

Plan

Logistics

Review

Power Method

Michael's talk at
noon in Warner 101

↳ Nuclear physics
and Brownian motion

Singular Value Decomposition

$$X \in \mathbb{R}^{n \times d} \quad \text{rank } k$$

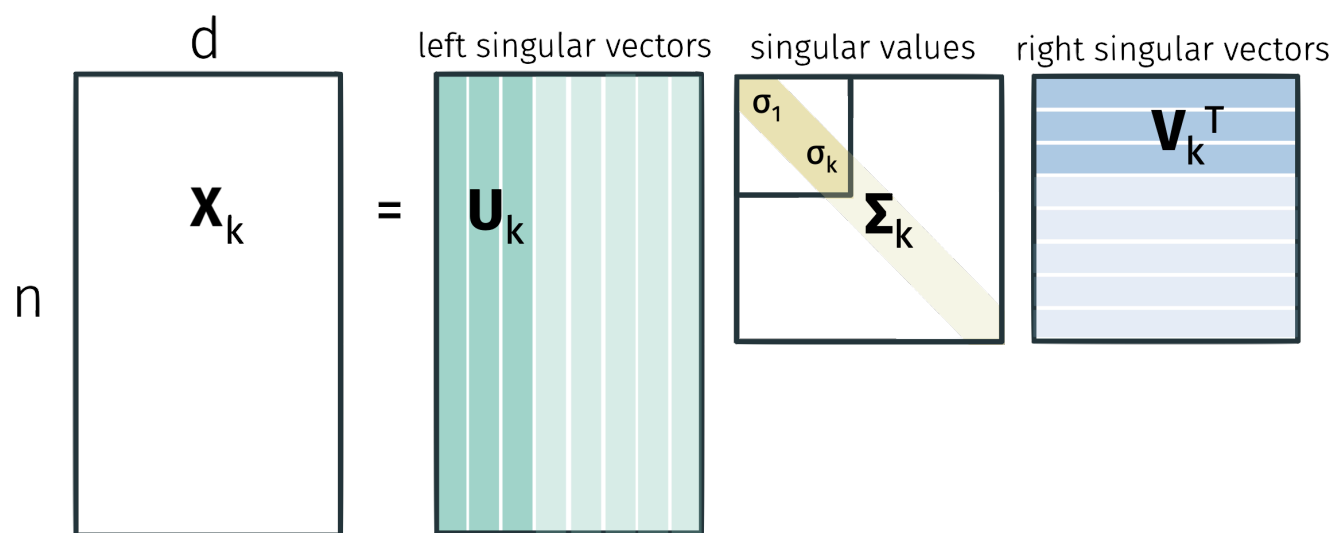
$$k \neq d$$

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

$$U^T U = I$$

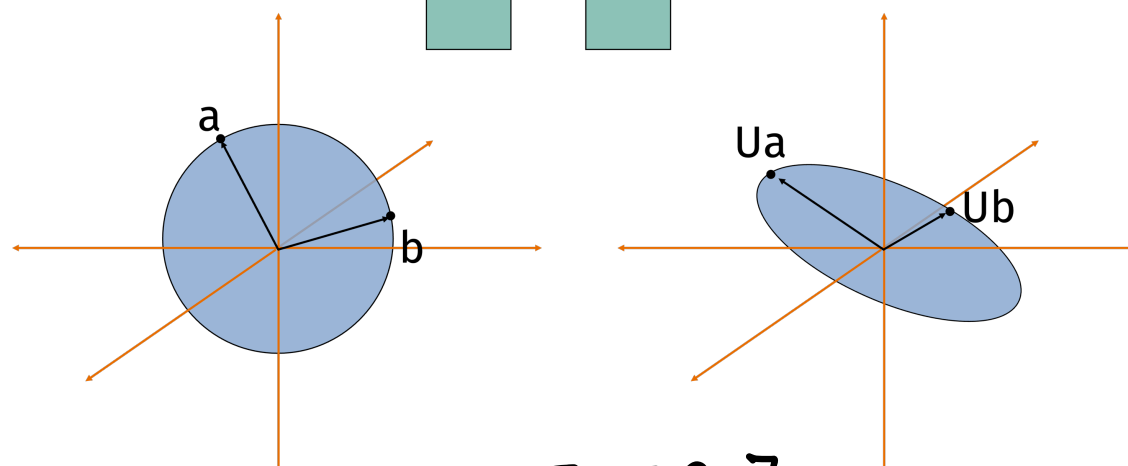
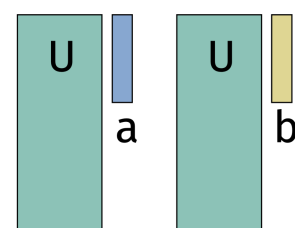
$$V^T V = I$$

$$n \times d \quad n \times k \quad k \times k \quad k \times d$$



$$\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_k \geq 0$$

Multiplying U



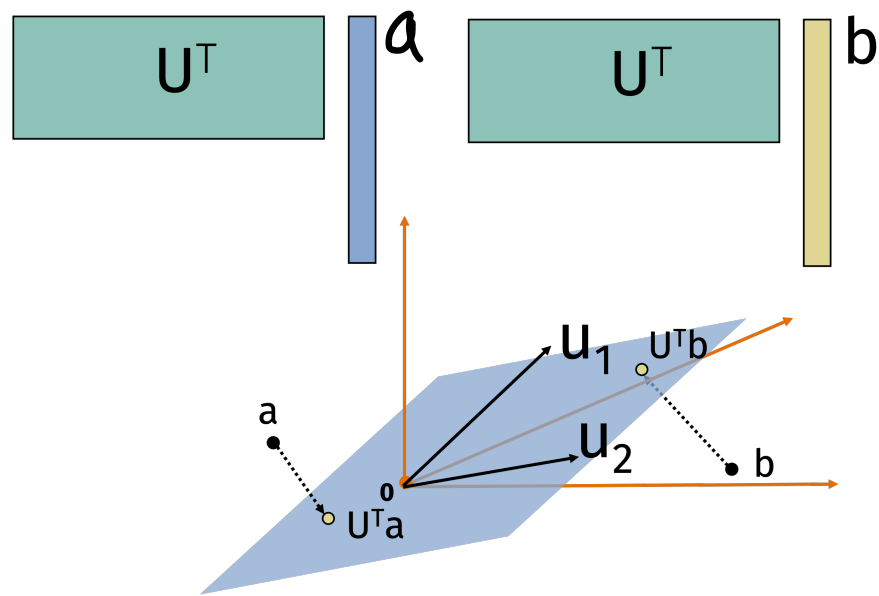
$$Ua = \begin{bmatrix} | & | & | \\ \bar{u}_1 & \bar{u}_2 & \bar{u}_k \\ | & | & | \end{bmatrix} \begin{bmatrix} a_1 \\ \vdots \\ a_k \end{bmatrix}$$

$$= \bar{u}_1 a_1 + \bar{u}_2 a_2 + \dots + \bar{u}_k a_k$$

$$\|Ua\|_2^2 = \langle \bar{u}_1 a_1 + \dots + \bar{u}_k a_k, \bar{u}_1 a_1 + \dots + \bar{u}_k a_k \rangle$$

$$= a_1^2 + a_2^2 + \dots + a_k^2 = \|a\|_2^2$$

Multiplying by U^T , projecting



$$U^T a = \begin{bmatrix} \text{---} u_1 \text{---} \\ \text{---} u_2 \text{---} \\ \vdots \\ \text{---} u_k \text{---} \end{bmatrix} \begin{bmatrix} \\ \\ \\ \\ \end{bmatrix} \begin{matrix} \\ \\ \\ \\ a \end{matrix}$$

$$= \begin{bmatrix} \langle u_1, a \rangle \\ \langle u_2, a \rangle \\ \vdots \\ \langle u_k, a \rangle \end{bmatrix}$$

$$Xa = U \Sigma V^T a \\ = U (\Sigma (V^T a))$$

Tools

$$\textcircled{1} \|V X\|_F^2 = \|X\|_F^2 \quad V^T V = I$$

$$\textcircled{2} \|X^T\|_F^2 = \|X\|_F^2$$

$$\textcircled{3} \|X\|_F^2 = \sum_{i=1}^k \sigma_i^2$$

$$= \|U \Sigma V^T\|_F^2 = \|\Sigma V^T\|_F^2 \quad \text{by } \textcircled{1}$$

$$\approx \|V \Sigma^T\|_F^2 = \|\Sigma\|_F^2 \quad \text{by } \textcircled{1}, \textcircled{2}$$

$$= \sum_{i=1}^k \sigma_i^2$$

Finding SVD

$$X = U \Sigma V^T \in \mathbb{R}^{n \times d} \quad n \geq d$$

Time

Compute $X^T X$
 $d \times d$

$$O(d^2 n)$$

Decompose $X^T X = V \Sigma^2 V^T = V \Lambda V^T$

$$O(d^3)$$

Compute $L = X V = U \Sigma V^T V = U \Sigma$
 $n \times d \quad d \times d$

$$O(n d \cdot d)$$

$$\sigma_i = \|L_i\|_2$$

$$u_i = L_i / \sigma_i$$

$$O(n d^2)$$

Power Method

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

$$X^T X = V \Sigma^2 V^T \triangleq A$$

A has eigenvalues $\sigma_1^2 \geq \sigma_2^2 \geq \dots \geq \sigma_d^2$
eigenvectors v_1, v_2, \dots, v_d

$$A = v_1 v_1^T \sigma_1^2 + v_2 v_2^T \sigma_2^2 + \dots + v_d v_d^T \sigma_d^2$$

$d \times d$ $d \times 1$ $1 \times d$

$$\begin{aligned} A v_i &= (v_1 v_1^T \sigma_1^2 + v_2 v_2^T \sigma_2^2 + \dots + v_d v_d^T \sigma_d^2) v_i \\ &= \sigma_1^2 v_1 v_1^T \cdot v_i + \sigma_2^2 v_2 v_2^T \cdot v_i + \dots + \sigma_d^2 v_d v_d^T \cdot v_i \\ &= \sigma_i^2 v_i \end{aligned}$$

$$A^g = \underbrace{A A A \dots A}_g$$

$$= V \Sigma^2 \underbrace{V^T V}_I V \Sigma^2 V^T \dots V \Sigma^2 V^T$$

$$= V \underbrace{\Sigma^2 \Sigma^2 \Sigma^2}_g V^T$$

$$= V \Sigma^{2g} V^T$$

<u>Algorithm</u>	$A \in \mathbb{R}^{d \times d}$	<u>Time</u>	$z^{(0)}, Az^{(0)}, A^2 z^{(0)}, \dots$
$z^{(0)} \sim \mathcal{N}(0, I)$	$z^{(0)} \in \mathbb{R}^d$	$O(d)$	$A^q z^{(0)}$
$z^{(0)} = z^{(0)} / \ z^{(0)}\ _2$		$O(d)$	
For $i = 1, \dots, q$			$A' = A - v_1 v_1^T \sigma_1^2$
$z^{(i)} = A z^{(i-1)}$		$O(d^2)$	
$n_i = \ z^{(i)}\ _2$		$O(d)$	
$z^{(i)} = z^{(i)} / n_i$		$O(d)$	
Return $z^{(q)}$		$O(d^2 \cdot q)$	

Because v_1, \dots, v_d

$$z^{(0)} = c_1^{(0)} v_1 + c_2^{(0)} v_2 + \dots + c_d^{(0)} v_d \quad \leftarrow c_i^{(0)} = \langle z^{(0)}, v_i \rangle$$

$$z^{(1)} = c_1^{(1)} v_1 + c_2^{(1)} v_2 + \dots + c_d^{(1)} v_d$$

⋮

$$z^{(q)} = c_1^{(q)} v_1 + c_2^{(q)} v_2 + \dots + c_d^{(q)} v_d$$

↑
Goal: Show this is large

$$z^{(q)} \approx v_1$$

$$\|v_1 - z^{(q)}\|_2^2 \leq \epsilon$$

or $\|v_1 - z^{(q)}\|_2^2 \leq \epsilon$

$$\begin{aligned}
 A z^{(0)} &= (v_1 v_1^T \sigma_1^2 + v_2 v_2^T \sigma_2^2 + \dots + v_d v_d^T \sigma_d^2) (c_1^{(0)} v_1 + c_2^{(0)} v_2 + \dots + c_d^{(0)} v_d) \\
 &= v_1 v_1^T v_1 \cdot \sigma_1^2 c_1^{(0)} + v_2 v_2^T v_2 \sigma_2^2 \cdot c_2^{(0)} + \dots + v_d v_d^T v_d \sigma_d^2 c_d^{(0)} \\
 &= v_1 \sigma_1^2 c_1^{(0)} + v_2 \sigma_2^2 c_2^{(0)} + \dots + v_d \sigma_d^2 c_d^{(0)}
 \end{aligned}$$

$$z^{(g)} = (v_1 \sigma_1^{2g} c_1^{(0)} + v_2 \sigma_2^{2g} c_2^{(0)} + \dots + v_d \sigma_d^{2g} c_d^{(0)}) \frac{1}{\prod_{l=1}^g n_l}$$

$$c_i^{(t)} = \frac{\sigma_i^2}{n_t} c_i^{(t-1)} = \frac{\sigma_i^2}{n_t} \cdot \frac{\sigma_i^2}{n_{t-1}} c_i^{(t-2)} = \frac{\sigma_i^{2t}}{\prod_{l=1}^t n_l} c_i^{(0)}$$

$$\left| \frac{c_i^{(g)}}{c_i^{(0)}} \right| = \left| \frac{\frac{\sigma_i^{2g} c_i^{(0)}}{\prod_{l=1}^g n_l}}{\sigma_i^{2g} c_i^{(0)}} \right| = \left| \frac{\sigma_i^{2g}}{\sigma_i^{2g}} \right| / \left| \frac{c_i^{(0)}}{c_i^{(0)}} \right|$$

$$\left(\frac{\sigma_i}{\sigma_1}\right)^{2q} = \left(\frac{\sigma_1 + \sigma_i - \sigma_1}{\sigma_1}\right)^{2q} = \left(1 - \frac{\sigma_1 - \sigma_i}{\sigma_1}\right)^{2q}$$

$$\gamma = \frac{\sigma_1 - \sigma_2}{\sigma_1} \quad \text{"spectral gap"}$$

$$q = \frac{\log(d^3 \sqrt{\epsilon/d})}{2\gamma} \quad \text{then} \quad \left(1 - \frac{\sigma_1 - \sigma_i}{\sigma_1}\right)^{2q} \leq \frac{\sqrt{\epsilon/d}}{d^3}$$

$$\left|\frac{c_i^{(q)}}{c_i^{(0)}}\right| = \left|\left(\frac{\sigma_i}{\sigma_1}\right)^{2q} \left(\frac{c_i^{(0)}}{c_i^{(0)}}\right)\right| \leq \frac{\sqrt{\epsilon/d}}{d^3} d^3 = \sqrt{\epsilon/d}$$

$$|c_1^{(q)}| \leq 1 \quad \Rightarrow \quad |c_i^{(q)}| \leq |c_i^{(0)}| \sqrt{\epsilon/d} \leq \sqrt{\epsilon/d}$$

$$\sum_{k=1}^d (c_k^{(q)})^2 = 1, \quad \sum_{k \neq 1} (c_k^{(q)})^2 \leq \sum_{k \neq 1} \epsilon/d < \epsilon$$

$$(C_1^{(q)})^2 = 1 - \sum_{k=2}^d (C_k^{(q)})^2 \geq 1 - \epsilon$$

constant
=>

$$|C_1^{(q)}| \geq (1 - \epsilon)^2 \approx (1 - \epsilon)$$

$$C_1^{(q)} = \langle v_1, z^{(q)} \rangle$$

$$\begin{aligned} \|v_1 - z^{(q)}\|_2^2 &= \|v_1\|_2^2 + \|z^{(q)}\|_2^2 - 2 \langle v_1, z^{(q)} \rangle \\ &= 2 - 2 \langle v_1, z^{(q)} \rangle \leq 2 - 2(1 - \epsilon) = 2\epsilon \end{aligned}$$

We ran for $q = O\left(\frac{\log(d/\epsilon)}{\gamma}\right)$ steps

Using Lanczos, we ran for $q = O\left(\frac{\log(d/\epsilon)}{\sqrt{\gamma}}\right)$ steps