## 18.700 - LINEAR ALGEBRA, DAY 8 MATRICES

#### SAM SCHIAVONE

#### **CONTENTS**

י ות ו ת ד	1
I. Pre-class Planning	1
I.1. Goals for lesson	1
I.2. Methods of assessment	1
I.3. Materials to bring	1
II. Lesson Plan	2
II.1. Last time	2
II.2. The Rank-Nullity Theorem	2
II.3. Worksheet	4
II.4. The matrix of a linear map	4

### I. PRE-CLASS PLANNING

# I.1. Goals for lesson.

- (1) Students will learn the definition of the range of a linear map.
- (2) Students will learn the Rank-Nullity Theorem.

## I.2. Methods of assessment.

- (1) Student responses to questions posed during lecture
- (2) Student responses to worksheet

# I.3. Materials to bring. (1) Laptop + adapter (2) Worksheets

#### II. LESSON PLAN

## Announcements: • Final exam: Monday, December 16, 1:30 - 4:30pm, 6-120

- II.1. Last time.
  - Gave the definition of dimension.
  - Proved some basic properties about dimension.
  - Defined linear maps.
  - Show that a linear map is uniquely determined by its action on a basis.
  - Defined the null space of a linear map.
  - *T* one-to-one  $\iff$  ker $(T) = \{0\}$ .

### II.2. The Rank-Nullity Theorem.

**Definition 1.** Let X and Y be sets and  $f : X \to Y$  be a function. The *range* or *image* of f is

$$range(f) = img(f) = f(X) := \{f(x) : x \in X\}.$$

[Draw picture of blobs, showing that img(f) need not fill up all of Y.]

**Definition 2.** If img(f) = Y, then f is onto or surjective.

Remark 3. Warning: You must specify the codomain for the notion of surjectivity to make sense! E.g.,  $f(x) = x^2$  as a function  $\mathbb{R} \to \mathbb{R}$  or  $\mathbb{R} \to [0, \infty)$ .

**Definition 4.** Let  $T: V \to W$  be linear. The dimension of range(*T*) is called the *rank* of *T*.

**Lemma 5.** If  $T: V \to W$  is linear, then img(T) is a subspace of W.

Proof. Exercise. Apply subspace criterion.

II.2.1. *Rank-nullity theorem*. The sizes of the kernel and the image are inversely correlated. E.g., the zero map  $0: V \to W$  has large null space [ask students]—all of V—and small range—just {0}. On the other hand, the identity map  $I: V \to V$  has small kernel [ask students]—just  $\{0\}$ —and large image—all of V. This relationship is captured precisely in the following result.

**Theorem 6** (Rank-Nullity Theorem). Suppose V is finite-dimensional and  $T \in \mathcal{L}(V, W)$ . Then img(T) is also finite-dimensional and

 $\dim(V) = \dim(\ker(T)) + \dim(\operatorname{img}(T)).$ 

In words, the dimension of the domain of T is equal to the sum of the nullity and rank of T.

*Proof.* Let  $u_1, \ldots, u_m$  be a basis of ker(*T*). By the Extension Theorem, we can extend this to a basis  $u_1, \ldots, u_m, v_1, \ldots, v_n$  of V. Thus dim $(\ker(T)) = m$  and dim(V) = m + n, so it suffices to show that  $\dim(\operatorname{img}(T)) = n$ .

We claim that  $T(v_1), \ldots, T(v_n)$  is a basis for img(T). [Ask students why we don't include any  $u_i$ .] Given  $v \in V$ , then

$$v = a_1u_1 + \cdots + a_mu_m + b_1v_1 + \cdots + b_nv_n$$

for some scalars  $a_i, b_i \in \mathbb{F}$ . Applying *T*, we have

$$T(v) = T\left(\sum_{i=1}^{m} a_i u_i + \sum_{j=1}^{n} b_j v_j\right) = \sum_i a_i T(u_i) + \sum_j b_j T(v_j)$$

(0:00)

since the  $u_i$  all map to 0 since they are in ker(T). Thus  $T(v_1), \ldots, T(v_n)$  spans img(T), hence it is finite-dimensional.

It remains to show they are linearly independent. Suppose there exists  $c_1, \ldots, c_n \in \mathbb{F}$ such that

$$0 = c_1 T(v_1) + \dots + c_n T(v_n) = T(c_1 v_1 + \dots + c_n v_n).$$

Then  $\sum_{k=1}^{n} c_k v_k \in \ker(T)$ , so there exist  $d_1, \ldots, d_m \in \mathbb{F}$  such that

$$c_1v_1+\cdots+c_nv_n=d_1u_1+\cdots d_mu_m$$

Then

$$0 = d_1 u_1 + \cdots + d_m u_m - c_1 v_1 - \cdots - c_n v_n$$

Since  $u_1, \ldots, u_m, v_1, \ldots, v_n$  is a basis of V, hence linearly independent, then  $0 = c_1 = c_1$  $\cdots$ ,  $c_n = d_1 = \cdots = d_m$ . Thus  $T(v_1), \ldots, T(v_n)$  is linearly independent, hence is a basis of img(T). 

**Corollary 7.** Suppose V and W are finite-dimensional vector spaces with  $\dim(V) > \dim(W)$ . Then no linear map  $T: V \to W$  is injective.

*Proof.* By the Rank-Nullity Theorem, then

$$\dim(\ker(T)) = \dim(V) - \dim(\operatorname{img}(T)).$$

Since  $\operatorname{img}(T) \subseteq W$ , then  $\operatorname{dim}(\operatorname{img}(T)) \leq \operatorname{dim}(W)$ , so  $-\operatorname{dim}(W) \leq -\operatorname{dim}(\operatorname{img}(T))$ . Then  $\dim(\ker(T)) = \dim(V) - \dim(\operatorname{img}(T)) \ge \dim(V) - \dim(W) > 0.$ 

Thus ker(*T*)  $\neq$  {0}, so *T* is not injective.

**Corollary 8.** Suppose V and W are finite-dimensional vector spaces with  $\dim(V) < \dim(W)$ . *Then no linear map*  $T : V \to W$  *is surjective.* 

*Proof.* Exercise. Similar to the above.

II.2.2. Linear maps and systems of equations. Fix  $m, n \in \mathbb{Z}_{>0}$  and suppose  $A_{ii} \in \mathbb{F}$  for i =1,..., *m* and j = 1,...,n. Consider the homogeneous system of equations

$$\sum_{k=1}^{n} A_{1k} x_k = 0$$
$$\vdots$$
$$\sum_{k=1}^{n} A_{mk} x_k = 0.$$

We can interpret this system using linear maps by defining

$$T: \mathbb{F}^n \to \mathbb{F}^m$$
$$(x_1, \dots, x_n) \mapsto \left(\sum_{k=1}^n A_{1k} x_k, \dots, \sum_{k=1}^n A_{mk} x_k\right).$$

One can show that *T* is linear. Thus the above linear system is equivalent to the equation T(x) = 0. Therefore computing the solutions to the system is the same as computing [ask students] ker(*T*).

Let  $b_1, \ldots, b_m \in \mathbb{F}$ . Similarly, we can reinterpret searching for solutions to the linear system

$$\sum_{k=1}^{n} A_{1k} x_k = b_1$$
$$\vdots$$
$$\sum_{k=1}^{n} A_{mk} x_k = b_m$$

as asking whether  $b := (b_1, \dots, b_m)$  is in img(T) or not.

### II.3. Worksheet.

#### II.4. The matrix of a linear map.

**Definition 9.** Let  $\mathcal{B} := (u_1, ..., u_n)$  be a basis for the finite-dimensional vector space *V*. Given  $x \in V$ , let  $a_1, ..., a_n \in \mathbb{F}$  be the unique scalars such that

$$x = \sum_{i=1}^{n} a_i u_i$$

The coordinate vector or matrix of x with respect to  $\mathcal{B}$ , denoted by  $[x]_{\mathcal{B}}$ , is

$$[x]_{\mathcal{B}} := \begin{pmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{pmatrix} \in \mathbb{F}^n \,.$$

[Ask students: what is  $[u_1]_{\mathcal{B}}$ ?]

**Example 10** (Polynomial example with respect to 1, x,  $x^2$ .).

Similarly, we can encode linear maps as matrices.

**Definition 11.** Let  $m, n \in \mathbb{Z}_{\geq 0}$ . An *m*-by-*n* matrix *A* is a rectangular array of elements of  $\mathbb{F}$  with *m* rows and *n* columns:

$$\begin{pmatrix} A_{11} & \cdots & A_{1n} \\ \vdots & \ddots & \vdots \\ A_{m1} & \cdots & A_{mn} \end{pmatrix}$$

The entry in row *i*, column *j* is called the (i, j)-entry and is denoted  $A_{ij}$ .

Suppose *V* and *W* are finite-dimensional vector spaces with bases  $\mathcal{B} := (v_1, \ldots, v_n)$  and  $\mathcal{C} := (w_1, \ldots, w_m)$ , respectively. Let  $T : V \to W$  be linear. We have seen that the values  $T(v_1), \ldots, T(v_n)$  uniquely determine *T*.

**Definition 12.** With notation as above, for each j = 1, ..., n there are unique scalars  $A_{1j}, ..., A_{mj} \in \mathbb{F}$  such that

$$T(v_i) = A_{1i}w_1 + \cdots + A_{mi}w_m.$$

The matrix whose *i*, *j* entry is  $A_{ij}$  is the *matrix of T with respect to*  $\mathcal{B}$  *and*  $\mathcal{C}$  and is denoted  $_{\mathcal{C}}[T]_{\mathcal{B}}$  or  $\mathcal{M}(T; \mathcal{B}, \mathcal{C})$ . When the bases are clear from context, we simply write [T] or  $\mathcal{M}(T)$ .

Note that the *j*<sup>th</sup> column of [T] is the coordinate vector of  $T(v_i)$ :

$$_{\mathcal{C}}[T]_{\mathcal{B}} = \begin{pmatrix} | & | \\ [T(v_1)]_{\mathcal{C}} & \cdots & [T(v_n)]_{\mathcal{C}} \\ | & | \end{pmatrix}$$

• For  $V = \mathbb{F}^n$ , let  $\mathcal{E}_n$  be the basis

$$\begin{pmatrix} 1\\0\\0\\\vdots\\0\\0 \end{pmatrix}, \begin{pmatrix} 0\\1\\0\\\vdots\\0\\0 \end{pmatrix}, \begin{pmatrix} 0\\0\\0\\\vdots\\0\\1 \end{pmatrix}$$

We call this the *standard basis* for  $\mathbb{F}^n$  and use this basis unless otherwise specified.

• For  $V = \mathcal{P}_m(\mathbb{F})$ , we similarly use the standard monomial basis  $1, x, x^2, \ldots, x^m$  unless otherwise specified.

**Example 13.** Let  $T : \mathcal{P}_2(\mathbb{R}) \to \mathcal{P}_1(\mathbb{R})$  be the differentiation map T(f) = f'. Then

$$T(1) = 0 = 0 \cdot 1 + 0 \cdot x$$
  

$$T(x) = 1 = 1 \cdot 1 + 0 \cdot x$$
  

$$T(x^{2}) = 2x = 0 \cdot 1 + 2 \cdot x$$

so

$$[T] = \begin{pmatrix} 0 & 1 & 0 \\ 0 & 0 & 2 \end{pmatrix} \,.$$

We define addition and scalar multiplication of matrices to agree with the corresponding operations for linear maps.

### **Definition 14.**

- Given matrices *A* and *B* of the same size, we define their sum entrywise, i.e., A + B is the matrix whose *i*, *j* entry is  $A_{ij} + B_{ij}$ .
- Given a matrix *A* and  $\lambda \in \mathbb{F}$ , we define  $\lambda A$  to be the matrix whose *i*, *j* entry is  $\lambda A_{ij}$ .

**Lemma 15.** Suppose  $S, T \in \mathcal{L}(V, W)$  and  $\lambda \in \mathbb{F}$ . Then

- [S+T] = [S] + [T], and
- $[\lambda T] = \lambda [T].$

Proof. Exercise.

Denote the set of all  $m \times n$  matrices by  $M_{m \times n}(\mathbb{F})$  or  $Mat_{m \times n}$  or  $\mathbb{F}^{m,n}$ .

**Lemma 16.** With the operations of addition and scalar multiplication above,  $M_{m \times n}(\mathbb{F})$  is a vector space of dimension mn.

Proof. Exercise.

II.4.1. *Matrix multiplication*. Suppose that U, V, W are finite-dimensional vector spaces with bases

$$\mathcal{B} := (u_1, \dots, u_p)$$
$$\mathcal{C} := (v_1, \dots, v_n)$$
$$\mathcal{D} := (w_1, \dots, w_m)$$

Suppose  $T : U \to V$  and  $S : V \to W$  are linear maps. We previously saw that the composition  $ST : U \to W$  is linear. We define matrix multiplication in such a way that

$$[ST] = [S][T].$$

Let A := [S] and B := [T]. Then for each j = 1, ..., p we have

$$(ST)(u_j) = S\left(\sum_{k=1}^n B_{kj}v_k\right) = \sum_{k=1}^n B_{kj}S(v_k) = \sum_{k=1}^n B_{kj}\sum_{i=1}^m A_{ik}w_k = \sum_{i=1}^m \sum_{k=1}^n \left(A_{ik}B_{kj}\right)w_k$$

Thus [*ST*] is the  $m \times p$  matrix whose *i*, *j* entry is  $\sum_{k=1}^{n} (A_{ik}B_{kj})$ .

**Definition 17.** Given an  $m \times n$  matrix A and a  $n \times p$  matrix B, their product AB is defined to be the  $m \times p$  matrix whose i, j entry is  $\sum_{k=1}^{n} (A_{ik}B_{kj})$ .

So we multiply the entries of row j of A by those of column k of B, then add these together.

#### Example 18.

$$\begin{pmatrix} 1 & 2 \\ 3 & 4 \\ 5 & 6 \end{pmatrix} \begin{pmatrix} 6 & 5 & 0 & 0 \\ 2 & 1 & 0 & -1 \end{pmatrix} = \cdots$$

[Ask students about the other order *BA*.]

**Proposition 19.** *If*  $T \in \mathcal{L}(U, V)$  *and*  $S \in \mathcal{L}(V, W)$ *, then* [ST] = [S][T]*.* 

*Proof.* This is true by the definition of matrix multiplication and the earlier calculation done as motivation.  $\Box$ 

Let *A* be an  $m \times n$  matrix.

- For i = 1, ..., m, let  $A_{i}$ , denote row i of A, which is a  $1 \times n$  matrix.
- For j = 1, ..., n, let  $A_{.,j}$  denote column j of A, which is an  $m \times 1$  matrix.

The next few results give different interpretations of matrix multiplication. Let *A* be an  $m \times n$  matrix and *B* be an  $n \times p$  matrix.

Lemma 20.

for all 
$$i = 1, ..., m$$
 and all  $j = 1, ..., p$ . [Draw picture of row and column.]

*Proof.* True by formula defining matrix multiplication.

### Lemma 21.

$$(AB)_{\cdot,j} = A(B_{\cdot,j})$$

 $(AB) \dots = A \dots B$ 

for all j = 1, ..., p.

*Proof.* Exercise. Both are  $m \times 1$  matrices. Check that their *i*<sup>th</sup> entries are equal using the formula. [Draw picture applying *A* to each of the columns of *B*.]

**Lemma 22.** Suppose A is 
$$m \times n$$
 and  $x = \begin{pmatrix} x_1 \\ \ddots \\ x_n \end{pmatrix}$  is  $n \times 1$ . Then  
 $Ax = x_1 A_{\cdot 1} + \cdots + x_n A_{\cdot n}$ .

*I.e., Ax is the linear combination of the columns of A with coefficients given by the entries of x.* 

- Proof. Exercise.
- **Lemma 23.** (a) For j = 1, ..., p,  $(AB)_{.,j}$  (column j) is a linear combination of the columns of A with coefficients from  $B_{.,j}$  (column j).
  - (b) For i = 1, ..., m,  $(AB)_{i,.}$  (row i) is a linear combination of the rows of B with coefficients from  $A_{i,.}$  (row i).

*Proof.* Exercise. [Draw picture of second part.]

#### **Definition 24.**

- The *column space* of *A*, denoted Col(*A*), is the span of the columns of *A*. The *column rank* is the dimension of Col(*A*).
- The *row space* of *A*, denoted Row(*A*), is the span of the rows of *A*. The *row rank* is the dimension of Row(*A*).

We'll see that these two quantities are actually equal!

**Definition 25.** The *transpose* of a matrix A, denoted  $A^t$ , is obtained from A by interchanging rows and columns. I.e.,

$$(A^t)_{ij} = A_{ji}.$$

**Lemma 26** (Column-row factorization). Suppose A is  $m \times n$  and has column rank  $c \in \mathbb{Z}_{\geq 1}$ . Then there exist an  $m \times c$  matrix C and a  $c \times n$  matrix R such that A = CR.

*Proof.* The columns  $A_{.,1}, ..., A_{.,n}$ , each an  $m \times 1$  matrix, span Col(A). By a previous result, this list can be reduced to a basis  $v_1, ..., v_c$  of Col(A), which by definition must have length *c*. Use these as the columns of a  $m \times c$  matrix *C*.

For k = 1, ..., n, column k of A is a linear combination of the columns of C (since these are a basis), so there exist scalars  $R_{1k}, ..., R_{ck} \in \mathbb{F}$  such that

$$A_k = R_{1k}v_1 + \cdots + R_{ck}v_c.$$

Use the coefficients  $R_{1k}, \ldots, R_{ck}$  as the entries of the  $k^{\text{th}}$  column of a  $c \times n$  matrix R. Then A = CR.

**Theorem 27** (Column rank = row rank). *Suppose*  $A \in M_{m \times n}(\mathbb{F})$ . *Then the column rank and row rank of A are equal.* 

*Proof.* Let *c* be the column rank of *A*. Let A = CR be the column-row factorization of *A* given by the previous lemma, where *C* is  $m \times c$  and *R* is  $c \times n$ . Since every row of *A* can be written as a linear combination of the rows of *R*, and *R* has *c* rows, then the row rank of *A* is  $\leq c$ , which is the column rank of *A*.

We obtain the reverse inequality by applying the same argument to  $A^t$ , which yields

column rank of A = row rank of  $A^t \leq \text{column rank}$  of  $A^t = \text{row rank}$  of A.

**Definition 28.** The *rank* of a matrix is its column rank (= its row rank).