Optimization and Computational Linear Algebra for Data Science
Lecture 3: Rank

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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:

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

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

Definition 1.2 (*Rank of a matrix*)

Let $M \in \mathbb{R}^{n \times m}$. Let $c_1, \dots, c_m \in \mathbb{R}^n$ be its columns. We define

$$\mathrm{rank}(M) \stackrel{\text{def}}{=} \mathrm{rank}(c_1, \dots, c_m) = \dim(\mathrm{Im}(M)). \tag{1}$$

Proposition 1.1

Let $M \in \mathbb{R}^{n \times m}$. Let $r_1, \dots, r_n \in \mathbb{R}^m$ be the rows of M and $c_1, \dots, c_m \in \mathbb{R}^n$ be its columns. Then we have

$$\mathrm{rank}(r_1, \dots, r_n) = \mathrm{rank}(c_1, \dots, c_m) = \mathrm{rank}(M). \tag{2}$$

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*

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

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) $\mathrm{rank}(A) \leq \min(n, m)$.

(ii) $\mathrm{rank}(AB) \leq \min(\mathrm{rank}(A), \mathrm{rank}(B))$.

Exercise 2.1 (Important)**.** *Let* $M \in \mathbb{R}^{n\times m}$ *and* $r = \mathrm{rank}(M)$*. 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 (***Rank-nullity theorem***)

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

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

Theorem 2.1 is proved at the end of these notes.

Theorem 2.2

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

(i) M *is invertible.*

(ii) $\mathrm{rank}(M) = n$*.*

(iii) $\mathrm{Ker}(M) = \{0\}$*.*

Proof. Points (ii) and (iii) are equivalent by Theorem 2.1 below. The fact that (i) $\Leftrightarrow$ [(ii)-(iii)] follows from Proposition 3.1 from Lecture 2. □

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

3 Transpose of a matrix, symmetric matrices

Definition 3.1 (***Transpose***)

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

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

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

Remark 3.1.

- *We have* $(M^\mathsf{T})^\mathsf{T} = M$*.*
- *The mapping* $M \mapsto M^\mathsf{T}$ *is linear.*

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

Proposition 3.1

$\mathrm{rank}(M) = \mathrm{rank}(M^\mathsf{T})$.

Proposition 3.2

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

$$(AB)^\mathsf{T} = B^\mathsf{T} A^\mathsf{T}.$$

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:

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

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" $A \overset{\text{def}}{=} M^\top M$ is symmetric.

Proof of Theorem 2.1

We will need the following result.

Proposition 3.3

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 $k = \dim(\mathrm{Ker}(L))$ and let us fix a basis $(x_1,\dots,x_k)$ of $\mathrm{Ker}(L)$. By Proposition 3.3 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) $\mathrm{Span}(L(x_{k+1}),\dots,L(x_m)) = \mathrm{Im}(L)$.

(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 $\mathrm{Im}(L)$ which implies that

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

hence the result.

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

Let us prove the converse inclusion. Let $y \in \mathrm{Im}(L)$, 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 $(x_1,\dots,x_m)$: $z = \alpha_1 x_1 + \cdots + \alpha_m x_m$. We have then by linearity of L

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

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

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

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

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 $\alpha_{k+1} L(x_{k+1}) + \cdots + \alpha_m L(x_m) = 0$. Our goal is to show that $\alpha_{k+1} = \cdots = \alpha_m = 0$. We have by linearity of L:

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

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

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

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