

## Math 535 - Functional Analysis Notes 3 Morrow, Spring 2006

**Bounded Linear Operators.** Let  $X$  and  $Y$  be normed spaces and let  $T : \mathcal{D}(T) \rightarrow Y$  be a linear operator where  $\mathcal{D}(T) \subset X$ .  $T$  is said to be a bounded linear operator if there exists a constant  $c \geq 0$  such that

$$\|Tx\| \leq c\|x\| \quad \text{for all } x \in \mathcal{D}(T).$$

The norm on the left is of course the norm in  $Y$  while the norm on the right side of this inequality is the norm in  $X$ . Exercise 2.7.2. Let  $T : X \rightarrow Y$  be a linear operator. Show that  $T$  is bounded (by the above definition) if and only if  $T$  sends bounded sets in  $X$  into bounded sets in  $Y$  as follows. Suppose first that  $M$  is a bounded set in  $X$ . This means that there exists a constant  $k \geq 0$  such that  $\|x\| \leq k$  for every  $x \in M$ . Now apply  $T$  to each element of  $M$  and denote the set of images  $TM$ . Let  $y = Tx$  for some  $x \in M$ , so  $\|y\| = \|Tx\| \leq c\|x\| \leq ck$ . Since this inequality must hold for every  $y \in TM$  we have shown that  $TM$  is bounded. Conversely, suppose for any bounded set  $M \subset X$  we have that  $TM$  is bounded in  $Y$ . Let  $M = \bar{B}(0;1) \subset X$  (the closed unit ball in  $X$ ). Then by assumption we have that there exists a constant  $c \geq 0$  such that  $\|y\| \leq c$  for every  $y \in TM$ . We claim that  $T$  is bounded with constant  $c$  as in the above definition. Indeed, since  $T$  is linear we have for any  $x \neq 0$  that  $\|Tx\| = \|x\| \cdot \|T(x/\|x\|)\| \leq \|x\|c$ . QED.

**The norm of a linear operator.** We define the norm of a bounded linear operator as the smallest possible  $c \geq 0$  such that the above definition holds, or what is the same, the supremum of  $\|Tx\|/\|x\|$  over all  $x \in \mathcal{D}(T)$  with  $x \neq 0$ . Call this quantity  $\|T\|$ . By the same scaling trick as shown in the last part of exercise 2.7.2, this definition of the norm of  $T$  is equivalent to

$$\|T\| = \sup_{x \in \mathcal{D}(T), \|x\|=1} \|Tx\|.$$

Exercise 2.7.10. Let  $X = C[0,1]$  and define two linear operators  $S$  and  $T$  on  $X$  by

$$y = Sx \text{ where } y(s) = s \int_0^1 x(t)dt, \quad \text{and, } z = Tx, \text{ where } z(s) = sx(s); \quad s \in [0,1].$$

First we consider whether or not  $S$  and  $T$  commute. We have  $(TSx)(s) = s(Sx)(s) = s^2 \int_0^1 x(t)dt$ . Next,  $(STx)(s) = s \int_0^1 (Tx)(t)dt = s \int_0^1 tx(t)dt$ . These two expressions are not equal unless both are zero since the first is quadratic in  $s$  and the second is linear in  $s$ . Therefore  $S$  and  $T$  do not commute. Now we investigate the norms of these operators. First, because

$$\|y\| \leq \left(\max_{0 \leq s \leq 1} s\right) \cdot \int_0^1 |x(t)|dt \leq 1 \cdot \int_0^1 \|x\|dt = \|x\|,$$

we have that  $\|S\| \leq 1$ . To prove that  $\|S\| = 1$ , it suffices to demonstrate a function  $x$  of norm 1 such that  $y$  also has norm 1. But if  $x$  is the constant function that is equal to 1 for all  $t$ , then obviously  $\|x\| = 1$ , while  $y = Sx$  is the function  $y(s) = s$ , so that also  $\|y\| = \max_{0 \leq s \leq 1} s = 1$ . Next it is obvious that  $\|T\| \leq 1$  while by the same choice of the constant function  $x$  we also see that  $\|T\| \geq 1$ . Further by the same argument that we used to analyze  $\|S\|$ , we have that  $\|TS\| = 1$ . Finally consider  $\|ST\|$ . We have the estimation

$$\left(\max_{0 \leq s \leq 1} s\right) \cdot \int_0^1 tx(t)dt \leq \int_0^1 t\|x\|dt = (1/2)\|x\|.$$

Therefore we have  $\|ST\| \leq 1/2$ . By taking again  $x$  to be the constant function 1, We find that  $STx$  is the function  $y(s) = s/2$ . Hence we have  $\|ST\| \geq 1/2$ . Thus  $\|ST\| = 1/2$ .

**2.7-9. A Linear Operator is Bounded iff it is Continuous.** Let  $X$  and  $Y$  be normed spaces and let  $T : \mathcal{D}(T) \rightarrow Y$  be any operator (not necessarily linear) where  $\mathcal{D}(T) \subset X$ . We say that  $T$  is continuous at  $x_0 \in \mathcal{D}(T)$  if for every  $\epsilon > 0$  there is a  $\delta > 0$  such that if  $\|x - x_0\| \leq \delta$ ,  $x \in \mathcal{D}(T)$ , then  $\|Tx - Tx_0\| \leq \epsilon$ . Also we say  $T$  is continuous if  $T$  is continuous at every  $x \in \mathcal{D}(T)$ . Suppose now in addition that  $T$  is linear. Then we have that

**2.7-9.** (a)  $T$  is bounded if and only if  $T$  is continuous, and moreover,  
 (b), if  $T$  is continuous at a single point then  $T$  is continuous.

*Proof.* First if  $T$  is bounded, it is easily seen to be continuous. Indeed, let  $\epsilon > 0$  and choose  $\delta = \epsilon/\|T\|$  independent of  $x_0$ . Here we assume  $T \neq 0$  since otherwise the result is trivial. Then by boundedness and linearity,  $\|x - x_0\| \leq \delta$

implies that  $\|Tx - Tx_0\| = \|T(x - x_0)\| \leq \|T\| \cdot \|x - x_0\| \leq \delta \|T\| = \epsilon$ . Thus in fact  $T$  is not only continuous but is uniformly continuous ( $\delta$  may be chosen to be independent of  $x_0$  in the definition of continuity of  $T$  at  $x_0$ ). Next suppose that  $T$  is continuous at a single point  $x_0$ . Let  $\epsilon = 1$ . By definition there exists a  $\delta > 0$  so that if  $\|x - x_0\| \leq \delta$ , then  $\|T(x - x_0)\| = \|Tx - Tx_0\| \leq 1$ . Now let  $y$  be any non-zero vector in  $\mathcal{D}(T)$ , and put  $x = x_0 + \delta y/\|y\|$ . Then  $x$  is correspondingly any point at distance  $\delta$  from  $x_0$ . We have  $\|Ty\| = \|T(x - x_0)\| \cdot \|y\|/\delta \leq \|y\|/\delta$ . Since  $y$  is arbitrary, we have that  $T$  is bounded with norm  $\|T\| \leq 1/\delta$ . We have shown that continuity and linearity of  $T$  at one point implies boundedness of  $T$ , and thus by the first part of the proof, continuity of  $T$  at any point. QED

Example: linear mappings from  $\mathbb{R}^2$  to  $\mathbb{R}^2$ . We consider a linear mapping from  $\mathbb{R}^2$  to  $\mathbb{R}^2$  defined by a 2 by 2 matrix  $A = (\alpha_{j,k})_{j,k=1}^2$ . Put  $x = (\xi_1, \xi_2) \in \mathbb{R}^2$  and  $y = Ax = (\eta_1, \eta_2) \in \mathbb{R}^2$ . Thus  $\eta_1 = \alpha_{1,1}\xi_1 + \alpha_{1,2}\xi_2$ , and  $\eta_2 = \alpha_{2,1}\xi_1 + \alpha_{2,2}\xi_2$ . If we take the Euclidean norm on  $\mathbb{R}^2$  then by the Cauchy-Schwarz inequality

$$\|Ax\|^2 = \eta_1^2 + \eta_2^2 = (\alpha_{1,1}\xi_1 + \alpha_{1,2}\xi_2)^2 + (\alpha_{2,1}\xi_1 + \alpha_{2,2}\xi_2)^2 \leq (\alpha_{1,1}^2 + \alpha_{1,2}^2)\|x\|^2 + (\alpha_{2,1}^2 + \alpha_{2,2}^2)\|x\|^2 = \|x\|^2 \sum_{j=1}^2 \sum_{k=1}^2 \alpha_{j,k}^2$$

Thus the linear operator  $T : \mathbb{R}^2 \rightarrow \mathbb{R}^2$  defined by matrix multiplication as above satisfies  $\|T\| \leq \sqrt{\sum_{j=1}^2 \sum_{k=1}^2 \alpha_{j,k}^2}$ . However, as indicated in Exercises 2.7.12 and 2.7.13, the norm of  $T$  is not actually equal to this last expression. This is obvious for the case of the identity matrix, wherein the norm of  $T$  is 1 but the square root of the sum of squares of the identity matrix is  $\sqrt{2}$ .

An alternative bound for the norm of  $T$  is obtained by the method of 2.7-8 that gives the general result that any linear operator on a finite dimensional normed space is bounded. For the case of a linear operator  $T$  from  $\mathbb{R}^2$  to  $\mathbb{R}^2$  as above we follow the argument to see what estimate for  $\|T\|$  will arise. Put  $e_1 = (1, 0)$  and  $e_2 = (0, 1)$ . Then we write  $x = \xi_1 e_1 + \xi_2 e_2$  and estimate that

$$\|Tx\| = \|\xi_1 T e_1 + \xi_2 T e_2\| \leq |\xi_1| \cdot \|T e_1\| + |\xi_2| \cdot \|T e_2\| \leq (|\xi_1| + |\xi_2|) \max\{\|T e_1\|, \|T e_2\|\}.$$

But by Lemma 2.4-1 we have that  $|\xi_1| + |\xi_2| \leq \|\xi_1 e_1 + \xi_2 e_2\|/c = \|x\|/c$ . Here by Exercise 2.4.2(a) we have for the best constant  $c = c(e_1, e_2)$  that  $1/c = \sqrt{2}$ , so that putting together these estimates we have  $\|T\| \leq \sqrt{2} \max\{\|T e_1\|, \|T e_2\|\} = \sqrt{2} \max\{\sqrt{\alpha_{1,1}^2 + \alpha_{2,1}^2}, \sqrt{\alpha_{1,2}^2 + \alpha_{2,2}^2}\}$ . Note that this bound is always at least as large as the previous bound  $\sqrt{\sum_{j=1}^2 \sum_{k=1}^2 \alpha_{j,k}^2}$ .

**2.7-10.** Let  $T$  be a bounded linear operator. Then the null space is closed.

*Proof.* Denote the null space by  $\mathcal{N}$ . Let  $x \in \bar{\mathcal{N}}$ . We must show that  $x \in \mathcal{N}$ . By definition of closure there exists a sequence  $(x_n)$  in  $\mathcal{N}$  such that  $x_n \rightarrow x$ . But since  $T$  is bounded, then by 2.7-9,  $T$  is continuous so  $Tx_n \rightarrow Tx$ . But  $Tx_n = 0$  for every  $n$  so therefore  $Tx = 0$ . Hence  $x \in \mathcal{N}$ . QED

**2.7-11.** Let  $T : \mathcal{D}(T) \rightarrow Y$  be a bounded linear operator where  $\mathcal{D}(T) \subset X$  and where  $X$  is a normed space and  $Y$  is a Banach space. Then  $T$  has a bounded linear extension  $\tilde{T}$  to the closure of  $\mathcal{D}(T)$  where in fact  $\|\tilde{T}\| = \|T\|$ .

*Proof.* Denote the domain of  $T$  by  $\mathcal{D}$ . Let  $x \in \bar{\mathcal{D}}$ . We must show how to define  $\tilde{T}x$ . Let  $(x_n)$  in  $\mathcal{D}$  such that  $x_n \rightarrow x$ . Then  $(x_n)$  is a Cauchy sequence. But since  $T$  is bounded we have that  $\|Tx_n - Tx_m\| = \|T(x_n - x_m)\| \leq \|T\| \cdot \|x_n - x_m\|$ , so obviously the sequence of images  $(y_n = Tx_n)$  is Cauchy in  $Y$ . But  $Y$  is complete, so this sequence  $(y_n)$  converges in  $Y$  to an element  $y$ . The limit  $y$  is independent of the sequence  $(x_n)$  that converges to  $x$  as follows. If  $(z_n)$  is another sequence in  $\mathcal{D}$  that converges to  $x$  then we construct a sequence  $(v_m) = (x_1, z_1, x_2, z_2, \dots)$ . Since also  $(v_m)$  converges to  $x$ , by the proof we just gave (not by 2.7-10(a)), the limit of  $(Tv_m)$  exists in  $Y$ . Hence each of the subsequences  $(Tx_n)$  and  $(Tz_n)$  of this sequence themselves must converge to the same limit. Now it is obvious that the mapping  $\tilde{T}x = y$  is linear and extends  $T$ . Finally, use that  $x_n \rightarrow x$  in  $X$  implies that  $\|x_n\| \rightarrow \|x\|$  (continuity of the norm) and since also  $Tx_n \rightarrow \tilde{T}x$  we get likewise that  $\|Tx_n\| \rightarrow \|\tilde{T}x\|$ . Thus since  $\|Tx_n\| \leq \|T\| \cdot \|x_n\|$  is true for every  $n$  we obtain after taking the limit on  $n \rightarrow \infty$  that  $\|\tilde{T}x\| \leq \|T\| \cdot \|x\|$ . Hence  $\|\tilde{T}\| = \|T\|$ .

**Linear Functionals.** A linear functional  $f : \mathcal{D}(f) \rightarrow K$  is a linear operator with a domain  $\mathcal{D}(f)$  that is a subspace of a vector space  $X$  and with a range in the field of scalars  $K$ . Unless a given linear functional is the zero functional its range is in fact all of  $K$  by the scaling property  $f(\alpha x) = \alpha f(x)$ . Since a linear functional is a special case of a linear operator its norm  $\|f\|$  is defined in the same way:  $\|f\| := \sup_{x \in \mathcal{D}(f), \|x\|=1} |f(x)|/\|x\|$ .

Examples. Let  $X[0, 1]$  be the space of continuous functions on  $[0, 1]$  with the norm  $\|x\| := \sqrt{\int_0^1 x(t)^2 dt}$ .

Find the norm of the linear functional defined on  $X[0, 1]$  by  $f(x) = \int_0^1 tx(t)dt$  as follows. First, by the Cauchy-Schwarz inequality for integrals (see (1), p. 137 for  $\langle x, y \rangle := \int_0^1 x(t)y(t)dt$ ), we have  $|f(x)| \leq \sqrt{\int_0^1 t^2 dt} \sqrt{\int_0^1 x(t)^2 dt} = \sqrt{1/3} \|x\|$ .

Therefore  $\|f\| \leq \sqrt{1/3}$ . Next, if we take  $x(t) = t$ ,  $0 \leq t \leq 1$ , then  $f(x) = 1/3$  while  $\|x\| = \sqrt{1/3}$ . Hence  $\|f\| \geq |f(x)|/\|x\| = (1/3)/\sqrt{1/3} = \sqrt{1/3}$ . Thus  $\|f\| = \sqrt{1/3}$ .

Let  $f$  be the linear functional on  $X[0, 1]$  defined by  $f(x) = x(0)$ . Show that  $f$  is unbounded as follows. Let  $n \geq 1$ . Define  $x_n(t)$ ,  $t \in [0, 1]$ , to be a continuous function with  $x_n(0) = \sqrt{n}$  and  $x(t) = \sqrt{n} - (n\sqrt{n})t$ ,  $0 \leq t \leq 1/n$ , and  $x(t) = 0$ ,  $t \in [1/n, 1]$ . It is easy to compute that  $\|x_n\|^2 = \int_0^1 x_n(t)^2 dt = 1/3$ . But  $f(x_n) = \sqrt{n}$ . Therefore for each  $n$  we have  $\|f\| \geq |f(x_n)|/\|x_n\| = \sqrt{3n}$ . Thus  $f$  is not bounded.

**Algebraic Dual  $X^*$ .** The set of linear functionals  $f$  on a vector space  $X$  is itself a vector space that we call  $X^*$ . Indeed the linear combination  $\alpha f + \beta g$  with scalars  $\alpha, \beta$  and linear functionals  $f, g$  on  $X$ , is again a linear functional on  $X$ . Since  $X^*$  is a vector space then the linear functionals on  $X^*$  form another vector space  $X^{**}$ , called the second algebraic dual. Note that every  $x \in X$  belongs to  $X^{**}$  in the following sense. Define  $g_x : X^* \rightarrow K$  for a fixed  $x \in X$  by  $g_x(f) := f(x)$ , for all  $f \in X^*$ . So the values of the functional  $g_x$  on functionals  $f$  vary as  $f$  varies and  $x$  remains fixed. Obviously the element  $x \in X$  may be identified with  $g_x$ . We have that the mapping  $C : X \rightarrow X^{**}$  defined by  $C(x) = g_x$  is linear:  $C(x+y)(f) = f(x+y) = f(x) + f(y) = g_x(f) + g_y(f) = C(x)(f) + C(y)(f)$ , for all  $f \in X^*$ , so  $C(x+y) = C(x) + C(y)$ . We want to know whether  $C$  is one to one (injective). By **2.6-10**, the linear operator  $C$  will be one to one if the null space is equal to the zero vector space. This is established for the case of a finite dimensional vector space  $X$  in **2.9-2** below. It can also be shown as an application of the Hahn-Banach Theorem (see **4.3-4**) that for infinite dimensional normed vector spaces  $X$  this null space is zero so that  $C^{-1}$  exists on  $\mathcal{R}(C)$ . In the finite dimensional case it is shown in **2.9-3** below that  $\mathcal{R}(C) = X^{**}$ , and so we say that  $X$  is algebraically reflexive. In section **2.10** the dual space of a normed vector space is defined as the vector space  $X'$  of all bounded linear functionals  $f$  on  $X$ , with norm  $\|f\|$  as above. Then one asks (in the infinite dimensional case) whether or not a given normed space is reflexive (see **4.6**).

**Dual Basis of a Finite Dimensional Vector Space.** Let  $X$  be a finite dimensional vector space with basis  $\{e_1, e_2, \dots, e_n\}$ . Then, represent any  $x \in X$  uniquely by  $x = \sum_{j=1}^n \xi_j e_j$ . Thus for any linear functional  $f \in X^*$  we have  $f(x) = \sum_{j=1}^n \xi_j f(e_j) = \sum_{j=1}^n \xi_j \alpha_j$ , for  $f(e_j) = \alpha_j$ ,  $j = 1, \dots, n$ . Thus each linear functional is determined relative to the given basis for  $X$  by an  $n$ -tuple  $(\alpha_1, \dots, \alpha_n)$ . Now define a set of linear functionals  $\{f_1, \dots, f_n\}$  by the following special prescriptions for the values  $\alpha_j$ ,  $j = 1, \dots, n$ . For each  $k = 1, 2, \dots, n$ , put  $f_k(e_j) := \delta_{j,k}$ ,  $j = 1, \dots, n$ , where  $\delta_{j,k} = 1$  if  $j = k$ , and  $\delta_{j,k} = 0$  if  $j \neq k$ . Thus the representing  $n$ -tuples of these functionals are simply the standard basis vectors of  $\mathbb{R}^n$ , namely  $(1, 0, 0, \dots), (0, 1, 0, 0, \dots), \dots$ . In fact, this set of functionals gives a basis for  $X^*$ .

**2.9-1 Theorem** *Let  $X$  be a finite dimensional vector space with dimension  $n$ . Then the set  $\{f_1, \dots, f_n\}$  of functionals, defined above relative to a given basis of  $X$ , is a basis for  $X^*$ , so that  $\dim X = \dim X^* = n$ .*

*Proof.* Show first that  $\{f_1, \dots, f_n\}$  is a linearly independent set. If the linear combination  $\sum_{k=1}^n \beta_k f_k = 0$  then for any  $x \in X$  we have that  $\sum_{k=1}^n \beta_k f_k(x) = 0$ , so in particular by putting  $x = e_j$  and by evaluating the sum using  $f_k(e_j) = \delta_{j,k}$  we obtain for each  $j = 1, \dots, n$  that  $\beta_j = 0$ . Thus we get linear independence. To show that the set  $\{f_1, \dots, f_n\}$  spans  $X^*$  we must show that any  $f \in X^*$  may be written as a linear combination. But it follows easily that if  $f$  is represented by the  $n$ -tuple  $(\alpha_1, \dots, \alpha_n)$  then in fact  $f = \sum_{k=1}^n \alpha_k f_k$ . Indeed with  $x = \sum_{j=1}^n \xi_j e_j$  as before we have that  $f(x) = \xi_k$ . Hence  $\sum_{k=1}^n \alpha_k f_k(x) = \sum_{k=1}^n \alpha_k \xi_k$ , which is exactly the formula we must have for the value of  $f(x)$ .

Example. Let  $X = \mathbb{R}^3$  and let  $x = (\eta_1, \eta_2, \eta_3) \in \mathbb{R}^3$ . Let  $e_1 = (1, 1, 1)$ ,  $e_2 = (1, 2, -3)$ , and  $e_3 = (-5, 4, 1)$  be a basis for  $X$ . Finally let  $f(x) := \eta_1 + \eta_2 + \eta_3$  be a linear functional on  $X$ . (a) Find the representation of  $f$  in terms of the dual basis  $\{f_1, f_2, f_3\}$ . (b) Find  $f_1(1, 0, 0)$ .

(a) We only have to find  $\alpha_j = f(e_j)$ ,  $j = 1, 2, 3$ . Thus  $f = 3f_1 + 0f_2 + 0f_3 = 3f_1$ .

(b) We have that  $f_1(\sum \xi_j e_j) = \xi_1$ , where  $x = \sum \xi_j e_j$  is the representation of  $x \in \mathbb{R}^3$  relative to the basis  $\{e_1, e_2, e_3\}$ . Thus we must write  $x = (1, 0, 0)$  in terms of the given basis. This can be done as follows:  $(1, 0, 0) = \xi_1(1, 1, 1) + \xi_2(1, 2, -3) + \xi_3(-5, 4, 1)$ . By solving the linear equations we find  $\xi_1 = 1/3$ ,  $\xi_2 = 1/14$ , and  $\xi_3 = -5/42$ . Thus  $f_1(1, 0, 0) = 1/3$ .