21-241 MATRICES AND LINEAR TRANSFORMATIONS SUMMER 1 2012 COURSE NOTES MAY 29

PAUL MCKENNEY

Definition. A subset S of \mathbb{R}^n is called a *subspace* (of \mathbb{R}^n) if:

- (1) $0 \in S$.
- (2) For all $x \in S$, and $\lambda \in \mathbb{R}$, λx is also in S.
- (3) For all $x, y \in S$, x + y is also in S.

Note that the second condition implies the first, so long as S is nonempty. Thus the first condition is just there to ensure that a subspace is nonempty.

Fact 1. If S is a subspace of \mathbb{R}^n and $x_1, \ldots, x_k \in S$ and $\lambda_1, \ldots, \lambda_k \in \mathbb{R}$, then

$$\lambda_1 x_1 + \dots + \lambda_k x_k \in S$$

Example. Let A be an $m \times n$ matrix. Then

$$\{x \in \mathbb{R}^n \mid Ax = 0\}$$

is a subspace of \mathbb{R}^n . This is called the *null space of* A and is denoted by null(A). On the other hand,

 $\{Ax \mid x \in \mathbb{R}^n\}$

is a subspace of \mathbb{R}^m , and is called the *range space of* A, written ran(A).

Definition. Let S be a subspace of \mathbb{R}^n . A subset $X \subseteq S$ of S is said to span S if for every $s \in S$, there are some $x_1, \ldots, x_k \in X$ and $\lambda_1, \ldots, \lambda_k \in \mathbb{R}$ such that

$$s = \lambda_1 x_1 + \dots + \lambda_k x_k$$

If $X \subseteq \mathbb{R}^n$, then the span of X is the set

$$\operatorname{span}(X) = \{\lambda_1 x_1 + \dots + \lambda_k x_k \mid k \in \mathbb{N} \land x_1, \dots, x_k \in X \land \lambda_1, \dots, \lambda_k \in \mathbb{R}\}$$

This last definition provides us with a wealth of examples of subspaces of \mathbb{R}^n .

Fact 2. If X is any subset of \mathbb{R}^n then span(X) is a subspace of \mathbb{R}^n .

It's easy to see that if $X \subseteq Y \subseteq \mathbb{R}^n$, then $\operatorname{span}(X) \subseteq \operatorname{span}(Y)$. However, the converse doesn't hold. In fact, we have the following example where $X \not\subseteq Y$ and $Y \not\subseteq X$, but $\operatorname{span}(X) = \operatorname{span}(Y)$.

Example. Consider the following two finite subsets of \mathbb{R}^3 .

$$X = \left\{ \begin{pmatrix} 1\\3\\-2 \end{pmatrix}, \begin{pmatrix} 1\\1\\-1 \end{pmatrix}, \begin{pmatrix} 0\\2\\-1 \end{pmatrix} \right\} \qquad Y = \left\{ \begin{pmatrix} 1\\3\\-2 \end{pmatrix}, \begin{pmatrix} 1\\1\\-1 \end{pmatrix}, \begin{pmatrix} 2\\4\\-3 \end{pmatrix} \right\}$$

Then we have $\operatorname{span}(X) = \operatorname{span}(Y)$.

The proof of the above is made much easier using the following, which we call the "linear combination lemma."

Lemma 1. Let $x_1, \ldots, x_k \in \mathbb{R}^n$ be vectors in \mathbb{R}^n . If each of y_1, \ldots, y_ℓ is a linear combination of x_1, \ldots, x_k then so is any linear combination of y_1, \ldots, y_ℓ .

Proof. The hardest part of this proof is figuring out what the statement of the lemma is, in formal terms. We have our vectors $x_1, \ldots, x_k \in \mathbb{R}^n$; suppose y_1, \ldots, y_ℓ are vectors in \mathbb{R}^n , each of which is a linear combination of x_1, \ldots, x_k ;

$$y_i = \lambda_{i1} x_1 + \dots + \lambda_{ik} x_k \qquad 1 \le i \le \ell$$

Now suppose $z = \mu_1 y_1 + \cdots + \mu_\ell y_\ell$ is a linear combination of y_1, \ldots, y_ℓ . Then,

$$z = \sum_{i=1}^{\ell} \mu_i y_i$$

= $\sum_{i=1}^{\ell} \mu_i \sum_{j=1}^{k} \lambda_{ij} x_j$
= $\sum_{j=1}^{k} \sum_{i=1}^{\ell} \mu_i \lambda_{ij} x_j$
= $\sum_{j=1}^{k} \left(\sum_{i=1}^{\ell} \mu_i \lambda_{ij} \right) x_j$

So z is also a linear combination of x_1, \ldots, x_k , namely the one whose coefficient for x_j is

$$\sum_{i=1}^\ell \mu_i \lambda_{ij}$$

Lemma 2. Suppose S is a subspace of \mathbb{R}^n , and $X \subseteq S$. Then $\operatorname{span}(X) \subseteq S$.

Proof. Suppose $y \in \text{span}(X)$; then there are $x_1, \ldots, x_k \in X$ and $\lambda_1, \ldots, \lambda_k \in \mathbb{R}$ such that $y = \lambda_1 x_1 + \cdots + \lambda_k x_k$. But $x_1, \ldots, x_k \in S$, and so

$$y = \lambda_1 x_1 + \dots + \lambda_k x_k \in S$$

Definition. If A is an $m \times n$ matrix with columns $c_1, \ldots, c_n \in \mathbb{R}^m$, and rows $r_1, \ldots, r_m \in \mathbb{R}^n$, then we write

$$\operatorname{col}(A) = \operatorname{span}\{c_1, \dots, c_n\}$$
 $\operatorname{row}(A) = \operatorname{span}\{r_1, \dots, r_m\}$

We call col(A) and row(A) the *column space* and *row space* of A, respectively.

Fact 3. If A is any matrix, then ran(A) = col(A).

Proof. Suppose A is $m \times n$ and $c_1 \dots, c_n \in \mathbb{R}^m$ are the column vectors of A. We've seen before that if $x \in \mathbb{R}^n$, then

$$Ax = x_1c_1 + \dots + x_nc_n$$

The right-hand side of the above equation is a member of col(A), since it's a linear combination of the columns of A. Since $x \in \mathbb{R}^n$ was arbitrary, this shows $ran(A) \subseteq col(A)$. Now if $y \in col(A)$, then y is a linear combination of the columns of A, and hence for some $\lambda_1, \ldots, \lambda_n \in \mathbb{R}$,

$$y = \lambda_1 c_1 + \dots + \lambda_n c_n$$

But then by the same fact,

$$y = \lambda_1 c_1 + \dots + \lambda_n c_n = A \begin{pmatrix} \lambda_1 \\ \vdots \\ \lambda_n \end{pmatrix}$$

and the right-hand side of this equation is in ran(A). This shows $col(A) \subseteq ran(A)$. \Box

You might guess now, since row(A) and null(A) are both subspaces of \mathbb{R}^n , that they are equal; but you'd be wrong! They *are* related, but we won't see how for a while yet. For now, let's see how we can phrase a problem related to spanning sets in terms of Gaussian elimination.

Example. Let

$$X = \left\{ \begin{pmatrix} 0\\1\\-2\\3 \end{pmatrix}, \begin{pmatrix} 2\\4\\6\\0 \end{pmatrix}, \begin{pmatrix} 3\\-5\\7\\-1 \end{pmatrix} \right\}$$

Is the vector $b = \begin{pmatrix} 2\\ 3\\ 5\\ 7 \end{pmatrix}$ in the span of X?

To solve this, let

$$A = \begin{pmatrix} 0 & 2 & 3\\ 1 & 4 & -5\\ -2 & 6 & 7\\ 3 & 0 & -1 \end{pmatrix}$$

Then b is in the span of X if and only if there is some $x \in \mathbb{R}^3$ such that Ax = b.

Example. Let X be the following set.

$$\left\{ \begin{pmatrix} 0\\2\\1 \end{pmatrix}, \begin{pmatrix} 1\\1\\-1 \end{pmatrix}, \begin{pmatrix} 0\\2\\-1 \end{pmatrix} \right\}$$

Prove that $\operatorname{span}(X) = \mathbb{R}^3$.

To prove this it suffices to prove that the following matrix is right-invertible;

$$A = \begin{pmatrix} 0 & 1 & 0 \\ 2 & 1 & 2 \\ 1 & -1 & -1 \end{pmatrix}$$

for which it suffices to prove that A is fully invertible;

$$\begin{pmatrix} 0 & 1 & 0 \\ 2 & 1 & 2 \\ 1 & -1 & -1 \end{pmatrix} \qquad \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

$$\rho_{2} \rightarrow \rho_{2} - \rho_{1} \begin{pmatrix} 0 & 1 & 0 \\ 2 & 0 & 2 \\ 1 & 0 & -1 \end{pmatrix} \qquad \begin{pmatrix} 1 & 0 & 0 \\ -1 & 1 & 0 \\ 1 & 0 & 1 \end{pmatrix}$$

$$\rho_{2} \rightarrow \rho_{2} - 2\rho_{3} \begin{pmatrix} 0 & 1 & 0 \\ 0 & 0 & 4 \\ 1 & 0 & -1 \end{pmatrix} \qquad \begin{pmatrix} 1 & 0 & 0 \\ -3 & 1 & -2 \\ 1 & 0 & 1 \end{pmatrix}$$

$$\rho_{1} \leftrightarrow \rho_{2} \begin{pmatrix} 1 & 0 & -1 \\ 0 & 1 & 0 \\ 0 & 0 & 4 \end{pmatrix} \qquad \begin{pmatrix} 1 & 0 & 1 \\ 1 & 0 & 0 \\ -3 & 1 & -2 \end{pmatrix}$$

$$\rho_{3} \rightarrow \rho_{3}/4 \qquad \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \qquad \begin{pmatrix} 1/4 & 1/4 & 1/2 \\ 1 & 0 & 0 \\ -3/4 & 1/4 & -1/2 \end{pmatrix}$$

(I computed A^{-1} above, but this is not necessary to prove that A is invertible; it just suffices to show, since A is square, that A reduces to I.)