

Linear system of equations.

$$A\vec{x} = \vec{b}$$

$$A \in \mathbb{R}^{n \times p}$$

$$\left[\begin{array}{cccc} \vec{A}_1 & \vec{A}_2 & \dots & \vec{A}_p \end{array} \right] \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_p \end{bmatrix} = \vec{b}$$

Perform elementary row operations.

- Interchange two rows.
- Multiply a row by a non-zero number.
- Add a multiple of one row to another.

Row Echelon Form (REF).

- leading entry / pivot: the first non-zero entry in each row.
- leading zeros: # zeros before the pivot.
- REF: the # leading zeros increases.

Solutions of a linear system:

Look at REF

$$\left[\begin{array}{ccc|c} 1 & 2 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{array} \right]$$

$$0 = 1$$

inconsistent \Rightarrow No solution.

$$p=3.$$

$$\begin{array}{ccc|c} x_1 & x_2 & x_3 & \\ \hline 1 & 0 & 0 & 2 \\ 0 & 1 & 0 & 3 \\ 0 & 0 & 1 & 4 \end{array}$$

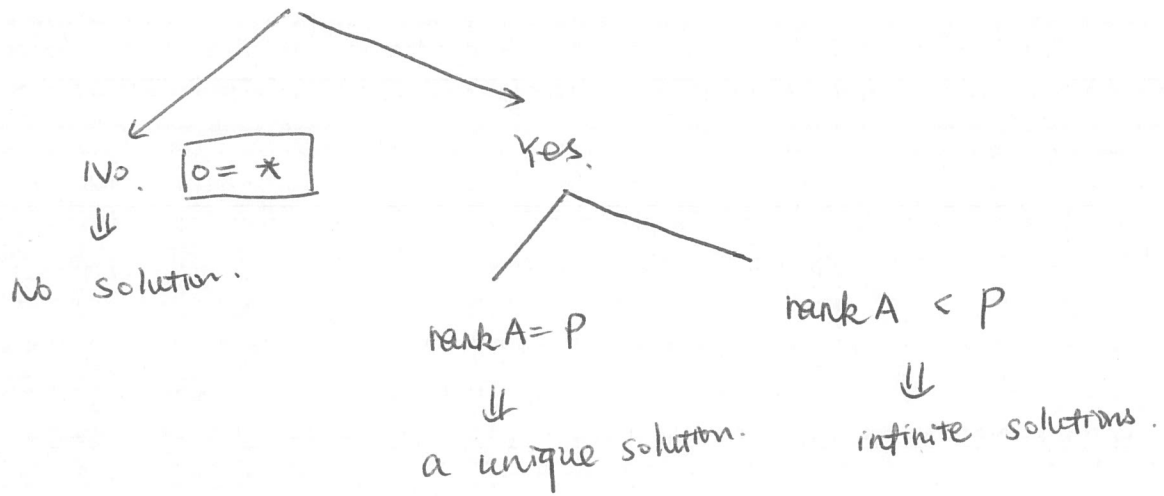
$$\text{rank } A = p.$$

$$\left[\begin{array}{ccc|c} 1 & 2 & 0 & 1 \\ 0 & 0 & 1 & 2 \\ 0 & 0 & 0 & 0 \end{array} \right]$$

$$\text{rank } A < p.$$

Does the linear system has a unique solution / infinite solutions
or no solution? 2

If the system is consistent



Least squares

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Linear system

$$A\vec{x} = \vec{b}$$

$$A \in \mathbb{R}^{n \times p}$$

$$A = \begin{bmatrix} \vec{v}_1 & \vec{v}_2 & \dots & \vec{v}_p \end{bmatrix}$$

$$\begin{bmatrix} \vec{v}_1 & \vec{v}_2 & \dots & \vec{v}_p \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_p \end{bmatrix} = \begin{bmatrix} \vec{b} \end{bmatrix}$$

$$x_1 \vec{v}_1 + x_2 \vec{v}_2 + \dots + x_p \vec{v}_p = \vec{b}$$

a linear combination of $\vec{v}_1, \vec{v}_2, \dots, \vec{v}_p$

Column space of A / Range of A .

$$V = \text{span} \{ \vec{v}_1, \vec{v}_2, \dots, \vec{v}_p \}$$

$A\vec{x} = \vec{b}$ has solutions $\Leftrightarrow \vec{b} \in V$.

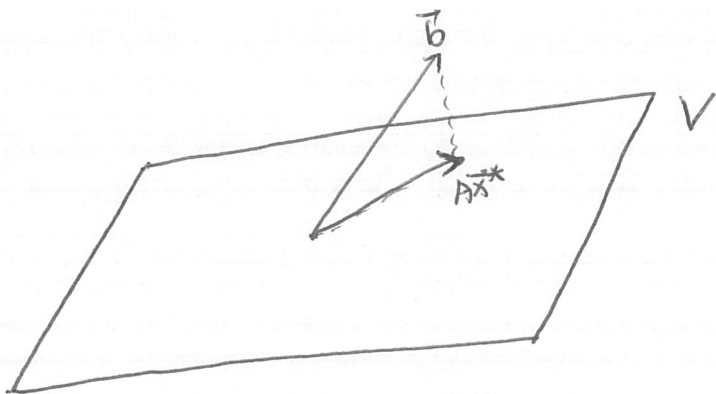
$A\vec{x} = \vec{b}$ does not have solution $\Leftrightarrow \vec{b} \notin V$.

What if $A\vec{x} = \vec{b}$ does not have solutions?

\Downarrow

Find the best possible solution

$$\min_x \|A\vec{x} - \vec{b}\|^2$$



Orthogonal projection: the orthogonal projection $\text{Proj}_V \vec{b}$ is the vector in V that is closest to \vec{b} .

$$\|\vec{b} - \text{Proj}_V \vec{b}\| \leq \|\vec{b} - \vec{v}\| \quad \text{for any } \vec{v} \in V.$$

Instead of solving $A\vec{x} = \vec{b}$, Least Squares suggests solving.

$$A\vec{x} = \text{Proj}_V \vec{b}$$

Suppose \vec{x}^* is the least Squares solution such that.

$$\|\vec{b} - A\vec{x}^*\| \leq \|\vec{b} - A\vec{x}\| \quad \text{for all } \vec{x} \in \mathbb{R}^n.$$

$$\Leftrightarrow$$

$$A\vec{x}^* = \text{Proj}_V \vec{b}.$$

$$\Leftrightarrow$$

Theorem.

$$(\text{Image } A)^\perp = \text{Ker}(A^T)$$

$$\vec{b} - A\vec{x}^* \in V^\perp = (\text{Image } A)^\perp = \text{Ker}(A^T)$$

$$\Leftrightarrow$$

$$A^T(\vec{b} - A\vec{x}^*) = \vec{0}$$

$$\Leftrightarrow$$

$$A^T A \vec{x}^* = A^T \vec{b}$$

In the case that $\text{Ker}(A) = \{\vec{0}\} \Leftrightarrow \text{rank } A = p$, 5

$A^T A$ is invertible.

The LS solution is given by.

$$\vec{x}^* = (A^T A)^{-1} A^T \vec{b}$$

QR Factorization

Suppose A is an $n \times p$ matrix with p linearly independent columns, $(n \geq p)$.

$$A = \begin{bmatrix} | & & | \\ \vec{v}_1 & \dots & \vec{v}_p \\ | & & | \end{bmatrix} \quad \text{where } \vec{v}_1, \vec{v}_2, \dots, \vec{v}_p \text{ are linearly independent.}$$

$\Leftrightarrow \text{rank } A = p.$

Then there exists an $n \times p$ matrix $Q = \begin{bmatrix} | & & | \\ \vec{u}_1 & \dots & \vec{u}_p \\ | & & | \end{bmatrix}$

whose columns $\vec{u}_1, \dots, \vec{u}_p$ are orthonormal,

and an upper triangular matrix R with positive diagonal entries such that.

$$A = QR.$$

$$A = QR$$

$$\begin{bmatrix} \vec{v}_1 & \dots & \vec{v}_p \end{bmatrix} = \begin{bmatrix} \vec{u}_1 & \dots & \vec{u}_p \end{bmatrix} \begin{bmatrix} R_{11} & R_{12} & \dots & R_{1p} \\ 0 & R_{22} & & R_{2p} \\ \vdots & & \ddots & \vdots \\ 0 & & & R_{pp} \end{bmatrix}$$

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Proof: By Gram-Schmidt Process.

LS and QR Factorization

$$A = QR$$

$$A^T A = R^T Q^T Q R = R^T R$$

$$(A^T A)^{-1} = R^{-1} (R^T)^{-1}$$

$$\begin{aligned} \vec{x}^* &= (A^T A)^{-1} A^T \vec{b} \\ &= R^{-1} (R^T)^{-1} R^T Q^T \vec{b} \\ &= R^{-1} Q^T \vec{b} \end{aligned}$$

Solving $R\vec{x} = Q^T \vec{b}$ is easy since R is upper-triangular

Colinearity.

$$A = \begin{bmatrix} \vec{v}_1 & \vec{v}_2 & \dots & \vec{v}_p \end{bmatrix}$$

Colinearity refers to the situation where $\vec{v}_1 \vec{v}_2 \dots \vec{v}_p$ are linearly dependent : $\text{rank}(A) < p$

In this case, $A^T A$ is not invertible.

Example:

$$A = \begin{bmatrix} \vec{v}_1 & \vec{v}_2 & \vec{v}_3 \\ 1 & 2 & 1 \\ 1 & 2 & -1 \\ 1 & 2 & -1 \\ 1 & 2 & 1 \end{bmatrix} \quad \vec{v}_3 = 2\vec{v}_1$$

- $\text{rank}(A^T A) = 2$, $A^T A$ is not invertible.
- The LS solution $\min_x \|A\vec{x} - \vec{b}\|$ is not unique.

Why: If $\begin{pmatrix} x_1^* \\ x_2^* \\ x_3^* \end{pmatrix}$ is a solution, there are other

solutions like

$$\begin{pmatrix} x_1^* + 2x_2^* \\ 0 \\ x_3^* \end{pmatrix} \quad \text{or} \quad \begin{pmatrix} 0 \\ \frac{1}{2}x_1^* + x_2^* \\ x_3^* \end{pmatrix}$$