

Introduction to Mathematics for Political Science: Linear Spaces

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Suppose we observe some features of N countries related to their level of social and economic development. Each observation (a country) can be represented as a vector, where each element corresponds to a unique feature (life expectancy, per capita gdp, literacy rate, etc). Together, these countries constitute a set. Now suppose, due to poor data quality, we need to predict a country's per capita gdp after observing its life expectancy and literacy rate. By assuming that these data live in a broader *space*, we can extrapolate out of our set and "fill in the blanks." We only observe N countries, but we can consider a broader universe of countries that might have different features than the ones we observe. What allows us to do this extrapolation is the assumption that our data are drawn from a *linear space*, whose elements obey the familiar laws of arithmetic and algebra. Transformations of elements within and between linear spaces is at the core of applied data analysis. We seek to understand how these spaces work today. This lecture will work to unify your self-study of linear algebra with the more abstract notions of sets and spaces we've been studying in the last few days. In the next lecture, we'll attach a metric to these spaces to build "normed linear spaces."

A few preliminaries. As we've been doing so far, we'll use uppercase letters to denote sets and spaces (e.g. A subset of a linear space X will be expressed $S \subset X$). Elements of these sets will be bolded, as they may be multidimensional (e.g. $\mathbf{x} = (x_1, \dots, x_n)$). \mathbb{R} is the set of real numbers, \mathbb{R}^2 two-dimensional real space, and \mathbb{R}^n is n -dimensional real space. We'll start with things we know something about – sets and their elements.

Convex Sets

Definition: A set is *convex* if for all elements $\mathbf{x}, \mathbf{y} \in S$

$$\alpha \mathbf{x} + (1 - \alpha) \mathbf{y} \in S$$

for all $\alpha \in [0, 1]$.

The geometric intuition for convexity is straightforward. For a set to be convex, we must be able to connect any two points of the set with a straight line without leaving the set.¹ The line segment $\alpha \mathbf{x} + (1 - \alpha) \mathbf{y}$ is a *convex combination* of the elements \mathbf{x} and \mathbf{y} .² We can generalize this definition to combinations of many elements.

¹ What are a few shapes (or fruits) that are convex? Nonconvex?

² What subsets of \mathbb{R} are convex? Is $[0, 1]$ convex? $[0, 1] \cup [2, 3]$? $(0, 1)$?

Definition: A *convex combination* is a finite sum of $x_i \in S$

$$\alpha_1 x_1 + \dots + \alpha_n x_n$$

with $\sum_{i=1}^n \alpha_i = 1$.

For a set to be convex, it must contain all convex combinations of any points taken from it. Convex combinations are weighted averages of a set of elements.³ The set of all convex combinations of elements of a set.

³ How would one express a sample mean as a convex combination of values?

Definition: The convex hull of a set of elements $\{x_1, \dots, x_n\} \in S$ is

$$\{\alpha_1 x_1 + \dots + \alpha_n x_n\}$$

for all $\{\alpha_1, \dots, \alpha_n \mid \sum_{i=1}^n \alpha_i = 1\}$

Example: What is the convex hull of two points $a, b \in \mathbb{R}$?

Example: What is the convex hull of $\{(0, 0), (0, 1), (1, 1)\} \in \mathbb{R}^2$?

Linear Spaces

Linear spaces are sets whose elements can be combined and scaled while remaining in the set. \mathbb{R} and \mathbb{R}^n are the most common linear spaces, so the properties of linear spaces will be familiar to you – they’re the core arithmetic and algebraic rules you’ve been working with since primary school. \mathbb{R} and \mathbb{R}^n aren’t the only linear spaces, though. Formally, a linear space X satisfies the following axioms.

Additivity: For all $x, y \in X$, there is another element $x + y \in X$ with the following properties:

1. Commutativity: $x + y = y + x$
2. Associativity: $(x + y) + z = x + (y + z)$
3. Zero Element: There exists an element $0 \in X$ such that $x + 0 = x$
4. Negative: For every $x \in X$ there also exists a unique $-x \in X$ such that $x + (-x) = 0$.

Homogeneity: For all $x \in X$ and scalars $\alpha, \beta \in \mathbb{R}$, there exists an element $\alpha x \in X$ such that:

5. $(\alpha\beta)x = \alpha(\beta x)$
6. $1x = x$

Distributive Property:

7. $\alpha(x + y) = \alpha x + \alpha y$
8. $(\alpha + \beta)x = \alpha x + \beta x$

Example: “Construct” \mathbb{R} , starting with the numbers 4, 9.⁴

Linear spaces are also referred to as *vector spaces*. Why? Because their elements can always be expressed as vectors.⁵

Example: “Construct” \mathbb{R}^2 , starting with the vectors (2, 1) and (1, 4).

I mentioned $\mathbb{R}^1, \dots, \mathbb{R}^n$ weren’t the only linear spaces. The scalar 0, or any vector of zeros are also linear spaces.⁶ The set of all diagonal matrices

$$\begin{bmatrix} a & 0 \\ 0 & b \end{bmatrix}$$

is also a vector space.⁷ What are some examples of spaces that *are not* vector spaces?⁸

Unlike convex sets, which include all convex combinations of their elements, the axioms defining linear spaces imply that they contain all *linear combinations* of their elements.

Definition: A linear combination is a finite sum of $x_i \in S$

$$\alpha_1 x_1 + \dots + \alpha_n x_n$$

with $x_1, \dots, x_n \in S$ and $\alpha_1, \dots, \alpha_n \in \mathbb{R}$.⁹

Convex hulls also have cousins in linear spaces.

Definition: A *linear hull* or *span* of a set of elements $\{x_1, \dots, x_n\} \in S$ is

$$\{\alpha_1 x_1 + \dots + \alpha_n x_n\}$$

for all $\alpha_1, \dots, \alpha_n \in \mathbb{R}$

Example: We can plot the vectors (1, 0, 1) and (0, 1, 1)

Taking all linear combinations of these vectors gives a separating plane through \mathbb{R}^3

Example: What is the linear hull of the vectors $(-1, -1), (1, 1) \in \mathbb{R}^2$?

We’ll usually think about our data as living in a vector space, where each observation (x_1, \dots, x_n) is an element. Note, however, that this requires that certain things be true of the underlying data-generating process.¹⁰

Linear Subspaces

A plane is a linear space. Within a plane are infinitely many lines that pass through the origin. These lines are *linear subspaces* of the plane,

⁴ In other words, if $4, 9 \in \mathbb{R}$ and \mathbb{R} is a linear space, what other elements must be included in \mathbb{R} in order to satisfy the axioms.

⁵ How would you write a convex combination of $\{x_1, \dots, x_n\}$ in vector notation?

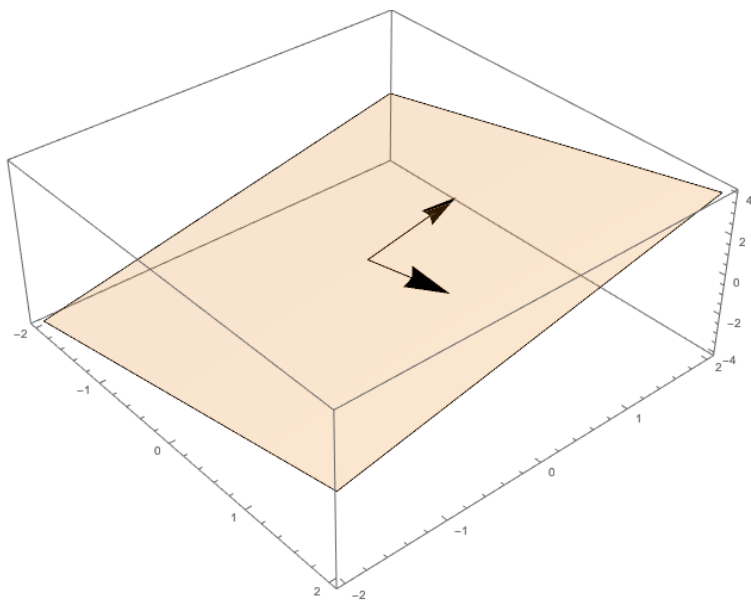
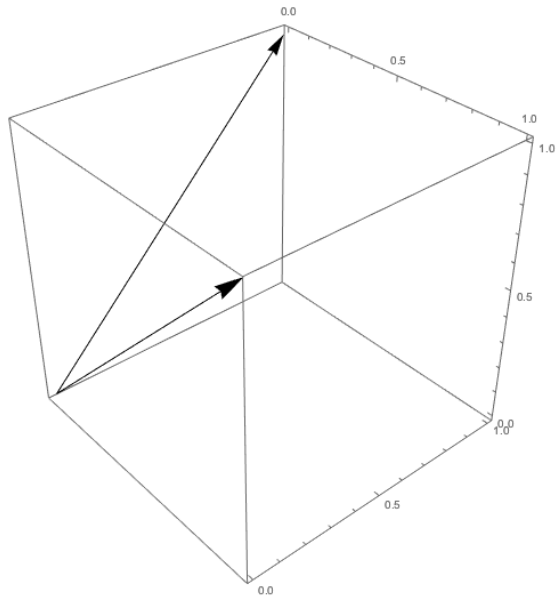
⁶ See for yourself, verify each of the axioms.

⁷ Apply the rules of matrix addition and multiplication to see why this is true.

⁸ Are the integers (\mathbb{Z}) a linear space? What about the rationals (\mathbb{Q})? Why or why not?

⁹ Compare this to the definition of a *convex combination*. How do the definitions differ?

¹⁰ E.g. data can take on negative values, they can be scaled up or scaled down, etc.



because they themselves are linear spaces, and all of their points are contained within the plane.

Definition: A subset S of a linear space X is a *linear subspace* of X if for every $x, y \in S$,

$$\alpha x + \beta y \in S$$

for $\alpha, \beta \in \mathbb{R}$.

Example: Show that linear subspaces are themselves linear spaces.

Example: What are the linear subspaces of \mathbb{R}^3 ?

Linear Independence

We briefly studied linear independence in the context of finding solutions to systems of linear equations of the form

$$Ax = b$$

If two rows of A were *linearly dependent*, then $Ax = b$ will not have a unique solution and is said to be *underdetermined*.

Now that we have a working understanding of linear spaces, we can think about *linear dependence* in terms of linear spaces and subspaces. When we solve $Ax = b$, we are attempting to express b as a linear combination of elements of A . So b must be in the linear space generated by linear combinations of elements of A .

Definition: An element y is *linearly dependent* on a set of vectors $x_1, \dots, x_n \in S$ if y is in the linear hull of S , or there exists $\alpha_1, \dots, \alpha_n \in \mathbb{R}$ such that

$$\alpha_1 x_1 + \dots + \alpha_n x_n = y$$

Example: Consider the system

$$\begin{bmatrix} 1 & 2 \\ 2 & 4 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 3 \\ 6 \end{bmatrix}$$

Show that the rows the matrix are linearly dependent. What does this imply about the solution vector (x_1, x_2) ?

Example: Now consider

$$\begin{bmatrix} 1 & 2 \\ 2 & 4 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 3 \\ 3 \end{bmatrix}$$

What is the linear hull generated by the vectors of A ? Is b in this space? What does this imply about the solution vector (x_1, x_2) ?

Definition: The *null space* of a set of vectors $\{x_1, \dots, x_n\} \in S$ is the set of vectors α such that

$$\alpha_1 x_1 + \dots + \alpha_n x_n = 0$$

The zero vector $\alpha = 0$ is trivially in the null space. If any nonzero vector is in the nullspace, then the vectors x_1, \dots, x_n are linearly dependent.¹¹

A *simplex* combines our definitions of convex sets and linear independence, so we introduce them here.

Definition: A *simplex* is the *convex hull* of a set of *linearly independent* vectors.¹²

Simplexes play important roles in game theory. *Mixed strategies* are convex combinations (probabilities that sum to one) of independent strategies.¹³ Multivariate proportions can also be expressed as simplexes, see Figure 1.

¹¹ The proof of this claim is left as an exercise.

¹² Use the definitions of convex hull and linear independence to write a definition that does not rely on prior knowledge of these concepts.

¹³ Think of a strategy in “Rock, Paper, Scissors.”

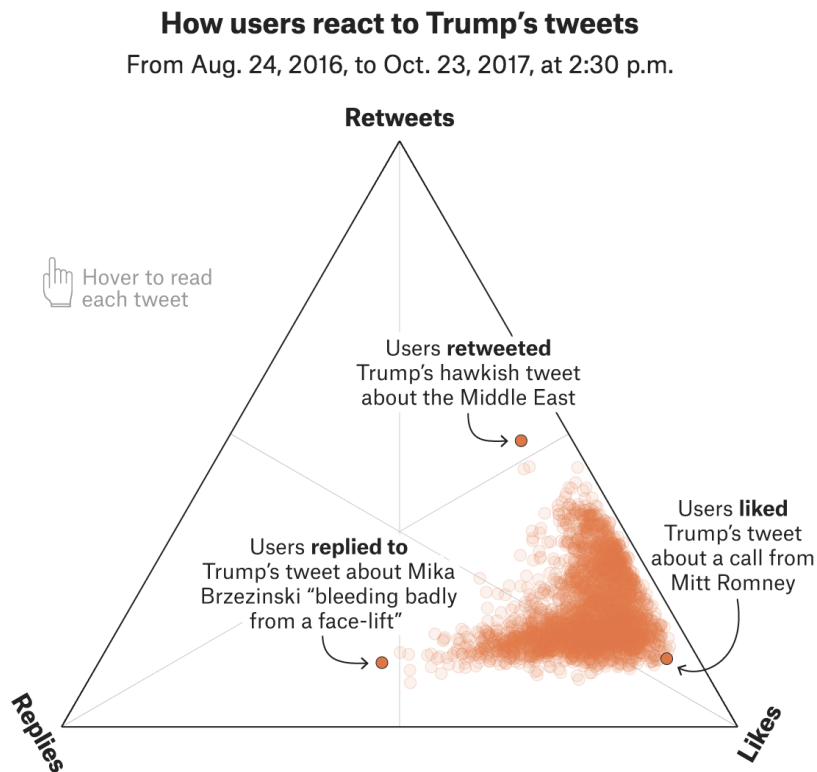


Figure 1: *FiveThirtyEight*, “The Worst Tweeter In Politics Isn’t Trump.” 24 October 2017.

Basis and Dimension

A basis is a set of independent vectors from which a given linear space can be constructed. You give me the set of vectors, and I can construct the linear space by applying the additivity and homogeneity axioms. In other words, all other elements of the space are linearly dependent on the basis vectors.

Definition: A *basis* for a linear space X is a set $y_1, \dots, y_n \in S$ such that for all $x \in X$,

$$\alpha_1 y_1 + \dots + \alpha_n y_n = x$$

Example: List some bases for \mathbb{R}^2 .¹⁴

Example: Are the vectors $(1, 1, 1), (0, 1, 1), (0, 0, 1)$ a basis for \mathbb{R}^3 ?

The easiest basis to visualize and work with is the *standard basis*, or the set of independent *unit vectors*. In the case of \mathbb{R}^2 , the vectors $(1, 0), (0, 1)$ are the standard basis.

Definition: The *dimension* of a linear space X is the number of elements in its bases.¹⁵

Note: The dimension of the linear space occupied by the vectors in a matrix

$$A = \begin{bmatrix} x_1 \\ \dots \\ x_n \end{bmatrix}$$

depends not on the number of rows (n) or columns, but on the number of *independent* rows.

¹⁴ Remember, we need vectors from which we can reconstruct by vector addition and scaling all of the 2-dimensional real space.

¹⁵ We now have a more formal definition accompanying our intuition for the dimension $\mathbb{R}^2, \mathbb{R}^3$, and \mathbb{R}^n .

Affine Set

Axiom 3 distinguishes linear spaces from their cousins, affine sets. Affine sets are like vector spaces, except we don't require that the zero vector, (the "origin"), is included in the space. Geometrically, this includes lines, planes, and *hyperplanes* that may or may not pass through the origin

Definition: An *affine set* is a subset S of a linear space X such that for all $x, y \in S$ and $\alpha \in \mathbb{R}$,

$$\alpha x + (1 - \alpha)y \in S$$

Example: Name all affine subsets of \mathbb{R}^3 .

Affine sets are really just linear spaces that have been shifted from the zero vector.¹⁶ Affine sets are said to be *parallel* to these linear spaces.

¹⁶ Verify that all of the axioms defining linear spaces hold for affine sets, except Axiom 3.

Remark: For each affine set S there exists a unique linear space X such that $S = x + X$ for some shifter $x \in S$.

Definition: Let an affine set S have dimension n . A *hyperplane* through S is a proper affine subset of S with dimension $n - 1$.

Example: What is a hyperplane in \mathbb{R}^3 ? \mathbb{R}^2 ?

Exercises

1. Prove the following: If a set S is convex, then all sets αS are also convex for all $\alpha \in \mathbb{R}$.¹⁷
2. Prove that if S_1 and S_2 are subspaces of a linear space X , then $S_1 + S_2$ is also a linear subspace of X .¹⁸
3. Prove that if S_1 and S_2 are subspaces of a linear space X , then $S_1 + S_2$ is the linear hull of $S_1 \cup S_2$.¹⁹
4. Prove the following: Any nonzero vector is in the nullspace of a set S iff (\iff) there exists a linearly dependent vector $y \in S$.

¹⁷ $x \in S \implies \alpha x \in \alpha S$ for all $\alpha \in \mathbb{R}$.
Carter 1.166

¹⁸ $x_1 \in S_1$ and $x_2 \in S_2$ implies $x_1 + x_2 \in S_1 + S_2$. Carter 1.131

¹⁹ Strang 3.1 #30.

References

- Moore, Will H. and David A. Siegel. *A Mathematics Course for Political and Social Research*. Chapters 4, 13.
- Strang, Gilbert. *Introduction to Linear Algebra*. Chapters 3, 4.
- Carter, Michael. *Foundations of Mathematical Economics*. Chapter 1.4.