

Optimization and Computational Linear Algebra for Data Science

Lecture 3: Rank

Léo MIOLANE · leo.miolane@gmail.com

September 2, 2019

Warning: *This material is not meant to be lecture notes. It only gathers the main concepts and results from the lecture, without any additional explanation, motivation, examples, figures...*

1 Definition of the rank

Definition 1.1 (*Rank of a family of vectors*)

We define the rank of a family x_1, \dots, x_k of vectors of \mathbb{R}^n as the dimension of its span:

$$\text{rank}(x_1, \dots, x_k) \stackrel{\text{def}}{=} \dim(\text{Span}(x_1, \dots, x_k)).$$

If the vectors x_1, \dots, x_k are linearly independent then $\text{rank}(x_1, \dots, x_k) = k$. Indeed, in that case (x_1, \dots, x_k) forms a basis of $\text{Span}(x_1, \dots, x_k)$ so $\dim(\text{Span}(x_1, \dots, x_k)) = k$.

Definition 1.2 (*Rank of a matrix*)

Let $M \in \mathbb{R}^{n \times m}$. Let $\ell_1, \dots, \ell_n \in \mathbb{R}^m$ be the lines of M and $c_1, \dots, c_m \in \mathbb{R}^n$ be its columns. Then we have

$$\text{rank}(\ell_1, \dots, \ell_n) = \text{rank}(c_1, \dots, c_m). \quad (1)$$

The rank of the matrix M is then defined as $\text{rank}(M) \stackrel{\text{def}}{=} \text{rank}(\ell_1, \dots, \ell_n) = \text{rank}(c_1, \dots, c_m)$.

Since $\text{Im}(M) = \text{Span}(c_1, \dots, c_m)$ an equivalent definition is $\text{rank}(M) = \dim(\text{Im}(M))$.

Proof. In order to prove (1) it suffices to show (since columns and rows are playing exchangeable roles) that $\text{rank}(\ell_1, \dots, \ell_n) \leq \text{rank}(c_1, \dots, c_m)$. Let $r \stackrel{\text{def}}{=} \text{rank}(\ell_1, \dots, \ell_n)$ and (x_1, \dots, x_r) be a basis of $\text{Span}(\ell_1, \dots, \ell_n)$. We will prove that

$$(Mx_1, \dots, Mx_r) \text{ is linearly independent.} \quad (2)$$

The result follows. Indeed (Mx_1, \dots, Mx_r) is then a linearly independent family of r vectors of $\text{Im}(M) = \text{Span}(c_1, \dots, c_m)$: this implies that $\text{rank}(c_1, \dots, c_m) = \dim(\text{Span}(c_1, \dots, c_m)) \geq r = \text{rank}(\ell_1, \dots, \ell_n)$.

It remains to prove (2). Let $\alpha_1, \dots, \alpha_r \in \mathbb{R}$ such that $\alpha_1 Mx_1 + \dots + \alpha_r Mx_r = 0$. We will show that in such case the α_i are all zero. Define $v \stackrel{\text{def}}{=} \alpha_1 x_1 + \dots + \alpha_r x_r$. We have by linearity

$$Mv = M(\alpha_1 x_1 + \dots + \alpha_r x_r) = \alpha_1 Mx_1 + \dots + \alpha_r Mx_r = 0.$$

Since the i^{th} coordinate of Mv is equal to $(Mv)_i = \ell_i \cdot v$, we get that v is orthogonal to all the ℓ_i , and therefore to $\text{Span}(\ell_1, \dots, \ell_n)$. Notice now that $v \in \text{Span}(x_1, \dots, x_r) = \text{Span}(\ell_1, \dots, \ell_n)$ by construction. The vector v is orthogonal to itself, hence $\alpha_1 x_1 + \dots + \alpha_r x_r = v = 0$. Recall that the family (x_1, \dots, x_r) is linearly independent (because it is a basis) so $\alpha_1 = \dots = \alpha_r = 0$. \square

Remark 1.1. For $v_1, \dots, v_k \in \mathbb{R}^n$, and $\alpha \in \mathbb{R} \setminus \{0\}$, $\beta \in \mathbb{R}$ one can easily verify that

$$\begin{aligned} \text{rank}(v_1, \dots, v_k) &= \text{rank}(v_1, \dots, v_{i-1}, \alpha v_i, v_{i+1}, \dots, v_k) \\ &= \text{rank}(v_1, \dots, v_{i-1}, v_i, v_{i+1}, \dots, v_{j-1}, v_j + \beta v_i, v_{j+1}, \dots, v_k). \end{aligned}$$

As a consequence, the Gaussian elimination method keeps the rank of a matrix unchanged!

2 Properties of the rank

Proposition 2.1

Let $A \in \mathbb{R}^{n \times m}$ and $B \in \mathbb{R}^{m \times k}$. Then the following holds

- (i) $\text{rank}(A) \leq \min(n, m)$.
- (ii) $\text{rank}(AB) \leq \min(\text{rank}(A), \text{rank}(B))$.

Exercise 2.1 (Important). Let $M \in \mathbb{R}^{n \times m}$ and $r = \text{rank}(M)$. Show that there exist $A \in \mathbb{R}^{n \times r}$ and $B \in \mathbb{R}^{r \times m}$ such that $M = AB$.

Theorem 2.1

Let $M \in \mathbb{R}^{n \times m}$. The following points are equivalent:

- (i) M is invertible.
- (ii) $\text{rank}(M) = n$.
- (iii) $\text{Ker}(M) = \{0\}$.

Proof. Points (ii) and (iii) are equivalent by Theorem 2.2 below. The fact that (i) \Leftrightarrow [(ii)-(iii)] follows from Proposition 3.1 from Lecture 2. \square

Theorem 2.2 (Rank-nullity theorem)

Let $L : \mathbb{R}^m \rightarrow \mathbb{R}^n$ be a linear transformation. Then

$$\text{rank}(L) + \dim(\text{Ker}(L)) = m.$$

Exercise 2.2. Let $A \in \mathbb{R}^{n \times m}$ and $B \in \mathbb{R}^{m \times m}$. Show that if B is invertible then $\text{rank}(AB) = \text{rank}(A)$. Similarly for $A \in \mathbb{R}^{n \times n}$ and $B \in \mathbb{R}^{n \times m}$, show that if A is invertible then $\text{rank}(AB) = \text{rank}(B)$.

Proof of Theorem 2.2. We will need the following result.

Proposition 2.2

Let V be a vector space of dimension n . Let $x_1, \dots, x_k \in V$. If x_1, \dots, x_k are linearly independent then one can find vectors $x_{k+1}, \dots, x_n \in V$ such that (x_1, \dots, x_n) forms a basis of V .

Let us write $k = \dim(\text{Ker}(L))$ and let us fix a basis (x_1, \dots, x_k) of $\text{Ker}(L)$. By Proposition 2.2 one can complete this family into a basis $(x_1, \dots, x_k, x_{k+1}, \dots, x_m)$ of \mathbb{R}^m . We will show that

- (i) $\text{Span}(L(x_{k+1}), \dots, L(x_m)) = \text{Im}(L)$.
- (ii) the family $(L(x_{k+1}), \dots, L(x_m))$ is linearly independent.

By proving (i) and (ii) we will get that $(L(x_{k+1}), \dots, L(x_m))$ is a basis of $\text{Im}(L)$ which implies that

$$\text{rank}(L) = \dim(\text{Im}(L)) = m - k = m - \dim(\text{Ker}(L)),$$

hence the result.

We start by proving (i). Since $L(x_{k+1}), \dots, L(x_m)$ are all in $\text{Im}(L)$ (which is a linear subspace) any linear combination of these vectors belongs to $\text{Im}(L)$, hence $\text{Span}(L(x_{k+1}), \dots, L(x_m)) \subset \text{Im}(L)$.

Let us prove the converse inclusion. Let $y \in \text{Im}(L)$, which means that we can find $z \in \mathbb{R}^m$ such that $y = L(z)$. Let $(\alpha_1, \dots, \alpha_m) \in \mathbb{R}^m$ be the coordinates of z in the basis (x_1, \dots, x_m) : $z = \alpha_1 x_1 + \dots + \alpha_m x_m$. We have then by linearity of L

$$y = L(z) = L(\alpha_1 x_1 + \dots + \alpha_m x_m) = \alpha_1 L(x_1) + \dots + \alpha_m L(x_m).$$

Recall now that x_1, \dots, x_k belong to $\text{Ker}(L)$. Therefore $L(x_1) = \dots = L(x_k) = 0$. We get

$$y = \alpha_{k+1} L(x_{k+1}) + \dots + \alpha_m L(x_m),$$

hence $y \in \text{Span}(L(x_{k+1}), \dots, L(x_m))$: $\text{Im}(L) \subset \text{Span}(L(x_{k+1}), \dots, L(x_m))$. We conclude that $\text{Im}(L) = \text{Span}(L(x_{k+1}), \dots, L(x_m))$.

Let us now prove (ii). To prove that $(L(x_{k+1}), \dots, L(x_m))$ are linearly independent, we consider scalars $\alpha_{k+1}, \dots, \alpha_m \in \mathbb{R}$ such that $\alpha_{k+1} L(x_{k+1}) + \dots + \alpha_m L(x_m) = 0$. Our goal is to show that $\alpha_{k+1} = \dots = \alpha_m = 0$. We have by linearity of L :

$$0 = \alpha_{k+1} L(x_{k+1}) + \dots + \alpha_m L(x_m) = L(\alpha_{k+1} x_{k+1} + \dots + \alpha_m x_m)$$

which gives that $\alpha_{k+1} x_{k+1} + \dots + \alpha_m x_m \in \text{Ker}(L)$. Recall that (x_1, \dots, x_k) is a basis of $\text{Ker}(L)$, so there exists scalars $\alpha_1, \dots, \alpha_k$ such that $\alpha_1 x_1 + \dots + \alpha_k x_k = \alpha_{k+1} x_{k+1} + \dots + \alpha_m x_m$. We obtain

$$\alpha_1 x_1 + \dots + \alpha_k x_k - \alpha_{k+1} x_{k+1} - \dots - \alpha_m x_m = 0$$

which implies that $\alpha_1 = \dots = \alpha_m = 0$ because (x_1, \dots, x_m) is a basis of \mathbb{R}^m . This proves (ii). \square

3 Transpose of a matrix, symmetric matrices

Definition 3.1 (*Transpose*)

Let $M \in \mathbb{R}^{n \times m}$. We define its transpose $M^\top \in \mathbb{R}^{m \times n}$ by

$$(M^\top)_{i,j} = M_{i,j}$$

for all $i \in \{1, \dots, m\}$ and $j \in \{1, \dots, n\}$.

Remark 3.1.

- We have $(M^\top)^\top = M$.
- The mapping $M \mapsto M^\top$ is linear.

We remark also that the rows of M become the columns of M^\top and that the columns of M become the rows of M^\top . By Definition 1.2, this gives:

Proposition 3.1

$$\text{rank}(M) = \text{rank}(M^\top).$$

Proposition 3.2

Let $A \in \mathbb{R}^{n \times m}$ and $B \in \mathbb{R}^{m \times k}$. Then

$$(AB)^\top = B^\top A^\top.$$

Corollary 3.1

If $M \in \mathbb{R}^{n \times n}$ is invertible, then so is M^\top and

$$(M^\top)^{-1} = (M^{-1})^\top.$$

Proof. We compute, using Proposition 3.2:

$$M^\top (M^{-1})^\top = (M^{-1}M)^\top = \text{Id}_n^\top = \text{Id}_n.$$

This proves that M^\top is invertible with inverse $(M^{-1})^\top$. □

Definition 3.2 (*Symmetric matrix*)

A square matrix $A \in \mathbb{R}^{n \times n}$ is said to be symmetric if

$$\forall i, j \in \{1, \dots, n\}, A_{i,j} = A_{j,i}$$

or, equivalently if $A = A^\top$.

The following example is fundamental:

Example 3.1 (Gram matrices). Let $M \in \mathbb{R}^{k \times n}$. Then the $n \times n$ “Gram matrix” $A \stackrel{\text{def}}{=} M^\top M$ is symmetric.

