

Today:

Recap SVD

Connect low rank
to functions

HW1 graded, HW2

$N \times N$ k

Nk^2

$QQ^T A$

ID Q vs ID A

What does row selection mean for the LRA?

Could we SVD $PA_{(j_i)}$?
→ No, that's all of A,
so N?

$$A \approx Q \underbrace{Q^T A}_{\text{row selection}}$$

$$Q \approx P \underbrace{Q}_{j_i}$$

↳ (same P) $A \approx P A_{(j_i)}$

$$A = P \underbrace{A}_{(j_i)} \\ N \times N \\ \approx \underline{P U \Sigma V^T}$$

$$A \approx QQ^T A$$

$$\begin{array}{c}
 Q \approx P Q_{[j,i]} \\
 \begin{array}{c} \left[\begin{array}{c} k \\ \vdots \end{array} \right] \\ N \end{array} \\
 \left[\begin{array}{c} \vdots \\ \square \end{array} \right]
 \end{array}
 \quad \Bigg| \quad
 \begin{array}{c}
 A_{(j,i)} \\
 (A_{(j,i)})^T = \begin{array}{c} \left[\begin{array}{c} \vdots \\ \square \end{array} \right] \\ \left[\begin{array}{c} \vdots \\ \square \end{array} \right] \end{array} \\
 \left[\begin{array}{c} \vdots \\ \square \end{array} \right]
 \end{array}
 \end{array}
 \quad \leftarrow \quad
 \begin{array}{c}
 \left[\begin{array}{c} \square \\ \square \end{array} \right] \\
 \left[\begin{array}{c} \square \\ \square \end{array} \right] \\
 \left[\begin{array}{c} \square \\ \square \end{array} \right]
 \end{array}
 \quad \leftarrow \quad N_{k^2}$$

$$\left[\begin{array}{c} \square \\ \square \end{array} \right] \left[\begin{array}{c} \square \\ \square \end{array} \right]^T = U \Sigma V^T \in N_{k^2}$$

$$C \cdot n^2$$

$$c \cdot n^3$$

Strassen

$$C \cdot n^{2.8}$$

$$c n^3$$

Storage: n^2

Operations: n^3

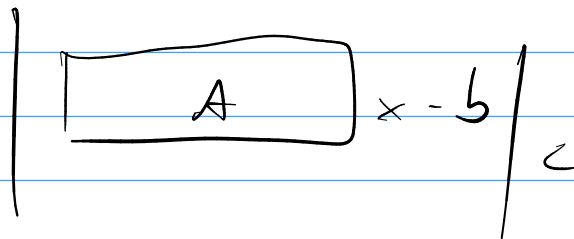
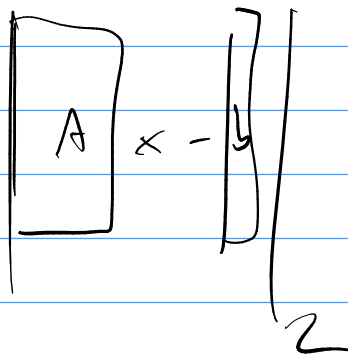
$$\begin{aligned} & U \Sigma \left(\overbrace{\bar{Q} \bar{V}}^V \right)^T \leftarrow \\ &= U C \bar{V}^T \bar{Q}^T \\ &= P \bar{R}^T \bar{Q}^T \\ &= P A_{(j_i)} \approx A \end{aligned}$$

$$Ax = b$$

$$A = U \Sigma V^T$$

$$x = V \Sigma^{-1} U^T b$$

$$V \Sigma^+ U^T$$



$$\min \|x\|_2$$

Leveraging the ID

Build a low-rank SVD with row extraction.

Where are we now?

3 Rank and Smoothness

Punchline

What do (numerical) rank and smoothness have to do with each other?

$$y(x) = \sum G_i(x) \alpha_i$$

$$G(x, y) = \frac{1}{\sqrt{|x - y|_2}} \\ \begin{matrix} \uparrow \\ (x_1 \\ x_2) \end{matrix}$$

Recap: Multivariate Taylor

How does Taylor's theorem get generalized to multiple dimensions?

$$f(c+h) \approx \sum_{i=0}^k \frac{f^{(i)}(c)}{i!} h^i$$

Suppose: $\left| \frac{f^{(i)}(c)}{i!} h^i \right| \leq \alpha^i$

$$\begin{aligned} \left| f(c+h) - \sum_{i=0}^k \frac{f^{(i)}(c)}{i!} h^i \right| &= \left| \sum_{i=k+1}^{\infty} \frac{f^{(i)}(c)}{i!} h^i \right| \\ &\leq \sum_{i=k+1}^{\infty} \alpha^i \leq \frac{1}{1-\alpha} \alpha^{k+1} \end{aligned}$$

$$\nu = (5, 3) \Rightarrow 20$$

$$\nu = (\nu_1, \dots, \nu_d)$$

$$|\nu| = \nu_1 + \dots + \nu_d$$

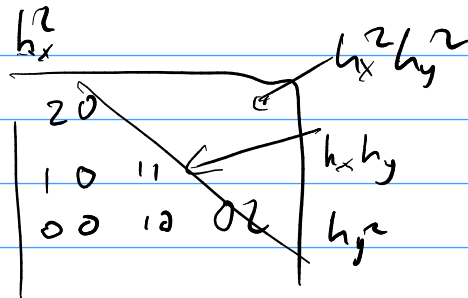
$$\vec{x}^\nu = \begin{pmatrix} x_1 \\ \vdots \\ x_d \end{pmatrix}^\nu = x_1^{\nu_1} \dots x_d^{\nu_d}$$

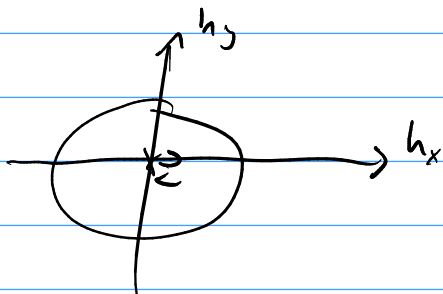
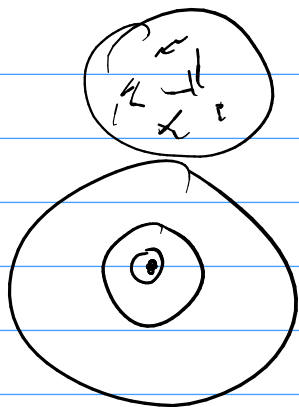
$$\nu! = \nu_1! \dots \nu_d!$$

$$D^\nu f = \frac{\partial^{\nu_1}}{\partial x_1^{\nu_1}} \dots \frac{\partial^{\nu_d}}{\partial x_d^{\nu_d}} f$$

$$1D: f(c+h) \approx \sum_{i=0}^k \frac{f^{(i)}(c)}{i!} h^i$$

$$nD: f(\vec{c} + \vec{h}) \approx \sum_{|\nu| \leq k} \frac{D^\nu f(\vec{c})}{\nu!} h^\nu$$





Connect Taylor and Low Rank

Can Taylor help us establish low rank of an interaction?

Taylor on Potentials

Compute a Taylor expansion of a 2D Laplace point potential.

Local expansions as a Computational Tool

Low rank makes evaluating interactions cheap(er). Do local expansions help with that goal?

Taylor on Potentials, Again

Stare at that Taylor formula again.