

## Homework #8

### #12.1

Suppose  $A \in \mathbb{R}^{262 \times 262}$  with  $\|A\|_2 = 100$  and  $\|A\|_F = 101$ . Give the sharpest possible lower bound on the 2-norm condition number  $K(A)$ .

Solution:

Since  $\|A\|_2 = 100$  and  $\|A\|_F = 101$  it follows that the singular values of  $A$  satisfy:

$$\sigma_1 = 100, \sigma_1^2 + \dots + \sigma_{262}^2 = 101^2, \sigma_1 \geq \dots \geq \sigma_{262}$$

Therefore,

$$\sigma_2^2 + \dots + \sigma_{262}^2 = 201$$

$$\Rightarrow 201 \geq 201 \sigma_{262}^2$$

$$\Rightarrow \frac{1}{\sigma_{262}} \geq 1$$

Therefore,

$$K(A) = \frac{\sigma_1}{\sigma_{262}} \geq \frac{100}{1} = 100.$$

### #14.1

- a. True
- b. True
- c.) True.
- d.) True.

### #14.2

Show that:

$$a.) (1 + O(\varepsilon_m))(1 + O(\varepsilon_m)) = 1 + O(\varepsilon_m)$$

$$b.) (1 + O(\varepsilon_m))^{-1} = 1 + O(\varepsilon_m).$$

Solution:

If  $f = (1 + O(\varepsilon_m))(1 + O(\varepsilon_m))$  then

$$f \leq (1 + k_1 \varepsilon_m)(1 + k_2 \varepsilon_m) = 1 + k_1 \varepsilon_m + k_2 \varepsilon_m + k_1 k_2 \varepsilon_m^2 \leq 1 + (k_1 + k_2 + k_1 k_2) \varepsilon_m$$

$$\Rightarrow f = 1 + O(\varepsilon_m).$$

If  $f = (1 + \Theta(\varepsilon_n))^{-1}$  then

$$f \leq \frac{1}{1 + k_1 \varepsilon}$$

$$= 1 - k_1 \varepsilon + k_1^2 \varepsilon^2 - k_1^3 \varepsilon^3 + \dots$$

$$\leq 1 - k_1 \varepsilon + D \varepsilon^2$$

$$\Rightarrow |f| \leq 1 + |k_1| \varepsilon + |D| \varepsilon^2$$

$$\leq 1 + |k_1| \varepsilon + |D| \varepsilon$$

$$\Rightarrow |f| = 1 + \Theta(\varepsilon_n)$$



## #15.1

a.) Data  $x \in \mathbb{R}$ ,  $f(x) = x^2$ .

Solution:

$$\begin{aligned}\hat{f}(x) &= f_1(x) \otimes f_2(x) \\ &= x(1 + \varepsilon_1) \otimes (1 + \varepsilon_2) \cdot x \\ &= x^2 (1 + \varepsilon_1)^2 (1 + \varepsilon_2) \\ &= x^2 (1 + \varepsilon_1) \sqrt{1 + \varepsilon_2} \\ &= f(x(1 + \varepsilon_1) \sqrt{1 + \varepsilon_2}) \\ &= f(\tilde{x}).\end{aligned}$$

Now,

$$\begin{aligned}\frac{|\tilde{x} - x|}{|x|} &= \frac{|x(1 + \varepsilon_1) \sqrt{1 + \varepsilon_2} - x|}{|x|} \\ &= \frac{|x(1 + \varepsilon_1)(1 + \frac{1}{2} \varepsilon_2 + D \varepsilon_2^2) - x|}{|x|} \\ &= |\varepsilon_1 + \frac{1}{2} \varepsilon_2 + D \varepsilon_2^2 + \frac{1}{2} \varepsilon_1 \varepsilon_2 + D \varepsilon_1 \varepsilon_2^2| \\ &\leq (1 + \frac{1}{2} + |D| + \frac{1}{2} + |D|) \varepsilon_m.\end{aligned}$$

Therefore, this algorithm is backstable.

b.) Data  $x \in \mathbb{R}$ ,  $f(x) = 2x$ .

Solution:

$$\begin{aligned}\tilde{f}(x) &= f_1(x) \oplus f_1(x) \\ &= x(1+\varepsilon_1) \oplus x(1+\varepsilon_1) \\ &= 2x(1+\varepsilon_1) \cdot (1+\varepsilon_1) \\ &= f(x(1+\varepsilon_1)(1+\varepsilon_1)) \\ &= f(\tilde{x})\end{aligned}$$

Now,

$$\frac{|x - \tilde{x}|}{|x|} = \frac{|x\varepsilon_1 + x\varepsilon_2 + x\varepsilon_1\varepsilon_2|}{|x|} \leq 3\varepsilon.$$

c.) Data  $x \in \mathbb{R}$ ,  $f(x) = \frac{x}{x} = 1$ .

Solution:

$$\begin{aligned}\tilde{f}(x) &= f_1(x) \oplus f_1(x) \\ &= \frac{x(1+\varepsilon_1)}{x(1+\varepsilon_1)} \cdot (1+\varepsilon_2) \\ &= 1 + \varepsilon_2 \\ &\neq f(\tilde{x}).\end{aligned}$$

Consequently,  $\tilde{f}$  cannot be backwards stable. However,

$$\frac{|\tilde{f}(x) - f(x)|}{|\tilde{f}|} = \varepsilon,$$

which implies the algorithm is stable.

d.) Data  $x \in \mathbb{R}$ ,  $f(x) = x - x$ .

Solution:

$$\begin{aligned}\tilde{f}(x) &= f_1(x) \oplus f_1(x) \\ &= x(1+\varepsilon_1) \oplus x(1+\varepsilon_1) \\ &= [x(1+\varepsilon_1) - x(1+\varepsilon_1)](1+\varepsilon_2) \\ &= 0.\end{aligned}$$

This algorithm is backstable.

#15.2

- a.) For this algorithm to be backwards stable the matrices  $\tilde{U}$  and  $\tilde{V}$  would have to be unitary.
- b.) Clearly, this algorithm cannot be backwards stable due to roundoff error in  $\tilde{U}, \tilde{V}$ . That is, the columns of  $\tilde{U}, \tilde{V}$  will not be orthonormal.
- c.) Stability implies that  $\tilde{U}, \tilde{V}, \tilde{\Sigma}$  are relatively close to  $U, V, \Sigma$ . I.e.

$$\left| \frac{\tilde{U} - U}{\|U\|} \right| = O(\epsilon_m), \quad \left| \frac{\tilde{V} - V}{\|V\|} \right| = O(\epsilon_m), \quad \left| \frac{\tilde{\Sigma} - \Sigma}{\|\Sigma\|} \right| = O(\epsilon_m).$$