## 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 $A$.

$$
\Sigma_{r}=\left[\begin{array}{lll}
\sigma_{1} & & \\
& \ddots & \\
& & \sigma_{r}
\end{array}\right]
$$

with $\sigma_{1} \geq \sigma_{2} \geq \ldots \geq \sigma_{r}$.
Next, $U_{r} \in \mathbb{R}^{m \times r}$ is given by,

$$
U_{r}=\left[\vec{u}_{1}, \vec{u}_{2}, \ldots, \vec{u}_{r}\right],
$$

where $u_{i}$ is a left singular vector corresponding to non-zero singular value, $\sigma_{i}$, for $i=1,2, \ldots, r$. The columns of $U_{r}$ are orthonormal and together they span the columnspace of $A$.
Finally, $V_{r}^{\top} \in \mathbb{R}^{r \times n}$ is given by,

$$
V_{r}^{\top}=\left[\begin{array}{c}
\vec{v}_{1}^{\top} \\
\vec{v}_{2}^{\top} \\
\vdots \\
\vec{v}_{r}^{\top}
\end{array}\right]
$$

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

The matrix $A$ can be expressed as,

$$
A=\sigma_{1} \vec{u}_{1} \vec{v}_{1}^{\top}+\sigma_{2} \vec{u}_{2} \vec{v}_{2}^{\top}+\ldots+\sigma_{r} \vec{u}_{r} \vec{v}_{r}^{\top}
$$

This is called the dyadic SVD, since it's expressed as the sum of dyads (matrices of the form $u v^{\top}$ ). 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:


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,

$$
U=\underbrace{\left[\begin{array}{lll}
U_{r} \\
& \underbrace{\vec{u}_{r+1}}_{m \times(m-r)} \ldots \ldots & \vec{u}_{m}
\end{array}\right]}_{m \times r}
$$

The columns $\vec{u}_{r+1}, \vec{u}_{r+2}, \ldots, \vec{u}_{n}$ 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,

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

The rows $\vec{v}_{r+1}^{\top}, \vec{v}_{r+2}^{\top}, \ldots, \vec{v}_{n}^{\top}$ 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) $U U^{\top}=I$

Solution: True. $U U^{\top}=I_{m}$ because $U$ is an orthonormal matrix.
(b) $U^{\top} U=I$

Solution: True. $U^{\top} U=I_{m}$ because $U$ is an orthonormal matrix.
(c) $V^{\top} V=I$

Solution: True. $V^{\top} V=I_{n}$ because $V$ is an orthonormal matrix.
(d) $V V^{\top}=I$

Solution: True. $V V^{\top}=I_{n}$ because $V$ is an orthonormal matrix.
(e) $U_{r}^{\top} U_{r}=I$

Solution: True. $U_{r}^{\top} U_{r}=I_{r}$ because the columns of $U_{r}$ are orthonormal.
(f) $U_{r} U_{r}^{\top}=I$

Solution: False. $U_{r} U_{r}^{\top}$ is a $m \times m$, matrix but has rank less than or equal to $r$ (since $U_{r}$ has rank $r$ and product of matrices has rank less than or equal to minimum of individual ranks).
(g) $V_{r} V_{r}^{\top}=I$

Solution: False. $V_{r} V_{r}^{\top}$ is a $n \times n$, matrix but has rank less than or equal to $r$ (since $V_{r}$ has rank $r$ and product of matrices has rank less than or equal to minimum of individual ranks).
(h) $V_{r}^{\top} V_{r}=I$

Solution: True. $V_{r}^{\top} V_{r}=I_{r}$ because the columns of $V_{r}$ are orthonormal.
(b) Find the compact SVD of $A$, given that it has the following full SVD:

$$
A=\left[\begin{array}{lll}
0 & 1 & 0 \\
1 & 0 & 0 \\
0 & 0 & 1
\end{array}\right]\left[\begin{array}{ll}
2 & 0 \\
0 & 0 \\
0 & 0
\end{array}\right]\left[\begin{array}{ll}
1 & 0 \\
0 & 1
\end{array}\right]
$$

Solution: The compact SVD of $A$ is given by:

$$
A=\left[\begin{array}{l}
0 \\
1 \\
0
\end{array}\right]\left[\begin{array}{l}
2
\end{array}\right]\left[\begin{array}{ll}
1 & 0
\end{array}\right]
$$

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

$$
A=\left[\begin{array}{cc}
\frac{1}{\sqrt{2}} & 0 \\
\frac{1}{\sqrt{2}} & 0 \\
0 & 1
\end{array}\right]\left[\begin{array}{ll}
2 & 0 \\
0 & 1
\end{array}\right]\left[\begin{array}{ll}
1 & 0 \\
0 & 1
\end{array}\right]
$$

Solution: Observe that in this case, the full SVD of $A$ has $\Sigma$ and $V^{\top}$ as those in the compact SVD but $U \in \mathbb{R}^{3 \times 3}$. Thus we need to find a unit-norm column $\vec{u}_{3}$ orthogonal to columns of $U_{r}$. We can use a system of linear equations to solve this. That is we want $u_{3}=\left[\begin{array}{ll}x, y, z\end{array}\right]$ so we must have

- $[1 / \sqrt{2}, 1 / \sqrt{2}, \quad 0]^{\top} \vec{u}_{3}=0$
- $[0,0,1]^{\top} \vec{u}_{3}=0$
- $\left\|\vec{u}_{3}\right\|_{2}=1$

Check that $\vec{u}_{3}=\left[\begin{array}{c}\frac{1}{\sqrt{2}} \\ -\frac{1}{\sqrt{2}} \\ 0\end{array}\right]$ satisfies our requirements.
Thus the full SVD of $A$ is given by:

$$
A=\left[\begin{array}{ccc}
\frac{1}{\sqrt{2}} & 0 & \frac{1}{\sqrt{2}} \\
\frac{1}{\sqrt{2}} & 0 & -\frac{1}{\sqrt{2}} \\
0 & 1 & 0
\end{array}\right]\left[\begin{array}{ll}
2 & 0 \\
0 & 1 \\
0 & 0
\end{array}\right]\left[\begin{array}{ll}
1 & 0 \\
0 & 1
\end{array}\right] .
$$

Alternatively we can use Gram-Schmidt procedure to find $\vec{u}_{3}$. This has the added advantage of being useful when we want to find the full SVD when more than one singular vector is missing.

## 2. SVD Part 2

Consider $A$ to be the $4 \times 3$ matrix

$$
A=\left[\begin{array}{lll}
\vec{a}_{1} & \vec{a}_{2} & \vec{a}_{3} \tag{1}
\end{array}\right]
$$

where $\vec{a}_{i}$ for $i \in\{1,2,3\}$ form a set of orthogonal vectors satisfying $\left\|\vec{a}_{1}\right\|_{2}=3,\left\|\vec{a}_{2}\right\|_{2}=2,\left\|\vec{a}_{3}\right\|_{2}=1$.
(a) What is the SVD of $A$ ? Express it as $A=U \Sigma V^{\top}$, with $\Sigma$ the diagonal matrix of singular values ordered in decreasing fashion, and explicitly describe $U$ and $V$.
Solution: The SVD of $A=U \Sigma V^{\top}$. Due to the orthogonality of the $\vec{a}_{i}$ we have that

$$
A^{\top} A=V \Sigma^{2} V^{\top}=\left[\begin{array}{lll}
9 & 0 & 0  \tag{2}\\
0 & 4 & 0 \\
0 & 0 & 1
\end{array}\right]
$$

Thus $V=I$ and $\Sigma=\operatorname{diag}(3,2,1)$. Finally we have that $U=A \Sigma^{-1}$ which becomes

$$
U=\left[\begin{array}{lll}
\frac{\vec{a}_{1}}{3} & \frac{\vec{a}_{2}}{2} & \frac{\vec{a}_{3}}{1} \tag{3}
\end{array}\right]
$$

(b) What is the dimension of the null space, $\operatorname{dim}(\mathcal{N}(A))$ ?

Solution: From part (a) all of the singular values of the $A$ are non-zero. So the dimension of the null space is 0 . Alternatively, all the columns of $A$ are orthogonal - so no (non-zero) linear combination of them can equal zero.
(c) What is the rank of $A, \operatorname{rank}(A)$ ? Provide an orthonormal basis for the range of $A$.

Solution: The rank of $A$ is simply the number of non-zero singular values. So $\operatorname{rank}(A)=3$. The columns of $U$ (defined above) provide an orthonormal basis for the range of $A$.
(d) Let $I_{3}$ denote the $3 \times 3$ identity matrix. Consider the matrix $\tilde{A}=\left[\begin{array}{l}A \\ I_{3}\end{array}\right] \in \mathbb{R}^{7 \times 3}$. What are the singular values of $\tilde{A}$ (in terms of the singular values of $A$ )?
Solution: We have that $\tilde{A}^{\top} \tilde{A}=A^{\top} A+I_{3}=V\left(\Sigma^{2}+I_{3}\right) V^{\top}$. Hence if we denote $\sigma_{i}$ as the singular values of $A$ then the singular values of $\tilde{A}$ are $\tilde{\sigma}_{i}=\sqrt{\sigma_{i}^{2}+1}$ which are $\sqrt{10}, \sqrt{5}, \sqrt{2}$.

