

Linear independence, spanning sets, bases, dimension

Before we start: Poll questions

- I'm a little confused on Theorem 6 in 1.4. The theorem itself makes sense, I'm just a bit confused on the wording within the proof. Going over it in lecture might help me to understand.

Theorem 6. *If A is an $m \times n$ matrix and $m < n$, then the homogeneous system of linear equations $AX = 0$ has a non-trivial solution.*

Proof. Let R be a row-reduced echelon matrix which is row-equivalent to A . Then the systems $AX = 0$ and $RX = 0$ have the same solutions by Theorem 3. If r is the number of non-zero rows in R , then certainly $r \leq m$, and since $m < n$, we have $r < n$. It follows immediately from our remarks above that $AX = 0$ has a non-trivial solution. ■

Before we start: Poll questions

- If every injective and surjective matrix is invertible, is every invertible matrix injective and surjective?

Suppose that we have a vector space V over a field F . We'd like to treat V like F^n . What do we need in order to do so?

Suppose that we have a vector space V over a field F . We'd like to treat V like F^n . What do we need in order to do so?

We need to find some vectors in V which we can treat like the vectors $\begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ \vdots \\ 0 \end{bmatrix}, \dots, \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 1 \end{bmatrix}$. These vectors, call them $\vec{u}_1, \vec{u}_2, \dots, \vec{u}_n$, should have two properties:

Spanning Every vector \vec{v} in V should be expressible as $a_1\vec{u}_1 + a_2\vec{u}_2 + \dots + a_n\vec{u}_n$ for some scalars a_1, a_2, \dots, a_n in F .

Linearly Independent No vector in V should be expressible as $a_1\vec{u}_1 + a_2\vec{u}_2 + \dots + a_n\vec{u}_n$ in two different ways.

Example

Let L be the plane $x + y + z = 0$ in \mathbb{R}^3 .

- If we take $\vec{u}_1 = \begin{bmatrix} 1 \\ -1 \\ 0 \end{bmatrix}$, then many vectors in L are not multiples of \vec{u}_1 . **Linearly independent, but not spanning.**
- If we take $\vec{u}_1 = \begin{bmatrix} 1 \\ -1 \\ 0 \end{bmatrix}$, $\vec{u}_2 = \begin{bmatrix} 0 \\ 1 \\ -1 \end{bmatrix}$, $\vec{u}_3 = \begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix}$, then $\vec{u}_3 = \vec{u}_1 + \vec{u}_2$, so vectors can be expressed in more than one way. **Spanning, but not linearly independent.**
- If $\vec{u}_1 = \begin{bmatrix} 1 \\ -1 \\ 0 \end{bmatrix}$, $\vec{u}_2 = \begin{bmatrix} 0 \\ 1 \\ -1 \end{bmatrix}$, then every vector in L can be written in exactly one way as a linear combination of \vec{u}_1 and \vec{u}_2 . Namely, $\begin{bmatrix} x \\ y \\ z \end{bmatrix} = x \begin{bmatrix} 1 \\ -1 \\ 0 \end{bmatrix} + (x + y) \begin{bmatrix} 0 \\ 1 \\ -1 \end{bmatrix}$. **Both spanning and linearly independent**

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A linearly independent set is “not too big”. A spanning set is “not too small”. A list of vectors which is both linearly independent and spanning is called a *basis*.

More on linear independence

Linear independence can be defined in a less intuitive but more useful way:

Theorem: Let $\vec{u}_1, \vec{u}_2, \dots, \vec{u}_n$ be a list of vectors in a vector space V . Then the following conditions are equivalent:

1. For every vector \vec{v} in V , there is **at most** one way to write \vec{v} as $a_1\vec{u}_1 + a_2\vec{u}_2 + \dots + a_n\vec{u}_n$ for some scalars a_1, a_2, \dots, a_n in F .
2. The only solution to $c_1\vec{u}_1 + c_2\vec{u}_2 + \dots + c_n\vec{u}_n = \vec{0}$ is $c_1 = c_2 = \dots = c_n = 0$.

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Remember our example of a set which was not linearly independent:

$$\vec{u}_1 = \begin{bmatrix} 1 \\ -1 \\ 0 \end{bmatrix}, \vec{u}_2 = \begin{bmatrix} 0 \\ 1 \\ -1 \end{bmatrix}, \vec{u}_3 = \begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix}. \text{ We have } \vec{u}_1 + \vec{u}_2 - \vec{u}_3 = \vec{0}.$$

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Proof: NOT(2) \implies NOT(1): If $c_1\vec{u}_1 + c_2\vec{u}_2 + \dots + c_n\vec{u}_n = \vec{0}$ then $c_1\vec{u}_1 + c_2\vec{u}_2 + \dots + c_n\vec{u}_n = 0\vec{u}_1 + 0\vec{u}_2 + \dots + 0\vec{u}_n$, so we have two ways to write $\vec{0}$ as a linear combination of the \vec{u}_i .

NOT(1) \implies NOT(2): Suppose that

$a_1\vec{u}_1 + \dots + a_n\vec{u}_n = b_1\vec{u}_1 + \dots + b_n\vec{u}_n$ for

$(a_1, a_2, \dots, a_n) \neq (b_1, b_2, \dots, b_n)$. Then

$$(a_1 - b_1)\vec{u}_1 + (a_2 - b_2)\vec{u}_2 + \dots + (a_n - b_n)\vec{u}_n = \vec{0}. \quad \square$$

More on spanning

If V is any vector space and X is a subset of V , the *span* of X is the set of all linear combinations $\sum a_i \vec{v}_i$ for scalars a_1, a_2, \dots, a_n and for $\vec{v}_1, \vec{v}_2, \dots, \vec{v}_n$ in X .

We write $\text{Span}(X)$ for the span of X . $\text{Span}(X)$ is a subspace of X .

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Lemma: If Y spans V , and Y is in $\text{Span}(X)$, then X spans V .

Proof: Let \vec{v} be in V . Write $\vec{v} = \sum_i a_i \vec{y}_i$ for \vec{y}_i in Y . Write $\vec{y}_i = \sum_j b_{ij} \vec{x}_j$. Then

$$\vec{v} = \sum_i a_i \left(\sum_j b_{ij} \vec{x}_j \right) = \sum_j \left(\sum_i a_i b_{ij} \right) \vec{x}_j.$$

So \vec{v} is a linear combination of vectors \vec{x}_j in X . \square

Since we want to work with infinite dimensional vector spaces, we also have definitions for infinite sets. Let V be a vector space and let X be a subset of V .

Definition: We say that X is *linearly independent* if there is not a finite subset $\{\vec{u}_1, \vec{u}_2, \dots, \vec{u}_n\}$ of X for which there are coefficients c_1, c_2, \dots, c_n , not all zero, with $c_1\vec{u}_1 + c_2\vec{u}_2 + \dots + c_n\vec{u}_n$.

Definition: We say that X is *spans* V if, for every \vec{v} in V , there is a finite subset $\{\vec{u}_1, \vec{u}_2, \dots, \vec{u}_n\}$ of X and coefficients a_1, a_2, \dots, a_n with $\vec{v} = a_1\vec{u}_1 + a_2\vec{u}_2 + \dots + a_n\vec{u}_n$.

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Note that we never talk about infinite sums of vectors. If our vector space is F^∞ , we would **not** say

$$(1, 1, 1, \dots) = (1, 0, 0, \dots) + (0, 1, 0, \dots) + (0, 0, 1, \dots) + \dots$$

because we wouldn't write down the right hand side at all.

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Definition: We say that X is a *basis* of V if it is both linearly independent and spans V .

To repeat again:

A linearly independent set can express each vector in **at most** one way. It is **not too big**.

A spanning set can express each vector in **at least** one way. It is **not too small**.

A basis can express each vector in **at most** one way. It is **just right**.

Key Lemma: Let V be a vector space. Let $\vec{u}_1, \vec{u}_2, \dots, \vec{u}_p$ be a spanning set, and let $\vec{v}_1, \vec{v}_2, \dots, \vec{v}_q$ be linearly independent. Then $p \geq q$.

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Now, suppose for the sake of contradiction that $p < q$. Consider the p equations in q variables:

$$\begin{array}{cccccc} A_{11}c_1 & + & A_{12}c_2 & + & \cdots & + & A_{1q}c_q & = & 0 \\ A_{21}c_1 & + & A_{22}c_2 & + & \cdots & + & A_{2q}c_q & = & 0 \\ & & & & & & \vdots & & \\ A_{p1}c_1 & + & A_{p2}c_2 & + & \cdots & + & A_{pq}c_q & = & 0 \end{array}$$

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Since $p < q$, they have a nonzero solution. Then,

$$\sum_j c_j \vec{v}_j = \sum_j c_j \left(\sum_i A_{ij} \vec{u}_i \right) = \sum_i \left(\sum_j A_{ij} c_j \right) \vec{u}_i = \sum_i 0 \vec{u}_i = \vec{0}.$$

This contradicts that the \vec{v} 's are supposed to be linearly independent. \square

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In other words: Any spanning set is larger than any linearly independent set.

Corollary: If $\vec{u}_1, \vec{u}_2, \dots, \vec{u}_p$ and $\vec{v}_1, \vec{v}_2, \dots, \vec{v}_q$ are both bases, then $p = q$.

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Proof: Since $\vec{u}_1, \vec{u}_2, \dots, \vec{u}_p$ is a basis, it is a spanning set; since $\vec{v}_1, \vec{v}_2, \dots, \vec{v}_q$ is a basis, it is linearly independent. So $p \geq q$.

But, switching the roles of \vec{u} and \vec{v} , we also have $p \leq q$. \square

Corollary: If $\vec{u}_1, \vec{u}_2, \dots, \vec{u}_p$ and $\vec{v}_1, \vec{v}_2, \dots, \vec{v}_q$ are both bases, then $p = q$.

We define the *dimension* of a vector space to be the number of elements in any basis. We say that a vector space is *finite dimensional* if it has a finite basis.

Which vector spaces have bases?

To see that there is an issue, notice that \mathbb{R} is a \mathbb{Q} vector space. It is hard to imagine that there is some set of real number B such that every real number is expressible in exactly one way as a rational linear combination of numbers from B .

To give another example, let \mathbb{R}^∞ be the vector space of all sequences (a_1, a_2, a_3, \dots) of real numbers. The vectors $(1, 0, 0, \dots)$, $(0, 1, 0, \dots)$, $(0, 0, 1, \dots)$ are linearly independent, but they don't span. It is not at all clear whether we could expand this list to give a basis.

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Whether or not you think all vector spaces have bases comes down to a question about the foundations of mathematics; if you believe in a claim called the "Axiom of Choice", then they do, otherwise, it isn't clear.

Which vector spaces have bases?

Without addressing this issue, here are two theorems which say that, in finite dimensions, there is no issue:

Theorem Let V be a finite dimensional vector space and let W be a subspace of V . Then W has a finite basis.

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We claim that B is a basis of W . We built B to be linearly independent, so the challenge is to show that it spans.

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Let \vec{w} be in W . If \vec{w} is in B , then clearly \vec{w} is in $\text{Span}(B)$.

If \vec{w} is not in B , then $B \cup \{\vec{w}\}$ must be linearly dependent. Say

$$a\vec{w} + \sum c_i \vec{b}_i = \vec{0}$$

for \vec{b}_i in B . Moreover, a must be nonzero, as B is linearly independent. Then

$$\vec{w} = -\frac{1}{a} \sum c_i \vec{b}_i$$

so \vec{w} is in $\text{Span}(B)$, as required. \square

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First, we show that S is in $\text{Span}(B)$. Let \vec{s} be in S . As before, if \vec{s} is in B , then obviously $\vec{s} \in \text{Span}(B)$. And, if \vec{s} is not in B , then $B \cup \{\vec{s}\}$ is linearly dependent and we use this to show that \vec{s} is in $\text{Span}(B)$.

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So S is in $\text{Span}(B)$, and $\text{Span}(S) = V$. But then B spans V , from our lemma from before. \square

Remark: These last two theorems were one of the first times we really needed to divide.

Suppose that we tried to do linear algebra with our scalars being the integers \mathbb{Z} . Let $V = \mathbb{Z}^2$, and consider $\vec{v}_1 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$, $\vec{v}_2 = \begin{bmatrix} 2 \\ 0 \end{bmatrix}$ and $\vec{v}_3 = \begin{bmatrix} 0 \\ 3 \end{bmatrix}$. Then one can check that \vec{v}_1 , \vec{v}_2 and \vec{v}_3 span \mathbb{Z}^2 . (Hint: $\begin{bmatrix} 1 \\ 0 \end{bmatrix} = 3\vec{v}_1 - \vec{v}_2 - \vec{v}_3$, $\begin{bmatrix} 0 \\ 1 \end{bmatrix} = -2\vec{v}_1 + \vec{v}_2 + \vec{v}_3$.) They are not linearly independent, since $6\vec{v}_1 = 3\vec{v}_2 + 2\vec{v}_3$.

However, no two of the \vec{v}_i span \mathbb{Z}^2 ! If $\begin{bmatrix} x \\ y \end{bmatrix}$ is in $\text{Span}(\vec{v}_1, \vec{v}_2)$ then $x - y$ is divisible by 2; if $\begin{bmatrix} x \\ y \end{bmatrix}$ is in $\text{Span}(\vec{v}_1, \vec{v}_3)$ then $x - y$ is divisible by 3 and, if $\begin{bmatrix} x \\ y \end{bmatrix}$ is in $\text{Span}(\vec{v}_2, \vec{v}_3)$, then x is even and y is divisible by 3. So none of these pairs spans all of \mathbb{Z}^2 .

This is a first example to show that linear algebra over a field is much nicer than linear algebra over what is called a ring. If you like studying hard, interesting, things, take commutative algebra! If you like studying easy, useful things, study linear algebra!