sum_{i=1}^m (u \bullet v_i) v_i$.

iii) If $B = (v_1, \dots, v_m)$ *is an ONB of* $V \subset \mathbb{R}^n$ *and* $u, w \in V$*, then*

$$u \bullet w = [u]_B \bullet [w]_B .$$

Definition 12.4. *For a subspace* $U \subset \mathbb{R}^n$ *we define the* **orthogonal complement of** U **in** $\mathbb{R}^n$ *by*

$$U^\perp = \{x \in \mathbb{R}^n \mid x \bullet u = 0 \text{ for all } u \in U\} .$$

Lemma 12.5. *Let* $U \subset \mathbb{R}^n$ *be a subspace.*

i) $U^\perp \subset \mathbb{R}^n$ *is a subspace.*

ii) We have $U \cap U^\perp = \{0\}$.

iii) If $(u_1, \dots, u_r)$ *is a basis of* U*,* $x \in \mathbb{R}^n$*, then*

$$x \in U^\perp \quad \Longleftrightarrow \quad x \bullet u_1 = \cdots = x \bullet u_r = 0 .$$

iv) Let $(f_1, \dots, f_r)$ *be an ONB of* U *and* $x \in \mathbb{R}^n$*. Then*

$$x = x_\parallel + x_\perp ,$$

where

$$x_\parallel = \sum_{i=1}^r (x \bullet f_i) f_i \in U$$
$$x_\perp = x - x_\parallel \in U^\perp .$$

Gram-Schmidt algorithm (GSA)

Let $B = (b_1, \ldots, b_m)$ be an arbitrary basis of a subspace $U \subset \mathbb{R}^n$. The GSA constructs an orthonormal basis $F = (f_1, \ldots, f_m)$ of U out of the basis B in the following way m steps:

Step 1**:** Set $f_1 = \widehat{b_1} = \frac{1}{\|b_1\|} b_1$.

Step l $(2 \leq l \leq m)$: We have constructed orthonormal vectors $f_1, \ldots, f_{l-1}$ in the steps before. Now set

$$w_l = b_l - (b_l \bullet f_1) f_1 - \cdots - (b_l \bullet f_{l-1}) f_{l-1} = b_l - \sum_{i=1}^{l-1} (b_l \bullet f_i) f_i$$

and define $f_l = \frac{1}{\|w_l\|} w_l$.

Theorem 12.6. *Every subspace of* $\mathbb{R}^n$ *has an ONB.*

Corollary 12.7. *Let* $U \subset \mathbb{R}^n$ *be a subspace. For all* $x \in \mathbb{R}^n$ *there exist unique* $x_\parallel \in U$ *and* $x_\perp \in U^\perp$ *with*

$$x = x_\parallel + x_\perp \, .$$

13 Orthogonal Projection & Least squares

Definition 13.1. *Let* $U \subset \mathbb{R}^n$ *be a subspace. The map*

$$\begin{aligned} P_U : \mathbb{R}^n &\longrightarrow \mathbb{R}^n \\ x &\longmapsto x_\parallel \end{aligned}$$

is the **orthogonal projection** *onto* U*.*

Proposition 13.2. *Let* $U \subset \mathbb{R}^n$ *be a subspace.*

i) P_U *is a linear map.*

ii) $P_U^2 = P_U$.

iii) $\ker(P_U) = U^\perp$ *and* $\operatorname{im} P_U = U$.

iv) If $(f_1, \ldots, f_m)$ *is an ONB of* U*, then*

$$P_U(x) = (x \bullet f_1) f_1 + \cdots + (x \bullet f_m) f_m \, .$$

Proposition 13.3. *Let* $U \subset \mathbb{R}^n$ *be a subspace and* $x \in \mathbb{R}^n$*. Then for all* $u \in U$ *we have*

$$\|x - P_U(x)\| \leq \|x - u\| \, .$$

We just have equality in the case when $u = P_U(x)$*.*

Definition 13.4. *The* **transpose** *of a matrix* $A = (a_{ij}) \in \mathbb{R}^{m\times n}$ *is the matrix* $A^T = (a_{ji}) \in \mathbb{R}^{n\times m}$*.*

Proposition 13.5. *i) For* $A, B \in \mathbb{R}^{m\times n}$ *and* $\lambda \in \mathbb{R}$ *we have*

$$(A+B)^T = A^T + B^T\,, \qquad (\lambda A)^T = \lambda A^T\,.$$

ii) For $A \in \mathbb{R}^{m\times n}$ *and* $B \in \mathbb{R}^{n\times l}$ *we have*

$$(AB)^T = B^T A^T \in \mathbb{R}^{l\times m}\,.$$

iii) For $x, y \in \mathbb{R}^n$ *we have* $x \bullet y = x^T y$*.*

For $A \in \mathbb{R}^{m\times n}$ we can define the linear map $F : x \mapsto Ax$. With this we define the image and kernel of the matrix A by $\mathrm{im}(A) = \mathrm{im}(F)$ and $\ker(A) = \ker(F)$.

Proposition 13.6. *For all* $A \in \mathbb{R}^{m\times n}$ *we have* $\mathrm{im}(A)^\perp = \ker(A^T)$*.*

Corollary 13.7. *Let* $A \in \mathbb{R}^{m\times n}$*.*

i) We have $\ker(A^T A) = \ker(A)$*.*

ii) We have the following equivalence

$$\ker(A) = \{0\} \quad \Longleftrightarrow \quad A^T A \in \mathbb{R}^{n\times n} \text{ is invertible}\,.$$