

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).

DEVIN BRESSER

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

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

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

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

$$\text{Condition \#} = \frac{\sigma_{\max}}{\sigma_{\min}}. \text{ If } \lambda = 0.1, C\# = 1/0.1 = 10$$

$$\text{If } \lambda = 10^{-8}, C\# = 1/10^{-8} = 1 \cdot 10^8$$

$$w_{\min} = V \Sigma^{-1} U^T y \text{ as shown in my solution for activity 11.}$$

$$\begin{matrix} 2 \times 1 & & 2 \times 2 & & 2 \times 2 & & 2 \times 4 & & 4 \times 1 \end{matrix} \quad \begin{matrix} \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & -1 \\ 1 & -1 \\ 1 & -1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & \lambda \end{bmatrix} \frac{1}{2} \begin{bmatrix} 1 & -1 & -1 & 1 \\ 1 & 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ 0 \\ 0 \\ 1 \end{bmatrix} \end{matrix} \xrightarrow{\text{calculator}} \begin{bmatrix} \frac{1}{\sqrt{2}} + \frac{1}{\sqrt{2}} \lambda \\ \frac{1}{\sqrt{2}} - \frac{1}{\sqrt{2}} \lambda \end{bmatrix}$$

$$\lambda = 0.1:$$

$$\begin{bmatrix} \frac{1}{\sqrt{2}} + \frac{1}{\sqrt{2}} \cdot 0.1 \\ \frac{1}{\sqrt{2}} - \frac{1}{\sqrt{2}} \cdot 0.1 \end{bmatrix} = \begin{bmatrix} 7.78 \\ -6.36 \end{bmatrix}, \quad \|w_{\min}\|_2^2 = 101.$$

$$\lambda = 10^{-8}:$$

$$\begin{bmatrix} \frac{1}{\sqrt{2}} + \frac{1}{\sqrt{2}} \cdot 10^{-8} \\ \frac{1}{\sqrt{2}} - \frac{1}{\sqrt{2}} \cdot 10^{-8} \end{bmatrix} = \begin{bmatrix} 7.071 \cdot 10^7 \\ -7.071 \cdot 10^7 \end{bmatrix}, \quad \|w_{\min}\|_2^2 = 1 \cdot 10^{16}$$

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

b.)

$$\tilde{\mathbf{y}} = \begin{bmatrix} 1 + \epsilon \\ 0 \\ 0 \\ 1 \end{bmatrix} \quad \underline{\mathbf{w}}_{\min} = \begin{bmatrix} \frac{1}{\sqrt{2}} + \frac{1}{\sqrt{2}}\lambda \\ \frac{1}{\sqrt{2}} - \frac{1}{\sqrt{2}}\lambda \end{bmatrix}$$

$$\underset{2 \times 2}{\underline{\mathbf{V}}} \cdot \underset{2 \times 2}{\underline{\mathbf{E}}}^{-1} \cdot \underset{2 \times 4}{\underline{\mathbf{U}}}^T = \frac{1}{2\sqrt{2}} \begin{bmatrix} 1 + \frac{1}{\lambda} & 1 - \frac{1}{\lambda} & 1 - \frac{1}{\lambda} & 1 + \frac{1}{\lambda} \\ 1 - \frac{1}{\lambda} & 1 + \frac{1}{\lambda} & 1 + \frac{1}{\lambda} & 1 - \frac{1}{\lambda} \end{bmatrix}$$

$$\Rightarrow \underset{2 \times 2}{\underline{\mathbf{V}}} \underset{2 \times 2}{\underline{\mathbf{E}}}^{-1} \underset{2 \times 4}{\underline{\mathbf{U}}}^T \underset{4 \times 1}{\tilde{\mathbf{y}}} = \underset{2 \times 4}{\frac{1}{2\sqrt{2}} \begin{bmatrix} 1 + \frac{1}{\lambda} & 1 - \frac{1}{\lambda} & 1 - \frac{1}{\lambda} & 1 + \frac{1}{\lambda} \\ 1 - \frac{1}{\lambda} & 1 + \frac{1}{\lambda} & 1 + \frac{1}{\lambda} & 1 - \frac{1}{\lambda} \end{bmatrix}} \underset{4 \times 1}{\begin{bmatrix} 1 + \epsilon \\ 0 \\ 0 \\ 1 \end{bmatrix}}$$

$$= \underset{2 \times 1}{\frac{1}{2\sqrt{2}}} \begin{bmatrix} (1 + \frac{1}{\lambda})(1 + \epsilon) + (1 + \frac{1}{\lambda}) \\ (1 - \frac{1}{\lambda})(1 + \epsilon) + (1 - \frac{1}{\lambda}) \end{bmatrix} \leftarrow \underline{\mathbf{w}}$$

$$\underline{\mathbf{w}} = \frac{1}{2\sqrt{2}} \left(\underset{\substack{\uparrow \\ \underline{\mathbf{w}}_o}}{\begin{bmatrix} 1 + \frac{1}{\lambda} \\ 1 - \frac{1}{\lambda} \end{bmatrix}} + \underset{\substack{\uparrow \\ \underline{\mathbf{w}}_\epsilon}}{\begin{bmatrix} (1 + \frac{1}{\lambda})(1 + \epsilon) \\ (1 - \frac{1}{\lambda})(1 + \epsilon) \end{bmatrix}} \right)$$

b.) continued:

$$\epsilon = 0.01, \lambda = 0.1:$$

$$\|\underline{w}_e\|_2^2 = \left\| \frac{1}{2\sqrt{2}} \begin{bmatrix} (1 + 1/0.1)(1 + 0.01) \\ (1 - 1/0.1)(1 + 0.01) \end{bmatrix} \right\|_2^2$$

$$\rightarrow \text{calculator} = 25.76.$$

$$\epsilon = 0.01, \lambda = 10^{-8}:$$

$$\|\underline{w}_e\|_2^2 = \left\| \frac{1}{2\sqrt{2}} \begin{bmatrix} (1 + 1/10^{-8})(1 + 0.01) \\ (1 - 1/10^{-8})(1 + 0.01) \end{bmatrix} \right\|_2^2$$

$$\rightarrow \text{calculator} = 2.55 \cdot 10^{15}$$

As the condition # increases, $\|\underline{w}_e\|_2^2$ increases.

$$\underline{w} = \frac{1}{2\sqrt{2}} \left(\underbrace{\begin{bmatrix} 1 + 1/\lambda \\ 1 - 1/\lambda \end{bmatrix}}_{\underline{w}_0} + \underbrace{\begin{bmatrix} (1 + 1/\lambda)(1 + \epsilon) \\ (1 - 1/\lambda)(1 + \epsilon) \end{bmatrix}}_{\underline{w}_\epsilon} \right)$$

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

$$(X^T X)^{-1} X^T = \sum_{i=1}^p \frac{1}{\sigma_i} v_i u_i^T$$

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

$$(X^T X)^{-1} X^T \approx \sum_{i=1}^r \frac{1}{\sigma_i} v_i u_i^T$$

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 $w = w_o + w_e$

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

In this case: $(\underline{X}^T \underline{X})^{-1} \underline{X}^T \approx \sum_{i=1}^1 \frac{1}{\sigma_i} \underline{v}_i \underline{u}_i^T = \frac{1}{1} \cdot \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ 1 \end{bmatrix} \frac{1}{2} \begin{bmatrix} 1 & 1 & 1 & 1 \end{bmatrix} = \frac{1}{2\sqrt{2}} \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \end{bmatrix}$

2×1 1×4

Now, $\underline{w}_{\min} = (\underline{X}^T \underline{X})^{-1} \underline{X}^T \underline{y}$

$$\frac{1}{2\sqrt{2}} \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} 1 + \epsilon \\ 0 \\ 0 \\ 1 \end{bmatrix} = \frac{1}{2\sqrt{2}} \begin{bmatrix} 1 + \epsilon + 1 \\ 1 + \epsilon + 1 \end{bmatrix} = \begin{bmatrix} 2 + \epsilon \\ 2 + \epsilon \end{bmatrix}$$

2×4 4×1

So, $\underline{w} = \frac{1}{2\sqrt{2}} \begin{bmatrix} 2 + \epsilon \\ 2 + \epsilon \end{bmatrix} = \frac{1}{2\sqrt{2}} \left(\begin{bmatrix} 2 \\ 2 \end{bmatrix} + \begin{bmatrix} \epsilon \\ \epsilon \end{bmatrix} \right)$

\underline{w}_o \underline{w}_ϵ

In this case, because we do not consider the singular value associated with λ , the expressions for \underline{w} , \underline{w}_o , and \underline{w}_ϵ are greatly simplified.

$$\underline{w} = \frac{1}{2\sqrt{2}} \left(\begin{bmatrix} 1 + 1/\lambda \\ 1 - 1/\lambda \end{bmatrix} + \begin{bmatrix} (1 + 1/\lambda)(1 + \epsilon) \\ (1 - 1/\lambda)(1 + \epsilon) \end{bmatrix} \right) \rightarrow \frac{1}{2\sqrt{2}} \left(\begin{bmatrix} 2 \\ 2 \end{bmatrix} + \begin{bmatrix} \epsilon \\ \epsilon \end{bmatrix} \right)$$

\underline{w}_o \underline{w}_ϵ \underline{w}_o \underline{w}_ϵ

And, we are no longer troubled by very large \underline{w} when λ is very small.