

# Least Squares, Null space, Row space, Projectors

Computational Intelligence, Lecture 2

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# LEAST SQUARES AT A GLANCE (1)

Consider the following problem: find the smallest 2-norm  $\mathbf{x}$  for which the equality  $\mathbf{Ax} = \mathbf{y}$  has least residual. This is the *least squares problem*.

- Residual is defined as  $\mathbf{e} = \mathbf{Ax} - \mathbf{y}$
- The idea that we need to find the smallest 2-norm  $\mathbf{x}$  and, at the same time, least residual  $\mathbf{e}$  seems to call for compromise. However, we will find that there exist a linear subspace of solutions with the exact same residual, and on that subspace we can find  $\mathbf{x}$  with the smallest norm.

# LEAST SQUARES AT A GLANCE (2)

Minimum of  $\|\mathbf{e}\|_2 = \|\mathbf{Ax} - \mathbf{y}\|_2$  is achieved at the same  $\mathbf{x}$  as minimum of  $(\mathbf{Ax} - \mathbf{y})^\top (\mathbf{Ax} - \mathbf{y})$ . With that in mind, let us find its extremum:

$$2\mathbf{A}^\top (\mathbf{Ax} - \mathbf{y}) = 0 \quad (1)$$

$$\mathbf{A}^\top \mathbf{Ax} = \mathbf{A}^\top \mathbf{y} \quad (2)$$

$$\mathbf{x} = (\mathbf{A}^\top \mathbf{A})^{-1} \mathbf{A}^\top \mathbf{y} \quad (3)$$

Thus we can define a *pseudoinverse*:

$$\mathbf{A}^+ = (\mathbf{A}^\top \mathbf{A})^{-1} \mathbf{A}^\top \quad (4)$$

# LEAST SQUARES AT A GLANCE (3)

Thus the least residual solution to  $\mathbf{Ax} = \mathbf{y}$  is written as:

$$\mathbf{x} = \mathbf{A}^+ \mathbf{y} \quad (5)$$

We proved that this is the least-residual solution, we will prove that the solution is smallest norm (out of all solutions with the same residual) in the following lectures.

# LEAST SQUARES AND CLOSEST ELEMENT

You are given an equation  $\mathbf{Ax} = \mathbf{y}$ . You want to find an  $\mathbf{x}$  that gets the value of  $\mathbf{y}$  as close as possible to  $\mathbf{y}^*$  in terms of the 2-norm.

We know that  $\mathbf{x} = \mathbf{A}^+\mathbf{y}^*$  gives us the least residual solution. Multiplying it by  $\mathbf{A}$  we get:

$$\mathbf{y} = \mathbf{AA}^+\mathbf{y}^* \tag{6}$$

This is the value of  $\mathbf{y}$  that we can achieve, which is closest to  $\mathbf{y}^*$ .

# FOUR FUNDAMENTAL SUBSPACES

One of the key ideas in Linear Algebra is that every linear operator has four fundamental subspaces:

- Null space
- Row space
- Column space
- Left null space

Our goal is to understand them. The usefulness of this concept is enormous.

# NULL SPACE

## Definition

Consider the following task: find all solutions to the system of equations  $\mathbf{A}\mathbf{x} = \mathbf{0}$ .

It can be re-formulated as follows: find all elements of the *null space* of  $\mathbf{A}$ .

### Definition 1

*Null space* of  $\mathbf{A}$  is the set of all vectors  $\mathbf{x}$  that  $\mathbf{A}$  maps to  $\mathbf{0}$

We will denote null space as  $\mathcal{N}(\mathbf{A})$ . In the literature, it is often denoted as  $\ker(\mathbf{A})$  or  $\text{null}(\mathbf{A})$ .



# NULL SPACE

## Calculation

Now we can find all solutions to the system of equations  $\mathbf{Ax} = \mathbf{0}$  by using functions that generate an orthonormal *basis* in the null space of  $\mathbf{A}$ . In MATLAB it is function `null`, in Python/Scipy - `null_space`:

- `N = null(A).`

- `N = scipy.linalg.null_space(A).`

That is it! Space of solutions of  $\mathbf{Ax} = \mathbf{0}$  is the span of the columns of  $\mathbf{N}$ , and all solutions  $\mathbf{x}^*$  can be represented as  $\mathbf{x}^* = \mathbf{Nz}$ ; for any  $\mathbf{z}$  we get a unique solution, and for any solution - a unique  $\mathbf{z}$ .

# NULL SPACE PROJECTION

## Local coordinates

Let  $\mathbf{N}$  be the orthonormal basis in the null space of matrix  $\mathbf{A}$ . Then, if a vector  $\mathbf{x}$  lies in the null space of  $\mathbf{A}$ , it can be represented as:

$$\mathbf{x} = \mathbf{N}\mathbf{z} \tag{7}$$

where  $\mathbf{z}$  are coordinates of  $\mathbf{x}$  in the basis  $\mathbf{N}$ .

However, there are vectors which not only are not lying in the null space of  $\mathbf{A}$ , but the closest vector to them in the null space is the zero vector.

# CLOSEST ELEMENT FROM A LINEAR SUBSPACE

Let  $\mathbf{A} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}$ . Its null space has orthonormal basis  $\mathbf{N} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$ .

■  $\begin{bmatrix} -2 \\ 0 \end{bmatrix} = -2\mathbf{N}$ ,  $\begin{bmatrix} 10 \\ 0 \end{bmatrix} = 10\mathbf{N}$ , - both are in the null space.

■ for  $\mathbf{x} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$  the closest vector in the null space is  $\begin{bmatrix} 1 \\ 0 \end{bmatrix}$ .

■ for  $\mathbf{y} = \begin{bmatrix} 0 \\ 2 \end{bmatrix}$  the closest vector in the null space is  $\begin{bmatrix} 0 \\ 0 \end{bmatrix}$ .

# ORTHOGONALITY, DEFINITION (1)

## Definition

Any two vectors,  $\mathbf{x}$  and  $\mathbf{y}$ , whose dot product is zero are said to be *orthogonal* to each other.

## Definition

Vector  $\mathbf{x}$ , whose dot product with any  $\mathbf{y} \in \mathcal{L}$  is orthogonal to the subspace  $\mathcal{L}$

## Definition (equivalent)

If for a vector  $\mathbf{x}$ , the closest vector to it from a linear subspace  $\mathcal{L}$  is zero vector,  $\mathbf{x}$  is called orthogonal to the subspace  $\mathcal{L}$ .

## ORTHOGONALITY, DEFINITION (2)

### Definition

The space of all vectors  $\mathbf{y}$ , orthogonal to a linear subspace  $\mathcal{L}$  is called *orthogonal complement* of  $\mathcal{L}$  and is denoted as  $\mathcal{L}^\perp$ .

### Definition (equivalent)

The space of all vectors  $\mathbf{y}$ , such that  $\text{dot}(\mathbf{y}, \mathbf{x}) = 0, \forall \mathbf{x} \in \mathcal{L}$  is called *orthogonal complement* of  $\mathcal{L}$ .

Therefore  $\mathbf{x} \in \mathcal{L}$  and  $\mathbf{y} \in \mathcal{L}^\perp$  implies  $\text{dot}(\mathbf{y}, \mathbf{x}) = 0$ .

# PROJECTION

## Part 1

Let  $\mathbf{L}$  be an orthonormal basis in a linear subspace  $\mathcal{L}$ . Take vector  $\mathbf{a} = \mathbf{x} + \mathbf{y}$ , where  $\mathbf{x}$  lies in the subspace  $\mathcal{L}$ , and  $\mathbf{y}$  lies in the subspace  $\mathcal{L}^\perp$ .

### Definition

We call such vector  $\mathbf{x}$  a *projection* of  $\mathbf{a}$  onto subspace  $\mathcal{L}$ , and such vector  $\mathbf{y}$  a projection of  $\mathbf{a}$  onto subspace  $\mathcal{L}^\perp$ .

Projection is the closest element in the subspace to a given vector. Projection of  $\mathbf{a}$  onto  $\mathcal{L}$  can be found as:

$$\mathbf{x} = \mathbf{L}\mathbf{L}^+ \mathbf{a} \tag{8}$$

Since  $\mathbf{L}$  is orthonormal, this is the same as  $\mathbf{x} = \mathbf{L}\mathbf{L}^\top \mathbf{a}$

# PROJECTION

## Part 2

Since  $\mathbf{a} = \mathbf{x} + \mathbf{y}$ , and  $\mathbf{x} = \mathbf{L}\mathbf{L}^\top \mathbf{a}$ , we can write:

$$\mathbf{a} = \mathbf{L}\mathbf{L}^\top \mathbf{a} + \mathbf{y} \quad (9)$$

from which it follows that the projection of  $\mathbf{a}$  onto  $\mathcal{L}^\perp$  can be found as:

$$\mathbf{y} = (\mathbf{I} - \mathbf{L}\mathbf{L}^\top) \mathbf{a} \quad (10)$$

where  $\mathbf{I}$  is an identity matrix. Since  $\mathbf{L}$  is orthonormal, this is the same as  $\mathbf{y} = (\mathbf{I} - \mathbf{L}\mathbf{L}^\top) \mathbf{a}$

# ROW SPACE

## Definition

### Definition

Let  $\mathcal{N}$  be null space of  $\mathbf{A}$ . Then orthogonal subspace  $\mathcal{N}^\perp$  is called *row space* of  $\mathbf{A}$ .

### Definition

*Row space* of  $\mathbf{A}$  is the space of all smallest-norm solutions of  $\mathbf{A}\mathbf{x} = \mathbf{y}$ , for  $\forall \mathbf{y}$ .

We will denote row space as  $\mathcal{R}$ .



# VECTORS IN NULL SPACE, ROW SPACE

Given vector  $\mathbf{x}$ , matrix  $\mathbf{A}$  and its nulls space basis  $\mathbf{N}$ , and we check if  $\mathbf{x}$  is in the null space of  $\mathbf{A}$ . The simplest way is to check if  $\mathbf{A}\mathbf{x} = 0$ . But sometimes we may want to avoid computing  $\mathbf{A}\mathbf{x}$ , for example if the number of elements of  $\mathbf{A}$  is much larger than the number of elements of  $\mathbf{N}$ .

If  $\mathbf{x}$  is in the null space of  $\mathbf{A}$ , it will have zero projection onto the row space of  $\mathbf{A}$ . This gives us the condition we can check:

$$(\mathbf{I} - \mathbf{N}\mathbf{N}^\top)\mathbf{x} = 0 \quad (11)$$

By the same logic, condition for being in the row space is as follows:

$$\mathbf{N}\mathbf{N}^\top \mathbf{x} = 0 \quad (12)$$

# ROW AND NULL SPACES IN LINEAR EQUATIONS

## Part 1

Consider another task: find all solutions to the system of equations  $\mathbf{Ax} = \mathbf{y}$ .

Assume we have two solutions to the system:  $\mathbf{x}_1$  and  $\mathbf{x}_2$ . We know that  $\mathbf{Ax}_1 = \mathbf{Ax}_2 = \mathbf{y}$ , hence  $\mathbf{A}(\mathbf{x}_1 - \mathbf{x}_2) = \mathbf{0}$ . In other words, the difference between any two solutions lies in the null space of  $\mathbf{A}$ .

On the other hand, let  $\mathbf{x}^*$  be a solution, and  $\mathbf{x}^N \in \mathcal{N}(\mathbf{A})$  be a vector in the null space of  $\mathbf{A}$ . Then  $\mathbf{x}^* + \mathbf{x}^N$  is also a solution, since  $\mathbf{A}(\mathbf{x}^* + \mathbf{x}^N) = \mathbf{Ax}^* + \mathbf{Ax}^N = \mathbf{Ax}^* = \mathbf{y}$ .

Therefore, the solution space is given by a single partial solution  $\mathbf{x}^p \notin \mathcal{N}(\mathbf{A})$  and the whole null space of  $\mathbf{A}$ .

# ROW AND NULL SPACES IN LINEAR EQUATIONS

## Part 2

There are infinitely many ways to choose  $\mathbf{x}^p$ , since if  $\mathbf{x}^p \notin \mathcal{N}(\mathbf{A})$ , then  $(\mathbf{x}^p + \mathbf{x}^N) \notin \mathcal{N}(\mathbf{A})$ , if  $\mathbf{x}^N \in \mathcal{N}(\mathbf{A})$ . However:

### Statement 1

The smallest-norm  $\mathbf{x}^p$  will lie in the row space of  $\mathbf{A}$ .

We can prove it by observing that there can be only one  $\mathbf{x}^p \in \mathcal{R}(\mathbf{A})$  and adding to it any vector  $\mathbf{x}^N \in \mathcal{N}(\mathbf{A})$  can only increase its magnitude, as  $\mathbf{x}^p$  and  $\mathbf{x}^N$  are orthogonal.

# ROW AND NULL SPACES IN LINEAR EQUATIONS

## Part 3

If we have  $\mathbf{x}^*$ , which is a solution to  $\mathbf{Ax} = \mathbf{y}$ , we can find the particular solution  $\mathbf{x}^p \in \mathcal{R}(\mathbf{A})$  as a projection:

$$\mathbf{x}^p = (\mathbf{I} - \mathbf{NN}^\top)\mathbf{x}^* \quad (13)$$

where  $\mathbf{N}$  is the null space basis for  $\mathbf{A}$ . Alternatively, we can simply find it as:

$$\mathbf{x}^p = \mathbf{A}^+\mathbf{y} \quad (14)$$

All solutions to  $\mathbf{Ax} = \mathbf{y}$  are then given as:

$$\mathbf{x}^* = \mathbf{A}^+\mathbf{y} + \mathbf{Nz}, \quad \forall \mathbf{z} \quad (15)$$

Lecture slides are available via Moodle.

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[github.com/SergeiSa/Computational-Intelligence-Slides-Spring-2022](https://github.com/SergeiSa/Computational-Intelligence-Slides-Spring-2022)



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