

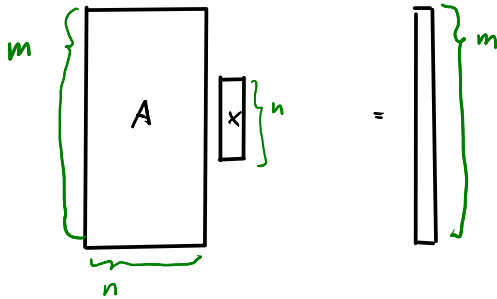
Overview

- Least squares/pseudoinv.
- Data fitting
- Norms and condition #s
- Low-rank approximation

Tall and Skinny Systems

$A = U \Sigma U^{-1}$ does n't always exist

- Consider a 'tall and skinny' linear system, i.e. one that has more equations than unknowns:



$A = U \Sigma V^T \leftarrow$ always exists

$\uparrow \quad \uparrow \quad \uparrow$
orth diag orth

In the figure: $m > n$. How could we solve that?

$Ax \approx b$

$\|Ax - b\|_2^2$

$\|Ax - b\|_2^2 = \|U \Sigma V^T x - b\|_2^2$ (want: small)

$= \|\Sigma V^T x - U^T b\|_2^2$ (if)

$\uparrow \quad \uparrow$
 $y \quad z$

$\Sigma = \begin{pmatrix} \sigma_1 & & & & & \\ & \sigma_2 & & & & \\ & & \ddots & & & \\ & & & \sigma_n & & \\ & & & & 0 & \\ & & & & & \ddots \\ & & & & & & 0 \end{pmatrix}$

$y = \begin{pmatrix} z_1 \\ \vdots \\ z_n \\ \vdots \\ z_m \end{pmatrix}$

$z_{n+1} = 0 \dots z_m = 0$

$y_k = z_k / \sigma_k$

$y_{n+1} = 0 \dots y_m = 0$

pseudo inverse
of Σ

$$\Sigma^+ = \begin{pmatrix} 1/\sigma_1 & & & \\ & \dots & & \\ & & 1/\sigma_k & \\ & & & \dots \\ & & & & 0 & \dots & 0 \end{pmatrix} \begin{matrix} m \\ \\ \\ \\ \\ \\ \\ \end{matrix}$$

$$V^T x^+ = y \rightarrow x^+ = V y$$

$$x^+ = V C^+ U^T b$$

A^+ ← pseudo inverse of A

Intention:

$$y = \begin{pmatrix} 0 \\ \vdots \\ f_0 \\ z \end{pmatrix} \begin{matrix} n \times m \\ \downarrow \\ \\ \\ \\ \\ \\ \\ \end{matrix}$$
$$\begin{pmatrix} \oplus \\ \oplus \\ \oplus \\ \oplus \\ \oplus \\ \oplus \\ \oplus \\ \oplus \end{pmatrix} y = \begin{pmatrix} \oplus \\ \oplus \\ \oplus \\ \oplus \\ \oplus \\ \oplus \\ \oplus \\ \oplus \end{pmatrix} (U^T b)$$

$\begin{matrix} n \\ \downarrow \\ \\ \\ \\ \\ \\ \\ \end{matrix}$

$\Leftarrow k+1$

$\Leftarrow n$

Solving Least-Squares

- How can I actually solve a least-squares problem $A\mathbf{x} \cong \mathbf{b}$?

In-class activity: SVD and Least Squares

The Pseudoinverse: A Shortcut for Least Squares

- How could the solution process for $A\mathbf{x} \cong \mathbf{b}$ be with an SVDA = $U\Sigma V^T$ be 'packaged up'?

The Normal Equations

- You may have learned the 'normal equations' $A^T A \mathbf{x} = A^T \mathbf{b}$ to solve $A \mathbf{x} \cong \mathbf{b}$. Why not use those?

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

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

↑ $\hat{=}$ "normal" equations

$$\text{cond}(A^T A) \leq \text{cond}(A) \cdot \frac{\text{cond}(A^T)}{\therefore \text{cond}(A)} \approx \text{cond}(A)^2$$

$$\text{cond}(A \mathbf{b}) \leq \text{cond}(A) \text{cond}(\mathbf{b})$$

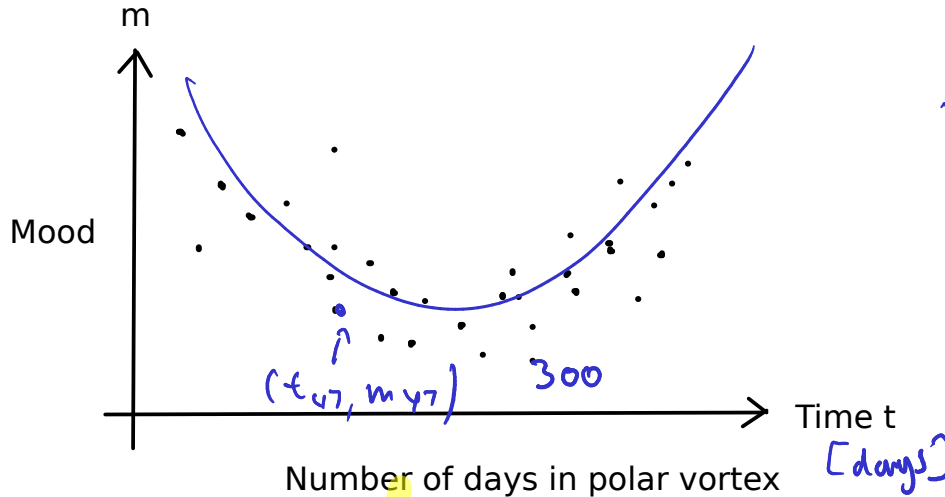
↳ tend to be poorly conditioned

↳ let's not

13.2 Data Fitting

Fitting a Model to Data

- How can I fit a model to measurements? E.g.:



$$\hat{m}(t) = \alpha + \beta t + \gamma t^2$$

$$\begin{aligned} \hat{m}(t_1) &= \alpha + \beta t_1 + \gamma t_1^2 \approx m_1 \\ \hat{m}(t_{47}) &= \alpha + \beta t_{47} + \gamma t_{47}^2 \approx m_{47} \\ \hat{m}(t_{300}) &= \alpha + \beta t_{300} + \gamma t_{300}^2 \approx m_{300} \end{aligned}$$

$$\begin{pmatrix} 1 & t_1 & t_1^2 \\ \vdots & \vdots & \vdots \\ 1 & t_{47} & t_{47}^2 \\ \vdots & \vdots & \vdots \\ 1 & t_{300} & t_{300}^2 \end{pmatrix} \begin{pmatrix} \alpha \\ \beta \\ \gamma \end{pmatrix} \approx \vec{m}$$

Demo: Data Fitting using Least Squares

13.3 Norms and Condition Numbers

Meaning of the Singular Values

$$\|Ux\|_2 = \|x\|_2$$

- What do the singular values mean? (in particular the first/largest one)

$$A = U \begin{pmatrix} \sigma_1 & & \\ & \ddots & \\ & & \sigma_n \end{pmatrix} V^T$$

← biggest

$$\begin{aligned} \|A\|_2 &= \|U \Sigma V^T\|_2 = \max_{\|x\|_2=1} \|\underline{u} \Sigma V^T x\|_2 = \max_{\|x\|_2=1} \|\Sigma \underbrace{V^T x}_{\underline{y}}\|_2 \\ &= \max_{\|V^T x\|_2=1} \|\Sigma V^T x\|_2 = \max_{\|y\|_2=1} \|\Sigma y\|_2 \\ &= \|\Sigma\|_2 = \sigma_1 \end{aligned}$$

Condition Numbers

- How would you compute a 2-norm condition number?

$$A = U \Sigma V^T = U \begin{pmatrix} \sigma_1 & & \\ & \ddots & \\ & & \sigma_n \end{pmatrix} V^T$$

$\sigma_i \geq 0$

$$\text{cond}(A) = \|A\| \|A^{-1}\| = \sigma_1 / \sigma_n$$

$$A^{-1} = V \Sigma^{-1} U^T = V \begin{pmatrix} 1/\sigma_1 & & \\ & \ddots & \\ & & 1/\sigma_n \end{pmatrix} U^T$$

(if $\sigma_n = 0 \Rightarrow A$ not invertible $\Rightarrow \text{cond}(A) = \infty$)

13.4 Low-Rank Approximation

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SVD as Sum of Outer Products

- What's another way of writing the SVD?