There is a circle of ideas related to linear independence, span, and basis for vector spaces, which it is good to try and understand carefully. That's what we'll do today. These ideas generalize (and use) ideas we've already explored more concretely, and facts we already know to be true for the vector spaces \mathbb{R}^n . (A vector space that does not have a basis with a finite number of elements is said to be *infinite dimensional*. For example the space of all polynomials of arbitrarily high degree is an infinite dimensional vector space. We often study finite dimensional subspaces of infinite dimensional vector spaces.)

<u>Theorem 1</u> (constructing a basis from a spanning set): Let V be a vector space of dimension at least one, and let $span\{\underline{v}_1, \underline{v}_2, \dots, \underline{v}_p\} = V$.

Then a subset of the spanning set is a basis for V. (We followed a procedure like this to extract bases for Col A.)

proof: If
$$\{\vec{v}_1, ..., \vec{v}_p\}$$
 is not already independent,
reorder the set so that
 $\vec{v}_p = d_1\vec{v}_1 + d_2\vec{v}_2 + ... + d_{p-1}\vec{v}_{p-1}$ (we know me
of the vector
is a combo
 $c_1\vec{v}_1 + c_2\vec{v}_2 + ... + c_{p-1}\vec{v}_{p-1} + c_p\vec{v}_p$
 $= c_1\vec{v}_1 + c_2\vec{v}_2 + ... + c_{p-1}\vec{v}_{p-1} + c_p(d_1\vec{v}_1 + d_2\vec{v}_2 + ... + d_{p-1}\vec{v}_{p-1})$
 $\in \text{span}\{\vec{v}_1, \vec{v}_2, ..., \vec{v}_{p-1}\}$
continue deleting dependent vectors until remaining
set is independent, with the same span you began with
 $\notin \text{ basis } \neq$

<u>Theorem 2</u> Let *V* be a vector space, with basis $\beta = \{\underline{b}_1, \underline{b}_2, \dots, \underline{b}_n\}$. Then any set in *V* containing more than *n* elements must be linearly dependent. (We used reduced row echelon form to understand this in \mathbb{R}^n .)

<u>Theorem 3</u> Let *V* be a vector space, with basis $\beta = \{\underline{\boldsymbol{b}}_1, \underline{\boldsymbol{b}}_2, \dots, \underline{\boldsymbol{b}}_n\}$. Then no set $\alpha = \{\underline{\boldsymbol{a}}_1, \underline{\boldsymbol{a}}_2, \dots, \underline{\boldsymbol{a}}_p\}$ with p < n vectors can span *V*. (We know this for \mathbb{R}^n .)

<u>Theorem 4</u> Let *V* be a vector space, with basis $\beta = \{\underline{b}_1, \underline{b}_2, \dots, \underline{b}_n\}$. Let $\alpha = \{\underline{a}_1, \underline{a}_2, \dots, \underline{a}_p\}$ be a set of independent vectors that don't span *V*. Then p < n, and additional vectors can be added to the set α to create a basis $\{\underline{a}_1, \underline{a}_2, \dots, \underline{a}_p, \dots, \underline{a}_n\}$ (We followed a procedure like this when we figured out all the subspaces of \mathbb{R}^3 .)

$$\frac{\text{proof}: \left\{\vec{a}_{1}, -\vec{a}_{p}\right\} \text{ dress it s pan., but is independent}}{\text{pick } \vec{a}_{p+1} \in V, \quad \vec{a}_{p+1} \notin \text{span}\left\{\vec{a}_{1}, \vec{a}_{2}, -\vec{a}_{p}\right\}.}$$

$$C \underbrace{\text{laim}}_{i} \left\{\vec{a}_{1}, \vec{a}_{2}, -\vec{a}_{p}, \vec{a}_{p+1}\right\} \text{ is still independent}}{\vec{p}_{1}} \left\{\vec{a}_{1}, \vec{a}_{2}, -\vec{a}_{p}, \vec{a}_{p+1}\right\} \text{ is still independent}}$$

$$\frac{\text{pf}}{\vec{p}_{1}} \left(\vec{c}_{1}\vec{a}_{1} + c_{2}\vec{a}_{2} + \cdots + c_{p}\vec{a}_{p} + c_{p+1}\vec{a}_{p+1} = \vec{O}\right).$$

$$\underbrace{Case 1}_{i} \left(\vec{c}_{2}\vec{a}_{1} + c_{2}\vec{a}_{2} + \cdots + c_{p}\vec{a}_{p} + c_{p+1}\vec{a}_{p+1} = \vec{O}\right).$$

$$\underbrace{Case 1}_{i} \left(\vec{c}_{2}\vec{a}_{2} + \cdots + c_{p}\vec{a}_{p} + c_{p+1}\vec{a}_{p+1} = \vec{O}\right).$$

$$\underbrace{Case 1}_{i} \left(\vec{c}_{2}\vec{a}_{2} + \cdots + c_{p}\vec{a}_{p} = \vec{O}\right) \text{ to be uon finned } \dots$$

$$\Rightarrow c_{1} = c_{2} = \cdots < c_{p} = \vec{O} \text{ to be uon finned } \dots$$

$$\Rightarrow c_{1} = c_{2} = \cdots < c_{p} = \vec{O} \text{ to be uon finned } \dots$$

$$\underbrace{Case 2}_{i} \left(c_{p+1} \neq O\right) = \text{ sdue for } \vec{a}_{p+1}: \quad c_{i}\vec{a}_{1} + c_{2}\vec{a}_{2} + \cdots + c_{i}\vec{a}_{p} = -c_{i}\vec{a}_{p+1}, \dots \\ \underbrace{Case 2}_{i} \left(c_{p+1} \neq O\right) = \text{ sdue for } \vec{a}_{p+1}: \quad c_{i}\vec{a}_{1} + c_{i}\vec{a}_{2} + \cdots + c_{i}\vec{a}_{p} = -c_{i}\vec{a}_{p+1}, \dots \\ \underbrace{Case 3}_{i} \left(c_{i}\vec{a}_{1}, c_{i}\vec{a}_{1}, \cdots \vec{a}_{p}\right) = \underbrace{Case 3}_{i} \left(c_{i}\vec{a}_{1}, c_{i}\vec{a}_{2}, \cdots \vec{a}_{p}\right) = \underbrace{Case 3}_{i} \left(c_{i}\vec{a$$

<u>Theorem 5</u> Let Let *V* be a vector space, with basis $\beta = \{\underline{b}_1, \underline{b}_2, \dots, \underline{b}_n\}$. Then every basis for *V* has exactly *n* vectors. (We know this for \mathbb{R}^n .)

<u>Theorem 6</u> Let Let *V* be a vector space, with basis $\beta = \{\underline{b}_1, \underline{b}_2, \dots, \underline{b}_n\}$. If $\alpha = \{\underline{a}_1, \underline{a}_2, \dots, \underline{a}_n\}$ is another collection of exactly *n* vectors in *V*, and if $span\{\underline{a}_1, \underline{a}_2, \dots, \underline{a}_n\} = V$, then the set α is automatically linearly independent and a basis. Conversely, if the set $\{\underline{a}_1, \underline{a}_2, \dots, \underline{a}_n\}$ is linearly independent, then $span\{\underline{a}_1, \underline{a}_2, \dots, \underline{a}_n\} = V$ is guaranteed, and α is a basis. (We know all these facts for \mathbb{R}^n from reduced row echelon form considerations.)

<u>Corollary</u> Let Let *V* be a vector space of dimension *n*. Then the subspaces of *V* have dimensions 0, 1, 2,...*n* – 1, *n*. (We know this for \mathbb{R}^n .)

<u>Remark</u> We used the coordinate transformation isomorphism between a vector space *V* with basis $\beta = \{\underline{b}_1, \underline{b}_2, \dots \underline{b}_n\}$ for Theorem 2, but argued more abstractly for the other theorems. An alternate (quicker) approach is to just note that because the coordinate transformation is an isomorphism it preserves sets of independent vectors, and maps spans of vectors to spans of the image vectors, so maps subspaces to subspaces. Then every one of the theorems above follows from their special cases in \mathbb{R}^n , which we've already proven. But this shortcut shortchanges the conceptual ideas to some extent, which is why we've discussed the proofs more abstractly.

Tues Mar 6

• 4.6 The four subspaces associated with a matrix. the rank of a matrix.

Announcements:

$$= \begin{bmatrix} \vec{a}_{1} & \vec{a}_{2} \end{bmatrix} \qquad \begin{bmatrix} \vec{b}_{1} & \vec{b}_{2} \end{bmatrix}$$

Warm-up Exercise: 'take two '' (et $A = \begin{bmatrix} 1 & 1 \\ 2 & 2 \end{bmatrix}$, $A^{T} = \begin{bmatrix} 1 & 2 \\ 1 & 2 \end{bmatrix}$
Find bases for
in domain $\begin{cases} Nul A = \begin{cases} \begin{bmatrix} -1 \\ 1 \end{bmatrix} \end{cases}$ null vectors are the weight
 $\vec{a}_{1} + \vec{a}_{2} = \vec{o}$
 $-\vec{a}_{1} + \vec{a}_{2} = \vec{o}$
 $\vec{a}_{1} + \vec{a}_{2} = \vec{o}$
 $\vec{a}_{2} + \vec{a}_{2} = \vec{o}$
 $\vec{a}_{1} + \vec{a}_{2} = \vec{o}$
 $\vec{a}_{2} + \vec{a}_{2} = \vec{o}$

Let *A* be an $m \times n$ matrix. There are four subspaces associated with *A*. To keep them straight, keep in mind the associated linear transformation

$$T: \mathbb{R}^n \to \mathbb{R}^m$$
 given by $T(\underline{x}) = A \underline{x}$.

And, as usual, we can express A in terms of its columns, $A = \begin{bmatrix} \underline{a}_1 & \underline{a}_2 & \dots & \underline{a}_n \end{bmatrix}$. Then the two subspaces we know well are

$$Col A = span\{\underline{a}_1, \underline{a}_2, \dots \underline{a}_n\} \subseteq \mathbb{R}^m$$

$$Nul A = \{ \underline{x} \in \mathbb{R}^n : A \underline{x} = \underline{0} \} \subseteq \mathbb{R}^n.$$

And, in your homework you already figured out the "rank + nullity" theorem, that

The reason for this is that if p is the number of pivots in the reduced row echelon form of A, then

$$dim(Col A) = p$$
$$dim(Nul A) = n - p.$$

The number of pivots, i.e. dim(Col A) is called the *rank* of the matrix A. What are the other two subspaces and why do we care? Well,

• First, recall the geometry fact that the dot product of two vectors in \mathbb{R}^n is zero if and only if the vectors are perpendicular, i.e.

$$\underline{u} \cdot \underline{v} = 0$$
 if and only if $\underline{u} \perp \underline{v}$.

(Well, we really only know this in \mathbb{R}^2 or \mathbb{R}^3 so far, from multivariable Calculus class. But it's true for all \mathbb{R}^n , as we'll see in Chapter 6.) So for a vector $\underline{x} \in Nul A$ we can interpret the equation A x = 0

as saying that \underline{x} is perpendicular to every row of A. Because the dot product distributes over addition, we see that each $\underline{x} \in Nul A$ is perpendicular to every linear combination of the rows of A. This motivates the next subspace associated with A, namely the rowspace. In other words, if we express A in terms of its rows,

$$A = \begin{bmatrix} \mathbf{R}_{1} \\ \mathbf{R}_{2} \\ \vdots \\ \mathbf{R}_{m} \end{bmatrix} \qquad A \stackrel{\rightarrow}{\mathbf{x}} = \begin{bmatrix} \vec{\mathbf{R}}_{1} \cdot \vec{\mathbf{x}} \\ \vec{\mathbf{R}}_{2} \cdot \vec{\mathbf{x}} \\ \vdots \\ \vec{\mathbf{R}}_{m} \cdot \vec{\mathbf{x}} \end{bmatrix}$$

$$Row A := span \{ \mathbf{R}_{1}, \mathbf{R}_{2}, \dots \mathbf{R}_{m} \} \subseteq \mathbb{R}^{n}. \qquad \begin{array}{c} \vdots \int \mathbf{A} \cdot \vec{\mathbf{x}} = \vec{\mathbf{0}} \\ \vdots \int \mathbf{A} \cdot \vec{\mathbf{x}} = \vec{\mathbf{0}} \\ \vec{\mathbf{x}} \perp \text{ each var} \cdot \vec{\mathbf{0}} \end{bmatrix} \mathbf{A}$$

then

And, Row $A \perp Nul A$.

As we do elementary operations on the rows of *A* we don't change their span, so we get a great basis for *Row A* by using the non-zero rows of *rref*(*A*)...as in your food for thought this past Friday, and this week's homework. So, the dimension of Row(A) is *p*, the number of pivots in the reduced matrix. So in the domain \mathbb{R}^n , we have this picture:

$$dim (Nul A) = n - p$$

$$dim (Row A) = p$$

$$Nul A \perp Row A.$$

The final subspace lives in the codomain \mathbb{R}^m , along with *Col A*. Well, *Col A* = *Row A^T*. And so *Nul A^T* is the final subspace. Since *A^T* has *m* columns an *p* pivots, there are *m* - *p* free parameters when we solve $A^T \mathbf{y} = 0$, so *dim*(*Nul A^T*) = *m* - *p* and in the codomain \mathbb{R}^m we have this picture:

$$Col A = Row(A^{T})$$
$$dim(Row A^{T}) = p$$
$$dim(Nul A^{T}) = m - p$$
$$Nul A^{T} \perp Row A^{T}.$$

small example.



Here's a schematic of what's going on, stolen from the internet. The web site I stole it from looks pretty good....





More details on the decompositions In the domain \mathbb{R}^n , the two subspaces associated to *A* are *Row A* and *Nul A*. Notice that the only vector in their intersection is the zero vector, since

$$\underline{x} \in Row A \cap Nul A \quad \Rightarrow \underline{x} \cdot \underline{x} = 0 \quad \Rightarrow \underline{x} = \underline{0}$$

So, let

 $\{\underline{\boldsymbol{u}}_1, \underline{\boldsymbol{u}}_2, \dots \underline{\boldsymbol{u}}_p\}$ be a basis for *Row A*

$$\{\underline{v}_1, \underline{v}_2, \dots \underline{v}_{n-p}\}$$
 be a basis for *Nul A*.

Then we can check that set of *n* vectors obtained by taking the union of the two sets,

$$\left\{\underline{\boldsymbol{u}}_{1}, \underline{\boldsymbol{u}}_{2}, \dots \underline{\boldsymbol{u}}_{p}, \underline{\boldsymbol{v}}_{1}, \underline{\boldsymbol{v}}_{2}, \dots \underline{\boldsymbol{v}}_{n-p}\right\}$$

is actually a basis for \mathbb{R}^n . This is because we can show that the *n* vectors in the set are linearly independent, so they automatically span \mathbb{R}^n and are a basis: To check independence, let

$$c_1 \underline{\boldsymbol{\mu}}_1 + c_2 \underline{\boldsymbol{\mu}}_2 + \dots + c_p \underline{\boldsymbol{\mu}}_p + d_1 \underline{\boldsymbol{\nu}}_1 + d_2 \underline{\boldsymbol{\nu}}_2 + \dots + d_{n-p} \underline{\boldsymbol{\nu}}_{n-p} = \underline{\boldsymbol{0}}.$$

then

$$c_1 \underline{\boldsymbol{u}}_1 + c_2 \underline{\boldsymbol{u}}_2 + \dots + c_p \underline{\boldsymbol{u}}_p = -d_1 \underline{\boldsymbol{v}}_1 - d_2 \underline{\boldsymbol{v}}_2 - \dots - d_{n-p} \underline{\boldsymbol{v}}_{n-p}$$

Since the vector on the left is in *Row A* and the one that it equals on the right is in *Nul A*, this vector is the zero vector:

$$c_1 \underline{\boldsymbol{u}}_1 + c_2 \underline{\boldsymbol{u}}_2 + \dots + c_p \underline{\boldsymbol{u}}_p = \underline{\boldsymbol{0}} = -d_1 \underline{\boldsymbol{v}}_1 - d_2 \underline{\boldsymbol{v}}_2 - \dots - d_{n-p} \underline{\boldsymbol{v}}_{n-p}.$$

Since $\{\underline{u}_1, \underline{u}_2, \dots, \underline{u}_p\}$ and $\{\underline{v}_1, \underline{v}_2, \dots, \underline{v}_{n-p}\}$ are linearly independent sets, we deduce from these two equations that

$$c_1 = c_2 = \dots = c_p = 0,$$
 $d_1 = d_2 = \dots = d_{n-p} = 0.$

O.E.D.

So the picture on the previous page is completely general, also for the decomposition of the codomain. One can check that the transformation $T(\underline{x}) = A \underline{x}$ restricts to an isomorphism from *Row A* to *Col A*, because it is 1 - 1 on these subspaces of equal dimension, so must also be onto. So, *T* squashes *Nul A*, and maps every translation of *Nul A* to a point in *Col A*. More precisely, Each

$$\underline{x} \in \mathbb{R}^n$$

can be written uniquely as

$$\underline{x} = \underline{u} + \underline{v}$$
 with $\underline{u} \in Row A$, $\underline{v} \in Nul A$.

and

$$T(\underline{u} + \underline{v}) = T(\underline{u}) + T(\underline{v}) = T(\underline{u}) \in Col(A)$$

As sets,

$$T(\{\underline{\boldsymbol{u}} + NulA\}) = T(\underline{\boldsymbol{u}}).$$