

CS/ECE/ME532 Assignment 5

1. Here we continue the problem studied in Activity 11. Let a 4-by-2 matrix \mathbf{X} have

$$\text{SVD } \mathbf{X} = \mathbf{U}\mathbf{S}\mathbf{V}^T \text{ where } \mathbf{U} = \frac{1}{2} \begin{bmatrix} 1 & 1 \\ 1 & -1 \\ 1 & -1 \\ 1 & 1 \end{bmatrix}, \mathbf{S} = \begin{bmatrix} 1 & 0 \\ 0 & \gamma \end{bmatrix}, \text{ and } \mathbf{V} = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$$

$$\text{Let } \mathbf{y} = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 1 \end{bmatrix}.$$

- a) The ratio of the largest to the smallest singular values is termed the condition number of \mathbf{X} . Find the condition number if $\gamma = 0.1$, and $\gamma = 10^{-8}$. Solve $\mathbf{X}\mathbf{w} = \mathbf{y}$ for \mathbf{w} and find $\|\mathbf{w}\|_2^2$ for these two values of γ .

- b) A system of linear equations with a large condition number is said to be “ill-conditioned”. One consequence of an ill-conditioned system of equations is solutions with large norms as you found in the previous part of this problem. A second consequence is that the solution is very sensitive to small errors in \mathbf{y} such as may

result from measurement error or numerical error. Suppose $\mathbf{y} = \begin{bmatrix} 1 + \epsilon \\ 0 \\ 0 \\ 1 \end{bmatrix}$. Write

$\mathbf{w} = \mathbf{w}_o + \mathbf{w}_\epsilon$ where \mathbf{w}_o is the solution for arbitrary γ when $\epsilon = 0$ and \mathbf{w}_ϵ is the perturbation in that solution due to some error $\epsilon \neq 0$. How does the norm of the perturbation due to $\epsilon \neq 0$, $\|\mathbf{w}_\epsilon\|_2^2$, depend on the condition number? Find $\|\mathbf{w}_\epsilon\|_2^2$ for $\epsilon = 0.01$ and $\gamma = 0.1$ and $\gamma = 10^{-8}$.

- c) Now consider a “low-rank” inverse. Instead of writing

$$(\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T = \sum_{i=1}^p \frac{1}{\sigma_i} \mathbf{v}_i \mathbf{u}_i^T$$

where p is the number of columns of \mathbf{X} (assumed less than the number of rows), we approximate

$$(\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \approx \sum_{i=1}^r \frac{1}{\sigma_i} \mathbf{v}_i \mathbf{u}_i^T$$

In this approximation we only invert the largest r singular values, and ignore all of them smaller than σ_r . Use $r = 1$ in the low-rank inverse to find $\mathbf{w} = \mathbf{w}_o + \mathbf{w}_\epsilon$

where $\mathbf{y} = \begin{bmatrix} 1 + \epsilon \\ 0 \\ 0 \\ 1 \end{bmatrix}$ as in part b). Compare the results to part b).

①

a) $w = \frac{1}{\sqrt{2}} \begin{bmatrix} 1+x^{-1} \\ 1-x^{-1} \end{bmatrix}$ from Activity 11

$\underline{x = 0.1}$

$$w = \frac{1}{\sqrt{2}} \begin{bmatrix} 1+10 \\ 1-10 \end{bmatrix} = \frac{1}{\sqrt{2}} \begin{bmatrix} 11 \\ -9 \end{bmatrix} \quad \textcircled{*} \text{ Condition number} = 10$$

$$\|w\|_2^2 = \left(\frac{11}{\sqrt{2}}\right)^2 + \left(\frac{-9}{\sqrt{2}}\right)^2 = \frac{121}{2} + \frac{81}{2} = \frac{202}{2} = 101$$

$\underline{x = 10^{-8}}$

$$w = \frac{1}{\sqrt{2}} \begin{bmatrix} 1+10^8 \\ 1-10^8 \end{bmatrix} \quad \textcircled{*} \text{ Condition number} = 10^8$$

$$\|w\|_2^2 = \frac{(1+10^8)^2 + (1-10^8)^2}{2} = 1 + (10^{-8})^{-2} \approx 10^{16}$$

b)

$$y = \begin{bmatrix} 1+\varepsilon \\ 0 \\ 0 \\ 1 \end{bmatrix} \rightarrow w_0 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1+x^{-1} \\ 1-x^{-1} \end{bmatrix} \quad w_\varepsilon = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1/x \end{bmatrix} \begin{bmatrix} \varepsilon/2 \\ \varepsilon/2 \end{bmatrix}$$

$$= \frac{\varepsilon}{2wb}$$

Then, $\|w_\varepsilon\|_2^2 = \frac{\varepsilon^2}{4\|w_0\|_2^2}$ increases as the condition number increases.

$$w = w_0 + w_\varepsilon \Rightarrow w = V S^{-1} U^T (y_0 + y_\varepsilon)$$

$$\Rightarrow w_\varepsilon = V S^{-1} U^T y_\varepsilon = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \frac{1}{1-x} \begin{bmatrix} x & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & -1 & -1 & 1 \end{bmatrix} \begin{bmatrix} 1+\varepsilon \\ 0 \\ 0 \\ 1 \end{bmatrix}$$

$$\Rightarrow w_\varepsilon = \sum_{i=1}^2 \frac{1}{\sigma_i} v_i (v_i^T y_\varepsilon) = \frac{1}{2\sqrt{2}} \begin{bmatrix} 1 \\ 1 \end{bmatrix} [1 \ 1 \ 1 \ 1] \begin{bmatrix} 1+\varepsilon \\ 0 \\ 0 \\ 1 \end{bmatrix} + \frac{1}{2x\sqrt{2}} \begin{bmatrix} 1 \\ -1 \end{bmatrix} [1 \ -1 \ -1 \ 1] \begin{bmatrix} 1+\varepsilon \\ 0 \\ 0 \\ 1 \end{bmatrix}$$

$$\Rightarrow w_\varepsilon = \frac{1}{2\sqrt{2}} \begin{bmatrix} 1 \\ 1 \end{bmatrix} (2+\varepsilon) + \frac{1}{2x\sqrt{2}} \begin{bmatrix} 1 \\ -1 \end{bmatrix} (2+\varepsilon)$$

$$\Rightarrow w_\varepsilon = \frac{2+\varepsilon}{2\sqrt{2}} \left(\begin{bmatrix} 1 \\ 1 \end{bmatrix} + \begin{bmatrix} x^{-1} \\ -x^{-1} \end{bmatrix} \right) = \frac{2+\varepsilon}{2\sqrt{2}} \begin{bmatrix} 1+x^{-1} \\ 1-x^{-1} \end{bmatrix}$$

$$\underline{\epsilon = 0.01}$$

$$\underline{\gamma = 0.1}$$

$$\|w_\epsilon\|_2^2 = \frac{2+0.01}{8} (121) + \frac{2.001}{8} (81) = \frac{101(2.01)}{4} \approx 50.53$$

$$\|w_\epsilon\|_2^2 = \frac{0.0101}{4}$$

$$\underline{\gamma = 10^{-8}}$$

$$\|w_\epsilon\|_2^2 = \frac{2.001}{2\sqrt{2}} (1+10^8)^2 + \frac{2.001}{2\sqrt{2}} (1-10^8)$$

$$\|w_\epsilon\|_2^2 \approx \frac{10^{12}}{4}$$

c)

$$\text{in b)} \quad w = \frac{1}{\sqrt{2}} \begin{bmatrix} 1+\gamma^{-1} \\ 1-\gamma^{-1} \end{bmatrix} + \frac{2+\epsilon}{2\sqrt{2}} \begin{bmatrix} 1+\gamma^{-1} \\ 1-\gamma^{-1} \end{bmatrix}$$

with rank-1 approximation: (next page)

$$X^{-1} = \begin{bmatrix} 0.5 & 0.5 \\ 0.5 & 0.5 \\ 0.5 & 0.5 \\ 0.5 & 0.5 \end{bmatrix} \Rightarrow w^T X y^T = \begin{bmatrix} 1+\epsilon & 1+\epsilon \end{bmatrix}$$

then

$$w = w_0 + w_\epsilon = \begin{bmatrix} 1 & 1 \end{bmatrix} + \begin{bmatrix} \epsilon & \epsilon \end{bmatrix}$$

$$w_0 = \sum_{i=1}^r \frac{1}{\sigma_i} v_i u_i^T y = \frac{1}{\sigma_1} v_1 u_1^T y = \frac{1}{2\sqrt{2}} \begin{bmatrix} 1 \\ 1 \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ 0 \\ 0 \\ 1 \end{bmatrix} = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

and

$$w_\epsilon = \sum_{i=1}^r \frac{1}{\sigma_i} v_i u_i^T y_\epsilon = \frac{1}{\sigma_1} v_1 u_1^T y_\epsilon = \frac{1}{2\sqrt{2}} \begin{bmatrix} 1 \\ 1 \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} \epsilon \\ 0 \\ 0 \\ 0 \end{bmatrix} = \frac{\epsilon}{2\sqrt{2}} \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

Hence, in the low-rank case, $\|w_\epsilon\|_2$ is proportional to ϵ and does not blow up as it does with the full-rank inverse. This case is much less sensitive to the error ϵ .

Assignment_5

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```
[ ]: # c)
import numpy as np
import matplotlib.pyplot as plt

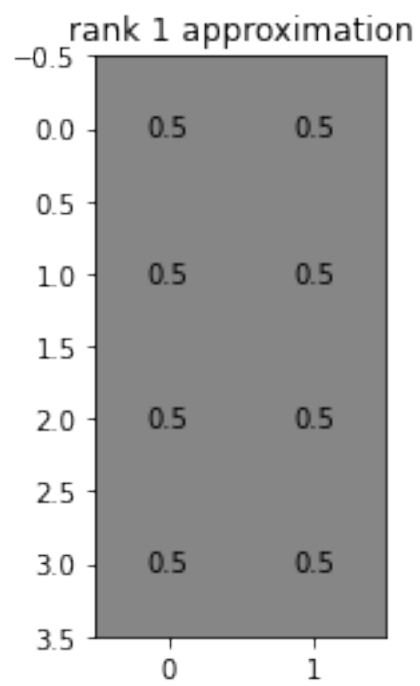
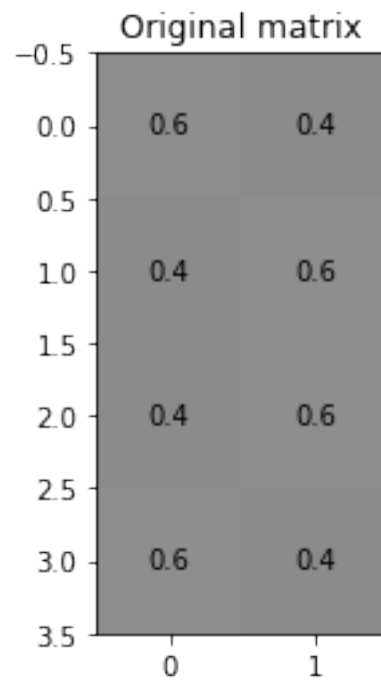
[ ]: gamma = 0.1
U = (1/2)*np.array([[1,1],[1,-1],[1,-1],[1,1]])
S_matrix = np.array([[1,0],[0,gamma]])
V = (1/((2)*1/2))*np.array([[1,1],[1,-1]])
VT = V.transpose()
A = U@S_matrix@VT

[ ]: # display images of various rank approximations

# original matrix
plt.figure(num=None)
for (j,i),label in np.ndenumerate(A):
    plt.text(i,j,np.round(label,1),ha='center',va='center')
plt.imshow(A, vmin=-5, vmax=5, interpolation='none', cmap='gray')
plt.title('Original matrix' )

# rank-1 approx
A_rank_r_approx = S_matrix[0,0]*U[:,0:1]@VT[0:1,:]
plt.figure(num=None)
for (j,i),label in np.ndenumerate(A_rank_r_approx):
    plt.text(i,j,np.round(label,1),ha='center',va='center')
plt.imshow(A_rank_r_approx, vmin=-10, vmax=10, interpolation='none',
    cmap='gray')
plt.title('rank ' + str(1) + ' approximation' )

[ ]: array([[0.5, 0.5],
          [0.5, 0.5],
          [0.5, 0.5],
          [0.5, 0.5]])
```



```
[ ]: print(U[:,0:1]@VT[0:1,:])  
      print(U[:,0:1])  
      print(VT[0:1,:])
```

```
[[0.5 0.5]  
 [0.5 0.5]  
 [0.5 0.5]  
 [0.5 0.5]]  
[[0.5]  
 [0.5]  
 [0.5]  
 [0.5]]  
[[1. 1.]]
```