Lecture 26 (hrs. 52,53) - November 25, 2025, 16:30 - 18:30 F3

(3.16) <u>Definition</u> (least squares solution of a linear system).

Let $A \in R^{r \times c}$ where r > c, and let $b \in R^r$. An element $x^* \in R^c$ is called a *least squares solution* of the system $A \times = b$ if x^* is the absolute minimum point of the function $SQ: R^c \to R$ defined by:

$$SQ(x) = ||Ax - b||^2$$

Note that: if $y \in R^c$ is a solution of Ax = b then y is *also* a solution of Ax = b in the least squares sense (why?) <u>but</u>, except in special cases, a solution of Ax = b in the least squares sense *is not* a solution of Ax = b.

Let us see how we can find the least squares solutions of Ax = b.

(3.17) Remark (orthogonal decomposition of a vector).

Let $A = (a_1, \ldots, a_c) \in R^{r \times c}$ where r > c, and let $b \in R^r$. Denoted by b_* <u>the</u> *orthogonal* projection¹ of b onto span{ a_1, \ldots, a_c } = C(A)², and set b_{\perp} = b - b_* we get the orthogonal decomposition:

$$b = b_* + b_\perp$$

Observe that:

- (1) Since $b_* \in C(A)$, there exists $y \in R^c$ such that $b_* = Ay$;
- (2) By the definition of orthogonal projection, the column b_{\perp} = b b_* is orthogonal to all the elements of C(A).

(3.18) Remark.

To find the least squares solutions of $A \times = b$, note that, using the orthogonal decomposition of b introduced in the previous remark, for each $x \in R^c$ we have:

$$SQ(x) = ||Ax - b||^2 = ||Ax - b_* + b_\perp||^2 = ||Ax - Ay + b_\perp||^2 = ||A(x - y) + b_\perp||^2$$

Since A (x - y) \in C(A) and b_{\perp} is orthogonal to all the elements of C(A), by Pythagoras's theorem³ we have:

$$\parallel$$
 A (x - y) + b_{\perp} \parallel ² = \parallel A (x - y) \parallel ² + \parallel b_{\perp} \parallel ²

Then:

- For every $x \in R^c$ it is: $SQ(x) = ||A(x y)||^2 + ||b_{\perp}||^2 \ge ||b_{\perp}||^2$
- SQ(x) = $\|\mathbf{b}_{\perp}\|^2 \Leftrightarrow \|\mathbf{A}(\mathbf{x} \mathbf{y})\|^2 = 0 \Leftrightarrow \mathbf{A}(\mathbf{x} \mathbf{y}) = 0$, i.e. $\mathbf{x} \mathbf{y} \in \ker \mathbf{A}$.
- 1 The orthogonal projection of $v \in R^n$ onto a subspace $W \subset R^n$ is the *unique* element $v_* \in W$ such that the difference $v v_*$ is orthogonal to all elements of W.
- 2 C(A) is also called the *column space of* A and coincides with the image of the linear application from R^c to R^r defined by $x \to A x$.
- 3 Let a,b be elements of R^n , and let $\langle a,b \rangle = b^t a$ be the scalar product of a and b. If a and b are orthogonal (that is, if $\langle a,b \rangle = 0$) then we have:

$$\| a + b \|^2 = \langle a + b, a + b \rangle = \langle a, a \rangle + 2 \langle a, b \rangle + \langle b, b \rangle = \langle a, a \rangle + \langle b, b \rangle = \| a \|^2 + \| b \|^2$$

4 If $A \in R^{r \times c}$, we denote by ker A the set of the solutions of the homogeneous system Az = 0. ker A is a vector subspace of R^c

Hence, the set $S_{MO}(A,b)$ of the least squares solutions of $A \times B$ is:

$$S_{MQ}(A,b) = y + ker A$$

(3.19) Remark (normal equations).

To find all the columns $y \in R^c$ such that b_* = A y observe that, by the definition of orthogonal projection onto C(A):

 $y \in R^c$ is such that $Ay = b_* \Leftrightarrow b - b_* = b - Ay$ is orthogonal to all the elements of C(A)

<u>But</u>: a column $v \in R^r$ is orthogonal to all the elements of C(A) if and only if v is orthogonal to the columns of A (prove it!). Hence: v is orthogonal to all the elements of $C(A) \Leftrightarrow \langle v, a_1 \rangle = a_1^t v = 0, \ldots, \langle v, a_c \rangle = a_c^t v = 0 \Leftrightarrow A^t v = 0$. Then:

$$y \, \in \, R^c \ \, \text{is such that A} \, y \, = \, b_* \ \, \Leftrightarrow \ \, A^t \, (b \, - \, A \, y) \, = \, 0 \ \, \Leftrightarrow \ \, A^t \, A \, y \, = \, A^t \, b$$

The system of liner equations $A^t A x = A^t b$ is called the *system of the normal equations* relative to the system A x = b.

Observe that: $\ker A = \ker A^t A$ (indeed: $x \in \ker A \Rightarrow A x = 0 \Rightarrow A^t (A x) = 0 \Rightarrow A^t A x = 0 \Rightarrow x \in \ker A^t A$; on the contrary: $x \in \ker A^t A \Rightarrow A^t A x = 0 \Rightarrow x^t (A^t A x) = 0 \Rightarrow (x^t A^t)(A x) = 0 \Rightarrow (A x)^t (A x) = 0 \Rightarrow \|A x\|^2 = 0 \Rightarrow A x = 0 \Rightarrow x \in \ker A$. Then:

$$S_{MQ}(A,b) = y + ker A = y + ker A^{t} A = \{ least squares solutions of A x = b \}$$

Moreover:

- The matrix $A^t A \in R^{c \times c}$ is symmetric and positive semidefinite (indeed, for every column $x \neq 0$ in R^c it is: $x^t (A^t A) x = (x^t A^t) (A x) = (A x)^t (A x) = || A x ||^2 \geqslant 0$) and it is positive definite if and only if the columns of A are linearly independent (prove it!).
- The columns of A are linearly independent \Leftrightarrow ker A = ker A^t A = {0} \Leftrightarrow the set of the solutions of the system of the normal equations has only one element \Leftrightarrow the matrix A^t A is invertible.
- The columns of A are linearly dependent \Leftrightarrow dim ker A = dim ker A^t A > 0 \Leftrightarrow the set of the solutions of the system of the normal equations has infinite elements \Leftrightarrow the matrix A^t A is not invertible.