## This homework is due on Thursday, November 5, 2020, at 10:59PM.

## Self-grades are due on Thursday, November 12, 2020, at 10:59PM.

## 1 SVD I

Find the singular value decomposition of the following matrix (leave all work in exact form, not decimal):

$$
A=\left[\begin{array}{cc}
2 & 2 \\
3 & -3
\end{array}\right]
$$

a) Find the eigenvalues of $A A^{\top}$ and order them from largest to smallest, $\lambda_{1}>\lambda_{2}$.
b) Find orthonormal eigenvectors $\vec{u}_{i}$ of $A A^{\top}$ (all eigenvectors are mutually orthogonal and unit length).
c) Find the singular values $\sigma_{i}=\sqrt{\lambda_{i}}$. Find the $\vec{v}_{i}$ vectors from:

$$
A^{\top} \vec{u}_{i}=\sigma_{i} \vec{v}_{i}
$$

d) Write out A as a weighted sum of rank-1 matrices:

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

## 2 Rank 1 Decomposition

In this problem, we will decompose a few images into linear combinations of rank 1 matrices. Remember that outer product of two vectors $\vec{s} \vec{g}^{T}$ gives a rank 1 matrix. It has rank 1 because clearly, the column span is one-dimensional - multiples of $\vec{s}$ only - and the row span is also one dimensional - multiples of $\vec{g}^{T}$ only.

For example, if $\vec{s}$ and $\vec{g}$ are two vectors of dimension 5 , then $\vec{s}^{T}$ is given as follows.

$$
\begin{gathered}
\vec{s}=\left[\begin{array}{l}
s_{1} \\
s_{2} \\
s_{3} \\
s_{4} \\
s_{5}
\end{array}\right] \quad \vec{g}=\left[\begin{array}{l}
g_{1} \\
g_{2} \\
g_{3} \\
g_{4} \\
g_{5}
\end{array}\right] \\
\vec{s} \vec{g}^{T}=\left[\begin{array}{l}
s_{1} \\
s_{2} \\
s_{3} \\
s_{4} \\
s_{5}
\end{array}\right]\left[\begin{array}{lllll}
g_{1} & g_{2} & g_{3} & g_{4} & g_{5}
\end{array}\right]=\left[\begin{array}{llllll}
s_{1} g_{1} & s_{1} g_{2} & s_{1} g_{3} & s_{1} g_{4} & s_{1} g_{5} \\
s_{2} g_{1} & s_{2} g_{2} & s_{2} g_{3} & s_{2} g_{4} & s_{2} g_{5} \\
s_{3} g_{1} & s_{3} g_{2} & s_{3} g_{3} & s_{3} g_{4} & s_{3} g_{5} \\
s_{4} g_{1} & s_{4} g_{2} & s_{4} g_{3} & s_{4} g_{4} & s_{4} g_{5} \\
s_{5} g_{1} & s_{5} g_{2} & s_{5} g_{3} & s_{5} g_{4} & s_{5} g_{5}
\end{array}\right]
\end{gathered}
$$

a) Consider a standard $8 \times 8$ chessboard shown in Figure 1. Assume that black colors represent -1 and that white colors represent 1 .


Figure 1: $8 \times 8$ chessboard.

Hence, that the chessboard is given by the following $8 \times 8$ matrix $C_{1}$ :

$$
C_{1}=\left[\begin{array}{cccccccc}
1 & -1 & 1 & -1 & 1 & -1 & 1 & -1 \\
-1 & 1 & -1 & 1 & -1 & 1 & -1 & 1 \\
1 & -1 & 1 & -1 & 1 & -1 & 1 & -1 \\
-1 & 1 & -1 & 1 & -1 & 1 & -1 & 1 \\
1 & -1 & 1 & -1 & 1 & -1 & 1 & -1 \\
-1 & 1 & -1 & 1 & -1 & 1 & -1 & 1 \\
1 & -1 & 1 & -1 & 1 & -1 & 1 & -1 \\
-1 & 1 & -1 & 1 & -1 & 1 & -1 & 1
\end{array}\right]
$$

Express $C_{1}$ as a linear combination of outer products. Hint: In order to determine how many rank 1 matrices you need to combine to represent the matrix, find the rank of the matrix you are trying to represent.
b) For the same chessboard shown in Figure 1. now assume that black colors represent 0 and that white colors represent 1.
Hence, the chessboard is given by the following $8 \times 8$ matrix $C_{2}$ :

$$
C_{2}=\left[\begin{array}{llllllll}
1 & 0 & 1 & 0 & 1 & 0 & 1 & 0 \\
0 & 1 & 0 & 1 & 0 & 1 & 0 & 1 \\
1 & 0 & 1 & 0 & 1 & 0 & 1 & 0 \\
0 & 1 & 0 & 1 & 0 & 1 & 0 & 1 \\
1 & 0 & 1 & 0 & 1 & 0 & 1 & 0 \\
0 & 1 & 0 & 1 & 0 & 1 & 0 & 1 \\
1 & 0 & 1 & 0 & 1 & 0 & 1 & 0 \\
0 & 1 & 0 & 1 & 0 & 1 & 0 & 1
\end{array}\right]
$$

Express $C_{2}$ as a linear combination of outer products.
c) Now consider the Swiss flag shown in Figure 2. Assume that red colors represent 0 and that white colors represent 1.


Figure 2: Swiss flag.

Assume that the Swiss flag is given by the following $5 \times 5$ matrix $S$ :

$$
S=\left[\begin{array}{lllll}
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 \\
0 & 1 & 1 & 1 & 0 \\
0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 0
\end{array}\right]
$$

Furthermore, we know that the Swiss flag can be viewed as a superposition of the following pairs of images:


Figure 3: Pairs of images - Option 1


Figure 4: Pairs of images - Option 2

Express the $S$ in two different ways: i) as a linear combination of the outer products inspired by the Option 1 images and ii) as a linear combination of outer products inspired by the Option 2 images.

## 3 SVD properties

In this question, we look at some properties of SVD. Below we consider a m by n matrix whose SVD writes $A=\sum_{i=1}^{r} \sigma_{i} \vec{u}_{i} \vec{v}_{i}^{T}$ where r is the rank of the matrix.
a) We know that $A$ can also be represented in matrix form as $A=\sum_{i=1}^{r} \sigma_{i} \vec{u}_{i} \vec{v}_{i}^{T}=U_{1} S V_{1}^{T}$ where $U_{1}=\left[\vec{u}_{1}, \vec{u}_{2}, \ldots, \vec{u}_{r}\right], S=\operatorname{diag}\left(\sigma_{1}, \sigma_{2}, \ldots, \sigma_{r}\right)$, and $V_{1}=\left[\vec{v}_{1}, \vec{v}_{2}, \ldots, \vec{v}_{r}\right]$. Show that $\sum_{i=1}^{r} \sigma_{i} \vec{u}_{i} \vec{v}_{i}^{T}=U_{1} S V_{1}{ }^{T}$. Note that the math does not assume any further property for $U_{1}$ and $V_{1}$ than that they are of compatible shape as long as $S$ is diagonal.
The full SVD of $A$ writes $A=U \Sigma V^{T}$ where $U=\left[\vec{u}_{1}, \vec{u}_{2}, \ldots, \vec{u}_{r}, \vec{u}_{r+1}, \ldots, \vec{u}_{m}\right]$ and $V=$ $\left[\vec{v}_{1}, \vec{v}_{2}, \ldots, \vec{v}_{r}, \vec{v}_{r+1}, \ldots, \vec{v}_{n}\right.$ ] are orthornormal matrices with the first $r$ columns being the same as those of $U^{\prime}$ and $V^{\prime}$.

$$
\Sigma=\left[\begin{array}{cc}
S_{r \times r} & 0_{r \times(n-r)} \\
0_{(m-r) \times r} & 0_{(m-r) \times(n-r)}
\end{array}\right] .
$$

b) Suppose $r<\min (m, n)$, what is a basis of the null space of $A$ ? Prove your answer.
c) What is the basis of the range of $A$ ? Prove your answer.
d) Suppose $n=m=r$, that is, $A$ is square and full rank. Find the inverse of $A$ in terms of $U, \Sigma$, and $V$.

## 4 Induced Matrix Norms

Often, the general effect of matrices on their inputs is really hard to predict. To overcome this, we usually try to "bound" the effect a matrix has on input vectors. We will work through a simple case of bounding the output of an $n \times n$ matrix $T$ given that $T$ is diagonalizable and symmetric. We will consider the system

$$
\vec{y}=T \vec{x}
$$

where $\vec{x}$ is the input vector and $\vec{y}$ is the output vector.
a) Let $U=\left[\vec{u}_{1}, \vec{u}_{2}, \ldots, \vec{u}_{n}\right]$ be a set of orthonormal eigenvectors of the matrix $T$. Decompose the generic input vector $\vec{x}$ into a linear combination of these eigenvectors.
b) Let the eigenvalues of $T$ be $\left\{\lambda_{1}, \lambda_{2}, \ldots, \lambda_{n}\right\}$ with $\left|\lambda_{1}\right| \geq\left|\lambda_{2}\right| \geq \ldots\left|\lambda_{n}\right|$. If we represent $\vec{x}$ as a linear combination of the eigenvectors of $T$, what is the Euclidean norm of the output vector $\vec{y},\|\vec{y}\|$ ?
Hint: You can use the fact that Euclidean norms are preserved with orthonormal transforms.
c) Say you do not know all the eigenvalues of $T$, but you know the largest eigenvalue $\lambda_{1}$. If the norm $\|\vec{x}\|=\alpha$, how big could $\|\vec{y}\|$ be?
The maximum factor by which a square matrix can grow the norm of a vector is called the induced norm for that matrix. Although we had you do the derivation above for a symmetric matrix $T$, the fact that $\|A \vec{x}\|=\sqrt{\vec{x}^{T} A^{T} A \vec{x}}$ can be used to show how to generalize this concept of induced norm for general matrices.

## 5 Closed-Loop Control of SIXT33N

To make our control more robust, we introduce feedback, turning our open-loop controller into a closed-loop controller. In this problem, we derive the closed-loop control scheme you will use to make SIXT33N reliably drive straight.

We introduce $\delta(k)=d_{L}(k)-d_{R}(k)$ as the difference in positions between the two wheels. We will consider a proportional control scheme, which introduces a feedback term into our input equation in which we apply gains $k_{L}$ and $k_{R}$ to $\delta(k)$ to modify our input at each timestep in an effort to prevent $|\delta(k)|$ from growing without bound. To do this, we will modify our inputs $u_{L}(k)$ and $u_{R}(k)$ to be:

$$
\begin{aligned}
& u_{L}(k)=\frac{v^{*}+\beta_{L}}{\theta_{L}}-k_{L} \frac{\delta(k)}{\theta_{L}} \\
& u_{R}(k)=\frac{v^{*}+\beta_{R}}{\theta_{R}}+k_{R} \frac{\delta(k)}{\theta_{R}}
\end{aligned}
$$

Substituting into the open-loop equations

$$
\begin{align*}
d_{L}(k+1)-d_{L}(k) & =\theta_{L} u_{L}(k)-\beta_{L}  \tag{1}\\
d_{R}(k+1)-d_{R}(k) & =\theta_{R} u_{R}(k)-\beta_{R}
\end{align*}
$$

we obtain:

$$
\begin{align*}
d_{L}(k+1)-d_{L}(k) & =v^{*}-k_{L} \delta(k)  \tag{2}\\
d_{R}(k+1)-d_{R}(k) & =v^{*}+k_{R} \delta(k)
\end{align*}
$$

a) Let's look a bit more closely at picking $k_{L}$ and $k_{R}$. First, we need to figure out what happens to $\delta(k)$ over time. Find $\delta(k+1)$ in terms of $\delta(k)$.
b) Given your work above, what is the eigenvalue of the system defined by $\delta(k)$ ? For discrete-time systems like our system, $\lambda \in(-1,1)$ is considered stable. Are $\lambda \in[0,1)$ and $\lambda \in(-1,0]$ identical in function for our system? Which one is "better"? (Hint: Preventing oscillation is a desired benefit.)
Based on your choice for the range of $\lambda$ above, how should we set $k_{L}$ and $k_{R}$ in the end?
c) Let's re-introduce the model mismatch in order to model environmental discrepancies, disturbances, etc. How does closed-loop control fare under model mismatch? Find $\delta_{s s}=\delta[k \rightarrow \infty]$, assuming that $\delta[0]=\delta_{0}$. What is $\delta_{s s}$ ? (To make this easier, you may leave your answer in terms of appropriately defined $c$ and $\lambda$ obtained from an equation in the form of $\delta(k+1)=\delta(k) \lambda+c$.) Check your work by verifying that you reproduce the equation in part (c) if all model mismatch terms are zero. Is it better than the open-loop model mismatch?

$$
\begin{array}{r}
d_{L}(k+1)-d_{L}(k)=\left(\theta_{L}+\Delta \theta_{L}\right) u_{L}(k)-\left(\beta_{L}+\Delta \beta_{L}\right) \\
d_{R}(k+1)-d_{R}(k)=\left(\theta_{R}+\Delta \theta_{R}\right) u_{R}(k)-\left(\beta_{R}+\Delta \beta_{R}\right)
\end{array}
$$

$$
\begin{aligned}
& u_{L}(k)=\frac{v^{*}+\beta_{L}}{\theta_{L}}-k_{L} \frac{\delta(k)}{\theta_{L}} \\
& u_{R}(k)=\frac{v^{*}+\beta_{R}}{\theta_{R}}+k_{R} \frac{\delta(k)}{\theta_{R}}
\end{aligned}
$$

## 6 Homework Process and Study Group

Citing sources and collaborators are an important part of life, including being a student! We also want to understand what resources you find helpful and how much time homework is taking, so we can change things in the future if possible.
a) What sources (if any) did you use as you worked through the homework?
b) If you worked with someone on this homework, who did you work with?

List names and student ID's. (In case of homework party, you can also just describe the group.)
c) Roughly how many total hours did you work on this homework?
d) Do you have any feedback on this homework assignment?

