

NOTES ON MATRIX NORMS

WARNING: the notation I use in these notes differs in some places from the notation in the textbook.

We will let M_n denote the set of all $n \times n$ real matrices. We can think of M_n as being a copy of \mathbf{R}^{n^2} , so it has a Euclidean norm. We denote this norm by $\|\cdot\|_2$.

Definition. Let $A \in M_n$. The *2-norm* of A is given by

$$\|A\|_2 = \left(\sum_{i,j=1}^n a_{ij}^2 \right)^{1/2}.$$

This is not the only norm that can be put on M_n . The most important norm is called the *operator norm*, which we write as $\|\cdot\|$:

Definition. Let $A \in M_n$. The *operator norm* of A is given by

$$\|A\| = \max_{|x|=1} |Ax|.$$

(Note that since the unit sphere in \mathbf{R}^n is compact, and the linear map defined by A is continuous, the maximum in the definition exists by the extreme value theorem.)

Examples. Let I_n denote the $n \times n$ identity matrix.

$$\begin{aligned} \|I_n\|_2 &= \sqrt{n} \\ \|I_n\| &= 1. \end{aligned}$$

Lemma. $\|\cdot\|$ is a norm on M_n .

Proof. (i) It is clear that $\|A\| \geq 0$.

(ii) If $\|A\| = 0$, then $Ax = 0$ for all $x \in \mathbf{R}^n$ with $|x| = 1$. But then $Ax = 0$ for all $x \in \mathbf{R}^n$, so that $A = 0$.

(iii) $\|cA\| = \max_{|x|=1} |cAx| = \max_{|x|=1} |c| |Ax| = |c| \max_{|x|=1} |Ax| = |c| \|A\|$.

(iv) Let $|x| = 1$. Then

$$|(A+B)x| = |Ax+Bx| \leq |Ax| + |Bx| \leq \|A\| + \|B\|.$$

This is true for all x with $|x| = 1$. Therefore

$$\|A+B\| = \max_{|x|=1} |(A+B)x| \leq \|A\| + \|B\|. \quad \blacksquare$$

Properties of the Operator Norm

1. For all $x \in \mathbf{R}^n$, $|Ax| \leq \|A\| |x|$. Moreover, if $C > 0$ is a constant such that $|Ax| \leq C|x|$ for all $x \in \mathbf{R}^n$, then $\|A\| \leq C$.

Proof. First, it is clear that $|Ax| \leq \|A\| |x|$ if $x = 0$. So suppose that $x \neq 0$. Let $y = x/|x|$. Then $|y| = 1$, so by the definition of operator norm we have $|Ay| \leq \|A\|$. Multiplying both sides by $|x|$ gives $|Ax| \leq \|A\| |x|$. Next let C be as in the statement. Then in particular, if $|x| = 1$, we have $|Ax| \leq C|x| = C$. Then if we consider the maximum over all x of norm 1 we see that $\|A\| \leq C$. ■

2. $\|A\| \leq \|A\|_2$.

Proof. Let $|x| = 1$. Realizing Ax as a linear combination of the columns of A , we have

$$\begin{aligned} |Ax| &= \left| \sum_{j=1}^n x_j A^{(j)} \right|, \text{ where } A^{(j)} \text{ denotes the } j\text{th column of } A, \\ &\leq \sum_{j=1}^n |x_j| |A^{(j)}| \\ &\leq \left(\sum_{j=1}^n x_j^2 \right)^{1/2} \left(\sum_{j=1}^n |A^{(j)}|^2 \right)^{1/2}, \text{ by Cauchy-Schwarz,} \\ &= 1 \cdot \left(\sum_{j=1}^n \sum_{i=1}^n a_{ij}^2 \right)^{1/2} \\ &= \|A\|_2. \end{aligned}$$

It follows that $\|A\| \leq \|A\|_2$. ■

3. $\|A\|_2 \leq n \|A\|$.

Proof. We first estimate the entries of A :

$$|a_{ij}| = |(Ae_j) \cdot e_i| \leq |Ae_j| |e_i| = |Ae_j| \leq \|A\| |e_j| = \|A\|.$$

Therefore,

$$\|A\|_2 = \left(\sum_{i,j} a_{ij}^2 \right)^{1/2} \leq \left(\sum_{i,j} \|A\|^2 \right)^{1/2} = \left(n^2 \|A\|^2 \right)^{1/2} = n \|A\|. \quad \blacksquare$$

Remark. With a bit more care one can improve this to show that $\|A\|_2 \leq \sqrt{n} \|A\|$.

Corollary. If $\|\cdot\|$ is used to define open balls in M_n , we get the same collection of open sets as when $\|\cdot\|_2$ is used.

Corollary. A function $G : \mathbf{R}^k \rightarrow M_n$ is continuous for $\|\cdot\|$ if and only if it is continuous for $\|\cdot\|_2$.

Corollary. Let $f : \mathbf{R}^n \rightarrow \mathbf{R}^n$ be of class C^1 . Then $f' : \mathbf{R}^n \rightarrow M_n$ is continuous for $\|\cdot\|$.

Proof.

$$\begin{aligned}\|f'(x) - f'(y)\|_2^2 &= \sum_{i,j=1}^n (D_j f_i(x) - D_j f_i(y))^2 \\ &\rightarrow 0, \quad \text{as } y \rightarrow x,\end{aligned}$$

since $D_j f_i$ are continuous functions on \mathbf{R}^n . Therefore f' is continuous for $\|\cdot\|_2$ on M_n . By the previous corollary, f' is continuous for $\|\cdot\|$. ■

4. $\|AB\| \leq \|A\| \|B\|$.

Proof. Let $x \in \mathbf{R}^n$. Then $|ABx| \leq \|A\| |Bx| \leq \|A\| \|B\| |x|$. By the second part of 1 above, we have $\|AB\| \leq \|A\| \|B\|$. ■

5. If $\|A - I\| < 1$, then A is invertible.

Proof. Let $x \neq 0$. Then

$$\begin{aligned}|Ax| &= |x + (A - I)x| \\ &\geq |x| - |(A - I)x| \\ &\geq |x| - \|A - I\| |x| \\ &> |x| - |x| \\ &= 0.\end{aligned}$$

Therefore A is one-to-one. Hence A is invertible. ■

6. The invertible $n \times n$ matrices form an open subset of M_n (for $\|\cdot\|$, and hence also for $\|\cdot\|_2$). More precisely, if A is invertible, and if $\|A - B\| < 1/\|A^{-1}\|$, then B is also invertible. (In other words, the open ball (with respect to the operator norm) centered at A with radius $1/\|A^{-1}\|$ is entirely contained in the set of invertible matrices.)

Proof. Let $\|A - B\| < 1/\|A^{-1}\|$. Then

$$\begin{aligned}\|I - A^{-1}B\| &= \|A^{-1}A - A^{-1}B\| \\ &= \|A^{-1}(A - B)\| \\ &\leq \|A^{-1}\| \|A - B\|, \quad \text{by 4, above,} \\ &< 1.\end{aligned}$$

Therefore $A^{-1}B$ is invertible, by property 5. But then $B = A(A^{-1}B)$ is the product of two invertible matrices, and hence is invertible. ■

The following companion to property 1 could have been proved at the same time.

7. If A is invertible, then for all $x \in \mathbf{R}^n$,

$$|Ax| \geq \frac{1}{\|A^{-1}\|} |x|.$$

Proof. $|x| = |A^{-1}Ax| \leq \|A^{-1}\| |Ax|$. The result follows by dividing by $\|A^{-1}\|$. ■