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

$$A = \begin{bmatrix} 1 & -1 \\ -2 & 2 \\ 2 & -2 \end{bmatrix}, \quad (3 \times 2) = (3 \times 3) (3 \times 2) (2 \times 2)$$
(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 $r \coloneqq \operatorname{rank}(A)$. 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

 - to find $U \in \mathbb{R}^{3 \times 3}$. (HINT: How can we extend a basis, and why is that needed here?)



- 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} ?









 $A^T A = V S^T 2 U^T$ $A^T A = Q A Q^T$



Ar = 18 $\Xi_r = \Lambda_r^{\gamma_2} = \sqrt{18}$ $\Xi = \begin{bmatrix} \sigma_1 & \circ \\ \circ & \sigma_2 \\ \circ & 0 \end{bmatrix} = \begin{bmatrix} \sqrt{16} & \circ \\ \circ & \circ \\ 0 & 0 \end{bmatrix}$ $u = \left[ur \quad u_{n-r} \right]$ $V_{r} = \begin{bmatrix} J_{2} \\ -J_{2} \\ -J_{2} \end{bmatrix}$ $u_r = A v_r \mathcal{Z}_r^{-1}$ $\Sigma_r = \sqrt{18}$ $U_{r} = \begin{bmatrix} 1 & -1 \\ -2 & 2 \\ 2 & -2 \end{bmatrix} \begin{bmatrix} -1 \\ -3 \\ -3 \\ -5 \\ -5 \end{bmatrix} \frac{1}{\sqrt{s}}$ $e_{i} = \begin{bmatrix} i \\ 0 \end{bmatrix} e_{\overline{z}} \begin{bmatrix} 0 \\ 0 \end{bmatrix}$ vse basis vectors for TF³ $= \begin{pmatrix} -1/3 \\ 2/3 \\ -2/3 \end{pmatrix}$ $\left\{ \begin{bmatrix} -\frac{1}{3} \\ \frac{2}{3} \\ -\frac{2}{3} \end{bmatrix}, e_1, e_2, e_3 \quad \left\{ \xrightarrow{-} G.S. \right\}$

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