

## 1. SVD

Suppose we have a matrix  $A \in \mathbb{R}^{m \times n}$  with rank  $r$ . It turns out that its SVD has multiple forms, all of which can be useful depending on the problem we're working on.

We define the compact SVD as follows:

$$\underbrace{A}_{m \times n} = \underbrace{U_r}_{m \times r} \underbrace{\Sigma_r}_{r \times r} \underbrace{V_r^\top}_{r \times n}.$$

Here,  $\Sigma_r \in \mathbb{R}^{r \times r}$  is a diagonal matrix containing non-zero singular values of  $A$ .

$$\Sigma_r = \begin{bmatrix} \sigma_1 & & \\ & \ddots & \\ & & \sigma_r \end{bmatrix},$$

with  $\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_r$ .

Next,  $U_r \in \mathbb{R}^{m \times r}$  is given by,

$$U_r = [\vec{u}_1, \vec{u}_2, \dots, \vec{u}_r],$$

where  $u_i$  is a left singular vector corresponding to non-zero singular value,  $\sigma_i$ , for  $i = 1, 2, \dots, r$ . The columns of  $U_r$  are orthonormal and together they span the column space of  $A$ .

Finally,  $V_r^\top \in \mathbb{R}^{r \times n}$  is given by,

$$V_r^\top = \begin{bmatrix} \vec{v}_1^\top \\ \vec{v}_2^\top \\ \vdots \\ \vec{v}_r^\top \end{bmatrix},$$

where  $\vec{v}_j$  is a right singular vector corresponding to non-zero singular value,  $\sigma_j$  for  $j = 1, 2, \dots, r$ . The rows of  $V_r^\top$  are orthonormal and span the row space of  $A$ . Equivalently the columns of  $V_r$  span the column space of  $A^\top$ .

The matrix  $A$  can be expressed as,

$$A = \sigma_1 \vec{u}_1 \vec{v}_1^\top + \sigma_2 \vec{u}_2 \vec{v}_2^\top + \dots + \sigma_r \vec{u}_r \vec{v}_r^\top.$$

This is called the dyadic SVD, since it's expressed as the sum of dyads (matrices of the form  $uv^\top$ ). Assume now that  $m \geq n$ .

Another type of SVD which might be more familiar is the full SVD of  $A$  which is defined as follows:

$$\underbrace{A}_{m \times n} = \underbrace{U}_{m \times m} \underbrace{\Sigma}_{m \times n} \underbrace{V^\top}_{n \times n}.$$

Here,  $\Sigma \in \mathbb{R}^{m \times n}$  has non-diagonal entries as zero. The diagonal entries of  $\Sigma$  contain the singular values and we can write  $\Sigma$  in terms of  $\Sigma_r$  as,

$$\Sigma = \left[ \begin{array}{c|c} \Sigma_r & 0_{r \times (n-r)} \\ \hline 0_{(m-r) \times r} & 0_{(m-r) \times (n-r)} \end{array} \right]$$

Next,  $U \in \mathbb{R}^{m \times m}$  is an orthonormal matrix.  $U$  can be expressed in terms of  $U_r$  as,

$$U = \begin{bmatrix} \underbrace{U_r}_{m \times r} & \underbrace{\vec{u}_{r+1} \ \dots \ \vec{u}_m}_{m \times (m-r)} \end{bmatrix}$$

The columns  $\vec{u}_{r+1}, \vec{u}_{r+2}, \dots, \vec{u}_m$  are left singular vectors corresponding to singular value 0, and together span the nullspace of  $A^\top$ .

Finally,  $V^\top$  is an orthonormal matrix and can be expressed in terms of  $V_r^\top$  as,

$$V^\top = \left\{ \begin{array}{l} \left[ \begin{array}{c} V_r^\top \\ \vec{v}_{r+1}^\top \\ \vdots \\ \vec{v}_n^\top \end{array} \right] \end{array} \right\} \begin{array}{l} r \times n \\ (n-r) \times n \end{array}$$

The rows  $\vec{v}_{r+1}^\top, \vec{v}_{r+2}^\top, \dots, \vec{v}_n^\top$  when transposed are the right singular vectors corresponding to singular value 0, and together they span the nullspace of  $A$ .

(a) For this problem assume that  $m > n > r$ . Label each of the following as True or False:

(a)  $UU^\top = I$

(b)  $U^\top U = I$

(c)  $V^\top V = I$

(d)  $VV^\top = I$

(e)  $U_r^\top U_r = I$

(f)  $U_r U_r^\top = I$

(g)  $V_r V_r^\top = I$

(h)  $V_r^\top V_r = I$

(b) Find the compact SVD of  $A$ , given that it has the following full SVD:

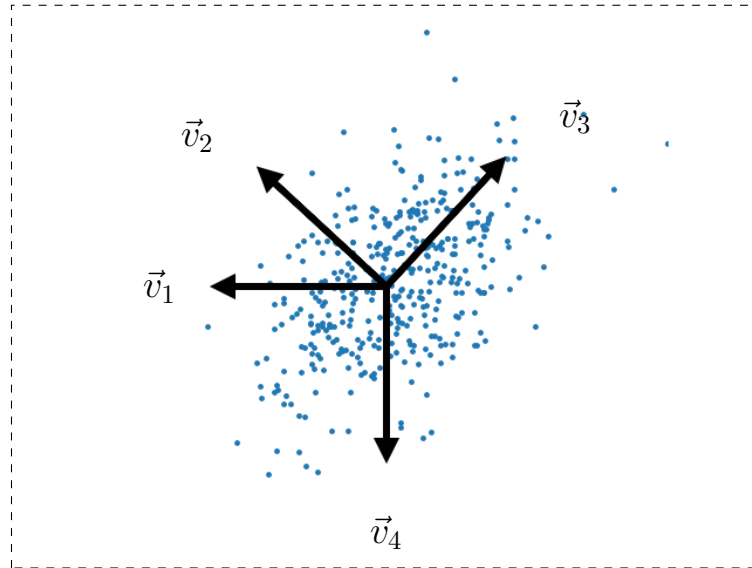
$$A = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 2 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}.$$

(c) Find the full SVD of  $A$ , given that it has the following compact SVD:

$$A = \begin{bmatrix} \frac{1}{\sqrt{2}} & 0 \\ \frac{1}{\sqrt{2}} & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 2 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}.$$

## 2. PCA and Regression

- (a) Given the following plot of data in  $\mathbb{R}^2$  (i.e., each dot is a data point in  $\mathbb{R}^2$ ) and candidate unit vectors  $\vec{v}_1, \vec{v}_2, \vec{v}_3, \vec{v}_4 \in \mathbb{R}^2$ , **identify the candidate vectors which could be the first principal component and second principal component of the data (and specify which is which).**



(b) Suppose we have data  $\vec{x}_1, \dots, \vec{x}_n \in \mathbb{R}^d$ , where  $n > d$ . We arrange these data points into a matrix, i.e.,

$$X = \begin{bmatrix} \vec{x}_1^\top \\ \vdots \\ \vec{x}_n^\top \end{bmatrix} \in \mathbb{R}^{n \times d}. \quad (1)$$

Assume that  $X$  is centered, i.e., each column has mean zero:  $(1/n) \sum_{i=1}^n \vec{x}_i = \vec{0}_d$ , where  $\vec{0}_d$  is the zero vector in  $\mathbb{R}^d$ . Suppose that  $X$  has compact SVD given by  $X = U_d \Sigma_d V_d^\top$  where

$$U_d = [\vec{u}_1, \dots, \vec{u}_d] \in \mathbb{R}^{n \times d}, \quad V_d = [\vec{v}_1, \dots, \vec{v}_d] \in \mathbb{R}^{d \times d}, \quad \Sigma_d = \begin{bmatrix} \sigma_1 & & \\ & \ddots & \\ & & \sigma_d \end{bmatrix} \in \mathbb{R}^{d \times d} \quad (2)$$

where  $\sigma_1 > \sigma_2 > \dots > \sigma_d > 0$ . **From this SVD, identify the top  $k$  principal components of the data  $\{\vec{x}_1, \dots, \vec{x}_n\} \subseteq \mathbb{R}^d$ , where  $k \leq d$ .**

*HINT: Recall that the first principal component solves the optimization problem  $\operatorname{argmax}_{\vec{w} \in \mathbb{R}^d: \|\vec{w}\|_2=1} \vec{w}^\top X^\top X \vec{w}$ .*

**3. Singular Values**

(a) Suppose  $A \in \mathbb{R}^{3 \times 2}$  is a matrix such that  $A^\top A$  is given by

$$A^\top A = \begin{bmatrix} 1/\sqrt{2} & -1/\sqrt{2} \\ 1/\sqrt{2} & 1/\sqrt{2} \end{bmatrix} \begin{bmatrix} 5 & 0 \\ 0 & 3 \end{bmatrix} \begin{bmatrix} 1/\sqrt{2} & 1/\sqrt{2} \\ -1/\sqrt{2} & 1/\sqrt{2} \end{bmatrix}. \quad (3)$$

**What are the singular values of  $A$ ?**

- (b) Suppose that  $B \in \mathbb{R}^{3 \times 2}$  has singular values 0,  $\sqrt{2}$ , and  $\sqrt{7}$ . Let  $C = \begin{bmatrix} B & -B & 3I_3 \end{bmatrix} \in \mathbb{R}^{3 \times 7}$ , where  $I_3 \in \mathbb{R}^{3 \times 3}$  is the  $3 \times 3$  identity matrix. **What are the singular values of  $C$ ?**

*HINT: Consider the matrix  $CC^\top \in \mathbb{R}^{3 \times 3}$ .*