

FoDA

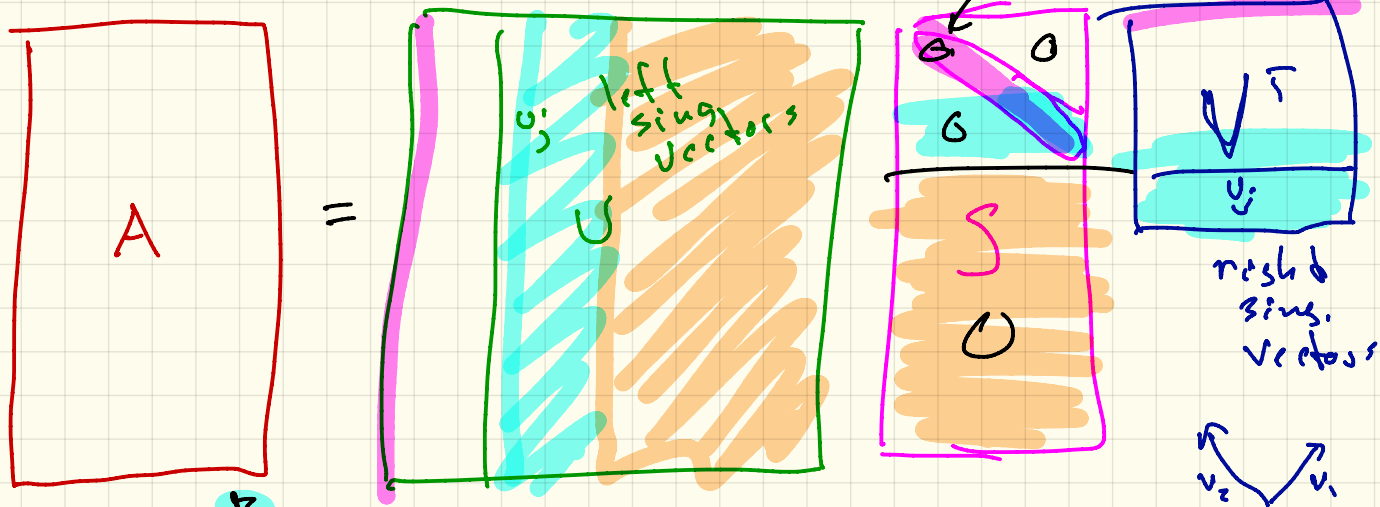
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the Power  
Method

Input  $A \in \mathbb{R}^{n \times d}$   $A \subset \mathbb{R}^d$   
 $\{a_1, a_2, \dots, a_n\}$

Data Matrix  $A_{i,j} = a_{ij}$  makes sense



$$A_{\mathbb{R}} = \sum_{j=1}^r \sigma_j u_j v_j^T$$

$\text{rank}(A_{\mathbb{R}}) = r$

$\sigma_1 > \sigma_2 > \dots > \sigma_r$   
 $\rightarrow$  most important

# Power Method

Input  $A \in \mathbb{R}^{n \times d}$

Output top right  
Sing. vector  
 $v_1$

$$M = A^T A \in \mathbb{R}^{d \times d}$$

positive semi-definite

top right svec (A) = top eigenvector (M)

$$v = M(M(\dots(Mu)))$$

$u \leftarrow$  random <sup>unit</sup> vector in  $\mathbb{R}^d$

$$v = M^g u$$

for  $i=1$  to  $g$

$$v^{(i)} = M v^{(i-1)}$$

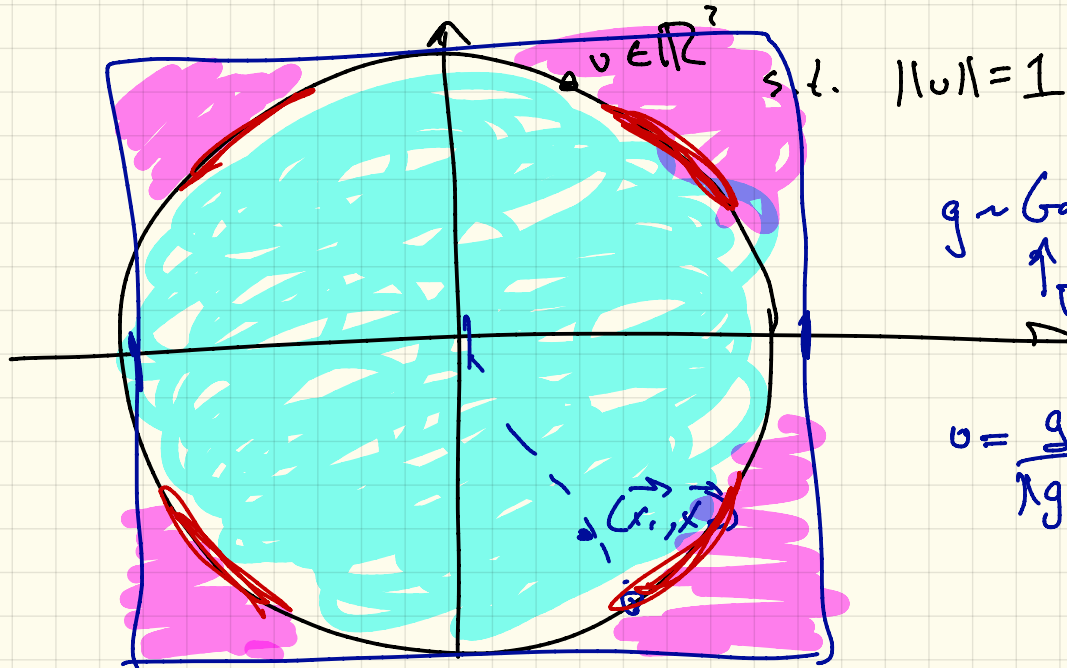
matrix-vector  
multiply  
 $g$  times

return  $v_1 = \frac{v}{\|v\|_2}$

$$M^g = \underbrace{M \cdot M \cdot \dots \cdot M}_g$$

matrix-matrix mult

# Random Unit Vector



$$\begin{aligned} x &\in \text{Unif}(0, 1) \\ x_1 &\sim \text{Unif}(0, 1) \rightarrow (2x_1 - 1) = \vec{x}_1 \\ x_2 &\sim \text{Unif}(0, 1) \rightarrow (2x_2 - 1) = \vec{x}_2 \end{aligned}$$

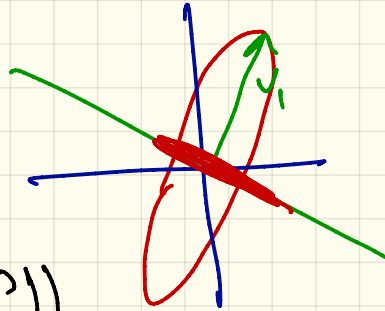
# Power Method ( $M = A^T A, g$ )

0. Init  $u^{(0)} \leftarrow$  random Gaussian

1. for  $i = 1$  to  $g$

$$u^{(i)} = M u^{(i-1)}$$

2. Returns  $v = u^{(g)} / \|u^{(g)}\|$



top  
eigen  
vector

$v_1$   
of  $M$

$$\sigma_1^2 = \lambda_1 = \|M v_1\|$$

$$A_1 = A - A v_1 v_1^T$$

$$M_1 = A_1^T A_1$$

$v_2 = \text{power-method}(M_1) \Rightarrow \text{recurse}$

$$M v_i = \lambda_i v_i$$

$$\|v_i\| = 1$$

$$\|M v_i\| = \|\lambda_i v_i\| = \lambda_i$$

$M = A^T A$ , assume  $\hookrightarrow 1$  rank

$$M \in \mathbb{R}^{d \times d}$$

eigen vectors  $M = \{v_1, v_2, \dots, v_d\}$

eigen values  $L = \{\lambda_1, \lambda_2, \dots, \lambda_d\}$

(unit vector

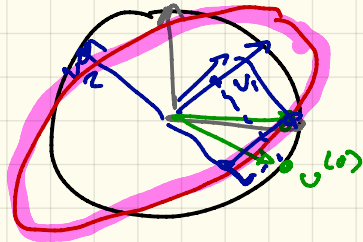
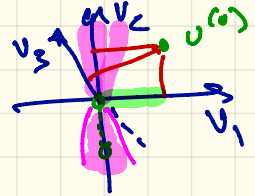
$$u^{(0)} \in \mathbb{R}^d$$

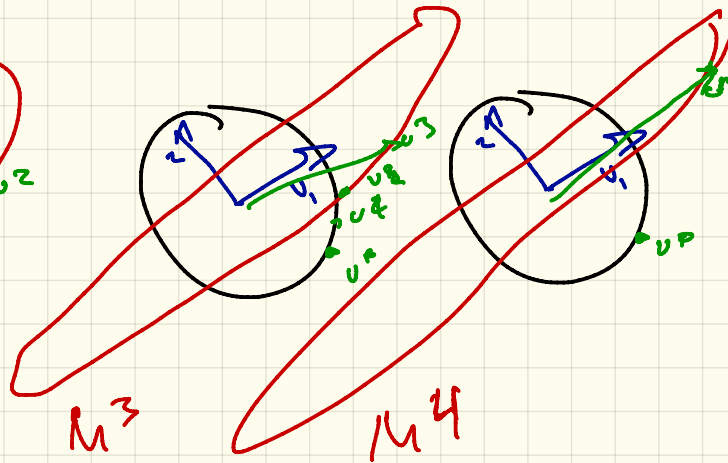
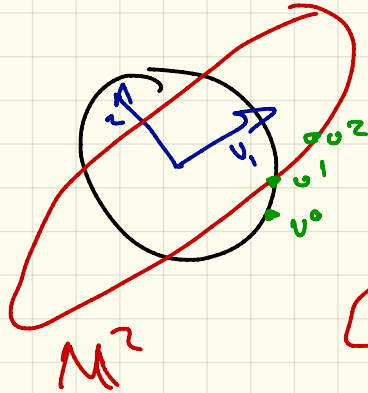
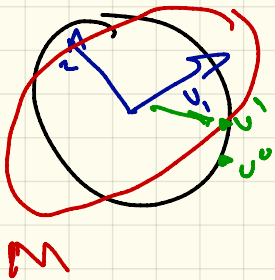
$$u^{(0)} = \sum_{j=1}^d \alpha_j v_j$$

$$\alpha_j = \langle u^{(0)}, v_j \rangle$$

assume

$$|\alpha_1| \geq \frac{1}{2} \frac{1}{\sqrt{d}}$$





eigen  
values of  $M^g = \lambda_1^g, \lambda_2^g, \lambda_3^g \dots \lambda_d^g$

vectors  $M^g = v_1, v_2, \dots, v_d$

$$\begin{aligned} M^g v_j &= M \cdot M \cdot \dots (M v_j) = M^{(g-1)} (v_j \lambda_j) \\ &= (M^{g-2}) (v_j \lambda_j) \lambda_j \\ &= M^{g-3} (v_j \lambda_j) \lambda_j^2 \\ &\quad \dots \\ &= M v_j \lambda_j^{g-1} \\ &= v_j \lambda_j^g \end{aligned}$$



$$\alpha_j = \langle v_j, v^{(0)} \rangle$$

$$\hat{v}_1 = \frac{M^0 v^{(0)}}{\|M^0 v^{(0)}\|} = \frac{\sum_{j=1}^d \alpha_j \lambda_j^0 v_j}{\sqrt{\sum_{j=1}^d (\alpha_j \lambda_j^0)^2}}$$



$$\langle v_j, v_1 \rangle = 0 \quad (j \neq 1)$$

$$|\langle \hat{v}_1, v_1 \rangle|$$

$$= \frac{\alpha_1 \lambda_1^0}{\sqrt{\sum_{j=1}^d (\alpha_j \lambda_j^0)^2}} \Rightarrow \frac{\alpha_1 \lambda_1^0}{\sqrt{\alpha_1^2 \lambda_1^0 + d \alpha_2^2 \lambda_2^0 + \dots}}$$

$$\alpha_1 > \frac{1}{2} \sqrt{d}$$

$$\Rightarrow \frac{\alpha_1 \lambda_1^0}{\alpha_1 \lambda_1^0 + \lambda_2^0 \sqrt{d}} = 1 - \frac{\lambda_2^0 \sqrt{d}}{\alpha_1 \lambda_1^0 + \lambda_2^0 \sqrt{d}}$$

$$\Rightarrow 1 - \frac{\lambda_2^0 \sqrt{d}}{\alpha_1 \lambda_1^0} \approx 1 - 2d \left( \frac{\lambda_2}{\lambda_1} \right)^0$$

# Convergence of Power Method

goes exponentially fast in

$$\frac{\lambda_2}{\lambda_1}$$

error  $\approx \left( \frac{\lambda_2}{\lambda_1} \right)^g$