Discussion 11B

1. Computing the SVD: A "Tall" Matrix Example

Define the matrix

xample
$$A = U Z U^{T}$$

$$A = \begin{bmatrix} 1 & -1 \\ -2 & 2 \\ 2 & -2 \end{bmatrix} . (3x2) = (3x3)(3x2)(2x2)$$
(1)

Here, we expect $U \in \mathbb{R}^{3\times 3}$, $\Sigma \in \mathbb{R}^{3\times 2}$, and $V \in \mathbb{R}^{2\times 2}$ (recall that U and V must be square since they are orthonormal matrices).

In this problem, we will walk through the SVD algorithm, prove some important theorems about the SVD matrices and column/null spaces, and consider an alternate way to approach the SVD.

(a) Let's start by trying to write A as an outer product in the form of $\sigma \vec{u} \vec{v}^{\top}$ where both \vec{u} and \vec{v}^{\top} have unit norm. (HINT: Are the columns of A linearly independent or dependent? What does that tell us about how we can represent them?)

- (b) In this part, we will walk through Algorithm 7 in Note 16. This algorithm applies for a general matrix $A \in \mathbb{R}^{m \times n}$.
 - i. Find $r := \operatorname{rank}(A)$. Compute $A^{\top}A$ and diagonalize it using the spectral theorem (i.e. find V and Λ).

ii. Unpack
$$V:=\begin{bmatrix}V_r & V_{n-r}\end{bmatrix}$$
 and unpack $\Lambda:=\begin{bmatrix}\Lambda_r & 0_{r\times (n-r)} \\ 0_{(n-r)\times r} & 0_{(n-r)\times (n-r)}\end{bmatrix}$.

iii. Find $\Sigma_r:=\Lambda_r^{1/2}$ and then find $\Sigma:=\begin{bmatrix}\Sigma_r & 0_{r\times (n-r)} \\ 0_{(m-r)\times r} & 0_{(m-r)\times (n-r)}\end{bmatrix}$.

iv. Find $U_r:=AV_r\Sigma_r^{-1}$, where $U_r\in\mathbb{R}^{3\times 1}$ and then extend the basis defined by columns of U_r

$$\text{iii. Find } \Sigma_r \coloneqq \Lambda_r^{1/2} \text{ and then find } \Sigma \coloneqq \begin{bmatrix} \Sigma_r & 0_{r \times (n-r)} \\ 0_{(m-r) \times r} & 0_{(m-r) \times (n-r)} \end{bmatrix}.$$

to find $U \in \mathbb{R}^{3\times 3}$.

(HINT: How can we extend a basis, and why is that needed here?)

$$A = \begin{bmatrix} 1 & -1 \\ -2 & 2 \\ 2 & -2 \end{bmatrix} = \begin{bmatrix} 1 \\ -2 \\ 2 \end{bmatrix} \begin{bmatrix} 1 & -1 \\ 1 \end{bmatrix}$$

4= 114114

A= uv = (||u|| û)(||v|) î)

0 = |(41) ||v|| = 3. J2

$$\sqrt{|t|^2 + |t|^2}$$

$$\sqrt{|t|^2 + |$$

U= NUII Û

= ||a|| ||v|| $\hat{u} \hat{v}^{T} = \sigma \hat{u} \hat{v}^{T} = 3\sqrt{2}$ | $\begin{bmatrix} \frac{1}{2} & \frac{1}{2} \\ -\frac{1}{2} & \frac{1}{2} \end{bmatrix}$

- v. Use the previous parts to write the full SVD of A.
- vi. If we were to calculate the SVD of our matrix using a calculator, are we guaranteed to always get the same SVD? Why or why not?

(c) We now want to create the SVD of A^{\top} . What are the relationships between the matrices composing A and the matrices composing A^{\top} ?

$$A^{T}A = \begin{pmatrix} 1 & -1 & 2 \\ -1 & 2 & -2 \end{pmatrix} \begin{pmatrix} 1 & -1 \\ -2 & 2 \\ 2 & -2 \end{pmatrix} = \begin{bmatrix} 9 & -9 \\ -9 & 9 \end{bmatrix}$$

$$(2\times3)(3\times2) \qquad (2\times2)$$

S= Q A Q T = Q T

$$= Q \wedge Q^{-1}$$

$$dot (A^{T}A - \lambda I) = dot (4 - \lambda - 1)$$

$$= (4-\lambda)^2 - 61 = 0$$

$$(4-\lambda)^2 = 61$$

$$4-\lambda = \pm 6$$

$$q-\lambda = q$$

$$\lambda = 0, (8)$$

$$\frac{\lambda=0}{2}$$

$$\operatorname{mod}\left(\begin{array}{cc} q & -q \\ -q & q \end{array}\right) = \operatorname{gan}\left\{\left(\begin{array}{c} 1 \\ 1 \end{array}\right)\right\}$$

$$V_1 = \begin{bmatrix} \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} \end{bmatrix}$$

$$|A=16|$$

$$|$$

$$U_2 = \begin{bmatrix} \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} \end{bmatrix}$$

$$(A^{T}A) = Q \Lambda Q^{T}$$

$$Q = \begin{bmatrix} \frac{1}{2} & \frac{1}{2} \\ \frac{1}{2} & \frac{1}{2} \end{bmatrix} \qquad A = \begin{bmatrix} 18 & 0 \\ 0 & 0 \end{bmatrix}$$

$$A = U \mathcal{E} V^{\mathsf{T}} \qquad \left(\begin{array}{c} \sigma_1 & \circ \\ \circ & \sigma_2 \end{array} \right) \left(\begin{array}{c} \sigma_1 & \circ \\ \circ & \sigma_2 \end{array} \right)$$

$$f^{\mathsf{T}} A = \left(u \mathcal{E} V^{\mathsf{T}} \right)^{\mathsf{T}} u \mathcal{E} V^{\mathsf{T}} \qquad \left(\begin{array}{c} \sigma_1 & \circ \\ \circ & \sigma_2 \end{array} \right)$$

$$A^{T}A = (u \Sigma v^{T})^{T} u \Sigma v^{T}$$

$$= (v \Sigma^{T} u^{T}) u \Sigma v^{T}$$

$$= v \Sigma^{T} \Sigma v^{T}$$

$$= v \Sigma^{T} \Sigma v^{T}$$

$$= (\sqrt{2}, \sqrt{4}) \sqrt{2} \sqrt{4}$$

$$= \sqrt{2} \sqrt{2} \sqrt{4}$$

$$A^{T}A = VE^{T}2U^{T}$$

$$A^{T}A = QAQ^{T}$$

$$V = Q = \begin{bmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ -\frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{bmatrix}$$

$$A = \begin{bmatrix} U & 0 \\ 0 & 1 \end{bmatrix}$$

$$V = \begin{bmatrix} U & 0 \\ 0 & 1 \end{bmatrix}$$

$$V = \begin{cases} v_1 & v_2 \\ v_3 & v_4 \end{cases}$$

$$V = \begin{cases} v_1 & v_4 - v_4 \\ v_4 & v_5 \end{cases}$$

$$A = \begin{cases} 16 & 0 \\ 0 & 0 \\ 0 & 0 \end{cases}$$

$$A = \begin{cases} 16 & 0 \\ 0 & 0 \\ 0 & 0 \end{cases}$$

$$V = \begin{bmatrix} v_r & v_{u-r} \end{bmatrix} = \begin{bmatrix} v_{u-r} & \vdots & \vdots \\ -v_{u-r} & \vdots & \vdots \\ -v_{u-r} & \vdots & \vdots \end{bmatrix}$$

$$V_{u-r} = \begin{bmatrix} v_{u-r} & \vdots & \vdots \\ v_{u$$

$$\begin{bmatrix}
\sigma_1 & \circ \\
\circ & \sigma_2
\end{bmatrix} = \begin{bmatrix}
\sqrt{6} & \circ \\
\circ & \circ
\end{bmatrix}$$

$$u = \left[u_r \ u_{n-r} \right]$$

$$u_r = A v_r \mathcal{E}_r^{-1}$$

$$v_r = \begin{bmatrix} 1 & -1 \\ 1 & -1 \end{bmatrix} \begin{bmatrix} \frac{1}{2} \\ \frac{1}{2} \end{bmatrix}$$

$$U_{r} = \begin{bmatrix} 1 & -1 \\ -1 & 2 \\ 2 & -2 \end{bmatrix} \begin{bmatrix} J_{2} \\ J_{3} \end{bmatrix} \frac{1}{\sqrt{16}}$$

$$= \begin{bmatrix} -1/3 \\ 2/3 \\ -2/3 \end{bmatrix}$$

V= | J2 | -12

Er = 18

$$\left\{ \begin{bmatrix} -2/3 \\ 2/3 \\ -2/3 \end{bmatrix}, e_1, e_2, e_3 \right\} \longrightarrow G.S.$$

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