

- Math-456-HW4 -

V. Let $A \in \mathbb{R}^{m \times m}$ have singular values $\sigma_1 \geq \dots \geq \sigma_{\min\{n, m\}} \geq 0$.

By Theorem 2.9,

$$Av_i = \begin{cases} \sigma_i u_i & i=1, \dots, r \\ 0 & i=r+1, \dots, m \end{cases}$$

So, if $m > n$, then there is a v_i such that

$Av_i = 0$, Hence, $\min_{\|x\|=1} \|Ax\| = 0$.

If $m \leq n$, then $Av_m = \sigma_m u_m$. Hence,

$$\|Av_m\| = \sigma_m \|u_m\| = \sigma_m$$

which implies that $\min_{\|x\|=1} \|Ax\| \leq \sigma_m$.

Now, let $x \in \mathbb{R}^m$ have unit length. Then, there are constants c_1, \dots, c_m such that

$$x = c_1 v_1 + \dots + c_m v_m$$

Therefore,

$$\begin{aligned} Ax &= c_1 Av_1 + \dots + c_m Av_m \\ &= c_1 \sigma_1 u_1 + \dots + c_m \sigma_m u_m \end{aligned}$$

which implies that

$$\|Ax\|_2^2 = (c_1 \sigma_1)^2 + \dots + (c_m \sigma_m)^2$$

$$\geq \sigma_m^2 (c_1^2 + \dots + c_m^2)$$

$$= \sigma_m^2 \Rightarrow \|Ax\|_2 \geq \sigma_m$$

Hence, $\min_{\|x\|=1} \|Ax\| = \sigma_m$.

VI. Let $A_\epsilon = U \Sigma_\epsilon V^T$ where $\Sigma_\epsilon = \Sigma + \epsilon I$
and I is the $n \times n$ identity matrix.
Since $\epsilon > 0$, it follows that A_ϵ has
full rank (all singular values are positive).

Moreover,

$$\|A - A_\epsilon\|_2 = \|U \Sigma V^T - U \Sigma_\epsilon V^T\|_2$$

$$= \|U(\Sigma - \Sigma_\epsilon)V^T\|_2$$

$$= \|\Sigma - \Sigma_\epsilon\|_2$$

$$= \|\epsilon I\|_2 = \epsilon.$$

VII.

Consider the SVD of A :

$$\begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 1/2 \\ 1/2 \\ 1/2 \\ 1/2 \end{bmatrix} \begin{bmatrix} 2 \\ 0 \\ 0 \\ 0 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix}$$

where the last 3 columns of U are
not important for solving the least squares problem

Then, the least squares solution is

$$y_1 = \frac{\langle b, u_1 \rangle}{\sigma_1} = \frac{(1/2 + 1/2 + 1/2 + 1/2)}{2} = \frac{2}{2}$$

$$x_1 = \sqrt{y_1} = \Sigma^{-1} \frac{2}{2} = \frac{1}{2}.$$