

• Least Norm Solution

$$\begin{aligned} \min_x \|x\|_2^2 \\ \text{s.t. } Ax = y \end{aligned}$$

$$x^* = A^T(AA^T)^{-1}y$$

$$\begin{aligned} L &= \|x\|_2^2 + v^T(Ax - y) \\ &= \|x\|_2^2 + (Av)^T x - v^T y \end{aligned}$$

$$Th \ L = 2x + A^T v := 0$$

$$x^* = -\frac{1}{2} A^T v$$

$$\begin{aligned} g(v) &= \frac{1}{4} \|A^T v\|_2^2 - \frac{1}{2} \|A^T v\|_2^2 - v^T y \\ &= -\frac{1}{4} \|A^T v\|_2^2 - v^T y \end{aligned}$$

$$\nabla_v g = -\frac{1}{2} AA^T v - y := 0$$

$$v^* = -2(AA^T)^{-1}y$$

$$x^* = A^T(AA^T)^{-1}y$$

$$\max_v -\frac{1}{4} \|A^T v\|_2^2 - v^T y$$

Let x_m be the least norm solution.

Let $Ax = y$ so $A(x - x_m) = 0$

$$\begin{aligned} (x - x_m)^T x_m &= (x - x_m)^T A^T(AA^T)^{-1}y \\ &= (A(x - x_m))^T (AA^T)^{-1}y \\ &= 0 \end{aligned}$$

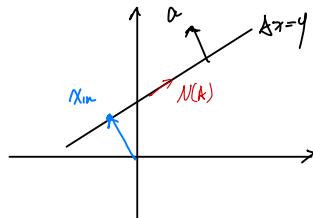
$$(x - x_m) \perp x_m$$

$\|x\|_2^2 = \|x + x_m - x_m\|_2^2 = \|x_m\|_2^2 + \|x - x_m\|_2^2 > \|x_m\|_2^2$ Any solution of $Ax = y$ has larger norm than x_m
 x_m is the projection of y on the solution set $\{x | Ax = y\}$

$A^\dagger = A^T(AA^T)^{-1}$ is (a right inverse / the pseudo-inverse) of full row-rank, fat A

$A^\dagger = (A^T A)^{-1} A^T$ is (a left inverse / the pseudo-inverse) of full column-rank, skinny A

$A^T(AA^T)^{-1}A$ gives projection onto $N(A)^\perp = R(A^T)$ $A(A^T A)^{-1}A^T$ gives projection on $R(A)$
 $I - A^T(AA^T)^{-1}A$ gives projection on to $N(A)$



• Least Norm Solution via QR

project \mathbf{y} on the solution set $\{\mathbf{x} \mid A\mathbf{x} = \mathbf{y}\}$

let $\bar{A}^T = QR$ $Q^T Q = I$ R uppertriangular and invertible

$$A^T (A A^T)^{-1} \mathbf{y} = A R (R^T Q^T R)^{-1} \mathbf{y} = Q R^{-1} \mathbf{y}$$

$$\|\mathbf{x}_m\|_2 = \|R^{-1} \mathbf{y}\|_2$$

• Least norm and Regularized least Square

$$\min \|\mathbf{x}\|_2$$

$$\text{s.t. } A\mathbf{x} = \mathbf{y}$$



$$\min_{\mathbf{x}} \|A\mathbf{x} - \mathbf{y}\|_2^2 + \mu \|\mathbf{x}\|_2$$



$$\mathbf{x}_m = A^T (A A^T)^{-1} \mathbf{y}$$

$$\mathbf{x}(w) = (A^T A + \mu I)^{-1} A^T \mathbf{y}$$

as $\mu \rightarrow 0$, $(A^T A + \mu I)^{-1} A^T \rightarrow A^T (A A^T)^{-1}$ for full row rank, fat A

• Autonomous Linear Dynamical System

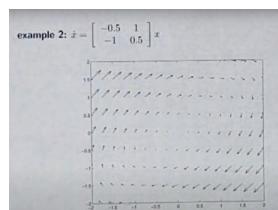
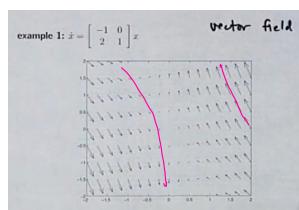
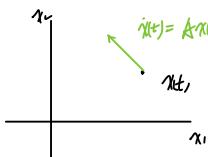
continuous-time autonomous LDS: $\dot{\mathbf{x}} = A\mathbf{x}$

when A is a scalar $\frac{dx}{dt} = ax$

$$\mathbf{x}(t) = e^{at} \cdot \mathbf{x}(0)$$

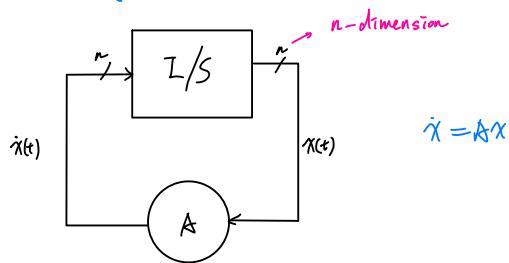
$\mathbf{x}(t)$ is the state

A is the dynamic matrix (system is time-invariant if A doesn't depend on t)

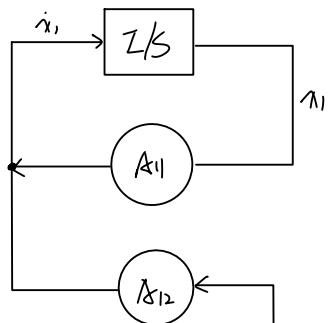


• Block Diagram

block diagram



$$\dot{x} = Ax$$



$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{bmatrix} = \begin{bmatrix} A_{11} & A_{12} \\ 0 & A_{22} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

