

Linear Algebra


MAT223 Workbook



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Inquiry Based Linear Algebra

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About the Document

This document is a hybrid of many linear algebra resources, including those of the IOLA (Inquiry Oriented Linear Algebra) project and Jason Siefken's IBL Linear Algebra project.

This document is a mix of short problems and more involved exploratory question. A typical class day looks like:

1. **Introduction by instructor.** This may involve giving a definition, a broader context for the day's topics, or answering questions.
2. **Students work on problems.** Students work individually or in pairs/small groups on the prescribed problem. During this time the instructor moves around the room addressing questions that students may have and giving one-on-one coaching.
3. **Instructor intervention.** When most students have successfully solved the problem, the instructor refocuses the class by providing an explanation or soliciting explanations from students. This is also time for the instructor to ensure that everyone has understood the main point of the exercise (since it is sometimes easy to miss the point!).

If students are having trouble, the instructor can give hints and additional guidance to ensure students' struggle is productive.

4. **Repeat step 2.**

Using this format, students are thinking (and happily so) most of the class. Further, after struggling with a question especially primed to hear the insights of the instructor.

These problems are geared towards concepts instead of computation, though some problems focus on simple computation. The questions also have a geometric lean. Vectors are initially introduced with familiar coordinate notation, but eventually, coordinates are understood to be *representations* of vectors rather than “true” geometric vectors, and objects like the determinant are defined via oriented volumes rather than formulas involving matrix entries.

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Contributors

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Sets, Vectors & Notation

In this module you will learn

- The basics of sets and set-builder notation.
- The definition of vectors and how they relate to points.
- Column vector notation and to how represent vectors in drawings.
- How to compute linear combinations of vectors and use systems of linear equations to answer questions about linear combinations of vectors.

Sets

Modern mathematics makes heavy use of *sets*. A set is an unordered collection of distinct objects. We won't try and pin it down more than this—our intuition about collections of objects will suffice.¹ We write a set with curly-braces $\{$ and $\}$ and list the objects inside. For instance

$$\{1, 2, 3\}.$$

This would be read aloud as “the set containing the elements 1, 2, and 3.” Things in a set are called *elements*, and the symbol \in is used to specify that something is an element of a set. In contrast, \notin is used to specify something is not an element of a set. For example,

$$3 \in \{1, 2, 3\} \quad 4 \notin \{1, 2, 3\}.$$

Sets can contain mixtures of objects, including other sets. For example,

$$\{1, 2, a, \{-70, \infty\}, x\}$$

is a perfectly valid set.

It is tradition to use capital letters to name sets. So we might say $A = \{6, 7, 12\}$ or $X = \{7\}$. However there are some special sets which already have names/symbols associated with them. The *empty set* is the set containing no elements and is written \emptyset or $\{\}$. Note that $\{\emptyset\}$ is *not* the empty set—it is the set containing the empty set! It is also traditional to call elements of a set *points* regardless of whether you consider them “point-like” objects.

Operations on Sets

If the set A contains all the elements that the set B does, we call B a *subset* of A . Conversely, we call A a *superset* of B .

Subset & Superset. The set B is a *subset* of the set A , written $B \subseteq A$, if for all $b \in B$ we also have $b \in A$. In this case, A is called a *superset* of B .^a

^a Some mathematicians use the symbol \subset instead of \subseteq .

Some simple examples are $\{1, 2, 3\} \subseteq \{1, 2, 3, 4\}$ and $\{1, 2, 3\} \subseteq \{1, 2, 3\}$. There's something funny about that last example, though. Those two sets are not only subsets/supersets of each other, they're *equal*. As surprising as it seems, we actually need to define what it means for two sets to be equal.

Set Equality. The sets A and B are *equal*, written $A = B$, if $A \subseteq B$ and $B \subseteq A$.

Having a definition of equality to lean on will help us when we need to prove things about sets.

Example. Let A be the set of numbers that can be expressed as $2n$ for some whole number n , and let B be the set of numbers that can be expressed as $m + 1$ where m is an odd whole number. We will show $A = B$.

First, let us show $A \subseteq B$. If $x \in A$ then $x = 2n$ for some whole number n . Therefore

$$x = 2n = 2(n - 1) + 1 + 1 = m + 1$$

where $m = 2(n - 1) + 1$ is, by definition, an odd number. Thus $x \in B$, which proves $A \subseteq B$.

¹ When you pursue more rigorous math, you rely on definitions to get yourself out of philosophical jams. For instance, with our definition of set, consider “the set of all sets that don't contain themselves.” Such a set cannot exist! This is called *Russel's Paradox*, and shows that if we start talking about sets of sets, we may need more than intuition.

Now we will show $B \subseteq A$. Let $x \in B$. By definition, $x = m + 1$ for some odd m and so by the definition of oddness, $m = 2k + 1$ for some whole number k . Thus

$$\begin{aligned} x &= m + 1 = (2k + 1) + 1 = 2k + 2 \\ &= 2(k + 1) = 2n, \end{aligned}$$

where $n = k + 1$, and so $x \in A$. Since $A \subseteq B$ and $B \subseteq A$, by definition $A = B$.

Set-builder Notation

Specifying sets by listing all their elements can be a hassle, and if there are an infinite number of elements, it's impossible! Fortunately, *set-builder notation* solves these problems. If X is a set, we can define a subset

$$Y = \{a \in X : \text{some rule involving } a\},$$

which is read “ Y is the set of a in X *such that* some rule involving a is true.” If X is intuitive, we may omit it and simply write $Y = \{a : \text{some rule involving } a\}$.² You may equivalently use “|” instead of “:”, writing $Y = \{a \mid \text{some rule involving } a\}$.

There are also some common operations we can do with two sets.

Unions & Intersections. Two common set operations are **unions** and **intersections**. Let X and Y be sets.
(union) $X \cup Y = \{a : a \in X \text{ or } a \in Y\}$.

(intersection) $X \cap Y = \{a : a \in X \text{ and } a \in Y\}$.

For example, if $A = \{1, 2, 3\}$ and $B = \{-1, 0, 1, 2\}$, then $A \cap B = \{1, 2\}$ and $A \cup B = \{-1, 0, 1, 2, 3\}$. Set unions and intersections are *associative*, which means it doesn't matter how you apply parentheses to an expression involving just unions or just intersections. For example $(A \cup B) \cup C = A \cup (B \cup C)$, which means we can give an unambiguous meaning to an expression like $A \cup B \cup C$ (just put the parentheses wherever you like). But watch out, $(A \cup B) \cap C$ means something different than $A \cup (B \cap C)$!

Some common sets have special notation:

$$\begin{aligned} \emptyset &= \{\}, \text{ the empty set} \\ \mathbb{N} &= \{0, 1, 2, 3, \dots\} = \{\text{natural numbers}\} \\ \mathbb{Z} &= \{\dots, -3, -2, -1, 0, 1, 2, 3, \dots\} = \{\text{integers}\} \\ \mathbb{Q} &= \{\text{rational numbers}\} \\ \mathbb{R} &= \{\text{real numbers}\} \\ \mathbb{R}^n &= \{\text{vectors in } n\text{-dimensional Euclidean space}\} \end{aligned}$$

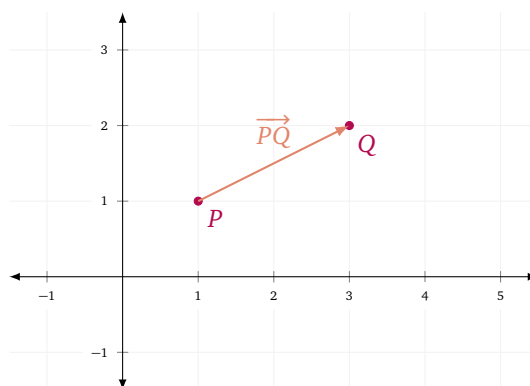
Vectors & Scalars

A *scalar* number (also referred to as a *scalar* or just an ordinary *number*) models a relationship between quantities. For example, a recipe might call for *six* times as much flour as sugar. In contrast, a *vector* models a relationship between points. For example, the store might be *2km East and 4km North* from my house. In this way, a vector may be thought of as a *displacement* with a *direction* and a *magnitude*.³

Given points $P = (1, 1)$ and $Q = (3, 2)$, we specify the *displacement* from P to Q as a vector \overrightarrow{PQ} whose magnitude is $\sqrt{5}$ (as given by the Pythagorean theorem) and whose direction is specified by a directed line segment from P to Q .

² If you want to get technical, to make this notation unambiguous, you define a *universe of discourse*. That is, a set \mathcal{U} containing every object you might want to talk about. Then $\{a : \text{some rule involving } a\}$ is short for $\{a \in \mathcal{U} : \text{some rule involving } a\}$

³ Though in this book we will treat vectors as geometric objects relating to Euclidean space, they are much more general. For instance, someone's internet browsing habits could be described by a vector—the topics they find most interesting might be the “direction” and the amount of time they browse might be the “magnitude.”

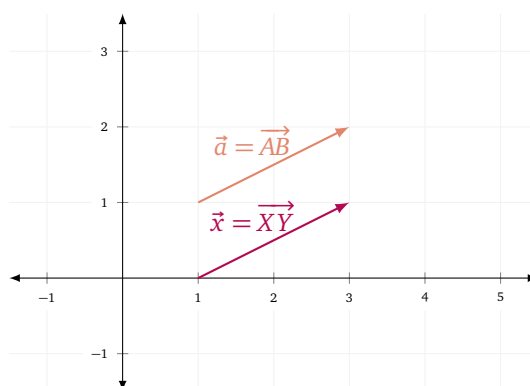


Vector Notation

There are many ways to represent vector quantities in writing. If we have two points, P and Q , we write \vec{PQ} to represent the vector from P to Q . Absent points, a bold-faced letter (like \mathbf{a}) or an arrow over a letter (like \vec{a}) are the most common vector notations. In this text, we will use \vec{a} to represent a vector. The notation $\|\vec{a}\|$ represents the magnitude of the vector \vec{a} , which is sometimes called the *norm* or *length* of \vec{a} .

Graphically, we may represent vectors as directed line segments (a line segment with an arrow at one end), however we must take care to distinguish between the picture we draw and the “true” vector. For example, directed line segments always *start* somewhere, but a vector models a displacement and has no sense of “origin”.

Consider the following: for the points $A = (1, 1)$, $B = (3, 2)$, $X = (1, 0)$, and $Y = (3, 1)$, define the vectors $\vec{a} = \vec{AB}$ and $\vec{x} = \vec{XY}$.



Are these the same or different vectors? As directed line segments, they are different because they are at different locations in space. However, both \vec{a} and \vec{x} have the same magnitude and direction. Thus, $\vec{a} = \vec{x}$ despite the fact that $A \neq X$.⁴

Takeaway. A vector is not the same as a line segment and a vector by itself has no “origin”.

Vectors and Points

The distinction between vectors and points is sometimes nebulous because the two are so closely related. A *point* in Euclidean space specifies an absolute position whereas a vector specifies a displacement (i.e., a magnitude and direction). However, given a point P , one associates P with the vector $\vec{p} = \vec{OP}$, where O is the origin. Similarly, we associate the vector \vec{v} with the point V so that $\vec{OV} = \vec{v}$. Thus, we have a way to unambiguously go back and forth between vectors and points.⁵ As such, *we will treat vectors and points interchangeably*.

⁴ Some theories use *rooted vectors* instead of vectors as the fundamental object of study. A rooted vector represents a magnitude, direction, and a starting point. And, as rooted vectors, $\vec{a} \neq \vec{x}$ (from the example above). But for us, vectors will always be unrooted, even though our graphical representations of vectors might appear rooted.

⁵ Mathematically, we say there is an *isomorphism* between vectors and points (once an origin is fixed, of course!).

Takeaway. Vectors and points can and will be treated interchangeably.

Vector Arithmetic

Vectors provide a natural way to give directions. For example, suppose \vec{e}_1 points one kilometer eastwards and \vec{e}_2 points one kilometer northwards. Now, if you were standing at the origin and wanted to move to a location 3 kilometers east and 2 kilometers north, you might say: “Walk 3 times the length of \vec{e}_1 in the \vec{e}_1 direction and 2 times the length of \vec{e}_2 in the \vec{e}_2 direction.” Mathematically, we express this as

$$3\vec{e}_1 + 2\vec{e}_2.$$

Of course, we’ve incidentally described a new vector. Namely, let P be the point at 3-east and 2-north. Then

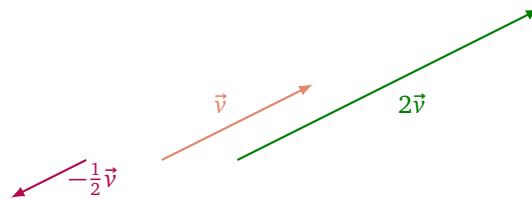
$$\overrightarrow{OP} = 3\vec{e}_1 + 2\vec{e}_2.$$

If the vector \vec{r} points north but has a length of 10 kilometers, we have a similar formula:

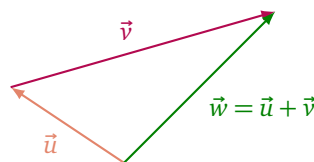
$$\overrightarrow{OP} = 3\vec{e}_1 + \frac{1}{5}\vec{r},$$

and we have the relationship $\vec{r} = 10\vec{e}_2$. Our notation here is very suggestive. Indeed, if we could make sense of “ $\alpha\vec{v}$ ” (scalar multiplication) and “ $\vec{v} + \vec{w}$ ” (vector addition) for any scalar α and any vectors \vec{v} and \vec{w} , we could do algebra with vectors.

We will define scalar multiplication and vector addition intuitively: For a vector \vec{v} and a scalar $\alpha > 0$, the vector $\vec{w} = \alpha\vec{v}$ is the vector pointing in the same direction as \vec{v} but with length scaled up by α . That is, $\|\vec{w}\| = \alpha\|\vec{v}\|$. Similarly, $-\vec{v}$ is the vector of the same length as \vec{v} but pointing in the exact opposite direction.



For two vectors \vec{u} and \vec{v} , the sum $\vec{w} = \vec{u} + \vec{v}$ represents the displacement vector created by first displacing along \vec{u} and then displacing along \vec{v} .



Takeaway. You add vectors tip to tail and you scale vectors by changing their length.

Now, there is one snag. What should $\vec{v} + (-\vec{v})$ be? Well, first we displace along \vec{v} and then we displace in the exact opposite direction by the same amount. So, we have gone nowhere. This corresponds to a displacement with zero magnitude. But, what direction did we displace? Here we make a philosophical stand.

Zero Vector. The **zero vector**, notated as $\vec{0}$, is the vector with no magnitude.

We will be pragmatic about the direction of the zero vector and say, *the zero vector does not have a well-defined direction*.⁶ That means sometimes we consider the zero vector to point in every direction and sometimes we consider it to point in no directions. It depends on our mood—but we must never talk about *the* direction of the zero vector, since it’s not defined.

Formalizing, for vectors \vec{u} , \vec{v} , \vec{w} and scalars α and β are scalars, the following are laws are always satisfied:

$$(\vec{u} + \vec{v}) + \vec{w} = \vec{u} + (\vec{v} + \vec{w}) \quad (\text{Associativity})$$

$$\vec{u} + \vec{v} = \vec{v} + \vec{u} \quad (\text{Commutativity})$$

$$\alpha(\vec{u} + \vec{v}) = \alpha\vec{u} + \alpha\vec{v} \quad (\text{Distributivity})$$

⁶ In the mathematically precise definition of vector, the idea of “magnitude” and “direction” are dropped. Instead, a set of vectors is defined to be a set over which you can reasonably define addition and scalar multiplication.

and

$$(\alpha\beta)\vec{v} = \alpha(\beta\vec{v}) \quad (\text{Associativity II})$$

$$(\alpha + \beta)\vec{v} = \alpha\vec{v} + \beta\vec{v} \quad (\text{Distributivity II})$$

Indeed, if we intuitively think about vectors in flat (Euclidean) space, all of these properties are satisfied.⁷ From now on, these properties of vector operations will be considered the *laws (or axioms) of vector arithmetic*.

We group scalar multiplication and vector addition under one name: *linear combinations*.

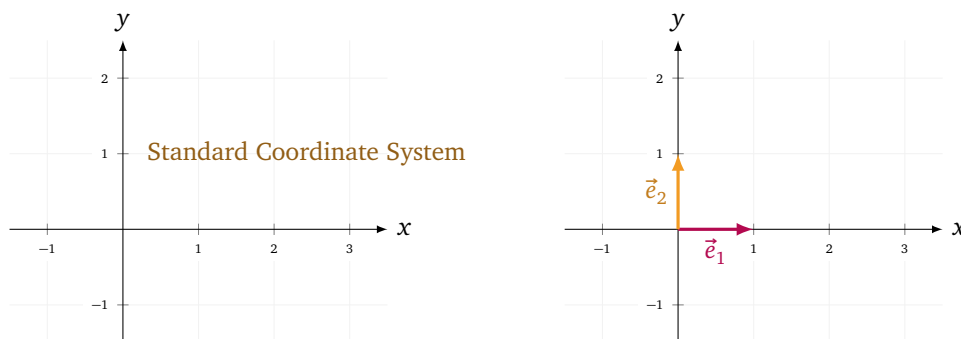
Linear Combination. A *linear combination* of the vectors $\vec{v}_1, \vec{v}_2, \dots, \vec{v}_n$ is a vector

$$\vec{w} = \alpha_1 \vec{v}_1 + \alpha_2 \vec{v}_2 + \dots + \alpha_n \vec{v}_n.$$

The scalars $\alpha_1, \alpha_2, \dots, \alpha_n$ are called the *coefficients* of the linear combination.

Coordinates and the Standard Basis

Consider the standard, flat, Euclidean plane (which is notated by \mathbb{R}^2). A coordinate system for \mathbb{R}^2 is a way to assign a unique pair of numbers to every point in \mathbb{R}^2 . Though there are infinitely many coordinate systems we could choose for the plane, there is one standard one: the *xy* coordinate system depicted below, which you're already familiar with.



In conjunction with the standard coordinate system, there are also *standard basis vectors*. The vector \vec{e}_1 always points one unit in the direction of the positive *x*-axis and \vec{e}_2 always points one unit in the direction of the positive *y*-axis.

Using the standard basis, we can represent every point (or vector) in the plane as a linear combination. If the point *P* has *xy*-coordinates (α, β) , then $\vec{OP} = \alpha\vec{e}_1 + \beta\vec{e}_2$. Not only that, but this is the *only* way to represent the vector \vec{OP} as a linear combination of α and β .

Takeaway. Every vector in \mathbb{R}^2 can be written uniquely as a linear combination of the standard basis vectors.

For a vector $\vec{w} = \alpha\vec{e}_1 + \beta\vec{e}_2$, we call the pair (α, β) the *standard coordinates* of the vector \vec{w} . There are many equivalent notations used to represent a vector in coordinates.

(α, β)	parenthesis
$\langle \alpha, \beta \rangle$	angle brackets
$\begin{bmatrix} \alpha & \beta \end{bmatrix}$	square brackets in a row (a row matrix)
$\begin{bmatrix} \alpha \\ \beta \end{bmatrix}$	square brackets in a column (a column matrix)

Coordinates and vectors go hand in hand, and we will often write

$$\vec{v} = \begin{bmatrix} \alpha \\ \beta \end{bmatrix}$$

as a shorthand for “ $\vec{v} = \alpha\vec{e}_1 + \beta\vec{e}_2$ ”.

⁷ If we deviate from flat space, some of these rules are no longer respected. Consider moving 100 kilometers north then 100 kilometers east on a sphere. Is this the same as moving 100 kilometers east and then 100 kilometers north?

Solving Problems with Coordinates

Coordinates allow for vector arithmetic to be carried out in a mechanical way. Suppose $\vec{u} = \begin{bmatrix} a \\ b \end{bmatrix}$ and $\vec{v} = \begin{bmatrix} x \\ y \end{bmatrix}$. Then,

$$\vec{u} = \vec{v} \iff \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} x \\ y \end{bmatrix} \iff a = x \text{ and } b = y.$$

Further,

$$\vec{u} + \vec{v} = \begin{bmatrix} a \\ b \end{bmatrix} + \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} a+x \\ b+y \end{bmatrix} \quad \text{and} \quad t\vec{v} = t \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} tx \\ ty \end{bmatrix}$$

for any scalar t .

Using these rules, otherwise complicated questions about vectors can be reduced to simple algebra questions.⁸

Example. Let $\vec{x} = \vec{e}_1 - \vec{e}_2$, $\vec{y} = 3\vec{e}_1 - \vec{e}_2$, and $\vec{r} = 2\vec{e}_1 + 2\vec{e}_2$. Is \vec{r} a linear combination of \vec{x} and \vec{y} ?

By definition, \vec{r} is a linear combination of \vec{x} and \vec{y} if there exist scalars a and b such that

$$\vec{r} = a\vec{x} + b\vec{y}.$$

We know that on the one hand,

$$\vec{r} = 2\vec{e}_1 + 2\vec{e}_2$$

and on the other hand,

$$\vec{r} = a\vec{x} + b\vec{y} = a(\vec{e}_1 - \vec{e}_2) + b(3\vec{e}_1 - \vec{e}_2) = (a + 3b)\vec{e}_1 + (a + b)\vec{e}_2.$$

Equating the two equations above, we have

$$2\vec{e}_1 + 2\vec{e}_2 = (a + 3b)\vec{e}_1 + (a + b)\vec{e}_2.$$

Therefore, solving the system

$$\begin{cases} a + 3b = 2 \\ a + b = -2 \end{cases},$$

we have $a = -4$ and $b = 2$ as the only solution. Thus, \vec{r} is a linear combination of \vec{x} and \vec{y} . More specifically,

$$\vec{r} = -4\vec{x} + 2\vec{y}.$$

Higher Dimensions

We coordinatize three dimensional space (notated by \mathbb{R}^3) by constructing x , y , and z axes. Again, \mathbb{R}^3 has standard basis vectors \vec{e}_1 , \vec{e}_2 , and \vec{e}_3 which each point one unit along the x , y , and z axes, respectively.

Since we live in three dimensional space, its study has a long history and many notations for the standard basis are in use. This text will use \vec{e}_1 , \vec{e}_2 , \vec{e}_3 , but other common notations include:

$$\begin{array}{ccc} \hat{x} & \hat{y} & \hat{z} \\ \hat{i} & \hat{j} & \hat{k} \\ \mathbf{i} & \mathbf{j} & \mathbf{k} \\ \vec{e}_1 & \vec{e}_2 & \vec{e}_3 \end{array}$$

Beyond three dimensions, drawing pictures becomes hard, but we can still use vectors. We use \mathbb{R}^n to notate n -dimensional Euclidean space. The standard basis for \mathbb{R}^n is $\vec{e}_1, \vec{e}_2, \dots, \vec{e}_n$. Again, every vector in \mathbb{R}^n can be written uniquely as a linear combination of the standard basis, and a coordinate representation of a vector in \mathbb{R}^n is the list of n scalars.

Example. Let $\vec{x}, \vec{y} \in \mathbb{R}^3$ be given by $\vec{x} = 2\vec{e}_1 - \vec{e}_3$ and $\vec{y} = 6\vec{e}_2 + 3\vec{e}_3$. Compute $\vec{z} = \vec{x} + 2\vec{y}$.

$$\vec{z} = \vec{x} + 2\vec{y} = \begin{bmatrix} 2 \\ 0 \\ -1 \end{bmatrix} + 2 \begin{bmatrix} 0 \\ 6 \\ 3 \end{bmatrix} = \begin{bmatrix} 2 \\ 0 \\ -1 \end{bmatrix} + \begin{bmatrix} 0 \\ 12 \\ 6 \end{bmatrix} = \begin{bmatrix} 2 \\ 12 \\ 5 \end{bmatrix} = 2\vec{e}_1 + 12\vec{e}_2 + 6\vec{e}_3$$

⁸ So simple, that computers are able to answer billions of such questions a second as you play your favorite video game!

Task 1.1: The Magic Carpet Ride

You are a young traveler, leaving home for the first time. Your parents want to help you on your journey, so just before your departure, they give you two gifts. Specifically, they give you two forms of transportation: a hover board and a magic carpet. Your parents inform you that both the hover board and the magic carpet have restrictions in how they operate:



We denote the restriction on the hover board's movement by the vector $\begin{bmatrix} 3 \\ 1 \end{bmatrix}$. By this we mean that if the hover board traveled "forward" for one hour, it would move along a "diagonal" path that would result in a displacement of 3 miles East and 1 mile North of its starting location.



We denote the restriction on the magic carpet's movement by the vector $\begin{bmatrix} 1 \\ 2 \end{bmatrix}$. By this we mean that if the magic carpet traveled "forward" for one hour, it would move along a "diagonal" path that would result in a displacement of 1 mile East and 2 miles North of its starting location.

Scenario One: The Maiden Voyage

Your Uncle Cramer suggests that your first adventure should be to go visit the wise man, Old Man Gauss. Uncle Cramer tells you that Old Man Gauss lives in a cabin that is 107 miles East and 64 miles North of your home.

Task:

Investigate whether or not you can use the hover board and the magic carpet to get to Gauss's cabin. If so, how? If it is not possible to get to the cabin with these modes of transportation, why is that the case?

Task 1.2: The Magic Carpet Ride, Hide and Seek

You are a young traveler, leaving home for the first time. Your parents want to help you on your journey, so just before your departure, they give you two gifts. Specifically, they give you two forms of transportation: a hover board and a magic carpet. Your parents inform you that both the hover board and the magic carpet have restrictions in how they operate:



We denote the restriction on the hover board's movement by the vector $\begin{bmatrix} 3 \\ 1 \end{bmatrix}$. By this we mean that if the hover board traveled "forward" for one hour, it would move along a "diagonal" path that would result in a displacement of 3 miles East and 1 mile North of its starting location.



We denote the restriction on the magic carpet's movement by the vector $\begin{bmatrix} 1 \\ 2 \end{bmatrix}$. By this we mean that if the magic carpet traveled "forward" for one hour, it would move along a "diagonal" path that would result in a displacement of 1 mile East and 2 miles North of its starting location.

Scenario Two: Hide-and-Seek

Old Man Gauss wants to move to a cabin in a different location. You are not sure whether Gauss is just trying to test your wits at finding him or if he actually wants to hide somewhere that you can't visit him.

Are there some locations that he can hide and you cannot reach him with these two modes of transportation?

Describe the places that you can reach using a combination of the hover board and the magic carpet and those you cannot. Specify these geometrically and algebraically. Include a symbolic representation using vector notation. Also, include a convincing argument supporting your answer.

Sets and Set Notation

Set

A **set** is a (possibly infinite) collection of items and is notated with curly braces (for example, $\{1, 2, 3\}$ is the set containing the numbers 1, 2, and 3). We call the items in a set **elements**.

If X is a set and a is an element of X , we may write $a \in X$, which is read “ a is an element of X .”

If X is a set, a **subset** Y of X (written $Y \subseteq X$) is a set such that every element of Y is an element of X . Two sets are called **equal** if they are subsets of each other (i.e., $X = Y$ if $X \subseteq Y$ and $Y \subseteq X$).

We can define a subset using **set-builder notation**. That is, if X is a set, we can define the subset

$$Y = \{a \in X : \text{some rule involving } a\},$$

which is read “ Y is the set of a in X **such that** some rule involving a is true.” If X is intuitive, we may omit it and simply write $Y = \{a : \text{some rule involving } a\}$. You may equivalently use “ $|$ ” instead of “ $:$ ”, writing $Y = \{a | \text{some rule involving } a\}$.

Some common sets are

$$\mathbb{N} = \{\text{natural numbers}\} = \{\text{non-negative whole numbers}\}.$$

$$\mathbb{Z} = \{\text{integers}\} = \{\text{whole numbers, including negatives}\}.$$

$$\mathbb{R} = \{\text{real numbers}\}.$$

$$\mathbb{R}^n = \{\text{vectors in } n\text{-dimensional Euclidean space}\}.$$

1 1.1 Which of the following statements are true?

- (a) $3 \in \{1, 2, 3\}$.
- (b) $1.5 \in \{1, 2, 3\}$.
- (c) $4 \in \{1, 2, 3\}$.
- (d) “b” $\in \{x : x \text{ is an English letter}\}$.
- (e) “ö” $\in \{x : x \text{ is an English letter}\}$.
- (f) $\{1, 2\} \subseteq \{1, 2, 3\}$.
- (g) For some $a \in \{1, 2, 3\}$, $a \geq 3$.
- (h) For any $a \in \{1, 2, 3\}$, $a \geq 3$.
- (i) $1 \subseteq \{1, 2, 3\}$.
- (j) $\{1, 2, 3\} = \{x \in \mathbb{R} : 1 \leq x \leq 3\}$.
- (k) $\{1, 2, 3\} = \{x \in \mathbb{Z} : 1 \leq x \leq 3\}$.

2 Write the following in set-builder notation

- 2.1 The subset $A \subseteq \mathbb{R}$ of real numbers larger than $\sqrt{2}$.
- 2.2 The subset $B \subseteq \mathbb{R}^2$ of vectors whose first coordinate is twice the second.

Unions & Intersections

Two common set operations are *unions* and *intersections*. Let X and Y be sets.

(union) $X \cup Y = \{a : a \in X \text{ or } a \in Y\}$.

(intersection) $X \cap Y = \{a : a \in X \text{ and } a \in Y\}$.

3 Let $X = \{1, 2, 3\}$ and $Y = \{2, 3, 4, 5\}$ and $Z = \{4, 5, 6\}$. Compute

3.1 $X \cup Y$

3.2 $X \cap Y$

3.3 $X \cup Y \cup Z$

3.4 $X \cap Y \cap Z$

Draw the following subsets of \mathbb{R}^2 .

4.1 $V = \left\{ \vec{x} \in \mathbb{R}^2 : \vec{x} = \begin{bmatrix} 0 \\ t \end{bmatrix} \text{ for some } t \in \mathbb{R} \right\}.$

4.2 $H = \left\{ \vec{x} \in \mathbb{R}^2 : \vec{x} = \begin{bmatrix} t \\ 0 \end{bmatrix} \text{ for some } t \in \mathbb{R} \right\}.$

4.3 $D = \left\{ \vec{x} \in \mathbb{R}^2 : \vec{x} = t \begin{bmatrix} 1 \\ 1 \end{bmatrix} \text{ for some } t \in \mathbb{R} \right\}.$

4.4 $N = \left\{ \vec{x} \in \mathbb{R}^2 : \vec{x} = t \begin{bmatrix} 1 \\ 1 \end{bmatrix} \text{ for all } t \in \mathbb{R} \right\}.$

4.5 $V \cup H.$

4.6 $V \cap H.$

4.7 Does $V \cup H = \mathbb{R}^2$?

Vector Combinations

Linear Combination

DEFINITION

A **linear combination** of the vectors $\vec{v}_1, \vec{v}_2, \dots, \vec{v}_n$ is a vector

$$\vec{w} = \alpha_1 \vec{v}_1 + \alpha_2 \vec{v}_2 + \dots + \alpha_n \vec{v}_n.$$

The scalars $\alpha_1, \alpha_2, \dots, \alpha_n$ are called the **coefficients** of the linear combination.

5 Let $\vec{v}_1 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$, $\vec{v}_2 = \begin{bmatrix} 1 \\ -1 \end{bmatrix}$, and $\vec{w} = 2\vec{v}_1 + \vec{v}_2$.

5.1 Write \vec{w} as a column vector. When \vec{w} is written as a linear combination of \vec{v}_1 and \vec{v}_2 , what are the coefficients of \vec{v}_1 and \vec{v}_2 ?

5.2 Is $\begin{bmatrix} 3 \\ 3 \end{bmatrix}$ a linear combination of \vec{v}_1 and \vec{v}_2 ?

5.3 Is $\begin{bmatrix} 0 \\ 0 \end{bmatrix}$ a linear combination of \vec{v}_1 and \vec{v}_2 ?

5.4 Is $\begin{bmatrix} 4 \\ 0 \end{bmatrix}$ a linear combination of \vec{v}_1 and \vec{v}_2 ?

5.5 Can you find a vector in \mathbb{R}^2 that isn't a linear combination of \vec{v}_1 and \vec{v}_2 ?

5.6 Can you find a vector in \mathbb{R}^2 that isn't a linear combination of \vec{v}_1 ?

Recall the *Magic Carpet Ride* task where the hover board could travel in the direction $\vec{h} = \begin{bmatrix} 3 \\ 1 \end{bmatrix}$ and the magic carpet could move in the direction $\vec{m} = \begin{bmatrix} 1 \\ 2 \end{bmatrix}$.

- 6.1 Rephrase the sentence “Gauss can be reached using just the magic carpet and the hover board” using formal mathematical language.
- 6.2 Rephrase the sentence “There is nowhere Gauss can hide where he is inaccessible by magic carpet and hover board” using formal mathematical language.
- 6.3 Rephrase the sentence “ \mathbb{R}^2 is the set of all linear combinations of \vec{h} and \vec{m} ” using formal mathematical language.

Sets of Vectors, Lines & Planes

In this module you will learn

- How to draw a set of vectors making an appropriate choice of when to use line segments and when to use dots to represent vectors.
- The *vector form* of lines and planes, including how to determine the intersection of lines and planes in vector form.
- Restricted linear combinations and how to use them to represent common geometric objects (like line segments or polygons).

With a handle on vectors, we can now use them to describe some common geometric objects: lines and planes.

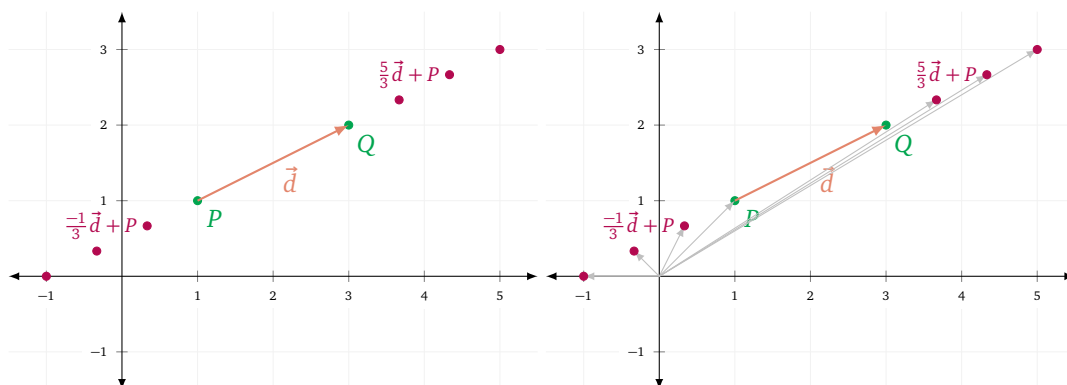
Lines

Consider for a moment the line ℓ through the points P and Q . When $P, Q \in \mathbb{R}^2$, we can describe ℓ with an equation of the form $y = mx + b$ (provided it isn't a vertical line), but if $P, Q \in \mathbb{R}^3$, it's much harder to describe ℓ with an equation. Using vectors provides an easier way.

Let $\vec{d} = \overrightarrow{PQ}$ and consider the set of points (or vectors) \vec{x} that can be expressed as

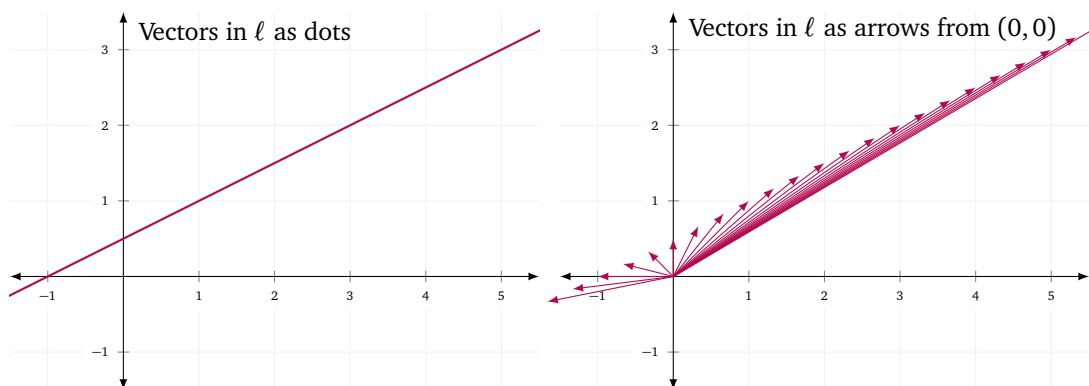
$$\vec{x} = t\vec{d} + P$$

for $t \in \mathbb{R}$. Geometrically, this is the set of all points we get by starting at P and displacing by some multiple of \vec{d} . This is a line!



We simultaneously interpret this line as a set of points (the points that make up the line) and as a set of vectors rooted at the origin (the vectors pointing from the origin to the line). Note that sometimes we draw vectors as directed line segments. Other times, drawing drawing vectors as line segments makes it hard to see what is going on, and so it is better to draw each vector by marking only its ending point.

Which picture below do you think best represents ℓ ?



Takeaway. When drawing a picture depicting several vectors, make an appropriate choice (arrows, dots, or a mix) so that the picture is clear.

The line ℓ described above can be written in set-builder notation as:

$$\ell = \{\vec{x} : \vec{x} = t\vec{d} + P \text{ for some } t \in \mathbb{R}\}.$$

Notice that in set-builder notation, we write “for some $t \in \mathbb{R}$.” Make sure you understand why replacing “for some $t \in \mathbb{R}$ ” with “for all $t \in \mathbb{R}$ ” would be incorrect.

Writing lines with set-builder notation all the time can be overkill, so we will allow ourselves to describe lines in a shorthand called *vector form*.⁹

Vector Form of a Line. Let ℓ be a line and let \vec{d} and \vec{p} be vectors. If $\ell = \{\vec{x} : \vec{x} = t\vec{d} + \vec{p} \text{ for some } t \in \mathbb{R}\}$ we say the vector equation

$$\vec{x} = t\vec{d} + \vec{p}$$

is ℓ expressed in *vector form*. The vector \vec{d} is called a *direction vector* for ℓ .

We can also use coordinates when writing a line in vector form. For example,

$$\begin{bmatrix} x \\ y \end{bmatrix} = t \begin{bmatrix} d_1 \\ d_2 \end{bmatrix} + \begin{bmatrix} p_1 \\ p_2 \end{bmatrix}$$

corresponds to the line passing through $\begin{bmatrix} p_1 \\ p_2 \end{bmatrix}$ with $\begin{bmatrix} d_1 \\ d_2 \end{bmatrix}$ as a direction vector.

The “ t ” that appears in a vector form is called the *parameter variable*, and for this reason, some textbooks use the term *parametric form* in place of “vector form”.

Writing a line in vector form only requires a point on the line and a direction for the line. Thus, converting to vector form from another form is straightforward.

Example. Find vector form of the line $\ell \subseteq \mathbb{R}^2$ with equation $y = 2x + 3$.

First, we find two points on the line. By guess-and-check we see $P = (0, 3)$ and $Q = (1, 5)$ are on ℓ . Thus, a direction vector for ℓ is given by

$$\vec{d} = (1, 5) - (0, 3) = (1, 2).$$

We may now express ℓ in vector form as

$$\vec{x} = t\vec{d} + P$$

or, in components,

$$\begin{bmatrix} x \\ y \end{bmatrix} = t \begin{bmatrix} 1 \\ 2 \end{bmatrix} + \begin{bmatrix} 0 \\ 3 \end{bmatrix}.$$

It’s important to note that when we write a line in vector form, it is a *specific shorthand* notation. If we augment the notation, we no longer have written a line in “vector form”.

Example. Let ℓ and let \vec{d} be a direction vector for ℓ and let $\vec{p} \in \ell$ be a point on ℓ . Writing

$$\vec{x} = t\vec{d} + \vec{p}$$

or

$$\vec{x} = t\vec{d} + \vec{p} \quad \text{where} \quad t \in \mathbb{R}$$

specifies ℓ in vector form and are both shorthands for $\{\vec{x} : \vec{x} = t\vec{d} + \vec{p} \text{ for some } t \in \mathbb{R}\}$. But,

$$\vec{x} = t\vec{d} + \vec{p} \quad \text{for some} \quad t \in \mathbb{R}$$

and

$$\vec{x} = t\vec{d} + \vec{p} \quad \text{for all} \quad t \in \mathbb{R}$$

are logical statements about the vectors \vec{x} , \vec{d} , and \vec{p} . These statements are either true or false; they do *not* specify ℓ in vector form.

⁹ $y = mx + b$ form of a line is also shorthand. The line ℓ described by the equation $y = mx + b$ is actually the set $\{(x, y) \in \mathbb{R}^2 : y = mx + b\}$.

Similarly, the statement

$$\ell = t\vec{d} + \vec{p}$$

is mathematically nonsensical and does not specify ℓ in vector form. (On the left is a *set* and on the right is a *vector*!)

But, why is vector form useful? For starters, every line can be expressed in vector form (you cannot write a vertical line in $y = mx + b$ form, and in \mathbb{R}^3 , you would need two linear equations to represent a line). But, the most useful thing about expressing a line in vector form is that you can easily generate points on that line.

Suppose ℓ can be represented in vector form as $\vec{x} = t\vec{d} + \vec{p}$. Then, for every $t \in \mathbb{R}$, the vector $t\vec{d} + \vec{p} \in \ell$. Not only that, but as t ranges over \mathbb{R} , all points on ℓ are “traced out”. Thus, we can find points on ℓ without having to “solve” any equations.

The downside to using vector form is that it is not unique. There are multiple direction vectors and multiple points for every line. Thus, merely by looking at the vector equation for two lines, it can be hard to tell if they’re equal.

For example,

$$\begin{bmatrix} x \\ y \end{bmatrix} = t \begin{bmatrix} 1 \\ 2 \end{bmatrix} + \begin{bmatrix} 0 \\ 3 \end{bmatrix}, \quad \begin{bmatrix} x \\ y \end{bmatrix} = t \begin{bmatrix} 2 \\ 4 \end{bmatrix} + \begin{bmatrix} 0 \\ 3 \end{bmatrix}, \quad \text{and} \quad \begin{bmatrix} x \\ y \end{bmatrix} = t \begin{bmatrix} 1 \\ 2 \end{bmatrix} + \begin{bmatrix} 1 \\ 5 \end{bmatrix}$$

all represent the same line. In the second equation, the direction vector is parallel but scaled, and in the third equation, a different point on the line was chosen.

Recall that in vector form, the variable t is called the *parameter variable*. It is an instance of a *dummy variable*. In other words, t is a placeholder—just because “ t ” appears in two different vector forms, doesn’t mean it’s the same quantity.

To drive this point home, we need to remember that vector form is shorthand for a set described in set-builder notation.

Let $\vec{d}_1, \vec{d}_2 \neq \vec{0}$ and \vec{p}_1, \vec{p}_2 be vectors and define the lines

$$\ell_1 = \{ \vec{x} : \vec{x} = t\vec{d}_1 + \vec{p}_1 \text{ for some } t \in \mathbb{R} \}$$

$$\ell_2 = \{ \vec{x} : \vec{x} = t\vec{d}_2 + \vec{p}_2 \text{ for some } t \in \mathbb{R} \}.$$

These lines have vector forms $\vec{x} = t\vec{d}_1 + \vec{p}_1$ and $\vec{x} = t\vec{d}_2 + \vec{p}_2$. However, declaring that $\ell_1 = \ell_2$ if and only if $t\vec{d}_1 + \vec{p}_1 = t\vec{d}_2 + \vec{p}_2$ does *not* make sense. Instead, as per the definition, $\ell_1 = \ell_2$ if $\ell_1 \subseteq \ell_2$ and $\ell_2 \subseteq \ell_1$. If $\vec{x} \in \ell_1$ then $\vec{x} = t\vec{d}_1 + \vec{p}_1$ for some $t \in \mathbb{R}$. If $\vec{x} \in \ell_2$ then $\vec{x} = t\vec{d}_2 + \vec{p}_2$ for some *possibly different* $t \in \mathbb{R}$. This can get confusing really quickly. The easiest way to avoid confusion is to use different parameter variables when comparing different vector forms.

Example. Determine if the lines ℓ_1 and ℓ_2 , given in vector form as

$$\vec{x} = t \begin{bmatrix} 1 \\ 1 \end{bmatrix} + \begin{bmatrix} 2 \\ 1 \end{bmatrix} \quad \text{and} \quad \vec{x} = t \begin{bmatrix} 2 \\ 2 \end{bmatrix} + \begin{bmatrix} 4 \\ 3 \end{bmatrix},$$

are the same line.

To determine this, we need to figure out if $\vec{x} \in \ell_1$ implies $\vec{x} \in \ell_2$ and if $\vec{x} \in \ell_2$ implies $\vec{x} \in \ell_1$.

If $\vec{x} \in \ell_1$, then $\vec{x} = t \begin{bmatrix} 1 \\ 1 \end{bmatrix} + \begin{bmatrix} 2 \\ 1 \end{bmatrix}$ for some $t \in \mathbb{R}$. If $\vec{x} \in \ell_2$, then $\vec{x} = s \begin{bmatrix} 2 \\ 2 \end{bmatrix} + \begin{bmatrix} 4 \\ 3 \end{bmatrix}$ for some $s \in \mathbb{R}$. Thus if

$$t \begin{bmatrix} 1 \\ 1 \end{bmatrix} + \begin{bmatrix} 2 \\ 1 \end{bmatrix} = \vec{x} = s \begin{bmatrix} 2 \\ 2 \end{bmatrix} + \begin{bmatrix} 4 \\ 3 \end{bmatrix}$$

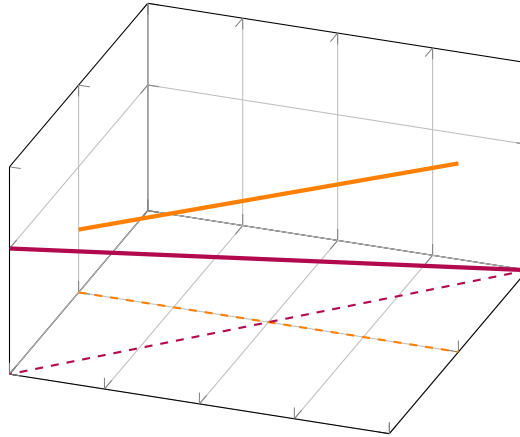
always has a solution, $\ell_1 = \ell_2$. Moving everything to one side we see

$$\begin{aligned} \vec{0} &= \begin{bmatrix} 4 \\ 3 \end{bmatrix} - \begin{bmatrix} 2 \\ 1 \end{bmatrix} + s \begin{bmatrix} 2 \\ 2 \end{bmatrix} - t \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 2 \\ 2 \end{bmatrix} + s \begin{bmatrix} 2 \\ 2 \end{bmatrix} - t \begin{bmatrix} 1 \\ 1 \end{bmatrix} \\ &= (s+1) \begin{bmatrix} 2 \\ 2 \end{bmatrix} - \frac{t}{2} \begin{bmatrix} 2 \\ 2 \end{bmatrix} \\ &= (s+1 - \frac{t}{2}) \begin{bmatrix} 2 \\ 2 \end{bmatrix}. \end{aligned}$$

This has a solution whenever $0 = s + 1 - t/2$. Since for every $t \in \mathbb{R}$ we can find an $s \in \mathbb{R}$ satisfying this equation and for every $s \in \mathbb{R}$ we can find a $t \in \mathbb{R}$ satisfying this equation, we know $\ell_1 = \ell_2$.

Vector Form in Higher Dimensions

The geometry of lines in space (\mathbb{R}^3 and above) is a bit more complicated than that of lines in the plane. Lines in the plane either intersect or are parallel. In space, we have to be a more careful about what we mean by “parallel lines,” since lines with entirely different directions can still fail to intersect.¹⁰



Example. Consider the lines described by

$$\begin{aligned}\vec{x} &= t(1, 3, -2) + (1, 2, 1) \\ \vec{x} &= t(-2, -6, 4) + (3, 1, 0).\end{aligned}$$

They have parallel directions since $(-2, -6, 4) = -2(1, 3, -2)$. Hence, in this case, we say the lines are *parallel*. (How can we be sure the lines are not the same?)

Example. Consider the lines described by

$$\begin{aligned}\vec{x} &= t(1, 3, -2) + (1, 2, 1) \\ \vec{x} &= t(0, 2, 3) + (0, 3, 9).\end{aligned}$$

They are not parallel because neither of the direction vectors is a multiple of the other. They may or may not intersect. (If they don't, we say the lines are *skew*.) How can we find out? Mirroring our earlier approach, we can set their equations equal and see if we can solve for the point of intersection *after ensuring we give their parametric variables different names*. We'll keep one parametric variable named t and name the other one s . Thus, we want

$$\vec{x} = t(1, 3, -2) + (1, 2, 1) = s(0, 2, 3) + (0, 3, 9),$$

which after collecting terms yields

$$(t + 1, 3t + 2, -2t + 1) = (0, 2s + 3, 3s + 9).$$

Picking out the components yields three equations

$$\begin{aligned}t + 1 &= 0 \\ 3t + 2 &= 2s + 3 \\ -2t + 1 &= 3s + 9\end{aligned}$$

in 2 unknowns s and t . This is an *overdetermined* system, and it may or may not have a consistent solution. The first two equations yield $t = -1$ and $s = -2$. Putting these values in the last equation yields $(-2)(-1) + 1 = 3(-2) + 9$, which is indeed true. Hence, the equations are consistent, and the lines intersect. To find the point of intersection, put $t = -1$ in the equation for the first line (or $s = -2$ in that for the second) to obtain $(0, -1, 3)$.

Planes

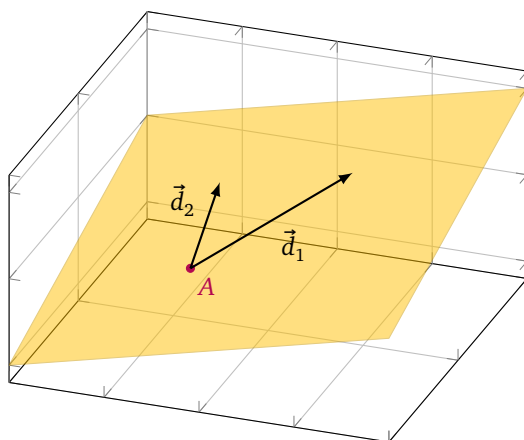
¹⁰ Recall that in Euclidean geometry two lines are defined to be parallel if they coincide or never intersect.

Any two distinct points define a line. To define a plane, we need three points. But there's a caveat: the three points cannot be on the same line, otherwise they'd define a line and not a plane. Let $A, B, C \in \mathbb{R}^3$ be three points that are not collinear and let \mathcal{P} be the plane that passes through A, B , and C .

Just like lines, planes have direction vectors. For \mathcal{P} , both $\vec{d}_1 = \vec{AB}$ and $\vec{d}_2 = \vec{AC}$ are direction vectors for \mathcal{P} . Of course, \vec{d}_1, \vec{d}_2 and their multiples are not the only direction vectors for \mathcal{P} . There are infinitely many more, including $\vec{d}_1 + \vec{d}_2$, and $\vec{d}_1 - 7\vec{d}_2$, and so on. However, since a plane is a *two-dimensional* object, we only need two different direction vectors to describe it.

Like lines, planes have a vector form. Using the direction vectors $\vec{d}_1 = \vec{AB}$ and $\vec{d}_2 = \vec{AC}$, the plane \mathcal{P} can be written in vector form as

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = t\vec{d}_1 + s\vec{d}_2 + A.$$



Vector Form of a Plane. A plane \mathcal{P} is written in **vector form** if it is expressed as

$$\vec{x} = t\vec{d}_1 + s\vec{d}_2 + \vec{p}$$

for some vectors \vec{d}_1 and \vec{d}_2 and point \vec{p} . That is, $\mathcal{P} = \{\vec{x} : \vec{x} = t\vec{d}_1 + s\vec{d}_2 + \vec{p} \text{ for some } t, s \in \mathbb{R}\}$. The vectors \vec{d}_1 and \vec{d}_2 are called **direction vectors** for \mathcal{P} .

Example. Describe the plane $\mathcal{P} \subseteq \mathbb{R}^3$ with equation $z = 2x + y + 3$ in vector form.

To describe \mathcal{P} in vector form, we need a point on \mathcal{P} and two direction vectors for \mathcal{P} . By guess-and-check, we see the points

$$A = \begin{bmatrix} 0 \\ 0 \\ 3 \end{bmatrix} \quad B = \begin{bmatrix} 1 \\ 0 \\ 5 \end{bmatrix} \quad C = \begin{bmatrix} 0 \\ 1 \\ 4 \end{bmatrix}$$

are all on \mathcal{P} . Thus

$$\vec{d}_1 = B - A = \begin{bmatrix} 1 \\ 0 \\ 2 \end{bmatrix} \quad \text{and} \quad \vec{d}_2 = C - A = \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix}$$

are both direction vectors for \mathcal{P} . Therefore, we can express \mathcal{P} in vector form as

$$\vec{x} = t\vec{d}_1 + s\vec{d}_2 + A = t \begin{bmatrix} 1 \\ 0 \\ 2 \end{bmatrix} + s \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 3 \end{bmatrix}.$$

Example. Find the line of intersection between \mathcal{P}_1 and \mathcal{P}_2 where \mathcal{P}_1 and \mathcal{P}_2 are expressed in vector form as ...

XXX Finish

Restricted Linear Combinations

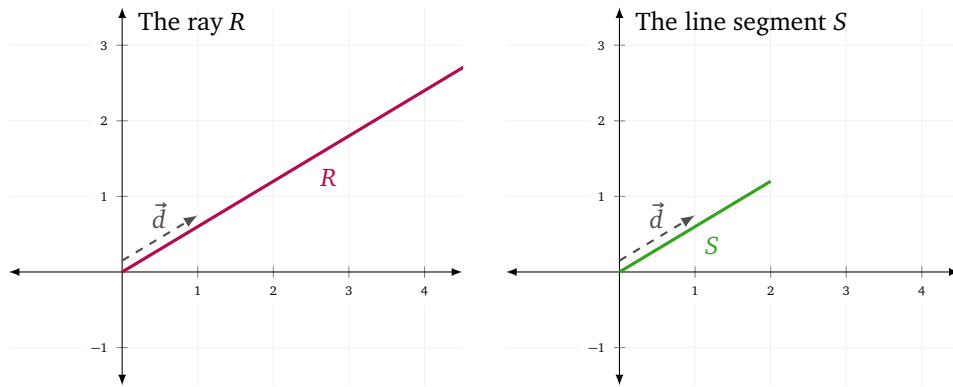
Using vectors, we can describe more than just lines and planes—we can describe all sorts of geometric objects. Recall that when we write $\vec{x} = t\vec{d} + \vec{p}$ to describe the line ℓ , what we mean is

$$\ell = \{\vec{x} : \vec{x} = t\vec{d} + \vec{p} \text{ for some } t \in \mathbb{R}\}.$$

The line ℓ stretches off infinitely in both directions. But, what if we wanted to describe just a part of ℓ ? We can do this by placing additional restrictions on t . For example, consider the ray R and the line segment S :

$$R = \{\vec{x} : \vec{x} = t\vec{d} + \vec{p} \text{ for some } t \geq 0\}$$

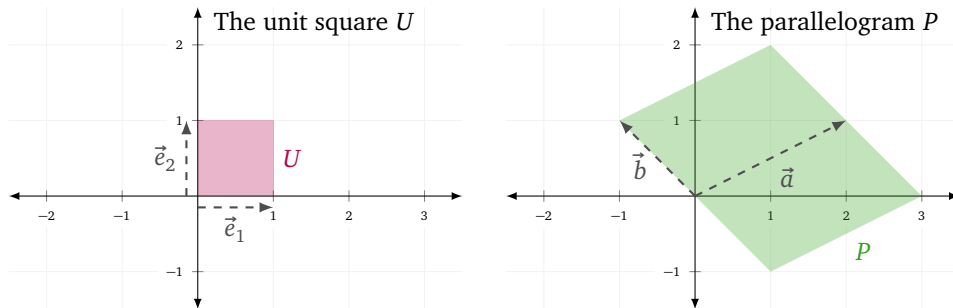
$$S = \{\vec{x} : \vec{x} = t\vec{d} + \vec{p} \text{ for some } t \in [0, 2]\}$$



We can also make polygons by adding restrictions to the vector form of a plane. Let $\vec{a} = \begin{bmatrix} 2 \\ 1 \end{bmatrix}$ and $\vec{b} = \begin{bmatrix} -1 \\ 1 \end{bmatrix}$ and consider the unit square U and the parallelogram P defined by

$$U = \{\vec{x} : \vec{x} = t\vec{e}_1 + s\vec{e}_2 \text{ for some } t, s \in [0, 1]\}$$

$$P = \{\vec{x} : \vec{x} = t\vec{a} + s\vec{b} \text{ for some } t \in [0, 1] \text{ and } s \in [-1, 1]\}$$



Each set so far is a set of linear combinations, and we have made different shapes by restricting the coefficients of those linear combinations. There are two ways of restricting linear combinations that arise up often enough to get their own names.

Non-negative & Convex Linear Combinations.

Let $\vec{w} = \alpha_1\vec{v}_1 + \alpha_2\vec{v}_2 + \cdots + \alpha_n\vec{v}_n$. The vector \vec{w} is called a **non-negative** linear combination of $\vec{v}_1, \vec{v}_2, \dots, \vec{v}_n$ if

$$\alpha_1, \alpha_2, \dots, \alpha_n \geq 0.$$

The vector \vec{w} is called a **convex** linear combination of $\vec{v}_1, \vec{v}_2, \dots, \vec{v}_n$ if

$$\alpha_1, \alpha_2, \dots, \alpha_n \geq 0 \quad \text{and} \quad \alpha_1 + \alpha_2 + \cdots + \alpha_n = 1.$$

You can think of a non-negative linear combinations as vector you can arrive at by only displacing “forward” along your vectors. Convex linear combinations can be thought of as weighted averages of vectors (the average of $\vec{v}_1, \dots, \vec{v}_n$ would be the convex linear combination with coefficients $\alpha_i = \frac{1}{n}$). A convex linear combination of two vectors gives a point on the line segment connecting them.

Example. Let $\vec{a} = \begin{bmatrix} 2 \\ 1 \end{bmatrix}$ and $\vec{b} = \begin{bmatrix} -1 \\ 1 \end{bmatrix}$ and define

$$\begin{aligned} A &= \{\vec{x} : \vec{x} \text{ is a convex linear combination of } \vec{a} \text{ and } \vec{b}\} \\ &= \{\vec{x} : \vec{x} = \alpha\vec{a} + (1 - \alpha)\vec{b} \text{ for some } \alpha \in [0, 1]\}. \end{aligned}$$

Draw A .

XXX Finish

XXX Figure

Non-negative & Convex Linear Combinations

DEFINITION

Let $\vec{w} = \alpha_1 \vec{v}_1 + \alpha_2 \vec{v}_2 + \cdots + \alpha_n \vec{v}_n$. The vector \vec{w} is called a **non-negative** linear combination of $\vec{v}_1, \vec{v}_2, \dots, \vec{v}_n$ if

$$\alpha_1, \alpha_2, \dots, \alpha_n \geq 0.$$

The vector \vec{w} is called a **convex** linear combination of $\vec{v}_1, \vec{v}_2, \dots, \vec{v}_n$ if

$$\alpha_1, \alpha_2, \dots, \alpha_n \geq 0 \quad \text{and} \quad \alpha_1 + \alpha_2 + \cdots + \alpha_n = 1.$$

7

Let

$$\vec{a} = \begin{bmatrix} 1 \\ 1 \end{bmatrix} \quad \vec{b} = \begin{bmatrix} -1 \\ 1 \end{bmatrix} \quad \vec{c} = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \quad \vec{d} = \begin{bmatrix} 0 \\ 2 \end{bmatrix} \quad \vec{e} = \begin{bmatrix} -1 \\ -1 \end{bmatrix}.$$

7.1 Out of \vec{a} , \vec{b} , \vec{c} , \vec{d} , and \vec{e} , which vectors are

- (a) linear combinations of \vec{a} and \vec{b} ?
- (b) non-negative linear combinations of \vec{a} and \vec{b} ?
- (c) convex linear combinations of \vec{a} and \vec{b} ?

7.2 If possible, find two vectors \vec{u} and \vec{v} so that

- (a) \vec{a} and \vec{c} are non-negative linear combinations of \vec{u} and \vec{v} but \vec{b} is not.
- (b) \vec{a} and \vec{e} are non-negative linear combinations of \vec{u} and \vec{v} .
- (c) \vec{a} and \vec{b} are non-negative linear combinations of \vec{u} and \vec{v} but \vec{d} is not.
- (d) \vec{a} , \vec{c} , and \vec{d} are convex linear combinations of \vec{u} and \vec{v} .

Otherwise, explain why it's not possible.

- 8 Let L be the set of points $(x, y) \in \mathbb{R}^2$ such that $y = 2x + 1$.
- 8.1 Describe L using set-builder notation.
- 8.2 Draw L as a subset of \mathbb{R}^2 .
- 8.3 Add the vectors $\vec{a} = \begin{bmatrix} -1 \\ -1 \end{bmatrix}$, $\vec{b} = \begin{bmatrix} 1 \\ 3 \end{bmatrix}$ and $\vec{d} = \vec{b} - \vec{a}$ to your drawing.
- 8.4 Is $\vec{d} \in L$? Explain.
- 8.5 For which $t \in \mathbb{R}$ is it true that $\vec{a} + t\vec{d} \in L$? Explain using your picture.

Vector Form of a Line

DEFINITION

Let ℓ be a line and let \vec{d} and \vec{p} be vectors. If $\ell = \{\vec{x} : \vec{x} = t\vec{d} + \vec{p} \text{ for some } t \in \mathbb{R}\}$ we say the vector equation

$$\vec{x} = t\vec{d} + \vec{p}$$

is ℓ expressed in **vector form**. The vector \vec{d} is called a **direction vector** for ℓ .

- 9 Let $\ell \subseteq \mathbb{R}^2$ be the line with equation $2x + y = 3$, and let $L \subseteq \mathbb{R}^3$ be the line with equations $2x + y = 3$ and $z = y$.
- 9.1 Write ℓ in vector form. Is vector form of ℓ unique?
- 9.2 Write L in vector form.
- 9.3 Find another vector form for L where both “ \vec{d} ” and “ \vec{p} ” are different from before.

Let A , B , and C be given in vector form by

$$\overbrace{\vec{x} = t \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}}^A \quad \overbrace{\vec{x} = t \begin{bmatrix} -1 \\ 1 \\ 1 \end{bmatrix} + \begin{bmatrix} -1 \\ 1 \\ 2 \end{bmatrix}}^B \quad \overbrace{\vec{x} = t \begin{bmatrix} 2 \\ -1 \\ 1 \end{bmatrix} + \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}}^C.$$

- 10.1 Do the lines A and B intersect? Justify your conclusion.
- 10.2 Do the lines A and C intersect? Justify your conclusion.
- 10.3 Let $\vec{p} \neq \vec{q}$ and suppose X has vector form $\vec{x} = t\vec{d} + \vec{p}$ and Y has vector form $\vec{x} = t\vec{d} + \vec{q}$. Is it possible that X and Y intersect?

Vector Form of a Plane

A plane \mathcal{P} is written in **vector form** if it is expressed as

$$\vec{x} = t\vec{d}_1 + s\vec{d}_2 + \vec{p}$$

for some vectors \vec{d}_1 and \vec{d}_2 and point \vec{p} . That is, $\mathcal{P} = \{\vec{x} : \vec{x} = t\vec{d}_1 + s\vec{d}_2 + \vec{p} \text{ for some } t, s \in \mathbb{R}\}$. The vectors \vec{d}_1 and \vec{d}_2 are called **direction vectors** for \mathcal{P} .

- 11 Recall the intersecting lines A and B given in vector form by

$$\overbrace{\vec{x} = t \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}}^A \quad \overbrace{\vec{x} = t \begin{bmatrix} -1 \\ 1 \\ 1 \end{bmatrix} + \begin{bmatrix} -1 \\ 1 \\ 2 \end{bmatrix}}^B.$$

Let \mathcal{P} the plane that contains the lines A and B .

- 11.1 Find two direction vectors for \mathcal{P} .
- 11.2 Write \mathcal{P} in vector form.
- 11.3 Describe how vector form of a plane relates to linear combinations.
- 11.4 Write \mathcal{P} in vector form using different direction vectors and a different point.

12 Let $Q \subseteq \mathbb{R}^3$ be a plane with equation $x + y + z = 1$.

12.1 Find three points in Q .

12.2 Find two direction vectors for Q .

12.3 Write Q in vector form.

Spans, Translated Spans, and Linear Independence/Dependence

In this module you will learn

- The definition of span and how to visualize spans.
- How to express lines/planes/volumes through the origin as spans.
- How to express lines/planes/volumes *not* through the origin as *translated* spans using set addition.
- Geometric and algebraic definitions of linear independence and linear dependence.
- How to find linearly independent subsets.

Let $\vec{u} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$ and $\vec{v} = \begin{bmatrix} 1 \\ -2 \end{bmatrix}$. Can the vectors $\vec{w} = \begin{bmatrix} 2 \\ 5 \end{bmatrix}$ be obtained as a linear combination of \vec{u} and \vec{v} ?

By drawing a picture, the answer appears to be yes.



Algebraically, we can use the definition of a *linear combination* to set up a system of equations. We know \vec{w} can be expressed as a linear combination of \vec{u} and \vec{v} if and only if the vector equation

$$\vec{w} = \begin{bmatrix} 2 \\ 5 \end{bmatrix} = \alpha \begin{bmatrix} 1 \\ 1 \end{bmatrix} + \beta \begin{bmatrix} 1 \\ -2 \end{bmatrix} = \alpha \vec{u} + \beta \vec{v}$$

has a solution. By inspection, we see $\alpha = 3$ and $\beta = -1$ solve this equation.

After initial success, we might ask the following: *what are all the locations in \mathbb{R}^2 that can be obtained as a linear combination of \vec{u} and \vec{v} ?* Geometrically, it appears any location can be reached. To verify this algebraically, consider the vector equation

$$\vec{x} = \begin{bmatrix} x \\ y \end{bmatrix} = \alpha \begin{bmatrix} 1 \\ 1 \end{bmatrix} + \beta \begin{bmatrix} 1 \\ -2 \end{bmatrix} = \alpha \vec{u} + \beta \vec{v}. \quad (1)$$

Here \vec{x} represents an arbitrary point in \mathbb{R}^2 . Thus, if equation (1) always has a solution,¹¹ any vector in \mathbb{R}^2 can be obtained as a linear combination of α and β .

We can solve this equation for α and β by considering the equations arising from the first and second coordinates. Namely,

$$\begin{aligned} x &= \alpha + \beta \\ y &= \alpha - 2\beta. \end{aligned}$$

¹¹ The official terminology would be to say that the equations is always *consistent*.

Subtracting the second equation from the first, we get $x - y = 3\beta$ and so $\beta = (x - y)/3$. Plugging β into the first equation and solving, we get $\alpha = (2x + y)/3$. Thus, equation (1) *always* has a solution. Namely,

$$\alpha = \frac{1}{3}(2x + y)$$

$$\beta = \frac{1}{3}(x - y).$$

There is a formal term for the set of vectors that can be obtained as linear combinations of others: *span*.

Span. The *span* of a set of vectors V is the set of all linear combinations of vectors in V . That is,

$$\text{span } V = \{\vec{v} : \vec{v} = \alpha_1 \vec{v}_1 + \alpha_2 \vec{v}_2 + \cdots + \alpha_n \vec{v}_n \text{ for some } \vec{v}_1, \vec{v}_2, \dots, \vec{v}_n \in V \text{ and scalars } \alpha_1, \alpha_2, \dots, \alpha_n\}.$$

Additionally, we define $\text{span}\{\} = \{\vec{0}\}$.

We just showed above that $\text{span}\left\{\begin{bmatrix} 1 \\ 1 \end{bmatrix}, \begin{bmatrix} -1 \\ 2 \end{bmatrix}\right\} = \mathbb{R}^2$.

Example. Let $\vec{u} = \begin{bmatrix} -1 \\ 2 \end{bmatrix}$ and $\vec{v} = \begin{bmatrix} 1 \\ -2 \end{bmatrix}$. Find $\text{span}\{\vec{u}, \vec{v}\}$.

XXX Finish

Example. Let $\vec{a} = \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix}$, $\vec{b} = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}$, and $\vec{c} = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$. Show that $\mathbb{R}^3 = \text{span}\{\vec{a}, \vec{b}, \vec{c}\}$.

XXX Finish

Representing Lines & Planes as Spans

If spans remind you of vector forms of lines and planes, your intuition is keen. Consider the line ℓ given in vector form by

$$\vec{x} = t\vec{d} + \vec{0}.$$

The line ℓ passes through the origin, and if we unravel its definition, we see

$$\ell = \{\vec{x} : \vec{x} = t\vec{d} + \vec{0} \text{ for some } t \in \mathbb{R}\} = \{\vec{x} : \vec{x} = t\vec{d} \text{ for some } t \in \mathbb{R}\} = \text{span}\{\vec{d}\}.$$

Similarly, if \mathcal{P} is a plane given in vector form by

$$\vec{x} = t\vec{d}_1 + s\vec{d}_2 + \vec{0},$$

then

$$\mathcal{P} = \{\vec{x} : \vec{x} = t\vec{d}_1 + s\vec{d}_2 \text{ for some } t, s \in \mathbb{R}\} = \text{span}\{\vec{d}_1, \vec{d}_2\}.$$

If the “ \vec{p} ” in our vector form is $\vec{0}$, then that vector form actually defines a span. This means, if you accept that every line/plane through the origin has a vector form, then every line/plane through the origin can be written as a span. Conversely, if $X = \text{span}\{\vec{v}_1, \dots, \vec{v}_n\}$ is a span, we know $\vec{0} = 0\vec{v}_1 + \cdots + 0\vec{v}_n \in X$, and so every span contains the origin.

As it turns out, spans exactly describe points, lines, planes, and volumes¹² through the origin.

Example. The line $\ell_1 \subseteq \mathbb{R}^2$ is described by the equation $x + 2y = 0$ and the line $\ell_2 \subseteq \mathbb{R}^2$ is described by the equation $4x - 2y = 6$. If possible, describe ℓ_1 and ℓ_2 using spans.

XXX Finish

However, not all points, lines, planes, and volumes pass through the origin and so we can’t describe every such object directly as a span.

Example. Show the line $\ell_2 \subseteq \mathbb{R}^2$ described by the equation $4x - 2y = 6$ cannot be written as a span.

XXX Finish

Takeaway. Lines and planes through the origin, and only lines and planes through the origin, can be expressed as spans.

¹² We use the word *volume* to indicate the higher-dimensional analogue of a plane.

Set Addition

We're going to work around the fact that only objects which pass through the origin can be written as spans, but first let's take a detour and learn about *set addition*.

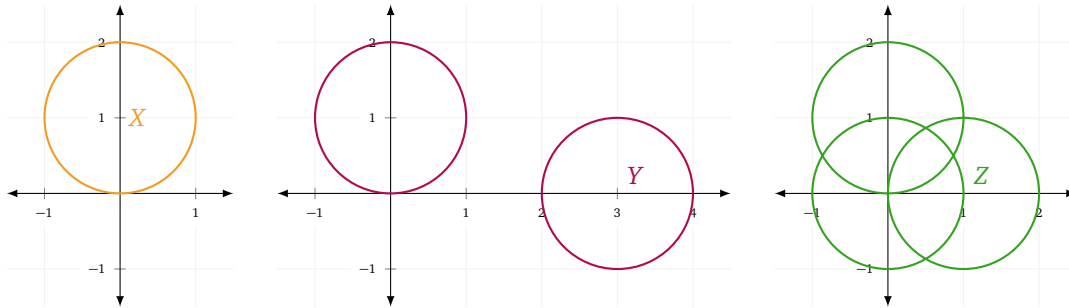
Set Addition. If A and B are sets of vectors, then the *set sum* of A and B , denoted $A + B$, is

$$A + B = \{\vec{x} : \vec{x} = \vec{a} + \vec{b} \text{ for some } \vec{a} \in A \text{ and } \vec{b} \in B\}.$$

Set sums are very different than regular sums despite using the same symbol, “+”.¹³ However, they are very useful. Let $C = \{\vec{x} \in \mathbb{R}^2 : \|\vec{x}\| = 1\}$ be the unit circle centered at the origin, and consider the sets

$$X = C + \{\vec{e}_2\} \quad Y = C + \{3\vec{e}_1, \vec{e}_2\} \quad Z = C + \{\vec{0}, \vec{e}_1, \vec{e}_2\}.$$

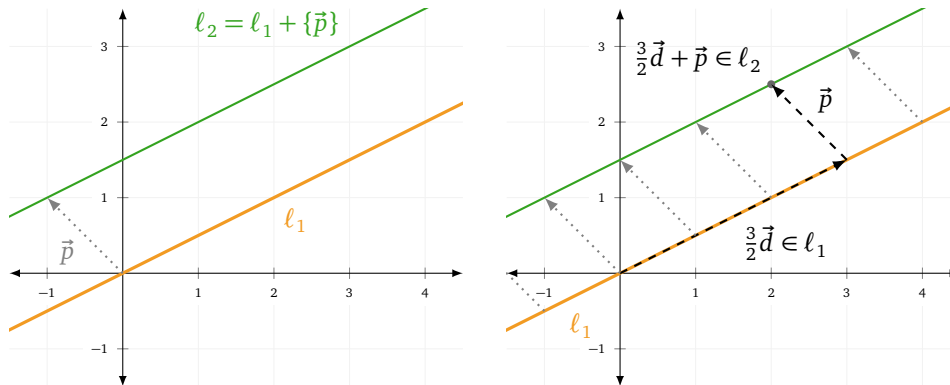
Rewriting, we see $X = \{\vec{x} + \vec{e}_2 : \|\vec{x}\| = 1\}$ is just C translated by \vec{e}_2 . Similarly, $Y = \{\vec{x} + \vec{v} : \|\vec{x}\| = 1 \text{ and } \vec{v} = 3\vec{e}_1 \text{ or } \vec{v} = \vec{e}_2\} = (C + \{3\vec{e}_1\}) \cup (C + \{\vec{e}_2\})$, and so Y is the union of two translated copies of C .¹⁴



Translated Spans

Set addition allows us to easily create parallel lines and planes by translation. For example, consider the lines ℓ_1 and ℓ_2 given in vector form as $\vec{x} = t\vec{d}$ and $\vec{x} = t\vec{d} + \vec{p}$, respectively, where $\vec{d} = \begin{bmatrix} 2 \\ 1 \end{bmatrix}$ and $\vec{p} = \begin{bmatrix} -1 \\ 1 \end{bmatrix}$. These lines differ from each other by a translation. That is, every point in ℓ_2 can be obtained by adding \vec{p} to a corresponding point in ℓ_1 . Using the idea of set addition, we can express this mathematically with the equation

$$\ell_2 = \ell_1 + \{\vec{p}\}.$$



Note that it would be incorrect to write “ $\ell_2 = \ell_1 + \vec{p}$ ”. Because ℓ_1 is a set and \vec{p} is not a set, “ $\ell_1 + \vec{p}$ ” does not make mathematical sense.

Example. Recall $\ell_2 \subseteq \mathbb{R}^2$ is the line described by the equation $4x - 2y = 6$. Describe ℓ_2 as a translated span.

XXX Finish

We can now see translated spans provide an alternative notation to vector form for specifying lines and planes. If Q is described in vector form by

$$\vec{x} = t\vec{d}_1 + s\vec{d}_2 + \vec{p},$$

¹³ For example, $A + \{\} = \{\}$, which might seem counterintuitive for an “addition” operation.

¹⁴ If you want to stretch your mind, consider what $C + C$ is as a set.

then

$$Q = \text{span}\{\vec{d}_1, \vec{d}_2\} + \{\vec{p}\}.$$

Takeaway. All lines and planes, whether through the origin or not, can be expressed as translated spans.

Linear Independence & Linear Dependence

Let

$$\vec{u} = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} \quad \vec{v} = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} \quad \vec{w} = \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}.$$

Since $\vec{w} = \vec{u} + \vec{v}$, we know that $\vec{w} \in \text{span}\{\vec{u}, \vec{v}\}$. Geometrically, this is also clear because $\text{span}\{\vec{u}, \vec{v}\}$ is the xy -plane in \mathbb{R}^3 and \vec{w} lies on that plane.

What about $\text{span}\{\vec{u}, \vec{v}, \vec{w}\}$? Intuitively, since \vec{w} is already a linear combination of \vec{u} and \vec{v} , we can't get anywhere *new* by taking linear combinations of \vec{u} , \vec{v} , and \vec{w} compared to linear combinations of just \vec{u} and \vec{v} . So $\text{span}\{\vec{u}, \vec{v}\} = \text{span}\{\vec{u}, \vec{v}, \vec{w}\}$.

Can we prove this from the definitions? Yes! Suppose $\vec{r} \in \text{span}\{\vec{u}, \vec{v}, \vec{w}\}$. By definition,

$$\vec{r} = \alpha\vec{u} + \beta\vec{v} + \gamma\vec{w}$$

for some $\alpha, \beta, \gamma \in \mathbb{R}$. Since $\vec{w} = \vec{u} + \vec{v}$, we see

$$\vec{r} = \alpha\vec{u} + \beta\vec{v} + \gamma(\vec{u} + \vec{v}) = (\alpha + \gamma)\vec{u} + (\beta + \gamma)\vec{v} \in \text{span}\{\vec{u}, \vec{v}\}.$$

Thus, $\text{span}\{\vec{u}, \vec{v}, \vec{w}\} \subseteq \text{span}\{\vec{u}, \vec{v}\}$. Conversely, if $\vec{s} \in \text{span}\{\vec{u}, \vec{v}\}$, by definition,

$$\vec{s} = a\vec{u} + b\vec{v} = a\vec{u} + b\vec{v} + 0\vec{w}$$

for some $a, b \in \mathbb{R}$, and so $\vec{s} \in \text{span}\{\vec{u}, \vec{v}, \vec{w}\}$. Thus $\text{span}\{\vec{u}, \vec{v}\} \subseteq \text{span}\{\vec{u}, \vec{v}, \vec{w}\}$. We conclude $\text{span}\{\vec{u}, \vec{v}\} = \text{span}\{\vec{u}, \vec{v}, \vec{w}\}$.

In this case, \vec{w} was a redundant vector—it wasn't needed for the span.

Linearly Dependent & Independent (Geometric).

We say the vectors $\vec{v}_1, \vec{v}_2, \dots, \vec{v}_n$ are **linearly dependent** if for at least one i ,

$$\vec{v}_i \in \text{span}\{\vec{v}_1, \vec{v}_2, \dots, \vec{v}_{i-1}, \vec{v}_{i+1}, \dots, \vec{v}_n\}.$$

Otherwise, they are called **linearly independent**.

We will also refer to sets of vectors (for example $\{\vec{v}_1, \dots, \vec{v}_n\}$) as being linearly independent or linearly dependent. For technical reasons, we didn't state the definition in terms of sets.¹⁵

The geometric definition of linear dependence says that the vectors $\vec{v}_1, \dots, \vec{v}_n$ are linearly dependent if you can remove at least one vector without changing the span. In other words, $\vec{v}_1, \dots, \vec{v}_n$ are linearly dependent if *there is a redundant vector*.

Example. Let $\vec{u} = \begin{bmatrix} 1 \\ 2 \end{bmatrix}$, $\vec{v} = \begin{bmatrix} 2 \\ 3 \end{bmatrix}$, and $\vec{w} = \begin{bmatrix} 4 \\ 5 \end{bmatrix}$. Determine whether $\{\vec{u}, \vec{v}, \vec{w}\}$ is linearly independent or linearly dependent.

XXX Finish

Example. Determine whether the planes ... (given in vector form) are the same.

XXX Finish

We can also think of linear independence/dependence from an algebraic perspective. Suppose the vectors \vec{u} , \vec{v} , and \vec{w} satisfy

$$\vec{w} = \vec{u} + \vec{v}. \quad (2)$$

The set $\{\vec{u}, \vec{v}, \vec{w}\}$ is linearly dependent since $\vec{w} \in \text{span}\{\vec{u}, \vec{v}\}$, but equation (2) can be rearranged to get

$$\vec{0} = \vec{u} + \vec{v} - \vec{w}. \quad (3)$$

¹⁵ The issue is, every element of a set is unique. Clearly, the vectors \vec{v} and \vec{v} are linearly dependent, but $\{\vec{v}, \vec{v}\} = \{\vec{v}\}$, and so $\{\vec{v}, \vec{v}\}$ is technically a linearly independent set. This issue would be resolved by talking about *multisets* instead of sets, but it isn't worth the hassle.

Here we have expressed $\vec{0}$ as a linear combination of \vec{u} , \vec{v} , and \vec{w} . By itself, this is nothing special. After all, without any thinking we know $\vec{0} = 0\vec{u} + 0\vec{v} + 0\vec{w}$ is a linear combination of \vec{u} , \vec{v} , and \vec{w} . However, the right side of equation (3) has non-zero coefficients, which makes the linear combination *non-trivial*.

Trivial Linear Combination.

The linear combination $\alpha_1\vec{v}_1 + \cdots + \alpha_n\vec{v}_n$ is called *trivial* if $\alpha_1 = \cdots = \alpha_n = 0$. If at least one $\alpha_i \neq 0$, the linear combination is called *non-trivial*.

We can always write $\vec{0}$ as a linear combination of vectors if we let all the coefficients be zero, but it turns out we can only write $\vec{0}$ as a *non-trivial* linear combination of vectors if those vectors are linearly dependent. This is the inspiration for another definition of linear independence/dependence.

Linear Independence & Linear Dependence (Algebraic). The vectors $\vec{v}_1, \dots, \vec{v}_n$ are called *linearly independent* if for the only linear combination satisfying

$$\vec{0} = \alpha_1\vec{v}_1 + \cdots + \alpha_n\vec{v}_n$$

is the trivial linear combination (where $\alpha_1 = \cdots = \alpha_n = 0$).

The idea of a “redundant vector” coming from the geometric definition of linear dependence is easy to visualize, but it can be hard to prove things with—checking for linear independence with the geometric definition involves verifying for every vector that it is not in the span of the others. The algebraic definition on the other hand is less obvious, but checking for linear independence or dependence of a set involves reasoning about solutions to just one equation.

Example. Let $\vec{u} = \begin{bmatrix} 1 \\ 2 \end{bmatrix}$, $\vec{v} = \begin{bmatrix} 2 \\ 3 \end{bmatrix}$, and $\vec{w} = \begin{bmatrix} 4 \\ 5 \end{bmatrix}$. Use the algebraic definition of linear independence to determine whether $\{\vec{u}, \vec{v}, \vec{w}\}$ is linearly independent or dependent.

XXX Finish

Theorem. The geometric and algebraic definitions of linear independence are equivalent.

Proof. To show the two definitions are equivalent, we need to show that geometric \implies algebraic and algebraic \implies geometric.

(geometric \implies algebraic) Suppose $\vec{v}_1, \dots, \vec{v}_n$ are linearly dependent by the geometric definition. That means that for some i , we have

$$\vec{v}_i \in \text{span}\{\vec{v}_1, \dots, \vec{v}_{i-1}, \vec{v}_{i+1}, \dots, \vec{v}_n\}.$$

Fix such an i . Then, by the definition of span we know

$$\vec{v}_i = \alpha_1\vec{v}_1 + \cdots + \alpha_{i-1}\vec{v}_{i-1} + \alpha_{i+1}\vec{v}_{i+1} + \cdots + \alpha_n\vec{v}_n,$$

and so

$$\vec{0} = \alpha_1\vec{v}_1 + \cdots + \alpha_{i-1}\vec{v}_{i-1} - \vec{v}_i + \alpha_{i+1}\vec{v}_{i+1} + \cdots + \alpha_n\vec{v}_n.$$

This must be a non-trivial linear combination because the coefficient of \vec{v}_i is $-1 \neq 0$. Therefore, $\vec{v}_1, \dots, \vec{v}_n$ is linearly dependent by the algebraic definition.

(geometric \implies algebraic) Suppose $\vec{v}_1, \dots, \vec{v}_n$ are linearly dependent by the algebraic definition. That means there exist $\alpha_1, \dots, \alpha_n$, not all zero, so that

$$\vec{0} = \alpha_1\vec{v}_1 + \cdots + \alpha_n\vec{v}_n.$$

Fix i so that $\alpha_i \neq 0$ (why do we know there is such an i ?). Rearranging we get

$$-\alpha_i\vec{v}_i = \alpha_1\vec{v}_1 + \cdots + \alpha_{i-1}\vec{v}_{i-1} + \alpha_{i+1}\vec{v}_{i+1} + \cdots + \alpha_n\vec{v}_n,$$

and since $\alpha_i \neq 0$, we can multiply both sides by $\frac{-1}{\alpha_i}$ to get

$$\vec{v}_i = \frac{-\alpha_1}{\alpha_i}\vec{v}_1 + \cdots + \frac{-\alpha_{i-1}}{\alpha_i}\vec{v}_{i-1} + \frac{-\alpha_{i+1}}{\alpha_i}\vec{v}_{i+1} + \cdots + \frac{-\alpha_n}{\alpha_i}\vec{v}_n.$$

This shows that

$$\vec{v}_i \in \text{span}\{\vec{v}_1, \dots, \vec{v}_{i-1}, \vec{v}_{i+1}, \dots, \vec{v}_n\},$$

and so $\vec{v}_1, \dots, \vec{v}_n$ is linearly dependent by the geometric definition. ■

Linear Independence and Unique Solutions

The algebraic definition of linear independence can teach us something about solutions to systems of equations.

Recall the linearly dependent vectors

$$\vec{u} = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} \quad \vec{v} = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} \quad \vec{w} = \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}$$

which satisfy the non-trivial relationship $\vec{u} + \vec{v} - \vec{w} = \vec{0}$. Since $\vec{u} + \vec{v} - \vec{w} = \vec{0}$ is a non-trivial relationship giving $\vec{0}$, we can use it to generate others. For example,

$$\begin{aligned} 17(\vec{u} + \vec{v} - \vec{w}) &= 17\vec{u} + 17\vec{v} - 17\vec{w} = 17\vec{0} = \vec{0} \\ -3(\vec{u} + \vec{v} - \vec{w}) &= -3\vec{u} - 3\vec{v} + 3\vec{w} = -3\vec{0} = \vec{0} \\ &\vdots \end{aligned}$$

are all different non-trivial linear combinations that give $\vec{0}$. In other words, if the equation $\alpha\vec{u} + \beta\vec{v} + \gamma\vec{w} = \vec{0}$ has a non-trivial solution, it has *infinitely many* non-trivial solutions. Conversely, if the equation $\alpha\vec{u} + \beta\vec{v} + \gamma\vec{w} = \vec{0}$ has infinitely many solutions, one of them has to be non-trivial!

Homogeneous System.

A system of linear equations or a vector equation in the variables $\alpha_1, \dots, \alpha_n$ is called *homogeneous* if it takes the form

$$\alpha_1\vec{v}_1 + \alpha_2\vec{v}_2 + \dots + \alpha_n\vec{v}_n = \vec{0},$$

where the right side of the equation is $\vec{0}$.

This insight links linear independence and homogeneous systems together, and is encapsulated in the following theorem.

Theorem. The vectors $\vec{v}_1, \dots, \vec{v}_n$ are linearly independent if and only if the homogeneous equation

$$\alpha_1\vec{v}_1 + \dots + \alpha_n\vec{v}_n = \vec{0}$$

has a unique solution.

This theorem has a practical application: suppose you wanted to decide if the vectors \vec{a} , \vec{b} , and \vec{c} were linearly independent. You could (i) find a non-trivial solution to $x\vec{a} + y\vec{b} + z\vec{c} = \vec{0}$, or (ii) merely show that $x\vec{a} + y\vec{b} + z\vec{c} = \vec{0}$ has more than one solution. Sometimes one is easier than the other.

Linear Independence and Vector Form

The equation

$$\vec{x} = t_1\vec{d}_1 + t_2\vec{d}_2$$

represents a plane in vector form of a plane whenever \vec{d}_1 and \vec{d}_2 are non-zero, non-parallel vectors. In other words, $\vec{x} = t_1\vec{d}_1 + t_2\vec{d}_2$ represents a plane whenever $\{\vec{d}_1, \vec{d}_2\}$ is linearly independent.

Does this reasoning work for lines too? The equation

$$\vec{x} = t\vec{d}$$

represents a line in vector form precisely when $\vec{d} \neq \vec{0}$. And $\{\vec{d}\}$ is linearly independent exactly when $\vec{d} \neq \vec{0}$.

This reasoning generalizes to volumes. The equation

$$\vec{x} = t_1\vec{d}_1 + t_2\vec{d}_2 + t_3\vec{d}_3$$

represents a *volume* in vector form exactly when $\{\vec{d}_1, \vec{d}_2, \vec{d}_3\}$ is linearly independent. To see this, suppose $\{\vec{d}_1, \vec{d}_2, \vec{d}_3\}$ were linearly dependent. That means one or more vectors could be removed from $\{\vec{d}_1, \vec{d}_2, \vec{d}_3\}$ without changing its span. Therefore, if $\{\vec{d}_1, \vec{d}_2, \vec{d}_3\}$ is linearly independent $\vec{x} = t_1\vec{d}_1 + t_2\vec{d}_2 + t_3\vec{d}_3$ at best represents a plane (though it could be a line or a point).

Takeaway. When writing an object in vector form, the direction vectors must always be linearly independent.

Span

Span

DEFINITION

The *span* of a set of vectors V is the set of all linear combinations of vectors in V . That is,

$$\text{span } V = \{ \vec{v} : \vec{v} = \alpha_1 \vec{v}_1 + \alpha_2 \vec{v}_2 + \cdots + \alpha_n \vec{v}_n \text{ for some } \vec{v}_1, \vec{v}_2, \dots, \vec{v}_n \in V \text{ and scalars } \alpha_1, \alpha_2, \dots, \alpha_n \}.$$

Additionally, we define $\text{span}\{\} = \{\vec{0}\}$.

13

Let $\vec{v}_1 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$, $\vec{v}_2 = \begin{bmatrix} 1 \\ -1 \end{bmatrix}$, and $\vec{v}_3 = \begin{bmatrix} 2 \\ 2 \end{bmatrix}$.

13.1 Draw $\text{span}\{\vec{v}_1\}$.

13.2 Draw $\text{span}\{\vec{v}_2\}$.

13.3 Describe $\text{span}\{\vec{v}_1, \vec{v}_2\}$.

13.4 Describe $\text{span}\{\vec{v}_1, \vec{v}_3\}$.

13.5 Describe $\text{span}\{\vec{v}_1, \vec{v}_2, \vec{v}_3\}$.

-
- 14 Let $\ell_1 \subseteq \mathbb{R}^2$ be the line with equation $x - y = 0$ and $\ell_2 \subseteq \mathbb{R}^2$ the line with equation $x - y = 4$.
- 14.1 If possible, describe ℓ_1 as a span. Otherwise explain why it's not possible.
- 14.2 If possible, describe ℓ_2 as a span. Otherwise explain why it's not possible.
- 14.3 Does the expression $\text{span}(\ell_1)$ make sense? If so, what is it? How about $\text{span}(\ell_2)$?

Set Addition

DEF

If A and B are sets of vectors, then the **set sum** of A and B , denoted $A + B$, is

$$A + B = \{\vec{x} : \vec{x} = \vec{a} + \vec{b} \text{ for some } \vec{a} \in A \text{ and } \vec{b} \in B\}.$$

15

Let $A = \left\{ \begin{bmatrix} 1 \\ 2 \end{bmatrix} \right\}$, $B = \left\{ \begin{bmatrix} 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ -1 \end{bmatrix} \right\}$, and $\ell = \text{span} \left\{ \begin{bmatrix} 1 \\ -1 \end{bmatrix} \right\}$.

15.1 Draw A , B , and $A + B$ in the same picture.

15.2 Is $A + B$ the same as $B + A$?

15.3 Draw $\ell + A$.

15.4 Consider the line ℓ_2 given in vector form by $\vec{x} = t \begin{bmatrix} 1 \\ -1 \end{bmatrix} + \begin{bmatrix} 1 \\ 2 \end{bmatrix}$. Can ℓ_2 be described using only a span? What about using a span and set addition?

Task 1.3: The Magic Carpet, Getting Back Home

Suppose you are now in a three-dimensional world for the carpet ride problem, and you have three modes of transportation:

$$\vec{v}_1 = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \quad \vec{v}_2 = \begin{bmatrix} 6 \\ 3 \\ 8 \end{bmatrix} \quad \vec{v}_3 = \begin{bmatrix} 4 \\ 1 \\ 6 \end{bmatrix}$$

You are only allowed to use each mode of transportation **once** (in the forward or backward direction) for a fixed amount of time (c_1 on \vec{v}_1 , c_2 on \vec{v}_2 , c_3 on \vec{v}_3).

1. Find the amounts of time on each mode of transportation (c_1 , c_2 , and c_3 , respectively) needed to go on a journey that starts and ends at home *or* explain why it is not possible to do so.
2. Is there more than one way to make a journey that meets the requirements described above? (In other words, are there different combinations of times you can spend on the modes of transportation so that you can get back home?) If so, how?
3. Is there anywhere in this 3D world that Gauss could hide from you? If so, where? If not, why not?

4. What is $\text{span}\left\{\begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 6 \\ 3 \\ 8 \end{bmatrix}, \begin{bmatrix} 4 \\ 1 \\ 6 \end{bmatrix}\right\}$?

Linearly Dependent & Independent (Geometric)

DEFINITION

We say the vectors $\vec{v}_1, \vec{v}_2, \dots, \vec{v}_n$ are **linearly dependent** if for at least one i ,

$$\vec{v}_i \in \text{span}\{\vec{v}_1, \vec{v}_2, \dots, \vec{v}_{i-1}, \vec{v}_{i+1}, \dots, \vec{v}_n\}.$$

Otherwise, they are called **linearly independent**.

16

$$\text{Let } \vec{u} = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}, \vec{v} = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}, \text{ and } \vec{w} = \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}.$$

16.1 Describe $\text{span}\{\vec{u}, \vec{v}, \vec{w}\}$.

16.2 Is $\{\vec{u}, \vec{v}, \vec{w}\}$ linearly independent? Why or why not?

Let $X = \{\vec{u}, \vec{v}, \vec{w}\}$.

16.3 Give a subset $Y \subseteq X$ so that $\text{span } Y = \text{span } X$ and Y is linearly independent.

16.4 Give a subset $Z \subseteq X$ so that $\text{span } Z = \text{span } X$ and Z is linearly independent and $Z \neq Y$.

Trivial Linear Combination

The linear combination $\alpha_1 \vec{v}_1 + \cdots + \alpha_n \vec{v}_n$ is called *trivial* if $\alpha_1 = \cdots = \alpha_n = 0$. If at least one $\alpha_i \neq 0$, the linear combination is called *non-trivial*.

17

Recall $\vec{u} = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}$, $\vec{v} = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}$, and $\vec{w} = \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}$.

- 17.1 Consider the linearly dependent set $\{\vec{u}, \vec{v}, \vec{w}\}$ (where $\vec{u}, \vec{v}, \vec{w}$ are defined as above). Can you write $\vec{0}$ as a non-trivial linear combination of vectors in this set?
- 17.2 Consider the linearly independent set $\{\vec{u}, \vec{v}\}$. Can you write $\vec{0}$ as a non-trivial linear combination of vectors in this set?

We now have an equivalent definition of linear dependence.

Linearly Dependent & Independent (Algebraic)

DEF

The vectors $\vec{v}_1, \vec{v}_2, \dots, \vec{v}_n$ are *linearly dependent* if there is a non-trivial linear combination of $\vec{v}_1, \dots, \vec{v}_n$ that equals the zero vector.

-
- 18 18.1 Explain how this algebraic definition (new) implies the geometric one (original).
18.2 Explain how the geometric definition (original) implies this algebraic one (new).

Since we have geometric def \implies algebraic def, and algebraic def \implies geometric def (\implies should be read aloud as ‘implies’), the two definitions are *equivalent* (which we write as algebraic def \iff geometric def).

19 Suppose for some unknown \vec{u} , \vec{v} , \vec{w} , and \vec{a} ,

$$\vec{a} = 3\vec{u} + 2\vec{v} + \vec{w} \quad \text{and} \quad \vec{a} = 2\vec{u} + \vec{v} - \vec{w}.$$

19.1 Could the set $\{\vec{u}, \vec{v}, \vec{w}\}$ be linearly independent?

Suppose that

$$\vec{a} = \vec{u} + 6\vec{r} - \vec{s}$$

is the *only* way to write \vec{a} using $\vec{u}, \vec{r}, \vec{s}$.

19.2 Is $\{\vec{u}, \vec{r}, \vec{s}\}$ linearly independent?

19.3 Is $\{\vec{u}, \vec{r}\}$ linearly independent?

19.4 Is $\{\vec{u}, \vec{v}, \vec{w}, \vec{r}\}$ linearly independent?

Task 1.4: Linear Independence and Dependence, Creating Examples

1. Fill in the following chart keeping track of the strategies you used to generate examples.

	Linearly independent	Linearly dependent
A set of 2 vectors in \mathbb{R}^2		
A set of 3 vectors in \mathbb{R}^2		
A set of 2 vectors in \mathbb{R}^3		
A set of 3 vectors in \mathbb{R}^3		
A set of 4 vectors in \mathbb{R}^3		

2. Write at least two generalizations that can be made from these examples and the strategies you used to create them.

Dot Products & Normal Forms

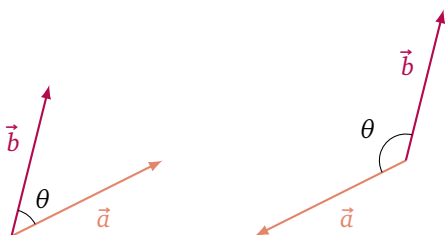
In this module you will learn

- Geometric and algebraic definitions of the dot product.
- How dot products relate to the length of a vector and the angle between two vectors.
- The *normal form* of lines, planes, and hyperplanes.

Let \vec{a} and \vec{b} be vectors rooted at the same point and let θ denote the *smaller* of the two angles between them, so $0 \leq \theta \leq \pi$. The *dot product* of \vec{a} and \vec{b} is defined to be

$$\vec{a} \cdot \vec{b} = \|\vec{a}\| \|\vec{b}\| \cos \theta.$$

We will call this the *geometric definition of the dot product*. The dot product is also sometimes called the *scalar product* because the result is a scalar. Note that $\vec{a} \cdot \vec{b} = 0$ when either \vec{a} or \vec{b} is zero or, more interestingly, if their directions are perpendicular.



Algebraically, we can define the dot product in terms of coordinates:

$$\begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{bmatrix} \cdot \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_n \end{bmatrix} = a_1 b_1 + a_2 b_2 + \cdots + a_n b_n.$$

We will call this the *algebraic definition of the dot product*.

By switching between algebraic and geometric definitions, we can use the dot product to find quantities that are otherwise difficult to find.

Example. Find the angle between the vectors $\vec{v} = (1, 2, 3)$ and $\vec{w} = (1, 1, -2)$.

From the algebraic definition of the dot product, we know

$$\vec{v} \cdot \vec{w} = 1(1) + 2(1) + 3(-2) = -3.$$

From the geometric definition, we know

$$\vec{v} \cdot \vec{w} = \|\vec{v}\| \|\vec{w}\| \cos \theta = \sqrt{14} \sqrt{6} \cos \theta = 2\sqrt{21} \cos \theta.$$

Equating the two definitions of $\vec{v} \cdot \vec{w}$, we see

$$\cos \theta = \frac{-3}{2\sqrt{21}}$$

and so $\theta = \arccos\left(\frac{-3}{2\sqrt{21}}\right)$.

The dot product has several interesting properties. Since the angle between \vec{a} and itself is 0, the geometric definition of the dot product tells us

$$\vec{a} \cdot \vec{a} = \|\vec{a}\| \|\vec{a}\| \cos 0 = \|\vec{a}\|^2.$$

In other words,

$$\|\vec{a}\| = \sqrt{\vec{a} \cdot \vec{a}},$$

and so dot products can be used to compute the length of vectors.¹⁶

From the algebraic definition of the dot product, we can deduce several distributive laws. Namely, for any vectors \vec{a} , \vec{b} , and \vec{c} and any scalar k we have

$$(\vec{a} + \vec{b}) \cdot \vec{c} = \vec{a} \cdot \vec{c} + \vec{b} \cdot \vec{c} \quad \vec{a} \cdot (\vec{b} + \vec{c}) = \vec{a} \cdot \vec{b} + \vec{a} \cdot \vec{c}$$

$$(k\vec{a}) \cdot \vec{b} = k(\vec{a} \cdot \vec{b}) = \vec{a} \cdot (k\vec{b})$$

and

$$\vec{a} \cdot \vec{b} = \vec{b} \cdot \vec{a}.$$

Orthogonality

Recall that for vectors \vec{a} and \vec{b} , the relationship $\vec{a} \cdot \vec{b} = 0$ can hold for two reasons: (i) either $\vec{a} = \vec{0}$, $\vec{b} = \vec{0}$, or both or (ii) \vec{a} and \vec{b} meet at 90° . Thus, the dot product can be used to tell if two vectors are perpendicular. There is some strangeness with the zero vector here, but it turns out this strangeness simplifies our lives mathematically.

Orthogonal. Two vectors \vec{u} and \vec{v} are **orthogonal** to each other if $\vec{u} \cdot \vec{v} = 0$. The word orthogonal is synonymous with the word perpendicular.

The definition of orthogonal encapsulates both the idea of two vectors forming a right angle and the idea of one of them being $\vec{0}$.

Before we continue, let's pin down the idea of one vector pointing in the *direction* of another. There are many ways we could define this idea, but we'll go with this one.

Direction. The vector \vec{u} points in the **direction** of the vector \vec{v} if $k\vec{u} = \vec{v}$ for some scalar k . The vector \vec{u} points in the **positive direction** of \vec{v} if $k\vec{u} = \vec{v}$ for some positive scalar k .

The vector $2\vec{e}_1$ points in the direction of \vec{e}_1 since $\frac{1}{2}(2\vec{e}_1) = \vec{e}_1$. Since $\frac{1}{2} > 0$, $2\vec{e}_1$ also points in the positive direction of \vec{e}_1 . In contrast, $-\vec{e}_1$ points in the direction \vec{e}_1 but not the positive direction of \vec{e}_1 .

When it comes to the relationship between two vectors, there are two extremes: they point in the same direction, or they are orthogonal. The dot product can be used to tell you which of these cases you're in, and more than that, it can tell you to what extent one vector points in the direction of another (even if they don't point in the same direction).

Example. Let $\vec{a} = \begin{bmatrix} 1 \\ 2 \end{bmatrix}$, $\vec{b} = \begin{bmatrix} 3 \\ 3 \end{bmatrix}$, $\vec{c} = \begin{bmatrix} 2 \\ 1 \end{bmatrix}$, and $\vec{v} = \begin{bmatrix} 3 \\ 4 \end{bmatrix}$. Which vector out of \vec{a} , \vec{b} , and \vec{c} has a direction closest to the direction of \vec{v} ?

XXX Finish

Normal Form of Lines and Planes

Let $\vec{n} = \begin{bmatrix} 1 \\ 2 \end{bmatrix}$. If a vector $\vec{v} = \begin{bmatrix} v_1 \\ v_2 \end{bmatrix}$ is orthogonal to \vec{n} , then

$$\vec{n} \cdot \vec{v} = v_1 + 2v_2 = 0,$$

and so $v_1 = -2v_2$. In other words, \vec{v} is orthogonal to \vec{n} exactly when $\vec{v} \in \text{span}\left\{\begin{bmatrix} -2 \\ 1 \end{bmatrix}\right\}$. What have we learned?

The set of all vectors orthogonal to \vec{n} forms a line $\ell = \text{span}\left\{\begin{bmatrix} -2 \\ 1 \end{bmatrix}\right\}$. In this case, we call \vec{n} a *normal vector* for ℓ .

XXX Figure

Normal Vector. A **normal vector** to a line (or plane or hyperplane) is a non-zero vector that is orthogonal to all direction vectors for the line (or plane or hyperplane).

In \mathbb{R}^2 , normal vectors provide yet another way to describe lines, including lines which don't pass through the origin.

¹⁶ Oftentimes in non-geometric settings, the dot product between two vectors is defined first and then the length of \vec{a} is actually *defined* to be $\sqrt{\vec{a} \cdot \vec{a}}$.

Let $n = \begin{bmatrix} 1 \\ 2 \end{bmatrix}$ as before, and fix $\vec{p} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$. If we draw the set of all vectors orthogonal to \vec{n} but *root all the vectors at \vec{p}* , again we get a line, but this time the line passes through \vec{p} .

XXX Figure

In fact, the line we get is $\ell_2 = \text{span}\left\{\begin{bmatrix} -2 \\ 1 \end{bmatrix}\right\} + \left\{\begin{bmatrix} 1 \\ 1 \end{bmatrix}\right\} = \ell + \{\vec{p}\}$, which is just ℓ (the parallel line through the origin) translated by \vec{p} .

Let's relate this to dot products and normal vectors. By definition, for every $\vec{v} \in \ell$, we have $\vec{n} \cdot \vec{v} = 0$. Since ℓ_2 is a translate of ℓ by \vec{p} , we deduce the relationship that for every $\vec{v} \in \ell_2$,

$$\vec{n} \cdot (\vec{v} - \vec{p}) = 0,$$

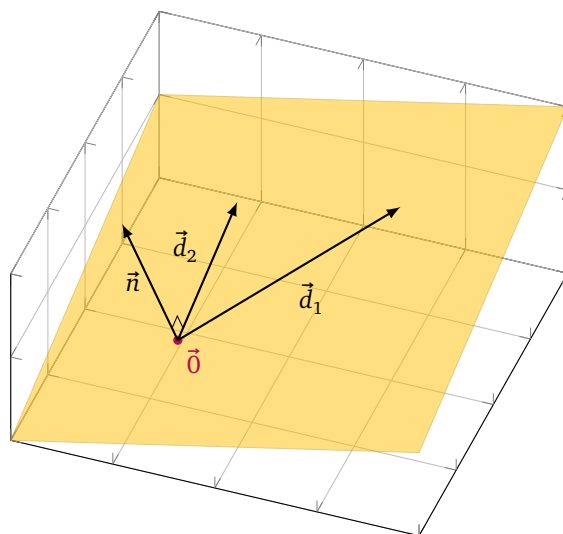
and this is the *normal form* of a line in \mathbb{R}^2 .

Normal Form of a Line. A line $\ell \subseteq \mathbb{R}^2$ is expressed in *normal form* if ℓ is the solution set to the equation

$$\vec{n} \cdot (\vec{x} - \vec{p}) = 0$$

where \vec{n} and \vec{p} are fixed vectors.

What about in \mathbb{R}^3 ? Fix a non-zero vector $\vec{n} \in \mathbb{R}^3$ and let $\mathcal{Q} \subseteq \mathbb{R}^3$ be the set of vectors orthogonal to \vec{n} . \mathcal{Q} is a plane through the origin, and again, we call \vec{n} a *normal vector* of the plane \mathcal{Q} .



In a similar way to the case of a line, \mathcal{Q} is the set of solutions to $\vec{n} \cdot \vec{x} = 0$. And, for any $\vec{p} \in \mathbb{R}^3$, the translated plane $\mathcal{Q} + \{\vec{p}\}$ is the solution set to

$$\vec{n} \cdot (\vec{x} - \vec{p}) = 0.$$

Thus, we see planes in \mathbb{R}^3 have a normal form just like lines in \mathbb{R}^2 do.

Example. Find vector form and normal form of the plane \mathcal{P} passing through the point $A = (1, 0, 0)$, $B = (0, 1, 0)$ and $C = (0, 0, 1)$.

To find vector form of \mathcal{P} , we need a point on the plane and two direction vectors. We have three points on the plane, so we can obtain two direction vectors by subtracting these points in different ways. Let

$$\vec{d}_1 = \vec{AB} = \begin{bmatrix} -1 \\ 1 \\ 0 \end{bmatrix} \quad \vec{d}_2 = \vec{AC} = \begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix}.$$

Using the point A , we may now write vector form of \mathcal{P} as

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = t \begin{bmatrix} -1 \\ 1 \\ 0 \end{bmatrix} + s \begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}.$$

To write normal form we need to find a normal vector to \mathcal{P} . By inspection, we can see that $\vec{n} = (1, 1, 1)$ is a normal vector to \mathcal{P} . If we weren't so insightful, we could also solve the system $\vec{n} \cdot \vec{d}_1 = 0$ and $\vec{n} \cdot \vec{d}_2 = 0$ to find a normal vector. Now, we may express \mathcal{P} in normal form as

$$\begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \cdot \left(\begin{bmatrix} x \\ y \\ z \end{bmatrix} - \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} \right) = 0.$$

In \mathbb{R}^2 , only lines have a normal form, and in \mathbb{R}^3 only planes have a normal form. In general, we call objects in \mathbb{R}^n which have a normal form *hyperplanes*.

Hyperplane. The set $X \subseteq \mathbb{R}^n$ is called a *hyperplane* if there exists $\vec{n} \neq \vec{0}$ and \vec{p} so that X is the set of solutions to the equation

$$\vec{n} \cdot (\vec{x} - \vec{p}) = 0.$$

Hyperplanes always have dimension one less than the space they're contained in. So, hyperplanes in \mathbb{R}^2 are (one-dimensional) lines, hyperplanes in \mathbb{R}^3 are regular (two-dimensional) planes, and hyperplanes in \mathbb{R}^4 are (three-dimensional) volumes.

Hyperplanes and Linear Equations

Suppose $\vec{n}, \vec{p} \in \mathbb{R}^3$ and $\vec{n} \neq \vec{0}$. Then, solutions to

$$\vec{n} \cdot (\vec{x} - \vec{p}) = 0$$

define a plane \mathcal{P} . But, $\vec{n} \cdot (\vec{x} - \vec{p}) = 0$ if and only if

$$\vec{n} \cdot \vec{x} = \vec{n} \cdot \vec{p} = \alpha.$$

Since \vec{n} and \vec{p} are fixed, α is a constant. Expanding using coordinates, we see

$$\vec{n} \cdot (\vec{x} - \vec{p}) = \vec{n} \cdot \vec{x} - \alpha = n_x x + n_y y + n_z z - \alpha = 0$$

and so \mathcal{P} is the set of solutions to

$$n_x x + n_y y + n_z z = \alpha. \quad (4)$$

Equation (4) is sometimes called *scalar form* of a plane. For us, it will not be important to distinguish between scalar and normal form, but what is important is that we can use the row reduction algorithm to write the complete solution to (4), and this complete solution will necessarily be written in vector form.

Example. Let $\mathcal{Q} \subseteq \mathbb{R}^3$ be the plane passing through \vec{p} and with normal vector \vec{n} where

$$\vec{p} = \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix} \quad \text{and} \quad \vec{n} = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}.$$

Write \mathcal{Q} in vector form.

We know \mathcal{Q} is the set of solutions to $\vec{n} \cdot (\vec{x} - \vec{p}) = 0$. In scalar form, this equation becomes

$$\vec{n} \cdot (\vec{x} - \vec{p}) = \vec{n} \cdot \vec{x} - \vec{n} \cdot \vec{p} = x + y + z - 2 = 0.$$

Rearranging, we see \mathcal{Q} is the set of all solutions to

$$x + y + z = 2.$$

Using the row reduction algorithm to write the complete solution,¹⁷ we get

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = t \begin{bmatrix} -1 \\ 1 \\ 0 \end{bmatrix} + s \begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix} + \begin{bmatrix} 2 \\ 0 \\ 0 \end{bmatrix}.$$

¹⁷ In some sense, this is overkill because the equation corresponds to the augmented matrix $\begin{bmatrix} 1 & 1 & 1 & | & 2 \end{bmatrix}$, which is already row reduced.

Dot Product

Norm

DEFINITION

The **norm** of a vector $\vec{v} = \begin{bmatrix} v_1 \\ \vdots \\ v_n \end{bmatrix}$ is the length/magnitude of \vec{v} . It is written $\|\vec{v}\|$ and can be computed from the Pythagorean formula

$$\|\vec{v}\| = \sqrt{v_1^2 + \cdots + v_n^2}.$$

Dot Product

DEFINITION

If $\vec{a} = \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{bmatrix}$ and $\vec{b} = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_n \end{bmatrix}$ are two vectors in n -dimensional space, then the **dot product** of \vec{a} and \vec{b} is

$$\vec{a} \cdot \vec{b} = a_1 b_1 + a_2 b_2 + \cdots + a_n b_n.$$

Equivalently, the dot product is defined by the geometric formula

$$\vec{a} \cdot \vec{b} = \|\vec{a}\| \|\vec{b}\| \cos \theta$$

where θ is the angle between \vec{a} and \vec{b} .

20

Let $\vec{a} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$, $\vec{b} = \begin{bmatrix} 3 \\ 1 \end{bmatrix}$, and $\vec{u} = \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix}$.

- 20.1 (a) Draw a picture of \vec{a} and \vec{b} .
 (b) Compute $\vec{a} \cdot \vec{b}$.
 (c) Find $\|\vec{a}\|$ and $\|\vec{b}\|$ and use your knowledge of the multiple ways to compute the dot product to find θ , the angle between \vec{a} and \vec{b} . Label θ on your picture.
- 20.2 Draw the graph of \cos and identify which angles make \cos negative, zero, or positive.
- 20.3 Draw a new picture of \vec{a} and \vec{b} and on that picture draw
 - (a) a vector \vec{c} where $\vec{c} \cdot \vec{a}$ is negative.
 - (b) a vector \vec{d} where $\vec{d} \cdot \vec{a} = 0$ and $\vec{d} \cdot \vec{b} < 0$.
 - (c) a vector \vec{e} where $\vec{e} \cdot \vec{a} = 0$ and $\vec{e} \cdot \vec{b} > 0$.
 - (d) Could you find a vector \vec{f} where $\vec{f} \cdot \vec{a} = 0$ and $\vec{f} \cdot \vec{b} = 0$? Explain why or why not.
- 20.4 Recall the vector \vec{u} whose coordinates are given at the beginning of this problem.
 - (a) Write down a vector \vec{v} so that the angle between \vec{u} and \vec{v} is $\pi/2$. (Hint, how does this relate to the dot product?)
 - (b) Write down another vector \vec{w} (in a different direction from \vec{v}) so that the angle between \vec{w} and \vec{u} is $\pi/2$.
 - (c) Can you write down other vectors different than both \vec{v} and \vec{w} that still form an angle of $\pi/2$ with \vec{u} ? How many such vectors are there?

For a vector $\vec{v} \in \mathbb{R}^n$, the formula

$$\|\vec{v}\| = \sqrt{\vec{v} \cdot \vec{v}}$$

always holds.

Distance

The **distance** between two vectors \vec{u} and \vec{v} is $\|\vec{u} - \vec{v}\|$.

Unit Vector

A vector \vec{v} is called a **unit vector** if $\|\vec{v}\| = 1$.

21

Let $\vec{u} = \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix}$ and $\vec{v} = \begin{bmatrix} 1 \\ 1 \\ 3 \end{bmatrix}$.

- 21.1 Find the distance between \vec{u} and \vec{v} .
- 21.2 Find a unit vector in the direction of \vec{u} .
- 21.3 Does there exist a *unit vector* \vec{x} that is distance 1 from \vec{u} ?
- 21.4 Suppose \vec{y} is a unit vector and the distance between \vec{y} and \vec{u} is 2. What is the angle between \vec{y} and \vec{u} ?

Orthogonal

DEF

Two vectors \vec{u} and \vec{v} are *orthogonal* to each other if $\vec{u} \cdot \vec{v} = 0$. The word orthogonal is synonymous with the word perpendicular.

22

22.1 Find two vectors orthogonal to $\vec{a} = \begin{bmatrix} 1 \\ -3 \end{bmatrix}$. Can you find two such vectors that are not parallel?

22.2 Find two vectors orthogonal to $\vec{b} = \begin{bmatrix} 1 \\ -3 \\ 4 \end{bmatrix}$. Can you find two such vectors that are not parallel?

22.3 Suppose \vec{x} and \vec{y} are orthogonal to each other and $\|\vec{x}\| = 5$ and $\|\vec{y}\| = 3$. What is the distance between \vec{x} and \vec{y} ?

23

- 23.1 Draw $\vec{u} = \begin{bmatrix} 2 \\ 3 \end{bmatrix}$ and *all* vectors orthogonal to it. Call this set A .
- 23.2 If $\vec{x} = \begin{bmatrix} x \\ y \end{bmatrix}$ and \vec{x} is orthogonal to \vec{u} , what is $\vec{x} \cdot \vec{u}$?
- 23.3 Expand the dot product $\vec{u} \cdot \vec{x}$ to get an equation for A .
- 23.4 If possible, express A as a span.

Normal Vector

DEF

A **normal vector** to a line (or plane or hyperplane) is a non-zero vector that is orthogonal to all direction vectors for the line (or plane or hyperplane).

24

Let $\vec{d} = \begin{bmatrix} 1 \\ 2 \end{bmatrix}$ and $\vec{p} = \begin{bmatrix} 1 \\ -1 \end{bmatrix}$, and define the lines

$$\ell_1 = \text{span}\{\vec{d}\} \quad \text{and} \quad \ell_2 = \text{span}\{\vec{d}\} + \{\vec{p}\}.$$

- 24.1 Find a vector \vec{n} that is a normal vector for both ℓ_1 and ℓ_2 .
- 24.2 Let $\vec{v} \in \ell_1$ and $\vec{u} \in \ell_2$. What is $\vec{n} \cdot \vec{v}$? What about $\vec{n} \cdot (\vec{u} - \vec{p})$? Explain using a picture.
- 24.3 A line is expressed in *normal form* if it is represented by an equation of the form $\vec{n} \cdot (\vec{x} - \vec{q}) = 0$ for some \vec{n} and \vec{q} . Express ℓ_1 and ℓ_2 in normal form.
- 24.4 Some textbooks would claim that ℓ_2 could be expressed in normal form as $\begin{bmatrix} 2 \\ -1 \end{bmatrix} \cdot \vec{x} = 3$. How does this relate to the $\vec{n} \cdot (\vec{x} - \vec{p}) = 0$ normal form? Where does the 3 come from?

Let $\vec{n} = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$.

- 25.1 Use set-builder notation to write down the set, X , of all vectors orthogonal to \vec{n} . Describe this set geometrically.
- 25.2 Describe X using an equation.
- 25.3 Describe X as a span.

Projections & Vector Components

In this module you will learn

- The definition of the projection of a vector and the vector component of one vector in the direction of another.
- The relationship between projection, orthogonality, and vector components.
- How to project a vector onto a line.

Consider the following situation: you're designing a 3d video game, but your users only have 2d screens. Or, you have a 900 dimensional dataset, but you want to visualize it on a continuum (i.e., as a line). Each of these is an example of finding the best approximation to a set of points given some restrictions. In general, this operation is called a *projection* and in the world of linear algebra, it has a very particular meaning.

Projection. Let X be a set. The *projection* of the vector \vec{v} onto X , written $\text{proj}_X \vec{v}$, is the closest point in X to \vec{v} .

Let $\mathcal{P}_{xy} \subseteq \mathbb{R}^3$ be the xy -plane in \mathbb{R}^3 and let $\vec{v} = \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix}$. Intuitively, $\text{proj}_{\mathcal{P}_{xy}} \vec{v}$ is the “shadow” that \vec{v} would cast on \mathcal{P}_{xy} if the sun were directly overhead. In other words,

$$\text{proj}_{\mathcal{P}_{xy}} \vec{v} = \begin{bmatrix} 1 \\ 2 \\ 0 \end{bmatrix}.$$

XXX Figure

Let $\ell_y \subseteq \mathbb{R}^3$ be the y -axis in \mathbb{R}^3 . It's a little bit harder to visualize what $\text{proj}_{\ell_y} \vec{v}$ is, so let's appeal to some definitions.

By definition, every vector in ℓ_y takes the form $\vec{u}_t = \begin{bmatrix} 0 \\ t \\ 0 \end{bmatrix}$ for some $t \in \mathbb{R}$. The distance between \vec{u}_t and \vec{v} is

$$\|\vec{u}_t - \vec{v}\| = \left\| \begin{bmatrix} 0 \\ t \\ 0 \end{bmatrix} - \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix} \right\| = \sqrt{1^2 + (t-2)^2 + 3^2}.$$

Since $(t-2)^2$ is always positive, the quantity $\sqrt{1^2 + (t-2)^2 + 3^2}$ is minimized when $(t-2)^2 = 0$. That is, when $t = 2$. Thus, we see \vec{u}_2 is the closest vector in ℓ_y to \vec{v} and so,

$$\text{proj}_{\ell_y} \vec{v} = \vec{u}_2 = \begin{bmatrix} 0 \\ 2 \\ 0 \end{bmatrix}.$$

Here, we appealed directly to the definition of projection to find the answer.

Example. Let $\ell \subseteq \mathbb{R}^2$ be the line given in vector form by $\vec{x} = t \begin{bmatrix} 1 \\ 1 \end{bmatrix} + \begin{bmatrix} 3 \\ -2 \end{bmatrix}$, and let $\vec{v} = \begin{bmatrix} -1 \\ -1 \end{bmatrix}$. Use the definition of projection to find $\text{proj}_{\ell} \vec{v}$.

XXX Finish

Every example of a projection so far shares a geometric property. In the case of lines and planes, the vector from the projection to the original point is a normal vector for the line or plane.

XXX Figure

Stated precisely, if X is a line or plane and $\vec{v} \notin X$ is a vector, then $\vec{v} - \text{proj}_X \vec{v}$ is a normal vector for X . Using this fact, we can find projections onto lines and planes without solving non-linear equations.

Example. Let $\ell \subseteq \mathbb{R}^2$ be the line given in vector form by $\vec{x} = t \begin{bmatrix} 1 \\ 1 \end{bmatrix} + \begin{bmatrix} 3 \\ -2 \end{bmatrix}$, and let $\vec{v} = \begin{bmatrix} -1 \\ -1 \end{bmatrix}$. Use the fact that $\vec{v} - \text{proj}_{\ell} \vec{v}$ is a normal vector to ℓ to find $\text{proj}_{\ell} \vec{v}$.

XXX Finish

Projections Onto Other Sets

For projections onto lines and planes, we can use what we know about normal vectors to simplify our life. The same is true when projecting onto other sets, but we must always keep the definition in mind.

Example. Let $\mathcal{T} \subseteq \mathbb{R}^2$ be the filled in triangle with vertices $\begin{bmatrix} 0 \\ 0 \end{bmatrix}$, $\begin{bmatrix} 1 \\ 0 \end{bmatrix}$, and $\begin{bmatrix} 0 \\ 2 \end{bmatrix}$, and let

$$\vec{a} = \begin{bmatrix} 1/4 \\ 1/4 \end{bmatrix} \quad \vec{b} = \begin{bmatrix} 3 \\ 1/2 \end{bmatrix} \quad \vec{c} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}.$$

Find $\text{proj}_{\mathcal{T}} \vec{a}$, $\text{proj}_{\mathcal{T}} \vec{b}$, and $\text{proj}_{\mathcal{T}} \vec{c}$.

XXX Finish XXX Figure

Subtleties of Projections

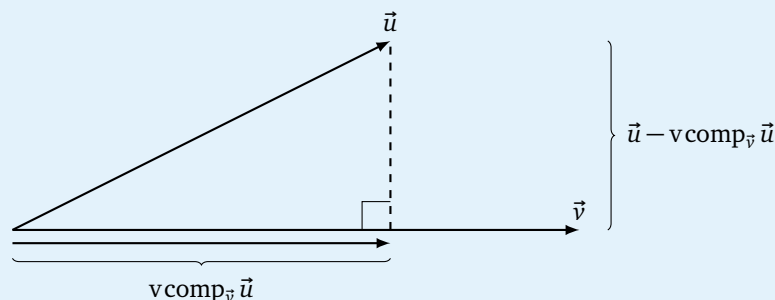
You might be wondering, what is $\text{proj}_X \vec{v}$ if \vec{v} is equidistant from *two* closest points in X . Or, what if X is an *open* set (for example, an open interval in \mathbb{R}^1). Then there might not be a closest point in X to \vec{v} . In both these cases, we say $\text{proj}_X \vec{v}$ is *undefined*.

Formally, for a fixed set X , we consider $P(\vec{v}) = \text{proj}_X \vec{v}$ as a function that inputs and outputs vectors. And, as a function, P has a domain consisting of exactly the vectors \vec{v} for which $P(\vec{v})$ is defined. As it happens, if X is a line or a plane, the domain of P is all of \mathbb{R}^n , and in this text, we will be sensible and only ask about projections restricted to an appropriate domain.

Vector Components

We've seen before that dot products can be used to measure how much one vector points in the direction of another. But, we can go further. Suppose $\vec{v} \neq \vec{0}$ and \vec{u} are vectors. We might want to *decompose* \vec{u} into the sum of two vectors, one which is in the direction of \vec{v} and the other which is orthogonal to \vec{v} . The tool to that does this is the vector component.

Vector Components. Let \vec{u} and $\vec{v} \neq \vec{0}$ be vectors. The **vector component of \vec{u} in the \vec{v} direction**, written $\text{vcomp}_{\vec{v}} \vec{u}$, is the vector in the direction of \vec{v} so that $\vec{u} - \text{vcomp}_{\vec{v}} \vec{u}$ is orthogonal to \vec{v} .



From the definition, it's obvious that

$$\vec{u} = \text{vcomp}_{\vec{v}} \vec{u} + (\vec{u} - \text{vcomp}_{\vec{v}} \vec{u})$$

is a decomposition of \vec{u} into the sum of two vectors, one, $\text{vcomp}_{\vec{v}} \vec{u}$, is in the direction of \vec{v} , and the other, $\vec{u} - \text{vcomp}_{\vec{v}} \vec{u}$, is orthogonal to \vec{v} .

Example. Find the component of $\vec{a} = \begin{bmatrix} 1 \\ 2 \end{bmatrix}$ in the direction of $\vec{b} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$.

XXX Finish

Since we'll be computing vector components often, let's try to find a formula for $\text{vcomp}_{\vec{v}} \vec{u}$.

By definition $\text{vcomp}_{\vec{v}} \vec{u}$ is a vector in the direction of \vec{v} , so

$$\text{vcomp}_{\vec{v}} \vec{u} = k\vec{v}.$$

Further, from the definition $\vec{u} - \text{vcomp}_{\vec{v}} \vec{u}$ is orthogonal to \vec{v} , and so

$$\vec{v} \cdot (\vec{u} - \text{vcomp}_{\vec{v}} \vec{u}) = \vec{v} \cdot (\vec{u} - k\vec{v}) = \vec{v} \cdot \vec{u} - k\vec{v} \cdot \vec{v} = 0,$$

Because $\vec{v} \neq \vec{0}$, we know $\vec{v} \cdot \vec{v} \neq 0$. Therefore, we may rearrange and solve for k to find

$$k = \frac{\vec{v} \cdot \vec{u}}{\vec{v} \cdot \vec{v}},$$

which means

$$\text{vcomp}_{\vec{v}} \vec{u} = \left(\frac{\vec{v} \cdot \vec{u}}{\vec{v} \cdot \vec{v}} \right) \vec{v}.$$

The Relationship Between Vector Components and Projections

Vector components and projections onto lines are closely related. So closely related that many textbooks use the single word *projection* to talk about both vector components and projections. Let's take a moment to explore this relationship.

Let $\vec{v} = \begin{bmatrix} 2 \\ 4 \end{bmatrix}$ and $\vec{u} = \begin{bmatrix} 2 \\ -1 \end{bmatrix}$ and let $\ell = \text{span}\{\vec{v}\}$. Drawing a picture of ℓ , \vec{u} , and $\text{proj}_{\ell} \vec{u}$, we see that $\text{proj}_{\ell} \vec{u}$ satisfies all the properties of $\text{vcomp}_{\vec{v}} \vec{u}$.

XXX Figure

Since $\ell = \text{span}\{\vec{v}\}$ and $\text{proj}_{\ell} \vec{u} \in \ell$, we know that $\text{proj}_{\ell} \vec{u}$ is in the direction of \vec{v} . Further, from geometric arguments, we know $\vec{u} - \text{proj}_{\ell} \vec{u}$ is a normal vector for ℓ and is therefore orthogonal to its direction vector, \vec{v} ! What's more, we didn't use anything in particular about \vec{u} and \vec{v} when making this argument (other than $\vec{v} \neq \vec{0}$). This means, we may establish a general formula.

Theorem. For vectors \vec{u} and $\vec{v} \neq \vec{0}$, we have

$$\text{proj}_{\text{span}\{\vec{v}\}} \vec{u} = \text{vcomp}_{\vec{v}} \vec{u}.$$

This is great news because vector components are easy to compute using dot products while projections are usually hard to compute.

Example. Compute the projection of $\vec{a} = \begin{bmatrix} 3 \\ 7 \end{bmatrix}$ onto $\ell = \text{span}\left\{\begin{bmatrix} 1 \\ -4 \end{bmatrix}\right\}$.

XXX Finish

It's worth noting, however, that vector components are equal to projections *only in the case when you're projecting onto a span*. In general, projections and vector components are unrelated.

Example. Let $\vec{a} = \begin{bmatrix} 3 \\ 7 \end{bmatrix}$, $\vec{b} = \begin{bmatrix} 1 \\ -4 \end{bmatrix}$, and let ℓ be the line given in vector form by $\vec{x} = t\vec{b} + \vec{a}$. Show that $\text{proj}_{\ell} \vec{a} \neq \text{vcomp}_{\vec{v}} \vec{a}$.

XXX Finish

Projections

Projection

DEF

Let X be a set. The **projection** of the vector \vec{v} onto X , written $\text{proj}_X \vec{v}$, is the closest point in X to \vec{v} .

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Let $\vec{a} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$, $\vec{b} = \begin{bmatrix} 4 \\ 0 \end{bmatrix}$, $\vec{v} = \begin{bmatrix} 2 \\ 2 \end{bmatrix}$ and $\ell = \text{span}\{\vec{a}\}$.

26.1 Draw \vec{a} , \vec{b} , and \vec{v} in the same picture.

26.2 Find $\text{proj}_{\{\vec{b}\}} \vec{v}$, $\text{proj}_{\{\vec{a}, \vec{b}\}} \vec{v}$.

26.3 Find $\text{proj}_\ell \vec{v}$. (Recall that a quadratic $at^2 + bt + c$ has a minimum at $t = -\frac{b}{2a}$).

26.4 Is $\vec{v} - \text{proj}_\ell \vec{v}$ a normal vector for ℓ ? Why or why not?

Let K be the line given in vector form by $\vec{x} = t \begin{bmatrix} 1 \\ 2 \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \end{bmatrix}$ and let $\vec{c} = \begin{bmatrix} 1 \\ 3 \end{bmatrix}$.

27.1 Make a sketch with \vec{c} , K , and $\text{proj}_K \vec{c}$ (you don't need to compute $\text{proj}_K \vec{c}$ exactly).

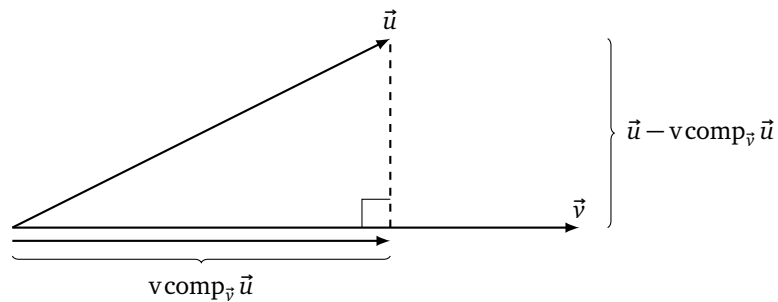
27.2 What should $(\vec{c} - \text{proj}_K \vec{c}) \cdot \begin{bmatrix} 1 \\ 2 \end{bmatrix}$ be? Explain.

27.3 Use your formula from the previous part to find $\text{proj}_K \vec{c}$ *without* computing any distances.

Vector Components

Let \vec{u} and $\vec{v} \neq \vec{0}$ be vectors. The **vector component of \vec{u} in the \vec{v} direction**, written $\text{vcomp}_{\vec{v}} \vec{u}$, is the vector in the direction of \vec{v} so that $\vec{u} - \text{vcomp}_{\vec{v}} \vec{u}$ is orthogonal to \vec{v} .

DEFINITION



28 Let $\vec{a}, \vec{b} \in \mathbb{R}^3$ be unknown vectors.

28.1 List two conditions that $\text{vcomp}_{\vec{b}} \vec{a}$ must satisfy.

28.2 Find a formula for $\text{vcomp}_{\vec{b}} \vec{a}$.

Let $\vec{d} = \begin{bmatrix} 3 \\ 3 \end{bmatrix}$ and $\vec{u} = \begin{bmatrix} 1 \\ 2 \end{bmatrix}$.

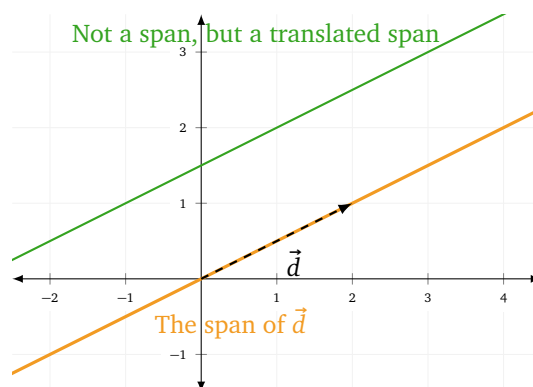
- 29.1 Draw \vec{d} , \vec{u} , $\text{span}\{\vec{d}\}$, and $\text{proj}_{\text{span}\{\vec{d}\}} \vec{u}$ in the same picture.
- 29.2 How do $\text{proj}_{\text{span}\{\vec{d}\}} \vec{u}$ and $\text{vcomp}_{\vec{d}} \vec{u}$ relate?
- 29.3 Compute $\text{proj}_{\text{span}\{\vec{d}\}} \vec{u}$ and $\text{vcomp}_{\vec{d}} \vec{u}$.
- 29.4 Compute $\text{vcomp}_{-\vec{d}} \vec{u}$. Is this the same as or different from $\text{vcomp}_{\vec{d}} \vec{u}$? Explain.

Subspaces & Bases

In this module you will learn

- Formal and intuitive definitions of subspaces.
- The relationship between subspaces and spans.
- How to prove whether or not a set is a subspace.
- How to find a basis for and the dimension of a subspace.

Lines or planes through the origin can be written as spans of their direction vectors. However, a line or plane that doesn't pass through the origin cannot be written as a span—it must be expressed as a *translated span*.



There's something special about sets that can be expressed as (untranslated) spans. In particular, since a linear combination of linear combinations is still a linear combination, a span is *closed* with respect to linear combinations. That is, by taking linear combinations of vectors in a span, you cannot escape the span. In general, sets that have this property are called *subspaces*.

Subspace. A non-empty subset $V \subseteq \mathbb{R}^n$ is called a **subspace** if for all $\vec{u}, \vec{v} \in V$ and all scalars k we have

(i) $\vec{u} + \vec{v} \in V$; and

(ii) $k\vec{u} \in V$.

In the definition of subspace, property (i) is called *being closed with respect to vector addition* and property (ii) is called *being closed with respect to scalar multiplication*.

Subspaces generalize the idea of *flat spaces through the origin*. They encompass lines, planes, volumes and more.

Example. Let $\mathcal{V} \subseteq \mathbb{R}^2$ be the complete solution to $x + 2y = 0$. Show that \mathcal{V} is a subspace.

XXX Finish

Example. Let $\mathcal{W} \subseteq \mathbb{R}^2$ be the line expressed in vector form as

$$\vec{x} = t \begin{bmatrix} 1 \\ 2 \end{bmatrix} + \begin{bmatrix} 1 \\ 1 \end{bmatrix}.$$

Determine whether \mathcal{W} is a subspace.

XXX Finish

As mentioned earlier, subspaces and spans are deeply connected by the following theorem.

Theorem. Every subspace is a span and every span is a subspace. More precisely, $\mathcal{V} \subseteq \mathbb{R}^n$ is a subspace if and only if $\mathcal{V} = \text{span } \mathcal{X}$ for some set \mathcal{X} .

Proof. We will start by showing every span is a subspace. Fix $\mathcal{X} \subseteq \mathbb{R}^2$ and let $\mathcal{V} = \text{span } \mathcal{X}$. First note that if $\mathcal{X} \neq \{\}$, then \mathcal{V} is non-empty because $\mathcal{X} \subseteq \mathcal{V}$ and if $\mathcal{X} = \{\}$, then $\mathcal{V} = \{\vec{0}\}$, and so is still non-empty.

Fix $\vec{v}, \vec{u} \in \mathcal{V}$. By definition there are $\vec{x}_1, \vec{x}_2, \dots, \vec{y}_1, \vec{y}_2, \dots \in \mathcal{X}$ and scalars $\alpha_1, \alpha_2, \dots, \beta_1, \beta_2, \dots$ so that

$$\vec{v} = \sum \alpha_i \vec{x}_i \quad \vec{u} = \sum \beta_i \vec{y}_i.$$

To verify property (i), observe that

$$\vec{u} + \vec{v} = \sum \alpha_i \vec{x}_i + \sum \beta_i \vec{y}_i$$

is also a linear combination of vectors in \mathcal{X} (because all \vec{x}_i and \vec{y}_i are in \mathcal{X}), and so $\vec{u} + \vec{v} \in \text{span } \mathcal{X} = \mathcal{V}$.

To verify property (ii), observe that for any scalar α ,

$$\alpha \vec{v} = \alpha \sum \alpha_i \vec{x}_i = \sum (\alpha \alpha_i) \vec{x}_i \in \text{span } \mathcal{X} = \mathcal{V}.$$

Since \mathcal{V} is non-empty and satisfies both properties (i) and (ii), it is a subspace.

Now we will prove that every subspace is a span. Let \mathcal{V} be a subspace and consider $\mathcal{V}' = \text{span } \mathcal{V}$. Since taking a span may only enlarge a set, we know $\mathcal{V} \subseteq \mathcal{V}'$. If we establish that $\mathcal{V}' \subseteq \mathcal{V}$, then $\mathcal{V} = \mathcal{V}' = \text{span } \mathcal{V}$, which would complete the proof.

Fix $\vec{x} \in \mathcal{V}'$. By definition, there are $\vec{v}_1, \vec{v}_2, \dots, \vec{v}_n \in \mathcal{V}$ and scalars $\alpha_1, \alpha_2, \dots, \alpha_n$ so that

$$\vec{x} = \sum \alpha_i \vec{v}_i.$$

Observe that $\alpha_i \vec{v}_i \in \mathcal{V}$ for all i , since \mathcal{V} is closed under scalar multiplication. It follows that $\alpha_1 \vec{v}_1 + \alpha_2 \vec{v}_2 \in \mathcal{V}$ because \mathcal{V} is closed under sums. Continuing, $(\alpha_1 \vec{v}_1 + \alpha_2 \vec{v}_2) + \alpha_3 \vec{v}_3 \in \mathcal{V}$ because \mathcal{V} is closed under sums. By finite induction we see

$$\vec{x} = \sum \alpha_i \vec{v}_i = \left((\alpha_1 \vec{v}_1 + \alpha_2 \vec{v}_2) + \alpha_3 \vec{v}_3 \right) + \dots + \alpha_{n-1} \vec{v}_{n-1} + \alpha_n \vec{v}_n \in \mathcal{V}.$$

Thus $\mathcal{V}' \subseteq \mathcal{V}$, which completes the proof. ■

The previous theorem is saying that spans and subspaces are two ways of talking about the same thing. Spans provide a *constructive* definition of lines/planes/volumes/etc. through the origin. That is, when you describe a line/plane/etc. through the origin as a span, you're saying "this is a line/plane/etc. through the origin because every point in it is a linear combination of *these specific vectors*". In contrast, subspaces provide a *categorical* definition of lines/planes/etc. through the origin. When you describe a line/plane/etc. through the origin as a subspace, you're saying "this is a line/plane/etc. through the origin because these *properties* are satisfied" even though you might not be able to specify any of the vectors inside.

Takeaway. Spans and subspaces are two different ways of talking about the same objects: points/lines/planes/etc. through the origin.

Special Subspaces

When thinking about \mathbb{R}^n there are two special subspaces that are always available. The first is \mathbb{R}^n itself. \mathbb{R}^n is obviously non-empty, and linear combinations of vectors in \mathbb{R}^n remain in \mathbb{R}^n . The second is the *trivial subspace*, $\{\vec{0}\}$.

Trivial Subspace. The subset $\{\vec{0}\} \subseteq \mathbb{R}^n$ is called the *trivial subspace*.

Theorem. The trivial subspace is a subspace.

Proof. First note that $\{\vec{0}\}$ is non-empty since $\vec{0} \in \{\vec{0}\}$. Now, since $\vec{0}$ is the only vector in $\{\vec{0}\}$, properties (i) and (ii) follow quickly:

$$\vec{0} + \vec{0} = \vec{0} \in \{\vec{0}\}$$

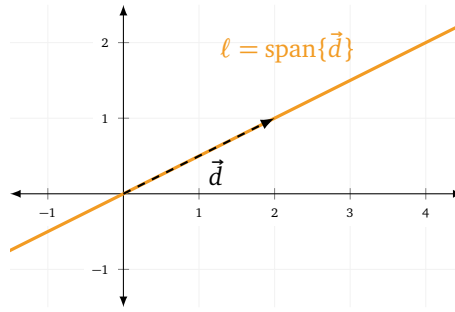
and

$$\alpha \vec{0} = \vec{0} \in \{\vec{0}\}.$$

■

Bases

Let $\vec{d} = \begin{bmatrix} 2 \\ 1 \end{bmatrix}$ and consider $\ell = \text{span}\{\vec{d}\}$.



We know that ℓ is a subspace and, for instance, $\ell = \text{span}\{\vec{d}, -2\vec{d}, \frac{1}{2}\vec{d}\}$. However, the simplest descriptions of ℓ involve the span of only one vector.

Analogously, let $\mathcal{P} = \text{span}\{\vec{d}_1, \vec{d}_2\}$ be the plane through the origin with direction vectors \vec{d}_1 and \vec{d}_2 . There are many ways to write \mathcal{P} as a span, but the simplest ones involve exactly two vectors. The idea of a *basis* comes from trying to find the simplest description of a subspace.

Basis. A *basis* for a subspace \mathcal{V} is a linearly independent set of vectors, \mathcal{B} , so that $\text{span } \mathcal{B} = \mathcal{V}$.

In short, a basis for a subspace is a linearly independent set that spans that subspace.

Example. Let $\ell = \text{span}\left\{\begin{bmatrix} 1 \\ 2 \end{bmatrix}, \begin{bmatrix} -2 \\ -4 \end{bmatrix}, \begin{bmatrix} 1/2 \\ 1 \end{bmatrix}\right\}$. Find two different bases for ℓ .

We are looking for a set of linearly independent vectors that spans ℓ . Notice that $\begin{bmatrix} 1 \\ 2 \end{bmatrix} = -1/2 \begin{bmatrix} -2 \\ -4 \end{bmatrix} = 2 \begin{bmatrix} 1/2 \\ 1 \end{bmatrix}$. Therefore,

$$\text{span}\left\{\begin{bmatrix} 1 \\ 2 \end{bmatrix}\right\} = \text{span}\left\{\begin{bmatrix} -2 \\ -4 \end{bmatrix}\right\} = \text{span}\left\{\begin{bmatrix} 1/2 \\ 1 \end{bmatrix}\right\} = \text{span}\left\{\begin{bmatrix} 1 \\ 2 \end{bmatrix}, \begin{bmatrix} -2 \\ -4 \end{bmatrix}, \begin{bmatrix} 1/2 \\ 1 \end{bmatrix}\right\} = \ell.$$

Because $\left\{\begin{bmatrix} 1 \\ 2 \end{bmatrix}\right\}$ is linearly independent and spans ℓ , we have that $\left\{\begin{bmatrix} 1 \\ 2 \end{bmatrix}\right\}$ is a basis for ℓ . Similarly, $\left\{\begin{bmatrix} 1/2 \\ 1 \end{bmatrix}\right\}$ is another basis for ℓ .

Unpacking the definition of basis a bit more, we can see that for a subspace \mathcal{V} , a basis for \mathcal{V} is a set of vectors that is *just the right size* to describe everything in \mathcal{V} . It's not too big—because it is linearly independent, there are no redundancies. It's not too small—because we require it to span \mathcal{V} .¹⁸

There are several facts everyone should know about bases:

- Bases are not unique. Every subspace (except the trivial subspace) has multiple bases.
- Given a basis for a subspace, every vector in the subspace can be written as a *unique* linear combination of vectors in that subspace.
- Any two bases for the same subspace have the same number of elements.

You can prove the first fact by observing that if $\mathcal{B} = \{\vec{b}_1, \vec{b}_2, \dots\}$ is a basis with at least one element,¹⁹ then $\{2\vec{b}_1, 2\vec{b}_2, \dots\}$ is a different basis. The second fact is a consequence of all bases being linearly independent. The third fact is less obvious and takes some legwork to prove, so we will accept it as is.

Dimension

Let \mathcal{V} be a subspace. Though there are many bases for \mathcal{V} , they all have the same number of vectors in them. And, this number says something fundamental about \mathcal{V} : it tells us the maximum number of linearly independent vectors that can simultaneously exist in \mathcal{V} . We call this number the *dimension* of \mathcal{V} .

Dimension. The *dimension* of a subspace V is the number of elements in a basis for V .

This definition agrees with our intuition about lines and planes: the dimension of a line through $\vec{0}$ is 1, and the dimension of a plane through $\vec{0}$ is 2. It even tells us the dimension of the single point $\{\vec{0}\}$ is 0.²⁰

¹⁸ If you're into British fairy tales, you might call a basis a *Goldilocks set*.

¹⁹ The empty set is a basis for the trivial subspace.

²⁰ The dimension of a line, plane, or point not through the origin is defined to be the dimension of the subspace obtained when translating it to the origin.

Example. Find the dimension of \mathbb{R}^2 .

Since $\{\vec{e}_1, \vec{e}_2\}$ is a basis for \mathbb{R}^2 , we know \mathbb{R}^2 is two dimensional.

Example. Let $\ell = \text{span}\left\{\begin{bmatrix} 1 \\ 2 \end{bmatrix}, \begin{bmatrix} -2 \\ -4 \end{bmatrix}, \begin{bmatrix} 1/2 \\ 1 \end{bmatrix}\right\}$. Find the dimension of the subspace ℓ .

This is the same subspace from the earlier example where we found $\left\{\begin{bmatrix} 1 \\ 2 \end{bmatrix}\right\}$ and $\left\{\begin{bmatrix} 1/2 \\ 1 \end{bmatrix}\right\}$ were bases for ℓ .

The basis $\left\{\begin{bmatrix} 1 \\ 2 \end{bmatrix}\right\}$ contains one element, and so ℓ is a one dimensional subspace.²¹

Example. Let $A = \{(x_1, x_2, x_3, x_4) : x_1 + 2x_2 - x_3 = 0 \text{ and } x_1 + 6x_4 = 0\}$. Find a basis for and the dimension of A .

XXX Finish

Like \mathbb{R}^2 and \mathbb{R}^3 , whenever we discuss \mathbb{R}^n , we always have a standard basis that comes along for the ride.

Standard Basis. The *standard basis* for \mathbb{R}^n is the set $\{\vec{e}_1, \dots, \vec{e}_n\}$ where

$$\vec{e}_1 = \begin{bmatrix} 1 \\ 0 \\ 0 \\ \vdots \end{bmatrix} \quad \vec{e}_2 = \begin{bmatrix} 0 \\ 1 \\ 0 \\ \vdots \end{bmatrix} \quad \vec{e}_3 = \begin{bmatrix} 0 \\ 0 \\ 1 \\ \vdots \end{bmatrix} \quad \dots$$

That is \vec{e}_i is the vector with a 1 in its i th coordinate and zeros elsewhere.

The notation \vec{e}_i is context specific. If we say $\vec{e}_i \in \mathbb{R}^2$, then \vec{e}_i must have exactly two components. If we say $\vec{e}_i \in \mathbb{R}^{45}$, then \vec{e}_i must have 45 components.

²¹ We could have considered $\left\{\begin{bmatrix} 1/2 \\ 1 \end{bmatrix}\right\}$ or one of the many other bases for ℓ and still reach the same conclusion: ℓ is one dimensional.

Subspaces and Bases

Subspace

DEFINITION

A non-empty subset $V \subseteq \mathbb{R}^n$ is called a **subspace** if for all $\vec{u}, \vec{v} \in V$ and all scalars k we have

(i) $\vec{u} + \vec{v} \in V$; and

(ii) $k\vec{u} \in V$.

Subspaces give a mathematically precise definition of a “flat space through the origin.”

30

For each set, draw it and explain whether or not it is a subspace of \mathbb{R}^2 .

30.1 $A = \left\{ \vec{x} \in \mathbb{R}^2 : \vec{x} = \begin{bmatrix} a \\ 0 \end{bmatrix} \text{ for some } a \in \mathbb{Z} \right\}.$

30.2 $B = \left\{ \vec{x} \in \mathbb{R}^2 : \vec{x} \neq \begin{bmatrix} 0 \\ 0 \end{bmatrix} \right\}.$

30.3 $C = \left\{ \vec{x} \in \mathbb{R}^2 : \vec{x} = \begin{bmatrix} 0 \\ t \end{bmatrix} \text{ for some } t \in \mathbb{R} \right\}.$

30.4 $D = \left\{ \vec{x} \in \mathbb{R}^2 : \vec{x} = \begin{bmatrix} 0 \\ t \end{bmatrix} + \begin{bmatrix} 1 \\ 1 \end{bmatrix} \text{ for some } t \in \mathbb{R} \right\}.$

30.5 $E = \left\{ \vec{x} \in \mathbb{R}^2 : \vec{x} = \begin{bmatrix} 0 \\ t \end{bmatrix} \text{ or } \vec{x} = \begin{bmatrix} t \\ 0 \end{bmatrix} \text{ for some } t \in \mathbb{R} \right\}.$

30.6 $F = \left\{ \vec{x} \in \mathbb{R}^2 : \vec{x} = t \begin{bmatrix} 3 \\ 1 \end{bmatrix} \text{ for some } t \in \mathbb{R} \right\}.$

30.7 $G = \text{span} \left\{ \begin{bmatrix} 1 \\ 1 \end{bmatrix} \right\}.$

30.8 $H = \text{span}\{\vec{u}, \vec{v}\}$ for some unknown vectors $\vec{u}, \vec{v} \in \mathbb{R}^2$.

DEF

Basis

A **basis** for a subspace \mathcal{V} is a linearly independent set of vectors, \mathcal{B} , so that $\text{span } \mathcal{B} = \mathcal{V}$.

DEF

Dimension

The **dimension** of a subspace V is the number of elements in a basis for V .

31

$$\text{Let } \vec{u} = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}, \vec{v} = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}, \vec{w} = \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}, \text{ and } V = \text{span}\{\vec{u}, \vec{v}, \vec{w}\}.$$

31.1 Describe V .

31.2 Is $\{\vec{u}, \vec{v}, \vec{w}\}$ a basis for V ? Why or why not?

31.3 Give a basis for V .

31.4 Give another basis for V .

31.5 Is $\text{span}\{\vec{u}, \vec{v}\}$ a basis for V ? Why or why not?

31.6 What is the dimension of V ?

Let $\vec{a} = \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix}$, $\vec{b} = \begin{bmatrix} 4 \\ 5 \\ 6 \end{bmatrix}$, $\vec{c} = \begin{bmatrix} 7 \\ 8 \\ 8 \end{bmatrix}$ (notice these vectors are linearly independent) and let $P = \text{span}\{\vec{a}, \vec{b}\}$ and $Q = \text{span}\{\vec{b}, \vec{c}\}$.

- 32.1 Give a basis for and the dimension of P .
- 32.2 Give a basis for and the dimension of Q .
- 32.3 Is $P \cap Q$ a subspace? If so, give a basis for it and its dimension.
- 32.4 Is $P \cup Q$ a subspace? If so, give a basis for it and its dimension.

Matrix Representations of Systems of Linear Equations

In this module you will learn

- How to represent a system of linear equations as a matrix equation.
- Multiple ways to interpret solutions of systems of linear equations.
- How linear independence/dependence relates to solutions to matrix equations.
- How to use matrix equations to find normal vectors to lines or planes.

Matrix-vector multiplication gives a compact way to represent systems of linear equations.

Consider the system

$$\begin{cases} x + 2y - 2z = -15 \\ 2x + y - 5z = -21, \\ x - 4y + z = 18 \end{cases} \quad (5)$$

which is equivalent to the vector equation

$$\begin{bmatrix} x + 2y - 2z \\ 2x + y - 5z \\ x - 4y + z \end{bmatrix} = \begin{bmatrix} -15 \\ -21 \\ 18 \end{bmatrix}.$$

But, we can also rewrite (5) using matrix-vector multiplication:

$$\underbrace{\begin{bmatrix} 1 & 2 & -2 \\ 2 & 1 & -5 \\ 1 & -4 & 1 \end{bmatrix}}_A \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} -15 \\ -21 \\ 18 \end{bmatrix}.$$

The matrix A on the left is called the *coefficient matrix* because it is made up of the coefficients from equation (5).

By using coefficient matrices, every system of linear equations can be rewritten as a single matrix equation of the form

$$A\vec{x} = \vec{b}$$

where A is a coefficient matrix, \vec{x} is a column vector of variables, and \vec{b} is a column vector of constants.

Example. Consider the one equation system

$$\{x - 4y + z = 5 \quad (6)$$

and the two-equation system

$$\begin{cases} x - 4y + z = 5 \\ y - z = 9 \end{cases}. \quad (7)$$

Rewrite each system as a single matrix equation.

We can rewrite (6) as

$$\begin{bmatrix} 1 & -4 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 5 \end{bmatrix}.$$

Multiplying out to verify, we see,

$$\begin{bmatrix} 1 & -4 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} x - 4y + z \end{bmatrix} = \begin{bmatrix} 5 \end{bmatrix},$$

which is indeed equivalent to (6).

Similarly, we can rewrite (7) as

$$\begin{bmatrix} 1 & -4 & 1 \\ 0 & 1 & -1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 5 \\ 9 \end{bmatrix}.$$

Multiplying out to verify, we see,

$$\begin{bmatrix} 1 & -4 & 1 \\ 0 & 1 & -1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} x - 4y + z \\ 0x + y - z \end{bmatrix} = \begin{bmatrix} 5 \\ 9 \end{bmatrix},$$

which is indeed equivalent to (7).

Interpretations of Matrix Equations

The solution set to a system of linear equations, like

$$\begin{cases} x + 2y - 2z = -15 \\ 2x + y - 5z = -21 \\ x - 4y + z = 18 \end{cases} \quad (8)$$

can be interpreted as the intersection of three planes (or hyperplanes if there were more variables)—each individual equation specifies one plane and so solutions to the system are in the intersection of the planes specified by each equation.

However, when this system is rewritten in matrix form, the two ways to interpret matrix-vector multiplication give rise to two additional ways to interpret the solution set.

The Column Picture

Using the column interpretation of matrix-vector multiplication, we see that system (8) is equivalent to

$$\begin{bmatrix} 1 & 2 & -2 \\ 2 & 1 & -5 \\ 1 & -4 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = x \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} + y \begin{bmatrix} 2 \\ 1 \\ -4 \end{bmatrix} + z \begin{bmatrix} -2 \\ -5 \\ 1 \end{bmatrix} = \begin{bmatrix} -15 \\ -21 \\ 18 \end{bmatrix}.$$

This means the question, “What are the solutions to system (8)?” is equivalent to the question, “What coefficients allow $\begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix}$, $\begin{bmatrix} 2 \\ 1 \\ -4 \end{bmatrix}$, and $\begin{bmatrix} -2 \\ -5 \\ 1 \end{bmatrix}$ to form $\begin{bmatrix} -15 \\ -21 \\ 18 \end{bmatrix}$ as a linear combination?” Here, $\begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix}$, $\begin{bmatrix} 2 \\ 1 \\ -4 \end{bmatrix}$, and $\begin{bmatrix} -2 \\ -5 \\ 1 \end{bmatrix}$ are the columns of the coefficient matrix.

The Row Picture

The row interpretation gives us another perspective. Let \vec{r}_1 , \vec{r}_2 , and \vec{r}_3 be the rows of the coefficient matrix for system (8). Then the system is equivalent to

$$\begin{bmatrix} 1 & 2 & -2 \\ 2 & 1 & -5 \\ 1 & -4 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} \vec{r}_1 \\ \vec{r}_2 \\ \vec{r}_3 \end{bmatrix} \vec{x} = \begin{bmatrix} \vec{r}_1 \cdot \vec{x} \\ \vec{r}_2 \cdot \vec{x} \\ \vec{r}_3 \cdot \vec{x} \end{bmatrix} = \begin{bmatrix} -15 \\ -21 \\ 18 \end{bmatrix}.$$

In other words, we can interpret solutions to system (8) as vectors whose dot product with \vec{r}_1 is -15 , whose dot product with \vec{r}_2 is -21 , and whose dot product with \vec{r}_3 is 18 . Given that the dot product has a geometric interpretation, this perspective will sometimes be enlightening.

Interpreting Homogeneous Systems

Consider the homogeneous system/matrix equation

$$\begin{aligned} x + 2y - 2z &= 0 \\ 2x + y - 5z &= 0 \\ x - 4y + z &= 0 \end{aligned} \quad \Longleftrightarrow \quad \underbrace{\begin{bmatrix} 1 & 2 & -2 \\ 2 & 1 & -5 \\ 1 & -4 & 1 \end{bmatrix}}_A \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}. \quad (9)$$

Now, the column interpretation of system (9) is: what linear combinations of the column vectors of A give $\vec{0}$? This directly relates to the question of whether the column vectors of A are linearly independent.

Let \vec{r}_1 , \vec{r}_2 , and \vec{r}_3 be the rows of A . The row interpretation of system (9) asks what vectors are simultaneously orthogonal to \vec{r}_1 , \vec{r}_2 , and \vec{r}_3 .

Takeaway. There are three ways to interpret solutions to a matrix equation $A\vec{x} = \vec{b}$: (i) the intersection of hyperplanes specified by the rows; (ii) what linear combinations of the columns of A give \vec{b} ; (iii) what vectors yield the entries of \vec{b} when dot producted with the rows of A .

Example. Find all vectors orthogonal to $\vec{a} = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$ and $\vec{b} = \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix}$.

To find all vectors orthogonal to \vec{a} and \vec{b} , it is equivalent to solve

$$\begin{bmatrix} \vec{a} \\ \vec{b} \end{bmatrix} \vec{x} = \begin{bmatrix} \vec{a} \cdot \vec{x} \\ \vec{b} \cdot \vec{x} \end{bmatrix} = \underbrace{\begin{bmatrix} 1 & 1 & 1 \\ 1 & 2 & 1 \end{bmatrix}}_A \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}.$$

By row reduction on matrix A , we get

$$\text{rref}(A) = \begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix},$$

and so we get that the complete solution expressed in vector form is

$$\vec{x} = t \begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix}.$$

The row picture is particularly applicable when trying to find normal vectors.

Example. Let \mathcal{Q} be the hyperplane specified in vector form by

$$\vec{x} = t \begin{bmatrix} 1 \\ 1 \\ -1 \\ 1 \end{bmatrix} + s \begin{bmatrix} 0 \\ 1 \\ 0 \\ 1 \end{bmatrix} + r \begin{bmatrix} 2 \\ 0 \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} 1 \\ 2 \\ 3 \\ 4 \end{bmatrix}.$$

Find a normal vector for \mathcal{Q} and write \mathcal{Q} in normal form.

Similarly to the above example, since normal vectors for \mathcal{Q} need to be orthogonal to $\vec{d}_1 = \begin{bmatrix} 1 \\ 1 \\ -1 \\ 1 \end{bmatrix}$, $\vec{d}_2 = \begin{bmatrix} 0 \\ 1 \\ 0 \\ 1 \end{bmatrix}$,

and $\vec{d}_3 = \begin{bmatrix} 2 \\ 0 \\ 0 \\ 0 \end{bmatrix}$, we can find the normal vectors by solving

$$\underbrace{\begin{bmatrix} 1 & 1 & -1 & 1 \\ 0 & 1 & 0 & 1 \\ 2 & 0 & 0 & 0 \end{bmatrix}}_A \begin{bmatrix} x \\ y \\ z \\ w \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}.$$

By row reduction on matrix A , we get

$$\text{rref}(A) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{bmatrix},$$

and so we get that the complete solution expressed in vector form is

$$\vec{x} = t \begin{bmatrix} 0 \\ 1 \\ 0 \\ -1 \end{bmatrix}.$$

Therefore, any non-zero multiple of $\begin{bmatrix} 0 \\ 1 \\ 0 \\ -1 \end{bmatrix}$ is a normal vector for \mathcal{Q} . For example, $\vec{n} = \begin{bmatrix} 0 \\ 1 \\ 0 \\ -1 \end{bmatrix}$ is a normal vector for \mathcal{Q} , and \mathcal{Q} can be written in normal form as

$$\vec{n} \cdot (\vec{x} - \vec{p}) = \vec{0}$$

where $\vec{p} = \begin{bmatrix} 1 \\ 2 \\ 3 \\ 4 \end{bmatrix}$.

33

Let $A = \begin{bmatrix} 1 & 2 \\ 3 & 3 \end{bmatrix}$, $\vec{x} = \begin{bmatrix} x \\ y \end{bmatrix}$, and $\vec{b} = \begin{bmatrix} -2 \\ -1 \end{bmatrix}$.

33.1 Compute the product $A\vec{x}$.

33.2 Write down a system of equations that corresponds to the matrix equation $A\vec{x} = \vec{b}$.

33.3 Let $\begin{bmatrix} x_0 \\ y_0 \end{bmatrix}$ be a solution to $A\vec{x} = \vec{b}$. Explain what x_0 and y_0 mean in terms of *linear combinations* (hint: think about the columns of A).

33.4 Let $\begin{bmatrix} x_0 \\ y_0 \end{bmatrix}$ be a solution to $A\vec{x} = \vec{b}$. Explain what x_0 and y_0 mean in terms of *intersecting lines* (hint: think about systems of equations).

$$\text{Let } \vec{u} = \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix}, \vec{v} = \begin{bmatrix} 4 \\ 5 \\ 6 \end{bmatrix}, \vec{w} = \begin{bmatrix} 7 \\ 8 \\ 9 \end{bmatrix}.$$

- 34.1 How could you determine if $\{\vec{u}, \vec{v}, \vec{w}\}$ was a linearly independent set?
- 34.2 Can your method be rephrased in terms of a matrix equation? Explain.

Consider the system represented by

$$\begin{bmatrix} 1 & -3 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \vec{b}.$$

35.1 If $\vec{b} = \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix}$, is the set of solutions to this system a point, line, plane, or other?

35.2 If $\vec{b} = \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}$, is the set of solutions to this system a point, line, plane, or other?

Let $\vec{d}_1 = \begin{bmatrix} 1 \\ 1 \\ 2 \end{bmatrix}$ and $\vec{d}_2 = \begin{bmatrix} -1 \\ 1 \\ 0 \end{bmatrix}$. Let \mathcal{P} be the plane given in vector form by $\vec{x} = t\vec{d}_1 + s\vec{d}_2$. Further, suppose M is a matrix so that $M\vec{r} \in \mathcal{P}$ for any $\vec{r} \in \mathbb{R}^2$.

- 36.1 How many rows does M have?
- 36.2 Find such an M .
- 36.3 Find necessary and sufficient conditions (phrased as equations) for \vec{n} to be a normal vector for \mathcal{P} .
- 36.4 Find a matrix K so that non-zero solutions to $K\vec{x} = \vec{0}$ are normal vectors for \mathcal{P} . How do K and M relate?

Coordinates & Change of Basis I

In this module you will learn

- Notation for representing a vector in multiple bases.
- The distinction between a vector and its representation.
- How to compute multiple representation of a vector.
- The definition of an *oriented* basis.

Recall that when we write $\vec{x} = \begin{bmatrix} 2 \\ 3 \end{bmatrix}$, what we actually mean is $\vec{x} = 2\vec{e}_1 + 3\vec{e}_2$. The numbers 2 and 3 are called the coordinates of the vector \vec{x} with respect to the standard basis. However, in general, subspaces have many bases, and so it is possible to represent a single vector in many ways as coordinates with respect to *many* bases.

Let $\vec{x} = \begin{bmatrix} 2 \\ 3 \end{bmatrix}$; let $\mathcal{E} = \{\vec{e}_1, \vec{e}_2\}$ be the standard basis for \mathbb{R}^2 and let $\mathcal{B} = \{\vec{b}_1, \vec{b}_2\}$ where $\vec{b}_1 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$ and $\vec{b}_2 = \begin{bmatrix} 1 \\ 2 \end{bmatrix}$ be another basis for \mathbb{R}^2 . Now, the coordinates of \vec{x} with respect to \mathcal{E} are (2, 3), but the coordinates of \vec{x} with respect to \mathcal{B} are (1, 1).

XXX Figure

The coordinates (2, 3) and (1, 1) represent \vec{x} equally well, and when solving problems, we should pick the coordinates that make our problem the easiest.²² However, now that we are representing vectors in multiple bases, we need a way to keep track of what coordinates correspond to which basis.

Representation in a Basis.

Let $\mathcal{B} = \{\vec{b}_1, \dots, \vec{b}_n\}$ be a basis for a subspace V and let $\vec{v} \in V$. The *representation of \vec{v} in the \mathcal{B} basis*, notated $[\vec{v}]_{\mathcal{B}}$, is the column matrix

$$[\vec{v}]_{\mathcal{B}} = \begin{bmatrix} \alpha_1 \\ \vdots \\ \alpha_n \end{bmatrix}.$$

where $\alpha_1, \dots, \alpha_n$ uniquely satisfy $\vec{v} = \alpha_1 \vec{b}_1 + \dots + \alpha_n \vec{b}_n$.

Conversely,

$$\begin{bmatrix} \alpha_1 \\ \vdots \\ \alpha_n \end{bmatrix}_{\mathcal{B}} = \alpha_1 \vec{b}_1 + \dots + \alpha_n \vec{b}_n$$

is notation for the linear combination of $\vec{b}_1, \dots, \vec{b}_n$ with coefficients $\alpha_1, \dots, \alpha_n$.

Example. Let $\mathcal{E} = \{\vec{e}_1, \vec{e}_2\}$ be the standard basis for \mathbb{R}^2 and let $\mathcal{B} = \{\vec{b}_1, \vec{b}_2\}$ where $\vec{b}_1 = \vec{e}_1 + \vec{e}_2$, and $\vec{b}_2 = 3\vec{e}_2$ be another basis for \mathbb{R}^2 . Given that $\vec{v} = 2\vec{e}_1 - \vec{e}_2$, find $[\vec{v}]_{\mathcal{E}}$ and $[\vec{v}]_{\mathcal{B}}$.

Given that $\vec{v} = 2\vec{e}_1 - \vec{e}_2$, we see

$$[\vec{v}]_{\mathcal{E}} = \begin{bmatrix} 2 \\ -1 \end{bmatrix}.$$

To find $[\vec{v}]_{\mathcal{B}}$, we can use a system of equations to find \vec{v} as a linear combination of \vec{b}_1 and \vec{b}_2 .

First, set

$$\vec{v} = x\vec{b}_1 + y\vec{b}_2$$

for some unknown scalars x and y . Then, since on the one hand,

$$\vec{v} = 2\vec{e}_1 - \vec{e}_2$$

and on the other hand,

$$\vec{v} = x\vec{b}_1 + y\vec{b}_2 = x(\vec{e}_1 + \vec{e}_2) + 3y\vec{e}_2 = x\vec{e}_1 + (x + 3y)\vec{e}_2,$$

²² For example, maybe in one choice of coordinates, we can avoid all fractions in our calculations—this could be good if you're programming a computer that rounds it.

equating the two equations above, we have

$$2\vec{e}_1 - \vec{e}_2 = x\vec{e}_1 + (x + 3y)\vec{e}_2.$$

Therefore, solving the system

$$\begin{cases} x = 2 \\ x + 3y = -1 \end{cases},$$

we have $\vec{v} = 2\vec{b}_1 - \vec{b}_2$. That is,

$$[\vec{v}]_{\mathcal{B}} = \begin{bmatrix} 2 \\ -1 \end{bmatrix}.$$

Notation Conventions

In light of this notation, we need to revisit some past notation. Again, we have been writing $\vec{x} = \begin{bmatrix} 1 \\ 3 \end{bmatrix}$ to mean $\vec{x} = 2\vec{e}_1 + 3\vec{e}_2$. However, given the representation-in-a-basis notation, we should be writing

$$\vec{x} = \begin{bmatrix} 2 \\ 3 \end{bmatrix}_{\mathcal{E}},$$

where \mathcal{E} is the standard basis for \mathbb{R}^2 . We should write $\begin{bmatrix} 2 \\ 3 \end{bmatrix}_{\mathcal{E}}$ because the coordinates $(2, 3)$ refer to *different* vectors for *different* bases. However, most of the time we are only thinking about the standard basis. So, the convention we will follow is:

- If a problem involves only one basis, we may write $\begin{bmatrix} x \\ y \end{bmatrix}$ to mean $\begin{bmatrix} x \\ y \end{bmatrix}_{\mathcal{E}}$ where \mathcal{E} is the standard basis.
- If there are multiple bases in a problem, we will always write $\begin{bmatrix} x \\ y \end{bmatrix}_{\mathcal{X}}$ to specify a vector in coordinates relative to a particular basis \mathcal{X} .

Takeaway. If a problem only involves the standard basis, we may use the notation we always have. If a problem involves multiple bases, we must *always* use representation-in-a-basis notation.

True Vectors vs. Representations



The Belgian surrealist René Magritte painted the work above, which is subtitled, “This is not a pipe”. Why? Because, of course, it is not a pipe. It is a painting of a pipe! In this work, Magritte points out a distinction that will soon become very important to us—the distinction between an object and a representation of that object.

Let $\vec{x} = 2\vec{e}_1 + 3\vec{e}_2 \in \mathbb{R}^2$. The vector \vec{x} is a *real-life geometrical thing*, and to emphasize this, we will call \vec{x} a *true* vector. In contrast, when we write the column matrix $[\vec{x}]_{\mathcal{E}} = \begin{bmatrix} 2 \\ 3 \end{bmatrix}$, we are writing a *list of numbers*. The list of numbers $\begin{bmatrix} 2 \\ 3 \end{bmatrix}$ has no meaning until we give it a meaning by assigning it a basis. For example, by writing $\begin{bmatrix} 2 \\ 3 \end{bmatrix}_{\mathcal{E}}$

²³Image taken from Wikipedia: <https://en.wikipedia.org/wiki/File:MagrittePipe.jpg>

we declare that the numbers 2 and 3 are coefficients of \vec{e}_1 and \vec{e}_2 . By writing $\begin{bmatrix} 2 \\ 3 \end{bmatrix}_{\mathcal{B}}$ where $\mathcal{B} = \{\vec{b}_1, \vec{b}_2\}$, we declare that the numbers 2 and 3 are coefficients of \vec{b}_1 and \vec{b}_2 . Since a list of numbers without a basis has no meaning, we must write

$$\vec{x} \neq [\vec{x}]_{\mathcal{E}} = \begin{bmatrix} 2 \\ 3 \end{bmatrix},$$

since the left side of the equation is a *true vector* and the right side is a *list of numbers*. Similarly, we must write

$$[\vec{x}]_{\mathcal{E}} \neq \begin{bmatrix} 2 \\ 3 \end{bmatrix}_{\mathcal{E}} = \vec{x},$$

since the left side is a *list of numbers* and the right side is a *true vector*.

To help keep the notation straight in your head, for a basis \mathcal{X} , remember the rule

$$[\text{true vector}]_{\mathcal{X}} = \text{list of numbers} \quad \text{and} \quad [\text{list of numbers}]_{\mathcal{X}} = \text{true vector}.$$

It's easy to get confused when answering questions that involve multiple bases; precision will make these problems much easier.

Orientation of a Basis

How can you tell the difference between a hand and a foot? They're similar in structure²⁴—a hand has five fingers and a foot has five toes—but they're different in shape—fingers are much longer than toes and the thumb sticks off the hand at a different angle than the big toe sticks off the foot.

How about a harder question: how can you tell the difference between a left hand and a right hand? Any length or angle measurement you make on an (idealized) left hand or right hand will be identical. But, we know they're different because they differ in *orientation*.²⁵

We'll build up to the definition of orientation in stages. Consider the ordered bases \mathcal{E} , \mathcal{A} , and \mathcal{B} shown below.

XXX Figure

The \mathcal{A} basis can be rotated to get the \mathcal{E} basis, but it is impossible to rotate the \mathcal{B} basis to get the \mathcal{E} basis. In this case, we say that \mathcal{E} and \mathcal{A} have the same orientation and \mathcal{E} and \mathcal{B} have opposite orientations. In this way, even though the lengths and angles between all vectors in the \mathcal{A} basis and the \mathcal{B} basis are the same, we can distinguish the \mathcal{A} and \mathcal{B} bases because they have different *orientations*.

Orientations of bases come in exactly two flavors: *right-handed* (or *positively oriented*) and *left-handed* (or *negatively oriented*). By convention, the standard basis is called right-handed.

Orthonormal bases—bases consisting of unit vectors that are orthogonal to each other—are called right-handed if they can be rotated to align with the standard basis, otherwise they are called left-handed. In this way, the right-hand–left-hand analogy should be clear: two right hands or two left hands can be rotated to align with each other, but a left hand and a right can never be rotated to alignment.

However, not all bases are orthonormal! Consider the bases \mathcal{E} , \mathcal{A}' , \mathcal{B}' .

XXX Figure where \mathcal{A}' and \mathcal{B}' differ only slightly from \mathcal{A} and \mathcal{B}

The bases \mathcal{A}' and \mathcal{B}' differ only slightly from \mathcal{A} and \mathcal{B} . Neither can be *rotated* to obtain \mathcal{E} , however we'd still like to say \mathcal{A}' is right-handed and \mathcal{B}' is left-handed. The following, fully general definition, allows us to do so.

Orientation of a Basis. The ordered basis $\mathcal{B} = \{\vec{b}_1, \dots, \vec{b}_n\}$ is *right-handed* or *positively oriented* if it can be continuously transformed to the standard basis (with $\vec{b}_i \mapsto \vec{e}_i$) while remaining linearly independent throughout the transformation. Otherwise, \mathcal{B} is called *left-handed* or *negatively oriented*.

The term *continuously transformed* can be given a precise definition,²⁶ but it will be enough for us to imagine that there is a continuous transform of one basis to another if there is a “movie” where one basis smoothly and without jumps transforms into another basis.

²⁴ We might say hands and feet are *topologically* equivalent.

²⁵ Other words for orientation include *chirality* and *handedness*.

²⁶ Because you crave precision, here it is: the basis $\vec{a}_1, \dots, \vec{a}_n$ can be *continuously transformed* to the basis $\vec{b}_1, \dots, \vec{b}_n$ if there exists a continuous function $\Phi : [0, 1] \rightarrow \{n\text{-tuples of vectors}\}$ so that $\Phi(0) = (\vec{a}_1, \dots, \vec{a}_n)$ and $\Phi(1) = (\vec{b}_1, \dots, \vec{b}_n)$. Here, continuity is defined in the multi-variable calculus sense.

Let's consider some examples. Let $\mathcal{X} = \{\vec{x}_1, \vec{x}_2\}$. We could imagine \vec{x}_1, \vec{x}_2 continuously transforming to \vec{e}_1, \vec{e}_2 by \vec{x}_1 staying in place and \vec{x}_2 smoothly moving along the dotted line.

XXX Figure

Because at every step along this motion, the set of \vec{x}_1 and the transformed \vec{x}_2 stayed linearly independent, \mathcal{X} is *positively* oriented.

Let $\mathcal{Y} = \{\vec{y}_1, \vec{y}_2\}$. We are in a similar situation, except this time, somewhere along \vec{y}_2 's path, the set of \vec{y}_1 and the transformed \vec{y}_2 becomes linearly dependent.

XXX Figure

Maybe that was just bad luck and we might be able to transform along a different path and stay linearly independent? It turns out, we are doomed to fail, because \mathcal{Y} is *negatively* oriented.

Using the definition of the orientation of a basis to answer questions is difficult because to determine that a basis is negatively oriented, you need to make a determination about *every possible* way to continuously transform a basis to the standard basis. This is hard enough in \mathbb{R}^2 and gets much harder in \mathbb{R}^3 . Fortunately, we will encounter computational tools that will allow us to numerically determine the orientation of a basis, but, for now, the idea is what's important.

Reversing Orientation

Reflections reverse orientation and can manifest in two ways.²⁷ Consider the reflection of $\mathcal{E} = \{\vec{e}_1, \vec{e}_2\}$ across the line $y = x$.

XXX Figure

This reflection sends $\{\vec{e}_1, \vec{e}_2\} \mapsto \{\vec{e}_2, \vec{e}_1\}$. Alternatively, reflection across the line $x = 0$ sends $\{\vec{e}_1, \vec{e}_2\} \mapsto \{-\vec{e}_1, \vec{e}_2\}$.

XXX Figure

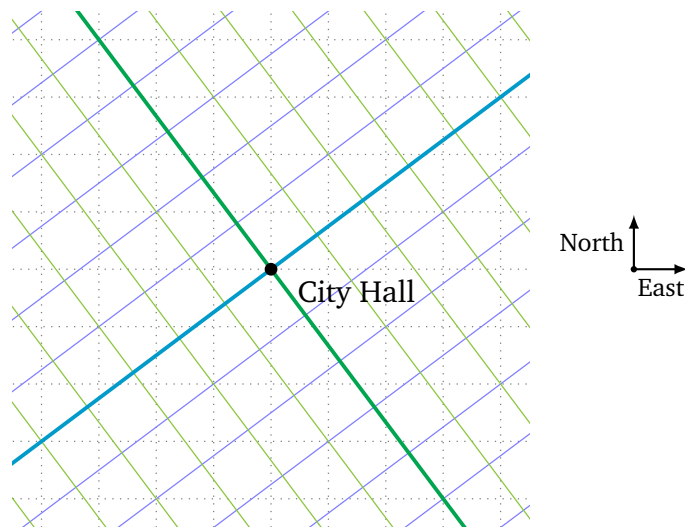
Both $\{\vec{e}_2, \vec{e}_1\}$ and $\{-\vec{e}_1, \vec{e}_2\}$, as ordered bases, are negatively oriented. This is indicative of a general theorem.

Theorem. Let $\mathcal{B} = \{\vec{b}_1, \dots, \vec{b}_n\}$ be an ordered basis. The ordered basis obtained from \mathcal{B} by replacing \vec{b}_i with $-\vec{b}_i$ and the ordered basis obtained from \mathcal{B} by swapping the order of \vec{b}_i and \vec{b}_{i+1} have the opposite orientation as \mathcal{B} .

²⁷ Think back to hands. The left and right hands *are* reflections of each other.

37

The fictional town of Oronto is not aligned with the usual compass directions. The streets are laid out as follows:



Instead, every street is parallel to the vector $\vec{d}_1 = \frac{1}{5} \begin{bmatrix} 4 \text{ east} \\ 3 \text{ north} \end{bmatrix}$ or $\vec{d}_2 = \frac{1}{5} \begin{bmatrix} -3 \text{ east} \\ 4 \text{ north} \end{bmatrix}$. The center of town is City Hall at $\vec{0} = \begin{bmatrix} 0 \text{ east} \\ 0 \text{ north} \end{bmatrix}$.

Locations in Oronto are typically specified in *street coordinates*. That is, as a pair (a, b) where a is how far you walk along streets in the \vec{d}_1 direction and b is how far you walk in the \vec{d}_2 direction, provided you start at city hall.

- 37.1 The points $A = (2, 1)$ and $B = (3, -1)$ are given in street coordinates. Find their east-north coordinates.
- 37.2 The points $X = (4, 3)$ and $Y = (1, 7)$ are given in east-north coordinates. Find their street coordinates.
- 37.3 Define $\vec{e}_1 = \begin{bmatrix} 1 \text{ east} \\ 0 \text{ north} \end{bmatrix}$ and $\vec{e}_2 = \begin{bmatrix} 0 \text{ east} \\ 1 \text{ north} \end{bmatrix}$. Does $\text{span}\{\vec{e}_1, \vec{e}_2\} = \text{span}\{\vec{d}_1, \vec{d}_2\}$?
- 37.4 Notice that $Y = 5\vec{d}_1 + 5\vec{d}_2 = \vec{e}_1 + 7\vec{e}_2$. Is the point Y better represented by the pair $(5, 5)$ or by the pair $(1, 7)$? Explain.

Representation in a Basis

Let $\mathcal{B} = \{\vec{b}_1, \dots, \vec{b}_n\}$ be a basis for a subspace V and let $\vec{v} \in V$. The *representation of \vec{v} in the \mathcal{B} basis*, notated $[\vec{v}]_{\mathcal{B}}$, is the column matrix

$$[\vec{v}]_{\mathcal{B}} = \begin{bmatrix} \alpha_1 \\ \vdots \\ \alpha_n \end{bmatrix}.$$

where $\alpha_1, \dots, \alpha_n$ uniquely satisfy $\vec{v} = \alpha_1 \vec{b}_1 + \dots + \alpha_n \vec{b}_n$.

Conversely,

$$\begin{bmatrix} \alpha_1 \\ \vdots \\ \alpha_n \end{bmatrix}_{\mathcal{B}} = \alpha_1 \vec{b}_1 + \dots + \alpha_n \vec{b}_n$$

is notation for the linear combination of $\vec{b}_1, \dots, \vec{b}_n$ with coefficients $\alpha_1, \dots, \alpha_n$.

DEFINITION

38

Let $\mathcal{E} = \{\vec{e}_1, \vec{e}_2\}$ be the standard basis for \mathbb{R}^2 and let $\mathcal{C} = \{\vec{c}_1, \vec{c}_2\}$ where $\vec{c}_1 = \begin{bmatrix} 2 \\ 1 \end{bmatrix}_{\mathcal{E}}$ and $\vec{c}_2 = \begin{bmatrix} 5 \\ 3 \end{bmatrix}_{\mathcal{E}}$ be another basis for \mathbb{R}^2 .

- 38.1 Express \vec{c}_1 and \vec{c}_2 as a linear combination of \vec{e}_1 and \vec{e}_2 .
- 38.2 Express \vec{e}_1 and \vec{e}_2 as a linear combination of \vec{c}_1 and \vec{c}_2 .
- 38.3 Let $\vec{v} = 2\vec{e}_1 + 2\vec{e}_2$. Find $[\vec{v}]_{\mathcal{E}}$ and $[\vec{v}]_{\mathcal{C}}$.
- 38.4 Can you find a matrix X so that $X[\vec{w}]_{\mathcal{C}} = [\vec{w}]_{\mathcal{E}}$ for any \vec{w} ?
- 38.5 Can you find a matrix Y so that $Y[\vec{w}]_{\mathcal{E}} = [\vec{w}]_{\mathcal{C}}$ for any \vec{w} ?
- 38.6 What is YX ?

Orientation of a Basis

DEF

The ordered basis $\mathcal{B} = \{\vec{b}_1, \dots, \vec{b}_n\}$ is *right-handed* or *positively oriented* if it can be continuously transformed to the standard basis (with $\vec{b}_i \mapsto \vec{e}_i$) while remaining linearly independent throughout the transformation. Otherwise, \mathcal{B} is called *left-handed* or *negatively oriented*.

- 39 Let $\{\vec{e}_1, \vec{e}_2\}$ be the standard basis for \mathbb{R}^2 and let \vec{u}_θ be a unit vector. Let θ be the angle between \vec{u}_θ and \vec{e}_1 measured counter-clockwise starting at \vec{e}_1 .
- 39.1 For which θ is $\{\vec{e}_1, \vec{u}_\theta\}$ a linearly independent set?
- 39.2 For which θ can $\{\vec{e}_1, \vec{u}_\theta\}$ be continuously transformed into $\{\vec{e}_1, \vec{e}_2\}$ and remain linearly independent the whole time?
- 39.3 For which θ is $\{\vec{e}_1, \vec{u}_\theta\}$ right-handed? Left-handed?
- 39.4 For which θ is $\{\vec{u}_\theta, \vec{e}_1\}$ (in that order) right-handed? Left-handed?
- 39.5 Is $\{2\vec{e}_1, 3\vec{e}_2\}$ right-handed or left-handed? What about $\{2\vec{e}_1, -3\vec{e}_2\}$?

Linear Transformations

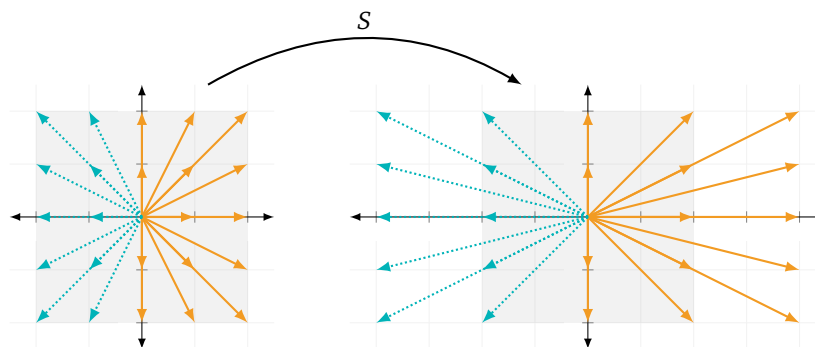
In this module you will learn

- The definition of a linear transformation.
- The definition of the image of a set under a transformation.
- How to prove whether a transformation is linear or not.
- How to find a matrix for a linear transformation.
- The difference between a matrix and a linear transformation.

Now that we have a handle on the basics of vectors, we can start thinking about *transformations*. A transformation or a map is another word for a function, and they show up any time you need to describe vectors changing. For example, the transformation

$$S : \mathbb{R}^2 \rightarrow \mathbb{R}^2 \quad \text{defined by} \quad \begin{bmatrix} x \\ y \end{bmatrix} \mapsto \begin{bmatrix} 2x \\ y \end{bmatrix}$$

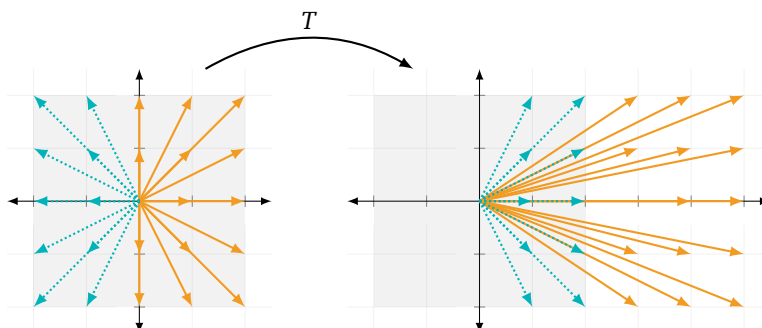
stretches all vectors in the \vec{e}_1 direction by a factor of 2.



The transformation

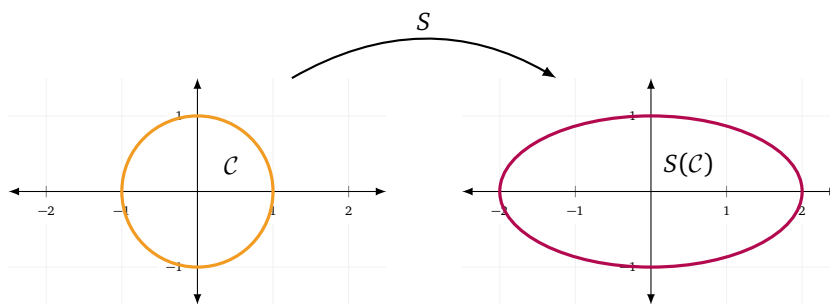
$$T : \mathbb{R}^2 \rightarrow \mathbb{R}^2 \quad \text{defined by} \quad \begin{bmatrix} x \\ y \end{bmatrix} \mapsto \begin{bmatrix} x + 3 \\ y \end{bmatrix}$$

translates all vectors 3 units in the \vec{e}_1 direction.



Images

Recall the transformation $S : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ defined by $\begin{bmatrix} x \\ y \end{bmatrix} \mapsto \begin{bmatrix} 2x \\ y \end{bmatrix}$. If we had a bunch of vectors in the plane, applying S would stretch those vectors in the \vec{e}_1 direction by a factor of 2. For example, if we start with \mathcal{C} , the circle of radius 1 centered at $\vec{0}$, then applying S to all the vectors that make up \mathcal{C} would produce an ellipse.



This operation of applying a transformation to a specific set of vectors and seeing what results is called taking the *image* of a set.

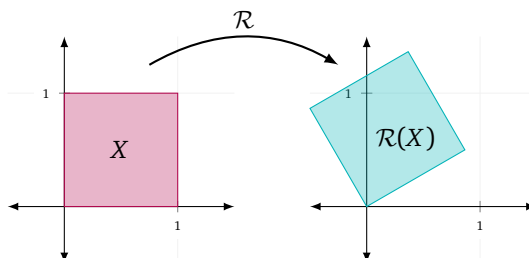
Image of a Set. Let $L : \mathbb{R}^n \rightarrow \mathbb{R}^m$ be a transformation and let $X \subseteq \mathbb{R}^n$ be a set. The *image of the set X under L* , denoted $L(X)$, is the set

$$L(X) = \{\vec{x} \in W : \vec{x} = L(\vec{y}) \text{ for some } \vec{y} \in X\}.$$

In plain language, the image of a set X under a transformation L is the set of all outputs of L when the inputs come from X .

If you think of sets in \mathbb{R}^n as black-and-white “pictures” (a point is black if it’s in the set and white if it’s not), then the image of a set under a transformation is the output after applying the transformation to the “picture”.

Images allow one to describe complicated geometric figures in terms of an original figure and a transformation. For example, let $\mathcal{R} : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ be rotation counter clockwise by 30° and let $X = \{x\vec{e}_1 + y\vec{e}_2 : x, y \in [0, 1]\}$ be the filled-in unit square. Then, $\mathcal{R}(X)$ is the filled-in unit square that meets the x -axis at an angle of 30° . Try describing that using set builder notation!



Linear Transformations

Linear algebra’s main focus is the study of a special category of transformations: the *linear* transformations. Linear transformations include rotations, dilations (stretches), shears, and more.



They arise when taking derivatives in higher dimensions, and just like in one-variable calculus where if you zoom into a function at a point its graph looks like a line, if you zoom into a (non-linear) transformation at a point, it looks like a linear one²⁸! All this is to say that linear transformations are worthy of our study.

Without further ado, let’s define what it means for a transformation to be linear.

Linear Transformation. Let V and W be subspaces. A function $T : V \rightarrow W$ is called a *linear transformation* if

$$T(\vec{u} + \vec{v}) = T\vec{u} + T\vec{v} \quad \text{and} \quad T(\alpha\vec{v}) = \alpha T\vec{v}$$

²⁸ If you’re being picky, you might say that you see an *affine* function, which is a linear function combined with a translation.

for all vectors $\vec{u}, \vec{v} \in V$ and all scalars α .

In plain language, the transformation T is linear if it distributes over addition and scalar multiplication. In other words, T distributes over linear combinations.

Example. Let $S : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ and $T : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ be defined by

$$\begin{bmatrix} x \\ y \end{bmatrix} \xrightarrow{S} \begin{bmatrix} 2x \\ y \end{bmatrix} \quad \text{and} \quad \begin{bmatrix} x \\ y \end{bmatrix} \xrightarrow{T} \begin{bmatrix} x \\ y + 4 \end{bmatrix}.$$

For each of S and T , determine whether the transformation is linear.

Let vectors $\vec{u} = \begin{bmatrix} u_1 \\ u_2 \end{bmatrix}$, $\vec{v} = \begin{bmatrix} v_1 \\ v_2 \end{bmatrix}$ and the scalar α be given.

For S :

We need to verify that $S(\vec{u} + \vec{v}) = S(\vec{u}) + S(\vec{v})$ and $S(\alpha\vec{u}) = \alpha S(\vec{u})$. Computing, we see

$$S(\vec{u} + \vec{v}) = S\left(\begin{bmatrix} u_1 + v_1 \\ u_2 + v_2 \end{bmatrix}\right) = \begin{bmatrix} 2u_1 + 2v_1 \\ u_2 + v_2 \end{bmatrix} = \begin{bmatrix} 2u_1 \\ u_2 \end{bmatrix} + \begin{bmatrix} 2v_1 \\ v_2 \end{bmatrix} = S(\vec{u}) + S(\vec{v})$$

and

$$S(\alpha\vec{u}) = \begin{bmatrix} 2\alpha u_1 \\ \alpha u_2 \end{bmatrix} = \alpha \begin{bmatrix} 2u_1 \\ u_2 \end{bmatrix} = \alpha S(\vec{u}).$$

Therefore, S is linear.

For T :

Notice that $T(\vec{u} + \vec{v}) = \begin{bmatrix} u_1 + v_1 \\ u_2 + v_2 + 4 \end{bmatrix}$ doesn't look like $T(\vec{u}) + T(\vec{v}) = \begin{bmatrix} u_1 + v_1 \\ u_2 + v_2 + 8 \end{bmatrix}$. Therefore, we will guess that T is not linear and look for a counter example.

Using $\vec{e}_1 = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$ and $\vec{e}_2 = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$, we see

$$T(\vec{e}_1 + \vec{e}_2) = T\left(\begin{bmatrix} 1 \\ 1 \end{bmatrix}\right) = \begin{bmatrix} 1 \\ 5 \end{bmatrix} \neq \begin{bmatrix} 1 \\ 4 \end{bmatrix} + \begin{bmatrix} 0 \\ 5 \end{bmatrix} = T(\vec{e}_1) + T(\vec{e}_2).$$

Therefore, T is not linear.

Function Notation vs. Linear Transformation Notation

Linear transformations are just special types of functions. In calculus it is traditional to use lower case letters for a function and parenthesis “(” and “)” around the input to the function.

$$\underbrace{f : \mathbb{R} \rightarrow \mathbb{R}}_{\text{a function}} \quad \underbrace{f(x)}_{f \text{ evaluated at } x}$$

For (linear) transformations, it is traditional to use capital letters to describe the function/transformation and parenthesis around the input are optional.

$$\underbrace{T : \mathbb{R}^n \rightarrow \mathbb{R}^m}_{\text{a transformation}} \quad \underbrace{T(\vec{x})}_{T \text{ evaluated at } \vec{x}} \quad \underbrace{T\vec{x}}_{\text{also } T \text{ evaluated at } \vec{x}}$$

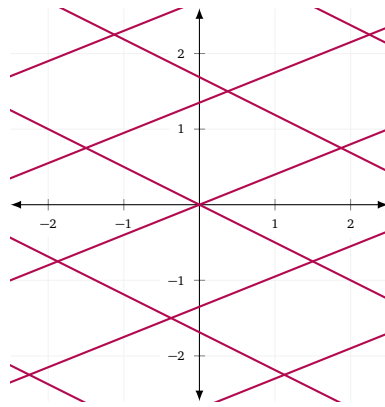
Since sets are also traditionally written using capital letters, sometimes a font variant is used to when writing the transformation or the set. For example, we might use a regular X to denote a set and a calligraphic \mathcal{T} to describe a transformation.

Another difference you might not be used to is that, in linear algebra, we make a careful distinction between a function and its output. Let $f : \mathbb{R} \rightarrow \mathbb{R}$ be a function. In calculus, you might consider the phrases “the function f ” and “the function $f(x)$ ”. In linear algebra, the first phrase is valid and the second is *not*. By writing $f(x)$, we are indicating “the output of the function f when x is input”. So, properly we should say “the *number* $f(x)$ ”.

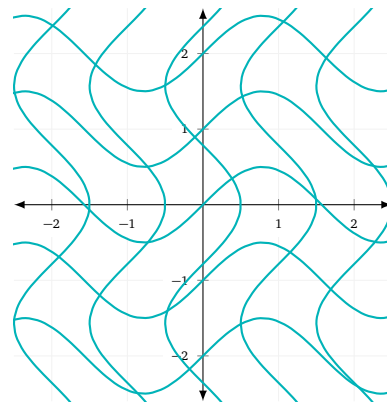
This distinction might seem pedantic now, but by keeping our functions as functions and our numbers/vectors as numbers/vectors, we can avoid some major confusion in the future.

The “look” of a Linear Transformation

Images under linear transformations have a certain look to them. Based just on the word *linear* you can probably guess which figure below represents the image of a grid under a linear transformation.



Linear



Non-linear

Let's prove some basic theorems about linear transformations.

Theorem. If $T : \mathbb{R}^n \rightarrow \mathbb{R}^m$ is a linear transformation, then $T(\vec{0}) = \vec{0}$.

Proof. Suppose $T : \mathbb{R}^n \rightarrow \mathbb{R}^m$ is a linear transformation and $\vec{v} \in \mathbb{R}^n$. We know that $0\vec{v} = \vec{0}$, so by linearity we have

$$T(\vec{0}) = T(0\vec{v}) = 0T(\vec{v}) = \vec{0}.$$

■

Theorem. If $T : \mathbb{R}^n \rightarrow \mathbb{R}^m$ is a linear transformation, then T takes lines to lines (or points).

Proof. Suppose $T : \mathbb{R}^n \rightarrow \mathbb{R}^m$ is a linear transformation and let $\ell \subseteq \mathbb{R}^n$ be the line given in vector form by $\vec{x} = t\vec{d} + \vec{p}$. We want to prove that $T(\ell)$, the image of ℓ under the transformation T , is a line or a point.

By definition, every point in ℓ takes the form $t\vec{d} + \vec{p}$ for some scalar t . Therefore, every point in $T(\ell)$ take the form $T(t\vec{d} + \vec{p})$ for some scalar t . But, T is a linear transformation, so

$$T(t\vec{d} + \vec{p}) = tT(\vec{d}) + T(\vec{p}).$$

If $T(\vec{d}) \neq \vec{0}$, then $\vec{x} = tT(\vec{d}) + T(\vec{p})$ describes a line in vector form and so $T(\ell)$ is a line. If $T(\vec{d}) = \vec{0}$, then $T(\ell) = \{t\vec{0} + T(\vec{p}) : t \text{ is a scalar}\} = \{T(\vec{p})\}$ is a point. ■

Theorem. If $T : \mathbb{R}^n \rightarrow \mathbb{R}^m$ is a linear transformation, then T takes parallel lines to parallel lines (or points).

Proof. Suppose $T : \mathbb{R}^n \rightarrow \mathbb{R}^m$ is a linear transformation and let ℓ_1 and ℓ_2 be parallel lines. Then, we may describe ℓ_1 in vector form as $\vec{x} = t\vec{d} + \vec{p}_1$ and we may describe ℓ_2 in vector form as $\vec{x} = t\vec{d} + \vec{p}_2$. Note that since the lines are parallel, the direction vectors are the same.

Now, $T(\ell_1)$ can be described in vector form by

$$\vec{x} = tT(\vec{d}) + T(\vec{p}_1)$$

and $T(\ell_2)$ can be described in vector form by

$$\vec{x} = tT(\vec{d}) + T(\vec{p}_2).$$

Written this way and provided $T(\ell_1)$ and $T(\ell_2)$ are actually lines, we immediately see that $T(\ell_1)$ and $T(\ell_2)$ have the same direction vectors and so are parallel.

If $T(\ell_1)$ is instead a point, then we must have $T(\vec{d}) = \vec{0}$, and so $T(\ell_2)$ must also be a point. ■

Theorem. If $T : \mathbb{R}^n \rightarrow \mathbb{R}^m$ is a linear transformation, then T takes subspaces to subspaces.

Proof. Let $T : \mathbb{R}^n \rightarrow \mathbb{R}^m$ be a linear transformation and let $V \subseteq \mathbb{R}^n$ be a subspace. We need to show that $T(V)$ satisfies the properties of a subspace.

Since V is non-empty, we know $T(V)$ is non-empty.

Let $\vec{x}, \vec{y} \in T(V)$. By definition, there are vectors $\vec{u}, \vec{v} \in V$ so that

$$\vec{x} = T(\vec{u}) \quad \text{and} \quad \vec{y} = T(\vec{v}).$$

Since T is linear, we know

$$\vec{x} + \vec{y} = T(\vec{u}) + T(\vec{v}) = T(\vec{u} + \vec{v}).$$

Because V is a subspace, we know $\vec{u} + \vec{v} \in V$ and so we conclude $\vec{x} + \vec{y} = T(\vec{u} + \vec{v}) \in T(V)$.

Similarly, for any scalar α we have

$$\alpha\vec{x} = \alpha T(\vec{u}) = T(\alpha\vec{u}).$$

Since V is a subspace, $\alpha\vec{u} \in V$ and so $\alpha\vec{x} = T(\alpha\vec{u}) \in T(V)$. ■

Linear Transformations and Proofs

When proving things in math, you have all of logic at your disposal, and that freedom can be combined with creativity to show some truly amazing things. But, for better or for worse, proving whether or not a transformation is linear usually doesn't require substantial creativity.

Let $T : \mathbb{R}^n \rightarrow \mathbb{R}^n$ defined by $T(\vec{v}) = 2\vec{v}$. To show that T is linear, we need to show that for *all* inputs \vec{x} and \vec{y} and for *all* scalars α we have

$$T(\vec{x} + \vec{y}) = T(\vec{x}) + T(\vec{y}) \quad \text{and} \quad T(\alpha\vec{x}) = \alpha T(\vec{x}).$$

But, there are an infinite number of choices for \vec{x} , \vec{y} , and α . How can we argue about all of them at once?

Consider the following proof that T is linear.

Proof. Let $\vec{x}, \vec{y} \in \mathbb{R}^n$ and let α be a scalar. By applying the definition of T , we see

$$T(\vec{x} + \vec{y}) = 2(\vec{x} + \vec{y}) = 2\vec{x} + 2\vec{y} = T(\vec{x}) + T(\vec{y}).$$

Similarly,

$$T(\alpha\vec{x}) = 2(\alpha\vec{x}) = \alpha(2\vec{x}) = \alpha T(\vec{x}).$$

Since T satisfies the two properties of a linear transformation, T is a linear transformation. ■

This proof starts out with “let $\vec{x}, \vec{y} \in \mathbb{R}^n$ and let α be a scalar”. In what follows, the only properties of \vec{x} and \vec{y} we use come from the fact that they're in \mathbb{R}^n (the domain of T) and the only fact about α we use is that it's a scalar. Because of this, \vec{x} , and \vec{y} are considered *arbitrary* vectors and α is an *arbitrary* scalar. Put another way, the argument that follows will work for every single pair of vectors $\vec{x}, \vec{y} \in \mathbb{R}^n$ and for every scalar α . Thus, by fixing arbitrary vectors at the start of our proof, we are (i) able to argue about all vectors at once while (ii) having named vectors that we can actually use in equations.

Takeaway. Starting a linearity proof with “let $\vec{x}, \vec{y} \in \mathbb{R}^n$ and let α be a scalar” allows you to argue about all vectors and scalars simultaneously.

The proof give above is very typical, and almost every proof of the linearity of a function $T : \mathbb{R}^n \rightarrow \mathbb{R}^m$ will look something like

Proof. Let $\vec{x}, \vec{y} \in \mathbb{R}^n$ and let α be a scalar. By applying the definition of T , we see

$$T(\vec{x} + \vec{y}) = \text{application(s) of the definition} = T(\vec{x}) + T(\vec{y}).$$

Similarly,

$$T(\alpha\vec{x}) = \text{application(s) of the definition} = \alpha T(\vec{x}).$$

Since T satisfies the two properties of a linear transformation, T is a linear transformation. ■

This isn't to say that proving whether or not a transformation is linear is *easy*, but all the cleverness and insight required appears in the “application(s) of the definition” parts.

What about showing a transformation is *not* linear? Here we don't need to show something true for all vectors and all scalars. We only need to show something is false for *one* pair of vectors or *one* pair of a vector and a scalar.

Because when we're proving something is not a linear transformation we only need to show that the definition of linearity breaks down in one place, we can pick and choose which property we want to show breaks down.

Example. Let $T : \mathbb{R}^n \rightarrow \mathbb{R}^n$ be defined by $T(\vec{x}) = \vec{x} + \vec{e}_1$. Show that T is *not* linear.

Proof. We will show that T does not distribute with respect to scalar multiplication.

Observe that

$$T(2\vec{0}) = T(\vec{0}) = \vec{e}_1 \neq 2\vec{e}_1 = 2T(\vec{0}).$$

Therefore, T cannot be a linear transformation. ■

Matrix Transformations

We already know two ways to interpret matrix multiplication—linear combinations of the columns and dot products with the rows—and we’re about to have a third.

Let $M = \begin{bmatrix} 1 & 2 \\ -1 & 1 \end{bmatrix}$. For a vector $\vec{v} \in \mathbb{R}^2$, $M\vec{v}$ is another vector in \mathbb{R}^2 . In this way, we can think of multiplication by M as a transformation on \mathbb{R}^2 . Define

$$T : \mathbb{R}^2 \rightarrow \mathbb{R}^2 \quad \text{by} \quad T(\vec{x}) = M\vec{x}.$$

Because T is defined by a matrix, we call T a *matrix transformation*. It turns out all matrix transformations are linear transformations and most linear transformations are matrix transformations.²⁹

Just as with writing systems of linear equations, matrices provide a compact way of specifying a linear transformation. For example, we could say, “The linear transformation $T : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ that doubles the x -coordinate and triples the y -coordinate”, or we could say, “The matrix transformation given by $\begin{bmatrix} 2 & 0 \\ 0 & 3 \end{bmatrix}$ ”.

When talking about matrices and linear transformations, we must keep in mind that they are not the same thing. A matrix is a box of numbers and has no meaning until we give it meaning. A linear transformation is a function that inputs vectors and outputs vectors. We can *specify* a linear transformation using a matrix, but a matrix by itself is *not* a linear transformation.³⁰

So what are some correct ways to specify a linear transformation using a matrix? Let’s list some. For a matrix M the following are ways of specifying the same linear transformation.

- The transformation T defined by $T(\vec{x}) = M\vec{x}$.
- The transformation given by multiplication by M .
- The transformation induced by M .
- The matrix transformation given by M .
- The linear transformation whose matrix is M .

Finding a Matrix for a Linear Transformation

Every linear transformation from \mathbb{R}^n to \mathbb{R}^m has a matrix, and we can use basic algebra to find an appropriate matrix.

Let $T : \mathbb{R}^n \rightarrow \mathbb{R}^m$ be a linear transformation. Since T inputs vectors with n coordinates and outputs vectors with m coordinates, we know any matrix for T must be $m \times n$. The process of finding a matrix for T can now be summarized as follows: (i) create an $m \times n$ matrix of variables, (ii) use known input-output pairs for T to set up a system of equations involving the unknown variables, (iii) solve for the variables.

Example. Let $\mathcal{T} : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ be defined by $\mathcal{T} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 2x + y \\ x \end{bmatrix}$. Find a matrix, M , for \mathcal{T} .

Because \mathcal{T} is a transformation for $\mathbb{R}^2 \rightarrow \mathbb{R}^2$, M will be a 2×2 matrix. Let

$$M = \begin{bmatrix} a & b \\ c & d \end{bmatrix}.$$

We now need to use input-output pairs to “calibrate” M . We know

$$\mathcal{T} \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 3 \\ 1 \end{bmatrix} \quad \text{and} \quad \mathcal{T} \begin{bmatrix} 0 \\ 1 \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}.$$

²⁹ If you believe in the axiom of choice and you allow infinitely sized matrices, every linear transformation can be expressed as a matrix transformation.

³⁰ Consider the function defined by $f(x) = 2x$. You would never say that the function f is 2!

If M is a matrix for \mathcal{T} , then we know $\mathcal{T}\vec{x} = M\vec{x}$ for all \vec{x} , and so

$$M \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \begin{bmatrix} a & b \\ c & d \end{bmatrix} \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \begin{bmatrix} a+b \\ c+d \end{bmatrix} = \begin{bmatrix} 3 \\ 1 \end{bmatrix}$$

and

$$M \begin{bmatrix} 0 \\ 1 \end{bmatrix} = \begin{bmatrix} a & b \\ c & d \end{bmatrix} \begin{bmatrix} 0 \\ 1 \end{bmatrix} = \begin{bmatrix} b \\ d \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}.$$

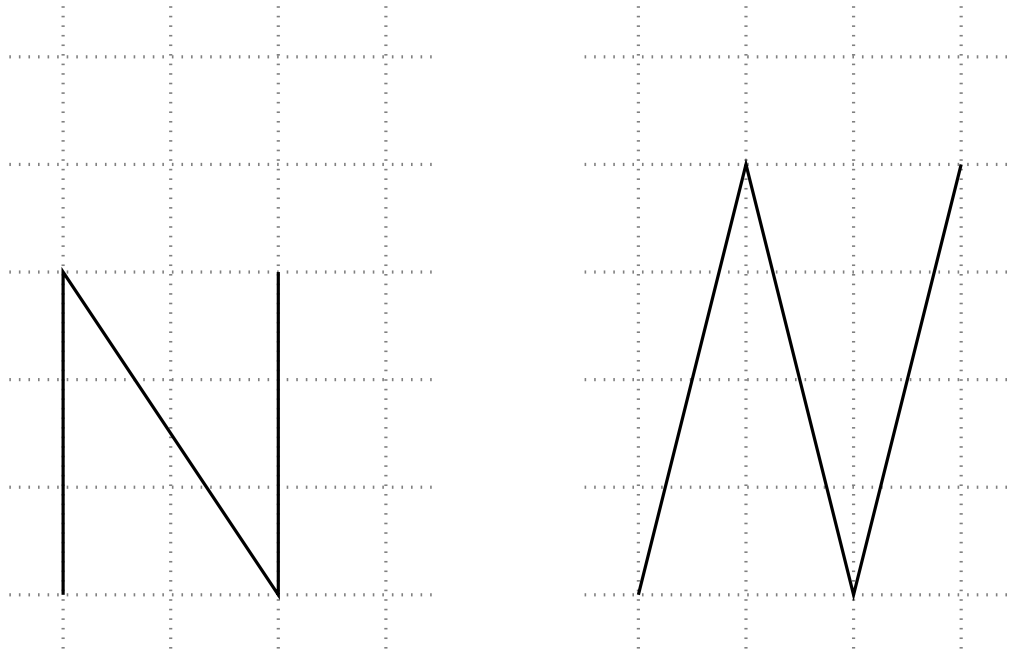
This gives us the system of equations

$$\begin{cases} a+b &= 3 \\ c+d &= 1 \\ b &= 1 \\ d &= 0 \end{cases},$$

and so

$$M = \begin{bmatrix} a & b \\ c & d \end{bmatrix} = \begin{bmatrix} 2 & 1 \\ 1 & 0 \end{bmatrix}.$$

Task 2.1: Italicizing N

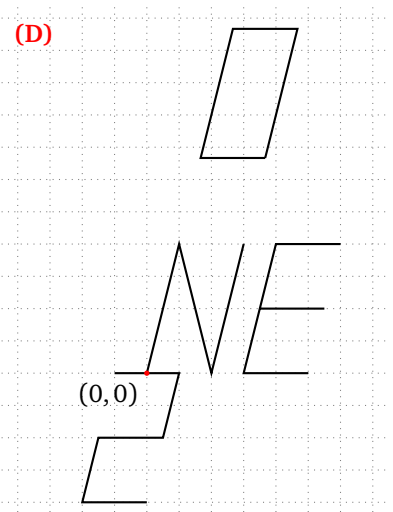
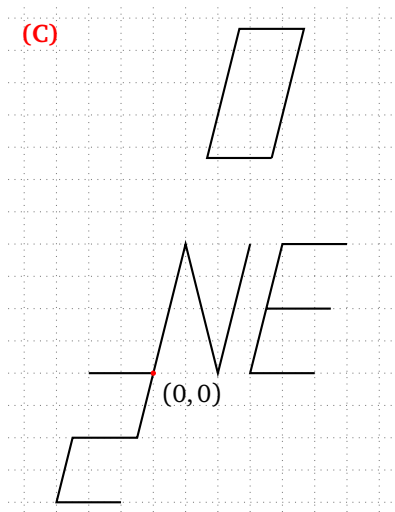
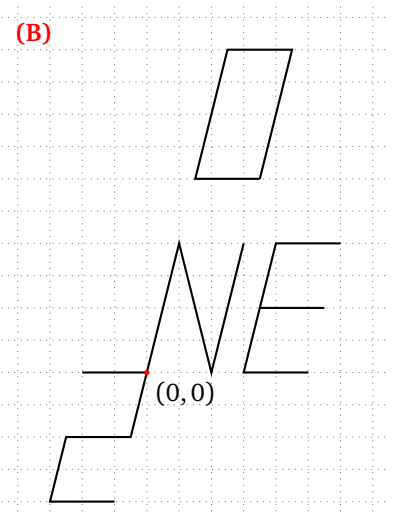
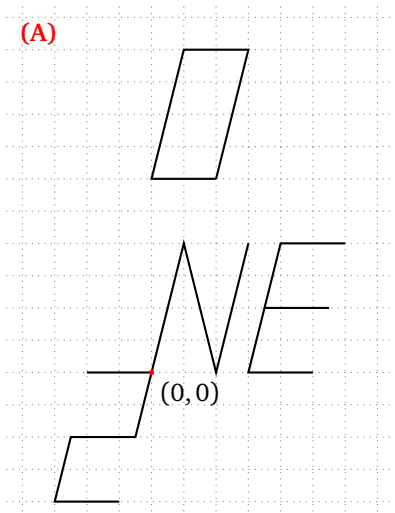
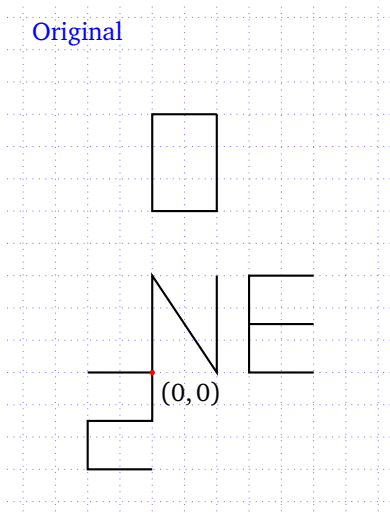


Suppose that the “N” on the left is written in regular 12-point font. Find a matrix A that will transform the “N” into the letter on the right which is written in an *italic* 16-point font.

Work with your group to write out your solution and approach. Make a list of any assumptions you notice your group making or any questions for further pursuit.

Task 2.2: Beyond the N

A few students were wondering how letters placed in other locations in the plane would be transformed under $A = \begin{bmatrix} 1 & 1/3 \\ 0 & 4/3 \end{bmatrix}$. If other letters are placed around the “N,” the students argued over four different possible results for the transformed letters. Which choice below, if any, is correct, and why? If none of the four options are correct, what would the correct option be, and why?



40 $\mathcal{R} : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ is the transformation that rotates vectors counter-clockwise by 90° .

40.1 Compute $\mathcal{R} \begin{bmatrix} 1 \\ 0 \end{bmatrix}$ and $\mathcal{R} \begin{bmatrix} 0 \\ 1 \end{bmatrix}$.

40.2 Compute $\mathcal{R} \begin{bmatrix} 1 \\ 1 \end{bmatrix}$. How does this relate to $\mathcal{R} \begin{bmatrix} 1 \\ 0 \end{bmatrix}$ and $\mathcal{R} \begin{bmatrix} 0 \\ 1 \end{bmatrix}$?

40.3 What is $\mathcal{R} \left(a \begin{bmatrix} 1 \\ 0 \end{bmatrix} + b \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right)$?

40.4 Write down a matrix R so that $R\vec{v}$ is \vec{v} rotated counter-clockwise by 90° .

Linear Transformation

Let V and W be subspaces. A function $T : V \rightarrow W$ is called a *linear transformation* if

$$T(\vec{u} + \vec{v}) = T\vec{u} + T\vec{v} \quad \text{and} \quad T(\alpha\vec{v}) = \alpha T\vec{v}$$

for all vectors $\vec{u}, \vec{v} \in V$ and all scalars α .

41 41.1 Classify the following as linear transformations or not.

(a) \mathcal{R} from before (rotation counter-clockwise by 90°).

(b) $W : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ where $W \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} x^2 \\ y \end{bmatrix}$.

(c) $T : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ where $T \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} x+2 \\ y \end{bmatrix}$.

(d) $\mathcal{P} : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ where $\mathcal{P} \begin{bmatrix} x \\ y \end{bmatrix} = \text{v comp}_{\vec{u}} \begin{bmatrix} x \\ y \end{bmatrix}$ and $\vec{u} = \begin{bmatrix} 2 \\ 3 \end{bmatrix}$.

Image of a Set

DEFINITION

Let $L : \mathbb{R}^n \rightarrow \mathbb{R}^m$ be a transformation and let $X \subseteq \mathbb{R}^n$ be a set. The *image of the set X under L* , denoted $L(X)$, is the set

$$L(X) = \{\vec{x} \in W : \vec{x} = L(\vec{y}) \text{ for some } \vec{y} \in X\}.$$

42

Let $S = \left\{ \begin{bmatrix} x \\ y \end{bmatrix} : 0 \leq x, y \leq 1 \right\} \subseteq \mathbb{R}^2$ be the filled-in unit square and let $C = \{\vec{0}, \vec{e}_1, \vec{e}_2, \vec{e}_1 + \vec{e}_2\} \subseteq \mathbb{R}^2$ be the corners of the unit square.

- 42.1 Find $\mathcal{R}(C)$, $W(C)$, and $T(C)$ (where \mathcal{R} , W , and T are from the previous question).
- 42.2 Draw $\mathcal{R}(S)$, $T(S)$, and $\mathcal{P}(S)$ (where \mathcal{R} , T , and \mathcal{P} are from the previous question).
- 42.3 Let $\ell = \{\text{all convex combinations of } \vec{a} \text{ and } \vec{b}\}$ be a line segment with endpoints \vec{a} and \vec{b} and let A be a linear transformation. Must $A(\ell)$ be a line segment? What are its endpoints?
- 42.4 Explain how images of sets relate to the *Italicizing N* task.

The Composition of Linear Transformations

In this module you will learn

- How to break a complicated transformation into the composition of simpler ones.
- How the composition of linear transformations relates to matrix multiplication.

In life, we encounter situations where we do one thing after another. For example, you put on your socks and then your shoes. We might call this whole operation (of first putting on your socks and then your shoes) “getting dressed”, and it is an example of *function composition*.

Composition of Functions. Let $f : A \rightarrow B$ and $g : B \rightarrow C$. The *composition* of g and f , notated $g \circ f$, is the function $h : A \rightarrow C$ defined by

$$h(x) = g \circ f(x) = g(f(x)).$$

We can formalize the shoes-socks example with mathematical notation.

$$\text{getting dressed} = (\text{putting on shoes}) \circ (\text{putting on socks})$$

Or, if X represented putting on socks, S represented putting on shoes, and D represented getting dressed, $D = S \circ X$.

This real-life example has utility when talking to children. Getting dressed is a complicated operation, but by breaking it up into simpler operations, even a young child can understand the process of getting dressed. In this vein, we can understand complicated linear transformations by breaking them up into the composition of simpler ones.

For example, define

$$\mathcal{T} : \mathbb{R}^2 \rightarrow \mathbb{R}^2 \quad \text{by} \quad \mathcal{T}(\vec{x}) = \begin{bmatrix} \sqrt{2} & -\sqrt{2} \\ \sqrt{2}/2 & \sqrt{2}/2 \end{bmatrix} \vec{x}.$$

It’s hard to understand what \mathcal{T} is doing just by looking at inputs and outputs. However, if we were keen enough to notice that

$$\mathcal{T} = \mathcal{S} \circ \mathcal{R}$$

where \mathcal{R} was rotation counter-clockwise by 45° and \mathcal{S} was a stretch in the \vec{e}_1 direction by a factor of 2, suddenly \mathcal{T} wouldn’t be so much of a mystery.

You might be wondering how does one figure out the “simple transformations” that when composed give the full transformation? In truth, there are many, many methods and there are whole books written about how to find these decompositions efficiently. We will encounter two algorithms for this,³¹ but for now our methods will be ad hoc.

Example. Let $\mathcal{U} : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ be the transformation given by $M = \begin{bmatrix} \sqrt{2}/2 & -\sqrt{2}/2 \\ 0 & 0 \end{bmatrix}$, let $\mathcal{R} : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ be rotation counter clockwise by 45° , and let $\mathcal{P} : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ be projection onto the x -axis. Write \mathcal{U} as the composition (in some order) of \mathcal{R} and \mathcal{P} .

For vectors \vec{e}_1 and \vec{e}_2 , Notice that

$$\mathcal{U}(\vec{e}_1) = \begin{bmatrix} \frac{\sqrt{2}}{2} \\ 0 \end{bmatrix} \quad \text{and} \quad \mathcal{U}(\vec{e}_2) = \begin{bmatrix} -\frac{\sqrt{2}}{2} \\ 0 \end{bmatrix}.$$

We will then compute $\mathcal{R} \circ \mathcal{P}$ and $\mathcal{P} \circ \mathcal{R}$ applied to \vec{e}_1 and \vec{e}_2 and see which ones match.

For $\mathcal{R} \circ \mathcal{P}$:

$$\begin{aligned} \mathcal{R} \circ \mathcal{P}(\vec{e}_1) &= \mathcal{R}(\mathcal{P}(\vec{e}_1)) = \mathcal{R} \begin{bmatrix} 1 \\ 0 \end{bmatrix} = \begin{bmatrix} \frac{\sqrt{2}}{2} \\ \frac{\sqrt{2}}{2} \end{bmatrix} \\ \mathcal{R} \circ \mathcal{P}(\vec{e}_2) &= \mathcal{R}(\mathcal{P}(\vec{e}_2)) = \mathcal{R} \begin{bmatrix} 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}. \end{aligned}$$

³¹ Phrased in terms of matrices instead of linear transformations, the decompositions we will study are called: (i) decomposition into elementary matrices, and (ii) diagonalization.

For $\mathcal{P} \circ \mathcal{R}$:

$$\begin{aligned}\mathcal{P} \circ \mathcal{R}(\vec{e}_1) &= \mathcal{P}(\mathcal{R}(\vec{e}_1)) = \mathcal{P}\begin{bmatrix} \frac{\sqrt{2}}{2} \\ \frac{\sqrt{2}}{2} \end{bmatrix} = \begin{bmatrix} \frac{\sqrt{2}}{2} \\ 0 \end{bmatrix} \\ \mathcal{P} \circ \mathcal{R}(\vec{e}_2) &= \mathcal{P}(\mathcal{R}(\vec{e}_2)) = \mathcal{P}\begin{bmatrix} -\frac{\sqrt{2}}{2} \\ \frac{\sqrt{2}}{2} \end{bmatrix} = \begin{bmatrix} -\frac{\sqrt{2}}{2} \\ 0 \end{bmatrix}.\end{aligned}$$

Since $\mathcal{P} \circ \mathcal{R}$ agrees with \mathcal{U} on the standard basis (i.e., they outputs the same vectors when \vec{e}_1 and \vec{e}_2 are input), they must agree for all vectors. Therefore $\mathcal{P} \circ \mathcal{R} = \mathcal{U}$.

Compositions and Matrix Products

Let $\mathcal{A} : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ and $\mathcal{B} : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ be matrix transformations with matrices

$$A = \begin{bmatrix} 1 & 2 \\ 0 & 2 \end{bmatrix} \quad \text{and} \quad B = \begin{bmatrix} -1 & -1 \\ -2 & 0 \end{bmatrix}.$$

Here we are using italic \mathcal{A} and \mathcal{B} to represent linear transformations and regular A and B to represent matrices. Make sure you understand why $\mathcal{A} \neq A$ before continuing.

Define $\mathcal{T} = \mathcal{A} \circ \mathcal{B}$. Since $\mathcal{T} : \mathbb{R}^2 \rightarrow \mathbb{R}^2$, we know \mathcal{T} has a matrix T . We can find T by the usual methods. First, compute some input-output pairs for \mathcal{T} .

$$\mathcal{T}\begin{bmatrix} 1 \\ 0 \end{bmatrix} = \mathcal{A}\left(\mathcal{B}\begin{bmatrix} 1 \\ 0 \end{bmatrix}\right) = \mathcal{A}\begin{bmatrix} -1 \\ -2 \end{bmatrix} = \begin{bmatrix} -5 \\ -4 \end{bmatrix} \quad \text{and} \quad \mathcal{T}\begin{bmatrix} 0 \\ 1 \end{bmatrix} = \mathcal{A}\left(\mathcal{B}\begin{bmatrix} 0 \\ 1 \end{bmatrix}\right) = \mathcal{A}\begin{bmatrix} -1 \\ 0 \end{bmatrix} = \begin{bmatrix} -1 \\ 0 \end{bmatrix}$$

Letting $T = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$, we use the input-output pairs to see

$$\begin{bmatrix} a \\ c \end{bmatrix} = T\begin{bmatrix} 1 \\ 0 \end{bmatrix} = \begin{bmatrix} -5 \\ -4 \end{bmatrix} \quad \text{and} \quad \begin{bmatrix} b \\ d \end{bmatrix} = T\begin{bmatrix} 0 \\ 1 \end{bmatrix} = \begin{bmatrix} -1 \\ 0 \end{bmatrix},$$

and so

$$T = \begin{bmatrix} -5 & -1 \\ -4 & 0 \end{bmatrix}.$$

We found T , the matrix for \mathcal{T} , using traditional techniques, but could we have used A and B to somehow find T ? As it turns out, yes, we could have!

By definition,

$$\mathcal{A}\vec{x} = A\vec{x} \quad \text{and} \quad \mathcal{B}\vec{x} = B\vec{x},$$

since \mathcal{A} and \mathcal{B} are matrix transformations. Therefore,

$$\mathcal{A}(\mathcal{B}\vec{x}) = A(B\vec{x}).$$

But, matrix multiplication is *associative*,³² and so

$$A(B\vec{x}) = (AB)\vec{x}.$$

Thus AB must be a matrix for $\mathcal{A} \circ \mathcal{B} = \mathcal{T}$. Indeed, computing the matrix product, we see

$$AB = \begin{bmatrix} 1 & 2 \\ 0 & 2 \end{bmatrix} \begin{bmatrix} -1 & -1 \\ -2 & 0 \end{bmatrix} = \begin{bmatrix} -5 & -1 \\ -4 & 0 \end{bmatrix} = T.$$

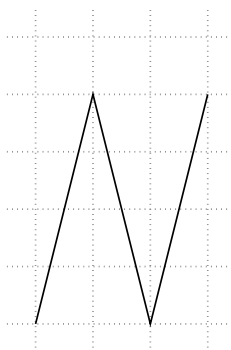
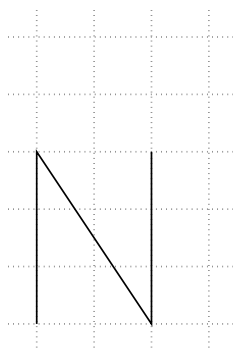
The fact that matrix multiplication corresponds to function composition is no coincidence. In fact, the reason matrix multiplication has the definition it does is so that function composition corresponds to matrix multiplication. This fact is reiterated in the following theorem.

Theorem. If $\mathcal{P} : \mathbb{R}^a \rightarrow \mathbb{R}^b$ and $\mathcal{Q} : \mathbb{R}^c \rightarrow \mathbb{R}^a$ are matrix transformations with matrices P and Q , then $\mathcal{P} \circ \mathcal{Q}$ is a matrix transformation whose matrix is given by the matrix product PQ .

It should now be clear why the order of matrix multiplication matters. The order of function composition matters (you must put on your socks before your shoes!), and since matrix multiplication corresponds to function composition, the order of matrix multiplication must matter.

³² If an operation is associative, it means that where you put the parenthesis doesn't matter.

Task 2.3: Pat and Jamie



Suppose that the “N” on the left is written in regular 12-point font. Find a matrix A that will transform the “N” into the letter on the right which is written in an italic 16-point font.

Two students—Pat and Jamie—explained their approach to the Italicizing N task as follows:

In order to find the matrix A , we are going to find a matrix that makes the “N” taller, find a matrix that italicizes the taller “N,” and a combination of those two matrices will give the desired matrix A .

1. Do you think Pat and Jamie’s approach allowed them to find A ? If so, do you think they found the same matrix that you did during Italicising N?
2. Try Pat and Jamie’s approach. Either (a) come up with a matrix A using their approach, or (b) explain why their approach does not work.

Define \mathcal{P} to be projection onto $\text{span}\{\vec{u}\}$ where $\vec{u} = \begin{bmatrix} 2 \\ 3 \end{bmatrix}$, and let \mathcal{R} be rotation counter-clockwise by 90° .

- 43.1 Find a matrix P so that $P\vec{x} = \mathcal{P}(\vec{x})$ for all $\vec{x} \in \mathbb{R}^2$.
- 43.2 Find a matrix R so that $R\vec{x} = \mathcal{R}(\vec{x})$ for all $\vec{x} \in \mathbb{R}^2$.
- 43.3 Write down matrices A and B for $\mathcal{P} \circ \mathcal{R}$ and $\mathcal{R} \circ \mathcal{P}$.
- 43.4 How do the matrices A and B relate to the matrices P and R ?

Range & Nullspace of a Linear Transformation

In this module you will learn

- The definition of the range and null space of a linear transformation.
- How to precisely notate the matrix for a linear transformation.
- The fundamental subspaces corresponding to a matrix (row space, column space, null space) and how they relate to the range and null space of a linear transformation.
- How to find a basis for the fundamental subspaces of a matrix.
- The definition of rank and the rank-nullity theorem.

Associated with every linear transformation are two specially named subspaces.

Range

The first special subspace is called the *range*.

Range. The *range* (or *image*) of a linear transformation $T : V \rightarrow W$ is the set of vectors that T can output. That is,

$$\text{range}(T) = \{\vec{y} \in W : \vec{y} = T\vec{x} \text{ for some } \vec{x} \in V\}.$$

The range of a linear transformation has the exact same definition as the range of a function—it's the set of all outputs. In other words, the range of a linear transformation is the *image* of the entire domain with respect to that linear transformation.³³ However, unlike the range of an arbitrary function, the range of a linear transformation is always a subspace.

Theorem. Let $T : \mathbb{R}^n \rightarrow \mathbb{R}^m$ be a linear transformation. Then $\text{range}(T) \subseteq \mathbb{R}^m$ is a subspace.

Proof. Since $\text{range}(T) = T(\mathbb{R}^n)$ and \mathbb{R}^n is non-empty, we know that $\text{range}(T)$ is non-empty. Therefore, to show that $\text{range}(T)$ is a subspace, we need to show (i) that it's closed under vector addition, and (ii) that it is closed under scalar multiplication.

- (i) Let $\vec{x}, \vec{y} \in \text{range}(T)$. By definition, there exist $\vec{u}, \vec{v} \in \mathbb{R}^n$ such that $T(\vec{u}) = \vec{x}$ and $T(\vec{v}) = \vec{y}$. Since T is linear,

$$\vec{x} + \vec{y} = T(\vec{u}) + T(\vec{v}) = T(\vec{u} + \vec{v}),$$

and so $\vec{x} + \vec{y} \in \text{range}(T)$.

- (ii) Let $\vec{x} \in \text{range}(T)$ and let α be a scalar. By definition, there exists $\vec{u} \in \mathbb{R}^n$ such that $T(\vec{u}) = \vec{x}$, and so by the linearity of T ,

$$\alpha\vec{x} = \alpha T(\vec{u}) = T(\alpha\vec{u}).$$

Therefore $\alpha\vec{x} \in \text{range}(T)$. ■

When analyzing subspaces, we are often interested in how big they are. That information is captured by a numbers—the *dimension* of the subspace. For transformations, we also have a notion of how “big” they are, which is captured in a number called the *rank*.

Rank of a Linear Transformation. For a linear transformation $T : \mathbb{R}^n \rightarrow \mathbb{R}^m$, the *rank* of T , denoted $\text{rank}(T)$, is the dimension of the range of T .

The rank of a linear transformation can be used as a measure of its complexity or compressibility. A rank 0 transformation must send all vectors to $\vec{0}$. A rank 1 transformation must send all vectors to a line, etc.. So, by just knowing a single number—the rank—you can judge how complicated the set of outputs of a linear transformation will be.

Example. Let \mathcal{P} be the plane given by $x + y + z = 0$, and let $T : \mathbb{R}^3 \rightarrow \mathbb{R}^3$ be projection onto \mathcal{P} . Find $\text{range}(T)$ and $\text{rank}(T)$.

³³ Some people say “the *image* of T ” as a short way of saying “the image of the entire domain of T under T ”. Used in this sense $\text{Image}(T) = \text{range}(T)$.

First we will find $\text{range}(T)$. Since T is a projection onto \mathcal{P} , we know $\text{range}(T) \subseteq \mathcal{P}$. Because $T(\vec{p}) = \vec{p}$ for all $\vec{p} \in \mathcal{P}$, we know $\mathcal{P} \subseteq \text{range}(T)$, and so

$$\text{range}(T) = \mathcal{P}.$$

Since \mathcal{P} is a plane, we know $\dim(\mathcal{P}) = 2 = \dim(\text{range}(T)) = \text{rank}(T)$.

Null Space

The second special subspace is called the *null space*.

Null Space. The *null space* (or *kernel*) of a linear transformation $T : V \rightarrow W$ is the set of vectors that get mapped to zero under T . That is,

$$\text{null}(T) = \{\vec{x} \in V : T\vec{x} = \vec{0}\}.$$

We've seen null spaces before, but in the context of matrices when we asked questions like, "Are these column vectors linearly independent?" Now that we understand linear transformation and subspaces, we can consider this question anew.

Just like the range of a linear transformation, the null space of a linear transformation is always a subspace.

Theorem. Let $T : \mathbb{R}^n \rightarrow \mathbb{R}^m$ be a linear transformation. Then $\text{null}(T) \subseteq \mathbb{R}^n$ is a subspace.

Proof. Since T is linear, $T(\vec{0}) = \vec{0}$ and so $\vec{0} \in \text{null}(T)$ which shows that $\text{null}(T)$ is non-empty. Therefore, to show that $\text{null}(T)$ is a subspace, we need to show (i) that it's closed under vector addition, and (ii) that it is closed under scalar multiplication.

(i) Let $\vec{x}, \vec{y} \in \text{null}(T)$. By definition, $T(\vec{x}) = T(\vec{y}) = \vec{0}$. By linearity we see

$$T(\vec{x} + \vec{y}) = T(\vec{x}) + T(\vec{y}) = \vec{0} + \vec{0} = \vec{0},$$

and so $\vec{x} + \vec{y} \in \text{null}(T)$.

(ii) Let $\vec{x} \in \text{null}(T)$ and let α be a scalar. By definition, $T(\vec{x}) = \vec{0}$, and so by the linearity of T ,

$$T(\alpha\vec{x}) = \alpha T(\vec{x}) = \alpha\vec{0} = \vec{0}.$$

Therefore $\alpha\vec{x} \in \text{null}(T)$. ■

Akin to the rank–range connection, there is a special number call the *nullity* of a linear transformation that relates to the dimension of the null space.

Nullity. For a linear transformation $T : \mathbb{R}^n \rightarrow \mathbb{R}^m$, the *nullity* of T , denoted $\text{nullity}(T)$, is the dimension of the null space of T .

Example. Let \mathcal{P} be the plane given by $x + y + z = 0$, and let $T : \mathbb{R}^3 \rightarrow \mathbb{R}^3$ be projection onto \mathcal{P} . Find $\text{null}(T)$ and $\text{nullity}(T)$.

First we will find $\text{null}(T)$. Since T is a projection onto \mathcal{P} (and because \mathcal{P} passes through $\vec{0}$), we know every normal vector for \mathcal{P} will get sent to $\vec{0}$ when T is applied. And, besides $\vec{0}$ itself, these are the only vectors that get sent to $\vec{0}$. Therefore

$$\text{null}(T) = \{\text{normal vectors}\} \cup \{\vec{0}\} = \text{span} \left\{ \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \right\}.$$

Since $\text{null}(T)$ is a line, we know $\text{nullity}(T) = 1$.

Fundamental Subspaces of a Matrix

Every linear transformation has a range and a null space. Analogously, every matrix is associated with three fundamental subspaces.

Fundamental Subspaces. Associated with any matrix M are three fundamental subspaces: the *row space* of M , denoted $\text{row}(M)$, is the span of the rows of M ; the *column space* of M , denoted $\text{col}(M)$, is the span of the columns of M ; and the *null space* of M , denoted $\text{null}(M)$, is the set of solutions to $M\vec{x} = \vec{0}$.

Computationally, it's much easier to find the row space/column space/null space of a matrix than it is to find the range/null space of a linear transformation. This is because everything we know about systems of equations and their relationship to matrix equations still holds.

Take the null space of a matrix M , for example. By definition it is the set of solutions to $M\vec{x} = \vec{0}$, which is the solution set to a homogeneous system of equations.

Example. Find the null space of $M = \begin{bmatrix} 1 & 2 & 5 \\ 2 & -2 & -2 \end{bmatrix}$.

To find the null space of M , we need to solve the homogeneous matrix equation $M\vec{x} = \vec{0}$. Row reducing, we see

$$\text{rref}(M) = \begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & 2 \end{bmatrix}$$

and so the z column is a free variable column. Therefore the complete solution can be expressed in vector form as

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = t \begin{bmatrix} -1 \\ -2 \\ 1 \end{bmatrix},$$

and so

$$\text{null}(M) = \text{span} \left\{ \begin{bmatrix} -1 \\ -2 \\ 1 \end{bmatrix} \right\}.$$

The column space and row space are just as easy to compute, since it just involves picking a basis from the existing row or column vectors.

Example. Let $M = \begin{bmatrix} 1 & 2 & 5 \\ 2 & -2 & -2 \end{bmatrix}$. Find a basis for the row space and the column space of M .

First the column space. We need to pick a basis for $\text{span} \left\{ \begin{bmatrix} 1 \\ 2 \end{bmatrix}, \begin{bmatrix} 2 \\ -1 \end{bmatrix}, \begin{bmatrix} 5 \\ -2 \end{bmatrix} \right\}$ which is the same thing as picking a maximal linearly independent subset of $\left\{ \begin{bmatrix} 1 \\ 2 \end{bmatrix}, \begin{bmatrix} 2 \\ -1 \end{bmatrix}, \begin{bmatrix} 5 \\ -2 \end{bmatrix} \right\}$.

Putting these vectors as columns in a matrix and row reducing, we see

$$\text{rref} \left(\begin{bmatrix} 1 & 2 & 5 \\ 2 & -2 & -2 \end{bmatrix} \right) = \begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & 2 \end{bmatrix}.$$

The first and second columns are the only pivot columns and so the first and second *original* vectors form a maximal linearly independent subset. Thus,

$$\text{col}(M) = \text{span} \left\{ \begin{bmatrix} 1 \\ 2 \end{bmatrix}, \begin{bmatrix} 2 \\ -1 \end{bmatrix} \right\} = \mathbb{R}^2 \quad \text{and a basis is} \quad \left\{ \begin{bmatrix} 1 \\ 2 \end{bmatrix}, \begin{bmatrix} 2 \\ -1 \end{bmatrix} \right\}.$$

To find the column space, we need to pick a basis for $\text{span} \left\{ \begin{bmatrix} 1 \\ 2 \\ 5 \end{bmatrix}, \begin{bmatrix} 2 \\ -2 \\ -2 \end{bmatrix} \right\}$. Repeating a similar procedure, we see

$$\text{rref} \left(\begin{bmatrix} 1 & 2 \\ 2 & -2 \\ 5 & -2 \end{bmatrix} \right) = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix},$$

and so $\left\{ \begin{bmatrix} 1 \\ 2 \\ 5 \end{bmatrix}, \begin{bmatrix} 2 \\ -2 \\ -2 \end{bmatrix} \right\}$ is linearly independent. Therefore

$$\text{row}(M) = \text{span} \left\{ \begin{bmatrix} 1 \\ 2 \\ 5 \end{bmatrix}, \begin{bmatrix} 2 \\ -2 \\ -2 \end{bmatrix} \right\} \quad \text{and a basis is} \quad \left\{ \begin{bmatrix} 1 \\ 2 \\ 5 \end{bmatrix}, \begin{bmatrix} 2 \\ -2 \\ -2 \end{bmatrix} \right\}.$$

When talking about fundamental subspaces, we often switch between talking about column vectors and row vectors belonging to a matrix. The operation of swapping rows for columns is called the *transpose*.

Transpose.

Let M be an $n \times m$ matrix defined by

$$M = \begin{bmatrix} a_{11} & a_{12} & a_{13} & \cdots & a_{1m} \\ a_{21} & a_{22} & a_{23} & \cdots & a_{2m} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & a_{n3} & \cdots & a_{nm} \end{bmatrix}.$$

The *transpose* of M , notated M^T is the $m \times n$ matrix M with its rows and columns swapped. That is

$$M^T = \begin{bmatrix} a_{11} & a_{21} & \cdots & a_{m1} \\ a_{12} & a_{22} & \cdots & a_{m2} \\ a_{13} & a_{23} & \cdots & a_{m3} \\ \vdots & \vdots & \ddots & \vdots \\ a_{1n} & a_{2n} & \cdots & a_{mn} \end{bmatrix}.$$

Using the transpose, we can make statements like

$$\text{col}(M) = \text{row}(M^T) \quad \text{and} \quad \text{row}(M) = \text{col}(M^T).$$

In addition it helps us state the following theorem.

Theorem. For a matrix A , the dimension of the row space equals the dimension of the column space. That is, $\text{rank}(A) = \text{rank}(A^T)$.

Proof. To prove $\text{rank}(A) = \text{rank}(A^T)$, we will rely on what we know about the row reduction algorithm and what the reduced row echelon form of a matrix tells us.

Claim 1: $\text{row}(\text{rref}(A)) \subseteq \text{row}(A)$. To see this, observe that to get $\text{rref}(A)$, we take linear combinations of the rows of A . Therefore, it must be that the span of the rows of $\text{rref}(A)$ is contained in the span of the rows of A .

Claim 2: $\text{row}(\text{rref}(A)) = \text{row}(A)$. To see this, observe that every elementary row operation is reversible. Therefore every row in A can be obtained as a linear combination of rows in $\text{rref}(A)$ (by just reversing the steps). Thus the row vectors of $\text{rref}(A)$ and the row vectors of A must have the same span.

Claim 3: The non-zero rows of $\text{rref}(A)$ form a basis for $\text{row}(A)$. We already know that the non-zero rows of $\text{rref}(A)$ span $\text{row}(A)$, so we only need to argue that they are linearly independent. However, this follows immediately from the fact that $\text{rref}(A)$ is in reduced row echelon form. Above and below every pivot in $\text{rref}(A)$ are zeros. Therefore, a row in $\text{rref}(A)$ with a pivot cannot be written as a linear combination of any other row. Since every non-zero row has a pivot, this shows the claim.

Now, note the following two facts.

- The columns of A corresponding to pivot columns of $\text{rref}(A)$ form a basis for $\text{col}(A)$.
- The non-zero rows of $\text{rref}(A)$ form a basis for $\text{row}(A)$.

To complete the proof, note that every pivot of $\text{rref}(A)$ lies in exactly one row and one column. Therefore, the number of basis vectors in $\text{row}(A)$ is the same as the number of basis vectors in $\text{col}(A)$. Thus $\text{rank}(A) = \text{rank}(A^T)$. ■

Equations, Null Spaces, and Geometry

Let $M = \begin{bmatrix} 1 & 2 & 5 \\ 2 & -2 & -2 \end{bmatrix}$. Using the typical row-reduction steps, we know that the complete solution to $M\vec{x} = \vec{0}$ (i.e., the null space of M) can be expressed in vector form as

$$\vec{x} = t \begin{bmatrix} -1 \\ -2 \\ 1 \end{bmatrix}.$$

Similarly, the complete solution to $M\vec{x} = \vec{b}$ where $\vec{b} = \begin{bmatrix} 1 \\ 2 \end{bmatrix}$ can be expressed in vector form as

$$\vec{x} = t \begin{bmatrix} -1 \\ -2 \\ 1 \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}.$$

The set of solutions to $M\vec{x} = \vec{0}$ and $M\vec{x} = \vec{b}$ look very similar. In fact,

$$\{\text{solutions to } M\vec{x} = \vec{b}\} = \{\text{solutions to } M\vec{x} = \vec{0}\} + \{\vec{p}\} \quad \text{where} \quad \vec{p} = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}.$$

Or, phrased another way, the solution set to $M\vec{x} = \vec{b}$ is

$$\text{null}(M) + \{\vec{p}\}.$$

In the context of what we already know about lines and translated subspaces, this makes perfect sense. We know that the solution set to $M\vec{x} = \vec{b}$ is a line (which doesn't pass through the origin) and may therefore be written as a translated span $\text{span}\{\vec{d}\} + \{\vec{p}\}$. Here \vec{d} is a direction vector for the line and \vec{p} is a point on the line.

Because $\vec{p} \in \text{span}\{\vec{d}\} + \{\vec{p}\}$, we call \vec{p} a *particular solution* to $M\vec{x} = \vec{b}$. Using a similar argument, we can show that for any matrix A , and any vector \vec{b} , the set of all solutions to $A\vec{x} = \vec{b}$ (provided there are any) can be expressed as

$$V + \{\vec{p}\}$$

where V is a subspace and \vec{p} is a particular solution. In fact, we can do better. We can say $V = \text{null}(A)$.

Theorem. Let A be a matrix and \vec{b} be a vector and let \vec{p} be a particular solution to $A\vec{x} = \vec{b}$. Then, the set of all solutions to $A\vec{x} = \vec{b}$ is

$$\text{null}(A) + \{\vec{p}\}.$$

Proof. Let $S = \{\text{all solutions to } A\vec{x} = \vec{b}\}$ and assume $\vec{p} \in S$. We will show $S = \text{null}(A) + \{\vec{p}\}$.

First we will show $\text{null}(A) + \{\vec{p}\} \subseteq S$. Let $\vec{v} \in \text{null}(A) + \{\vec{p}\}$. By definition, $\vec{v} = \vec{n} + \vec{p}$ for some $\vec{n} \in \text{null}(A)$. Now, by linearity of matrix multiplication and the definition of the null space,

$$A\vec{v} = A(\vec{n} + \vec{p}) = A\vec{n} + A\vec{p} = \vec{0} + \vec{b} = \vec{b},$$

and so $\vec{v} \in S$.

Next we will show $S \subseteq \text{null}(A) + \{\vec{p}\}$. First observe that for any $\vec{u}, \vec{v} \in S$ we have

$$A(\vec{u} - \vec{v}) = A\vec{u} - A\vec{v} = \vec{b} - \vec{b} = \vec{0},$$

and so $\vec{u} - \vec{v} \in \text{null}(A)$.

Fix $\vec{w} \in S$. By our previous observation, $\vec{w} - \vec{p} \in \text{null}(A)$. Therefore

$$\vec{w} = (\vec{w} - \vec{p}) + \vec{p} \in \text{null}(A) + \{\vec{p}\},$$

which completes the proof. ■

Takeaway. To write the complete solution to $A\vec{x} = \vec{b}$, all you need is the null space of A and a particular solution to $A\vec{x} = \vec{b}$.

Null spaces are also closely connected with row spaces. Let $\mathcal{P} \subseteq \mathbb{R}^3$ be the plane with equation $x + 2y + 2z = 0$. We can rewrite this equation as a matrix equation and as the equation of a plane in normal form.

$$\underbrace{\begin{bmatrix} 1 & 2 & 2 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix}}_{\text{a matrix equation}} = \vec{0} \qquad 111 \qquad \underbrace{\begin{bmatrix} 1 \\ 2 \\ 2 \end{bmatrix} \cdot \begin{bmatrix} x \\ y \\ z \end{bmatrix}}_{\text{normal form}} = 0$$

Now we see that $\mathcal{P} = \text{null}(\begin{bmatrix} 1 & 2 & 2 \end{bmatrix})$ and that every non-zero vector in $\text{row}(\begin{bmatrix} 1 & 2 & 2 \end{bmatrix})$ is a normal vector for \mathcal{P} . In other words, $\text{null}(\begin{bmatrix} 1 & 2 & 2 \end{bmatrix})$ is orthogonal to $\text{row}(\begin{bmatrix} 1 & 2 & 2 \end{bmatrix})$.

This is no coincidence. Let M be a matrix and let $\vec{r}_1, \dots, \vec{r}_n$ be the rows of M . By definition,

$$M\vec{x} = \begin{bmatrix} \vec{r}_1 \cdot \vec{x} \\ \vdots \\ \vec{r}_n \cdot \vec{x} \end{bmatrix},$$

and so solutions to $M\vec{x} = \vec{0}$ are precisely the vectors which are orthogonal to every row of M . In other words, $\text{null}(M)$ consists of all vectors orthogonal to the rows of M . Conversely, $\text{row}(M)$ consists of all vectors orthogonal to everything in $\text{null}(M)$. We can use this fact to approach questions in a new way.

Example. Let $\vec{a} = \begin{bmatrix} 1 \\ 2 \\ 5 \end{bmatrix}$ and $\vec{b} = \begin{bmatrix} 2 \\ -2 \\ -2 \end{bmatrix}$. Find the set of all vectors orthogonal to both \vec{a} and \vec{b} .

Let $M = \begin{bmatrix} 1 & 2 & 5 \\ 2 & -2 & -2 \end{bmatrix}$ be the matrix whose rows are \vec{a} and \vec{b} . Since $\text{null}(M)$ consists of all vectors orthogonal to $\text{row}(M)$, the set we are looking for is $\text{null}(M)$. Computing via row reduction we find

$$\text{null}(M) = \text{span}\{\begin{bmatrix} -1 & -2 & 1 \end{bmatrix}\}.$$

Transformations and Matrices

Matrices are connected to systems of linear equations via matrix equations (like $A\vec{x} = \vec{b}$) and to linear transformations through matrix transformations (like $\mathcal{T}(\vec{x}) = M\vec{x}$). This means that we can think about systems of equations in terms of linear transformations and we can gain insight about linear transformations by looking at systems of equations!

In preparation for this, let's reconsider matrix transformations and be pedantic about our notation.

Let $\mathcal{T} : \mathbb{R}^n \rightarrow \mathbb{R}^n$ be a linear transformation and let M be its corresponding matrix. \mathcal{T} is a function that inputs and outputs *vectors*. M is a box of numbers, which has no meaning by itself, but we know how to multiply M by lists of numbers (or other boxes of numbers). Therefore, strictly speaking, the expression " $M\vec{x}$ " doesn't make sense. The quantity " \vec{x} " is a vectors, but we only know how to multiply M by lists of numbers.

Ah! But we know how to turn \vec{x} into a list of numbers. Just pick a basis! The expression

$$M[\vec{x}]_{\mathcal{E}}$$

makes perfect sense since $[\vec{x}]_{\mathcal{E}}$ is a list of numbers. Continuing to be pedantic, we know $\mathcal{T}(\vec{x}) \neq M[\vec{x}]_{\mathcal{E}}$ since the left side is a vector and the right side is a list of numbers. We can fix this by either turning the right side into a vector or the left side into a list of numbers. Doing this, we see the precise relationship between a linear transformation $\mathcal{T} : \mathbb{R}^n \rightarrow \mathbb{R}^n$ and its matrix M is

$$[\mathcal{T}(\vec{x})]_{\mathcal{E}} = M[\vec{x}]_{\mathcal{E}}.$$

If we have a matrix M , by picking a basis (usually the standard basis), we can define a linear transformation by first taking the input vector and rewriting it in the basis, next multiplying by the matrix, and finally taking the list of numbers and using them as coefficients for a linear combination involving the basis vectors. This is what we actually mean when we say that a matrix *induces* a linear transformation.

Induced Transformation.

Let M be an $n \times m$ matrix. We say M *induces* a linear transformation $\mathcal{T}_M : \mathbb{R}^m \rightarrow \mathbb{R}^n$ defined by

$$[\mathcal{T}_M \vec{v}]_{\mathcal{E}'} = M[\vec{v}]_{\mathcal{E}},$$

where \mathcal{E} is the standard basis for \mathbb{R}^m and \mathcal{E}' is the standard basis for \mathbb{R}^n .

Before we would write " $\mathcal{T}(\vec{x}) = M\vec{x}$ " which hides the fact that when we relate a matrix and a linear transformation, there is a basis hidden in the background. And, like before, when we're only considering a single basis,

we can be sloppy with our notation and write things like “ $M\vec{x}$ ”, but when there are multiple bases or when we’re trying to be extra precise, we must make sure our boxes/lists of numbers and our transformations/vectors stay separate.

Example. Let \mathcal{T} be the transformation induced by the matrix $M = \begin{bmatrix} 1 & 2 & 5 \\ 2 & -2 & -2 \end{bmatrix}$, and let $\vec{v} = 3\vec{e}_1 - 3\vec{e}_3$. Compute $\mathcal{T}(\vec{v})$.

Since \mathcal{T} is induced by $M = \begin{bmatrix} 1 & 2 & 5 \\ 2 & -2 & -2 \end{bmatrix}$, by definition,

$$[\mathcal{T}_M \vec{v}]_{\mathcal{E}'} = M[\vec{v}]_{\mathcal{E}} = \begin{bmatrix} 1 & 2 & 5 \\ 2 & -2 & -2 \end{bmatrix} [\vec{v}]_{\mathcal{E}}.$$

Further, since $\vec{v} = 3\vec{e}_1 - 3\vec{e}_3$, by definition we have $[\vec{v}]_{\mathcal{E}} = \begin{bmatrix} 3 \\ 0 \\ -3 \end{bmatrix}$. Therefore,

$$[\mathcal{T}_M \vec{v}]_{\mathcal{E}'} = \begin{bmatrix} 1 & 2 & 5 \\ 2 & -2 & -2 \end{bmatrix} \begin{bmatrix} 3 \\ 0 \\ -3 \end{bmatrix} = \begin{bmatrix} -12 \\ 12 \end{bmatrix}.$$

In other words, $\mathcal{T}(\vec{v}) = \begin{bmatrix} -12 \\ 12 \end{bmatrix}_{\mathcal{E}'} = -12\vec{e}_1 + 12\vec{e}_2$.

Using induced transformations, we can extend linear-transformation definitions to matrix definitions. In particular, we can define the rank and nullity of a matrix.

Rank of a Matrix. Let M be a matrix. The **rank** of M , denoted $\text{rank}(M)$, is the rank of the linear transformation induced by M .

Nullity of a Matrix. Let M be a matrix. The **nullity** of M , denoted $\text{nullity}(M)$, is the nullity of the linear transformation induced by M .

Range vs. Column Space, Null Space vs. Null Space

Let $M = \begin{bmatrix} C_1 & C_2 & \cdots & C_m \end{bmatrix}$ be an $m \times m$ matrix with columns C_1, \dots, C_m , and let \mathcal{T} be the transformation induced by M . The column space of M is the set of all linear combinations of the columns of M . But, let’s be precise. The columns of M are lists of numbers, so to talk about the column space of M , we need to turn them into vectors. Fortunately, we have a nice notation for that. Since C_i is a list of numbers, $[C_i]_{\mathcal{E}}$ is a true vector, and

$$\text{col}(M) = \text{span}\{[C_1]_{\mathcal{E}}, [C_2]_{\mathcal{E}}, \dots, [C_m]_{\mathcal{E}}\}.$$

Can we connect this to the range of \mathcal{T} ? Well, by the definition of matrix multiplication, we know that

$$M \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix} = M[\vec{e}_1]_{\mathcal{E}} = C_1$$

and in general $M[\vec{e}_i]_{\mathcal{E}} = C_i$. By the definition of induced transformation, we know

$$[\mathcal{T}(\vec{e}_i)]_{\mathcal{E}} = M[\vec{e}_i]_{\mathcal{E}} = C_i,$$

and so

$$\mathcal{T}(\vec{e}_i) = [C_i]_{\mathcal{E}}.$$

Every input to \mathcal{T} can be written as a linear combination of \vec{e}_i ’s (because \mathcal{E} is a basis) and so, because \mathcal{T} is linear, every output of \mathcal{T} can be written as a linear combination of $[C_i]_{\mathcal{E}}$ ’s. In other words,

$$\text{range}(\mathcal{T}) = \text{col}(M).$$

This means that when trying to answer a question about the range of a linear transformation, we could think about the column space of its matrix instead (or vice versa).

Example. Let $\mathcal{T} : \mathbb{R}^3 \rightarrow \mathbb{R}^2$ be defined by

$$\mathcal{T} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 2x - z \\ 4x - 2z \end{bmatrix}.$$

Find $\text{range}(\mathcal{T})$ and $\text{rank}(\mathcal{T})$.

Let M be a matrix for \mathcal{T} . We know $\text{range}(\mathcal{T}) = \text{col}(M)$ and $\text{rank}(\mathcal{T}) = \dim(\text{range}(\mathcal{T})) = \dim(\text{col}(M))$. By inspection, we see that

$$M = \begin{bmatrix} 2 & 0 & -1 \\ 4 & 0 & -2 \end{bmatrix}.$$

Again, by inspection, we see that $\left\{ \begin{bmatrix} 2 \\ 4 \end{bmatrix} \right\}$ is a basis for $\text{col}(M)$ which is one dimensional. Therefore,

$$\text{range}(\mathcal{T}) = \text{span} \left(\left\{ \begin{bmatrix} 2 \\ 4 \end{bmatrix} \right\} \right) \quad \text{and} \quad \text{rank}(\mathcal{T}) = 1.$$

There is an alternative definition of the rank of a matrix which commonly appears. This time, we'll state it as a theorem.

Theorem. Let M be a matrix. The rank of M is equal to the number of pivots in $\text{rref}(M)$.

Proof. We know that $\text{rank}(M) = \dim(\text{range}(\mathcal{T}_M)) = \dim(\text{col}(M))$ where \mathcal{T}_M is the transformation induced by M . Further, a basis for $\text{col}(M)$ consists of a maximal linearly independent subset of the columns of M . To find such a subset, we row reduce M and look at the columns of M that correspond to pivot columns of $\text{rref}(M)$.

When all is said and done, the number of elements in a basis for $\text{col}(M)$ will be the number of pivots in $\text{rref}(M)$, which is the same as $\text{rank}(M)$. ■

Takeaway. If \mathcal{T} is a linear transformation and M a corresponding matrix, $\text{range}(\mathcal{T}) = \text{col}(M)$, and answering questions about M answers questions about \mathcal{T} .

Just like the range–column-space relationship, we also have a null-space–null-space relationship. More specifically, if \mathcal{T} is a linear transformation with matrix M , then $\text{null}(\mathcal{T}) = \text{null}(M)$. From this fact, we deduce the following theorem.

Theorem. Let \mathcal{T} be a linear transformation and let M be a matrix for \mathcal{T} . Then $\text{nullity}(\mathcal{T})$ is equal to the number of free variable columns in $\text{rref}(M)$.

Proof. We know $\text{nullity}(\mathcal{T}) = \dim(\text{null}(\mathcal{T})) = \dim(\text{null}(M))$. Further, we know that the complete solution to $M\vec{x} = \vec{0}$ will take the form

$$\vec{x} = t_1 \vec{d}_1 + \cdots + t_k \vec{d}_k$$

where k is the number of free variable columns in $\text{rref}(M)$. The algorithm for writing the complete solution to $M\vec{x} = \vec{0}$ ensures that $\{\vec{d}_1, \dots, \vec{d}_k\}$ is a basis for $\text{null}(M)$, and so $\text{nullity}(\mathcal{T}) = k$, which completes the proof. ■

The Rank-Nullity Theorem

The rank and the nullity of a linear transformation/matrix are connected by a powerful theorem.

Theorem. (Rank-nullity Theorem for Matrices) For a matrix A ,

$$\text{rank}(A) + \text{nullity}(A) = \# \text{ of columns in } A.$$

The Rank-nullity Theorem's statement is simple, but it is surprisingly useful. Consider the matrix

$$M = \begin{bmatrix} 1 & 2 & 2 \end{bmatrix}.$$

We already know that $\text{null}(M)$ is the plane with equation $x + 2y + 2z = 0$ and therefore is two dimensional. Since M has three columns, $\text{rank}(M) = 1$, and so $\dim(\text{col}(M)) = \dim(\text{row}(M)) = 1$, which means that M has a one-dimensional set of normal vectors.

By contrast, let $\mathcal{P} \subseteq \mathbb{R}^4$ be the plane in \mathbb{R}^4 given in vector form by

$$\vec{x} = t \begin{bmatrix} 1 \\ 2 \\ 2 \\ 2 \end{bmatrix} + s \begin{bmatrix} -1 \\ 1 \\ -1 \\ 1 \end{bmatrix}.$$

How many normal vectors does \mathcal{P} have? Well, the matrix $A = \begin{bmatrix} 1 & 2 & 2 & 2 \\ -1 & 1 & -1 & 1 \end{bmatrix}$ is rank 2, and so has nullity 2. Therefore, there exists two linearly independent normal directions for \mathcal{P} .

There is an equivalent Rank-nullity Theorem for linear transformations.

Theorem. (Rank-nullity Theorem for Linear Transformations) Let \mathcal{T} be a linear transformation. Then

$$\text{rank}(\mathcal{T}) + \text{nullity}(\mathcal{T}) = \dim(\text{domain of } \mathcal{T}).$$

Just like the Rank-nullity Theorem for matrices, the Rank-nullity Theorem for linear transformations can give insights about linear transformations that would be otherwise hard to see.

Range

DEF

The **range** (or **image**) of a linear transformation $T : V \rightarrow W$ is the set of vectors that T can output. That is,

$$\text{range}(T) = \{\vec{y} \in W : \vec{y} = T\vec{x} \text{ for some } \vec{x} \in V\}.$$

Null Space

DEF

The **null space** (or **kernel**) of a linear transformation $T : V \rightarrow W$ is the set of vectors that get mapped to zero under T . That is,

$$\text{null}(T) = \{\vec{x} \in V : T\vec{x} = \vec{0}\}.$$

44

Let $\mathcal{P} : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ be projection onto $\text{span}\{\vec{u}\}$ where $\vec{u} = \begin{bmatrix} 2 \\ 3 \end{bmatrix}$ (like before).

44.1 What is the range of \mathcal{P} ?

44.2 What is the null space of \mathcal{P} ?

45 Let $T : \mathbb{R}^n \rightarrow \mathbb{R}^m$ be an arbitrary linear transformation.

45.1 Show that the null space of T is a subspace.

45.2 Show that the range of T is a subspace.

Induced Transformation

DEFINITION

Let M be an $n \times m$ matrix. We say M *induces* a linear transformation $\mathcal{T}_M : \mathbb{R}^m \rightarrow \mathbb{R}^n$ defined by

$$[\mathcal{T}_M \vec{v}]_{\mathcal{E}'} = M[\vec{v}]_{\mathcal{E}},$$

where \mathcal{E} is the standard basis for \mathbb{R}^m and \mathcal{E}' is the standard basis for \mathbb{R}^n .

46 Let M be a 2×2 matrix and let $\vec{v} \in \mathbb{R}^2$. Further, let T_M be the transformation induced by M .

46.1 What is the difference between “ $M\vec{v}$ ” and “ $M[\vec{v}]_{\mathcal{E}}$ ”?

46.2 What is $[T_M \vec{e}_1]_{\mathcal{E}}$?

46.3 Can you relate the columns of M to the range of T_M ?

Fundamental Subspaces

Associated with any matrix M are three fundamental subspaces: the **row space** of M , denoted $\text{row}(M)$, is the span of the rows of M ; the **column space** of M , denoted $\text{col}(M)$, is the span of the columns of M ; and the **null space** of M , denoted $\text{null}(M)$, is the set of solutions to $M\vec{x} = \vec{0}$.

47

Consider $A = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix}$.

- 47.1 Describe the row space of A .
- 47.2 Describe the column space of A .
- 47.3 Is the row space of A the same as the column space of A ?
- 47.4 Describe the set of all vectors perpendicular to the rows of A .
- 47.5 Describe the null space of A .
- 47.6 Describe the range and null space of T_A , the transformation induced by A .

$$B = \begin{bmatrix} 1 & 2 & 3 \\ 1 & 1 & 1 \end{bmatrix} \quad C = \text{rref}(B) = \begin{bmatrix} 1 & 0 & -1 \\ 0 & 1 & 2 \end{bmatrix}$$

- 48.1 How does the row space of B relate to the row space of C ?
- 48.2 How does the null space of B relate to the null space of C ?
- 48.3 Compute the null space of B .

$$P = \begin{bmatrix} 0 & 0 \\ 1 & 2 \end{bmatrix} \quad Q = \text{rref}(P) = \begin{bmatrix} 1 & 2 \\ 0 & 0 \end{bmatrix}$$

- 49.1 How does the column space of P relate to the column space of Q ?
- 49.2 Describe the column space of P and the column space of Q .

Rank

DEF

For a linear transformation $T : \mathbb{R}^n \rightarrow \mathbb{R}^m$, the **rank** of T , denoted $\text{rank}(T)$, is the dimension of the range of T .

For an $n \times m$ matrix M , the **rank** of M , denoted $\text{rank}(M)$, is the number of pivots in $\text{rref}(M)$.

50

Let \mathcal{P} be projection onto $\text{span}\{\vec{u}\}$ where $\vec{u} = \begin{bmatrix} 2 \\ 3 \end{bmatrix}$, and let \mathcal{R} be rotation counter-clockwise by 90° .

- 50.1 Describe $\text{range}(\mathcal{P})$ and $\text{range}(\mathcal{R})$.
- 50.2 What is the rank of \mathcal{P} and the rank of \mathcal{R} ?
- 50.3 Let P and R be the matrices corresponding to \mathcal{P} and \mathcal{R} . What is the rank of P and the rank of R ?
- 50.4 Make a conjecture about how the rank of a transformation and the rank of its corresponding matrix relate. Can you justify your claim?

51.1 Determine the rank of (a) $\begin{bmatrix} 1 & 1 \\ 2 & 2 \end{bmatrix}$ (b) $\begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix}$ (c) $\begin{bmatrix} 1 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$ (d) $\begin{bmatrix} 3 \\ 3 \\ 2 \end{bmatrix}$ (e) $\begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$.

Consider the homogeneous system

$$\begin{array}{rrcr} x & +2y & +z & = 0 \\ x & +2y & +3z & = 0 \\ -x & -2y & +z & = 0 \end{array} \quad (10)$$

and the non-augmented matrix of coefficients $A = \begin{bmatrix} 1 & 2 & 1 \\ 1 & 2 & 3 \\ -1 & -2 & 1 \end{bmatrix}$.

- 52.1 What is $\text{rank}(A)$?
- 52.2 Give the general solution to system (10).
- 52.3 Are the column vectors of A linearly independent?
- 52.4 Give a non-homogeneous system with the same coefficients as (10) that has
 - (a) infinitely many solutions
 - (b) no solutions.

-
- 53 53.1 The rank of a 3×4 matrix A is 3. Are the column vectors of A linearly independent?
- 53.2 The rank of a 4×3 matrix B is 3. Are the column vectors of B linearly independent?

Rank-nullity Theorem

The **nullity** of a matrix is the dimension of the null space.

The rank-nullity theorem for a matrix A states

$$\text{rank}(A) + \text{nullity}(A) = \# \text{ of columns in } A.$$

-
- 54 54.1 Is there a version of the rank-nullity theorem that applies to linear transformations instead of matrices? If so, state it.

55 The vectors $\vec{u}, \vec{v} \in \mathbb{R}^9$ are linearly independent and $\vec{w} = 2\vec{u} - \vec{v}$. Define $A = [\vec{u} | \vec{v} | \vec{w}]$.

- 55.1 What is the rank and nullity of A^T ?
55.2 What is the rank and nullity of A ?

Inverse Functions & Inverse Matrices

In this module you will learn

- The definition of an inverse function and an inverse matrix.
- How to decompose a matrix into the product of elementary matrices and how to use elementary matrices to compute inverses.
- How the order of matrix multiplication matters.
- How row-reduction and matrix inverses relate.

When we think of transformations or functions in general, we should think of a machine that performs some manipulation of its input and then gives an output. This perspective allows us to divide functions into two natural categories: those that can be undone and those that cannot. The official term for a function that can be undone is an *invertible* function, and before we limit ourselves to talking about linear transformations, let's refresh on invertible functions.

Invertible Functions

The most natural function of them all is the *identity function*.

Identity Function.

Let X be a set. The *identity function* with domain and codomain X , notated $\text{id} : X \rightarrow X$, is the function satisfying

$$\text{id}(x) = x$$

for all $x \in X$.

The identity function is the function that does nothing to its input.³⁴ When doing precise mathematics, we say another function or composition of functions does nothing to its input if it *equals* the identity function.³⁵

In plain terms, a function is invertible if it can be undone. More precisely a function is invertible if there exists an inverse function that when composed with the original function produces the identity function and vice versa.

Inverse Function.

Let $f : X \rightarrow Y$ be a function. We say f is *invertible* if there exists a function $g : Y \rightarrow X$ so that $f \circ g = \text{id}$ and $g \circ f = \text{id}$. In this case, we call g an *inverse* of f and write

$$f^{-1} = g.$$

Let's consider a simple example. You have some money in your left and your right pockets. Let $f : \{\text{nickels in left pocket}\} \rightarrow \mathbb{N}$ be the function that adds up the value of all the nickels in your left pocket. Let $g : \{\text{nickels in either pocket}\} \rightarrow \mathbb{N}$ be the function that adds up the value of all the nickels in both of your pockets. In this case, f would be invertible—if you know that $f(\# \text{ nickels}) = 25$, you must have had 5 nickels in your left pocket. We can write down a formula for f^{-1} as

$$f^{-1}(n) = \frac{n}{5}.$$

However, g is not invertible. If $g(\# \text{ nickels}) = 25$, you *might* have had 5 nickels in your left pocket, but you might have 3 nickels in your left pocket and 2 in your right. We just don't know, so no inverse to g can exist.

What we've just learned is that for a function to be invertible, it must be *one-to-one*.

One-to-one.

Let $f : X \rightarrow Y$ be a function. We say f is *one-to-one* (or *surjective*) if distinct inputs to f produce distinct outputs. That is $f(x) = f(y)$ implies $x = y$.

Whenever a function f is one-to-one, there exists a function g so that $g \circ f = \text{id}$. However, this is not enough to declare that f is invertible³⁶ because we also need $f \circ g = \text{id}$. To ensure this, we also need f to be *onto*.

³⁴ Technically, for every set there exists a unique identity function with that set as the domain/codomain, but we won't belabor this point.

³⁵ This is similar to saying that we know $\vec{x} = \vec{y}$ if and only if $\vec{x} - \vec{y} = \vec{0}$.

³⁶ In this situation, we say that f is *left-invertible*.

Onto.

Let $f : X \rightarrow Y$ be a function. We say f is **onto** (or **injective**) if every point in the codomain of f gets mapped to. That is $\text{range}(f) = Y$.

Every invertible function is both one-to-one and onto, and every one-to-one and onto function is invertible. And, as we will learn, this has implications for the rank and nullity of linear transformations.

Invertibility and Linear Transformations

Let's now focus on linear transformations. We know that a linear transformation $\mathcal{T} : \mathbb{R}^n \rightarrow \mathbb{R}^m$ is invertible if and only if it is one-to-one and onto.

If \mathcal{T} is one-to-one, that means that distinct inputs to \mathcal{T} yield distinct outputs. In other words, the solution to $\mathcal{T}(\vec{x}) = \vec{b}$ is always unique. But, the set of all solutions to $\mathcal{T}(\vec{x}) = \vec{b}$ can be expressed as

$$\text{null}(\mathcal{T}) + \{\vec{p}\}.$$

Therefore, \mathcal{T} is one-to-one if and only if $\text{nullity}(\mathcal{T}) = 0$. If \mathcal{T} is onto, then $\text{range}(\mathcal{T}) = \mathbb{R}^m$ and so $\text{rank}(\mathcal{T}) = m$. Now, suppose \mathcal{T} is one-to-one and onto. By the Rank-nullity Theorem,

$$\text{rank}(\mathcal{T}) + \text{nullity}(\mathcal{T}) = 0 + m = m = n = \dim(\text{domain of } \mathcal{T}),$$

and so \mathcal{T} has the same domain and codomain (at least a domain and codomain of the same dimension).

Using the rank-nullity theorem, we can start developing a list of properties that are equivalent to \mathcal{T} being invertible.

- $\mathcal{T} : \mathbb{R}^n \rightarrow \mathbb{R}^m$ is invertible if and only if $\text{nullity}(\mathcal{T}) = 0$ and $\text{rank}(\mathcal{T}) = m$.
- $\mathcal{T} : \mathbb{R}^n \rightarrow \mathbb{R}^m$ is invertible if and only if $m = n$ and $\text{nullity}(\mathcal{T}) = 0$.
- $\mathcal{T} : \mathbb{R}^n \rightarrow \mathbb{R}^m$ is invertible if and only if $m = n$ and $\text{rank}(\mathcal{T}) = n$.

Example. Let $\mathcal{P} : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ be projection onto the x -axis and let $\mathcal{R} : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ be rotation counter-clockwise by 15° . Classify each of \mathcal{P} and \mathcal{R} as invertible or not.

Notice that $\mathcal{P}(\vec{e}_2) = \mathcal{P}(2\vec{e}_2) = \vec{0}$, therefore \mathcal{P} is not one-to-one.

Let $\mathcal{Q} : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ be rotation clockwise by 15° . Then \mathcal{R} and \mathcal{Q} will undo each other. In other words,

$$\mathcal{R} \circ \mathcal{R}^{-1} = \text{id} \quad \text{and} \quad \mathcal{R}^{-1} \circ \mathcal{R} = \text{id}.$$

Therefore by definition, \mathcal{R} is invertible.

One important fact about linear transformations is that if a linear transformation is invertible, its inverse is also a linear transformation.

Theorem. Let \mathcal{T} be an invertible linear transformation. Then \mathcal{T}^{-1} is also a linear transformation.

Proof. Let \mathcal{T} be an invertible linear transformation and let \mathcal{T}^{-1} be its inverse. We need to show that (i) \mathcal{T}^{-1} distributes over addition and (ii) \mathcal{T}^{-1} distributes over scalar multiplication.

(i) First observe that since $\mathcal{T} \circ \mathcal{T}^{-1} = \text{id}$ and because \mathcal{T} is linear, we have

$$\vec{a} + \vec{b} = \mathcal{T} \circ \mathcal{T}^{-1} \vec{a} + \mathcal{T} \circ \mathcal{T}^{-1} \vec{b} = \mathcal{T}(\mathcal{T}^{-1} \vec{a} + \mathcal{T}^{-1} \vec{b}).$$

Since $\mathcal{T}^{-1} \circ \mathcal{T} = \text{id}$, we know

$$\mathcal{T}^{-1}(\vec{a} + \vec{b}) = \mathcal{T}^{-1} \circ \mathcal{T}(\mathcal{T}^{-1} \vec{a} + \mathcal{T}^{-1} \vec{b}) = \mathcal{T}^{-1} \vec{a} + \mathcal{T}^{-1} \vec{b}.$$

(ii) Similarly to the proof of (i), we see

$$\mathcal{T}^{-1}(\alpha \vec{a}) = \mathcal{T}^{-1}(\alpha(\mathcal{T} \circ \mathcal{T}^{-1} \vec{a})) = \mathcal{T}^{-1} \circ \mathcal{T}(\alpha \mathcal{T}^{-1} \vec{a}) = \alpha \mathcal{T}^{-1} \vec{a}.$$

■

Invertibility and Matrices

In the world of matrices, the *identity matrix* takes the place of the identity function.

Identity Matrix.

An **identity matrix** is a square matrix with ones on the diagonal and zeros everywhere else. The $n \times n$ identity matrix is denoted $I_{n \times n}$, or just I when its size is implied.

We now define a matrix as invertible analogously to how we defined a function to be invertible. Except, we replace function composition with matrix multiplication.

Matrix Inverse.

The **inverse** of a matrix A is a matrix B such that $AB = I$ and $BA = I$. In this case, B is called the inverse of A and is notated by A^{-1} .

Example. Determine whether the matrices $A = \begin{bmatrix} 2 & 5 \\ -3 & -7 \end{bmatrix}$ and $B = \begin{bmatrix} -7 & -5 \\ 3 & 2 \end{bmatrix}$ are inverses of each other.

$$AB = \begin{bmatrix} 2 & 5 \\ -3 & -7 \end{bmatrix} \begin{bmatrix} -7 & -5 \\ 3 & 2 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} = I$$

$$BA = \begin{bmatrix} -7 & -5 \\ 3 & 2 \end{bmatrix} \begin{bmatrix} 2 & 5 \\ -3 & -7 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} = I.$$

Therefore, matrices A and B are inverses of each other.

Example. Determine whether the matrices $A = \begin{bmatrix} 2 & 5 & 0 \\ -3 & -7 & 0 \end{bmatrix}$ and $B = \begin{bmatrix} -7 & -5 \\ 3 & 2 \\ 1 & 1 \end{bmatrix}$ are inverses of each other.

$$AB = \begin{bmatrix} 2 & 5 & 0 \\ -3 & -7 & 0 \end{bmatrix} \begin{bmatrix} -7 & -5 \\ 3 & 2 \\ 1 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} = I$$

$$BA = \begin{bmatrix} -7 & -5 \\ 3 & 2 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} 2 & 5 & 0 \\ -3 & -7 & 0 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ -1 & -2 & 0 \end{bmatrix} \neq I.$$

Therefore, matrices A and B are not inverses of each other.

Since every matrix induces a linear transformation, we can use the facts we know about invertible linear transformations to produce facts about invertible matrices. In particular:

- An $n \times m$ matrix A is invertible if and only if $\text{nullity}(A) = 0$ and $\text{rank}(A) = n$.
- An $n \times n$ matrix A is invertible if and only if $\text{nullity}(A) = 0$.
- An $n \times n$ matrix A is invertible if and only if $\text{rank}(A) = n$.

Matrix Algebra

The linear equation $ax = b$ has solution $x = \frac{b}{a}$ whenever $a \neq 0$. We arrive at this solution by dividing both sides of the equation by a . Does a similar process exist for solving the matrix equation $A\vec{x} = \vec{b}$? It sure does!

Unfortunately, we cannot divide by a matrix, but to solve $A\vec{x} = \vec{b}$, we don't need to "divide" by a matrix, we just need to eliminate A from the left side. This could be accomplished by using an inverse.

Suppose A is invertible, then

$$A\vec{x} = \vec{b} \quad \implies \quad A^{-1}A\vec{x} = A^{-1}\vec{b} \quad \implies \quad \vec{x} = A^{-1}\vec{b}.$$

Thus, if we have the inverse of a matrix handy, we can use it to solve a system of equations.

Example. Use the fact that $\begin{bmatrix} 2 & 5 \\ -3 & -7 \end{bmatrix}^{-1} = \begin{bmatrix} -7 & -5 \\ 3 & 2 \end{bmatrix}$ to solve the system $\begin{cases} 2x + 5y = 2 \\ -3x - 7y = 1 \end{cases}$.

The system can be rewritten as

$$\begin{bmatrix} 2 & 5 \\ -3 & -7 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 2 \\ 1 \end{bmatrix}.$$

Multiplying both sides by $\begin{bmatrix} 2 & 5 \\ -3 & -7 \end{bmatrix}^{-1}$ gives

$$\begin{bmatrix} 2 & 5 \\ -3 & -7 \end{bmatrix}^{-1} \begin{bmatrix} 2 & 5 \\ -3 & -7 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 2 & 5 \\ -3 & -7 \end{bmatrix}^{-1} \begin{bmatrix} 2 \\ 1 \end{bmatrix}.$$

Therefore,

$$\begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 2 & 5 \\ -3 & -7 \end{bmatrix}^{-1} \begin{bmatrix} 2 \\ 1 \end{bmatrix} = \begin{bmatrix} -7 & -5 \\ 3 & 2 \end{bmatrix} \begin{bmatrix} 2 \\ 1 \end{bmatrix} = \begin{bmatrix} -19 \\ 8 \end{bmatrix}.$$

It's important to note that, unlike in the case with regular scalars, the order of matrix multiplication matters. So, whereas with scalars you could get away with something like

$$ax = b \quad \implies \quad \frac{1}{a}ax = b\frac{1}{a} \quad \implies \quad x = \frac{b}{a},$$

with matrices $A\vec{x} = \vec{b}$ does not imply $A^{-1}A\vec{x} = \vec{b}A^{-1}$. In fact, if \vec{b} is a column vector, the expression $\vec{b}A^{-1}$ is almost always undefined!

Finding a Matrix Inverse

Whereas before we only knew how to solve a matrix equation $A\vec{x} = \vec{b}$ using row reduction, we now know how to use A^{-1} to solve the same system. In fact, A^{-1} is the exact matrix so that $\vec{x} = A^{-1}\vec{b}$ is always the solution to $A\vec{x} = \vec{b}$. Therefore, by picking different \vec{b} 's and solving for \vec{x} , we can find A^{-1} .

Example. Let $A = \begin{bmatrix} 2 & 5 \\ -3 & -7 \end{bmatrix}$. Find A^{-1} .

We know $A^{-1} = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$ will be a 2×2 matrix, and we know $\vec{x} = A^{-1}\vec{b}$ will always be the unique solution to $A\vec{x} = \vec{b}$. Therefore, we can find A^{-1} by finding \vec{x}, \vec{b} pairs that satisfy $A\vec{x} = \vec{b}$.

Using row reduction, we see

$$A\vec{x} = \begin{bmatrix} 1 \\ 0 \end{bmatrix} \text{ has solution } \vec{x} = \begin{bmatrix} -7 \\ 3 \end{bmatrix}, \quad \text{and} \quad A\vec{x} = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \text{ has solution } \vec{x} = \begin{bmatrix} -5 \\ 2 \end{bmatrix}.$$

Therefore

$$A^{-1} \begin{bmatrix} 1 \\ 0 \end{bmatrix} = \begin{bmatrix} a \\ c \end{bmatrix} = \begin{bmatrix} -7 \\ 3 \end{bmatrix} \quad \text{and} \quad A^{-1} \begin{bmatrix} 0 \\ 1 \end{bmatrix} = \begin{bmatrix} b \\ d \end{bmatrix} = \begin{bmatrix} -5 \\ 2 \end{bmatrix},$$

and so

$$A^{-1} = \begin{bmatrix} -7 & -5 \\ 3 & 2 \end{bmatrix}.$$

Elementary Matrices

Finding the inverse of a matrix can be a lot of work. However, thinking in terms of linear transformations, if you already know how to reverse the operation, finding the inverse might not be so hard. For example, if R_{30} is the matrix that rotates vectors in \mathbb{R}^2 counter-clockwise by 30° , its inverse must be R_{-30} , the matrix that rotates vectors in \mathbb{R}^2 clockwise by 30° .

Like before when we analyzed linear transformations by breaking them up into compositions of simpler linear transformations, another strategy for find an inverse matrix is to break a matrix into simpler ones whose inverses we can just write down without computing.

Some of the simplest matrices around are the *elementary matrices*.

Elementary Matrix.

A matrix is called an *elementary matrix* if it is an identity matrix with a single elementary row operation applied.

Examples of elementary matrices include

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & -5 \end{bmatrix}, \quad \begin{bmatrix} 1 & 0 & 7 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}, \quad \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix},$$

which are obtained from the row operations “multiply the last row by -5 ”, “add 7 times the last row to the first”, and “swap the first two rows”.

Elementary matrices are incredible because multiplying by an elementary matrix performs the corresponding elementary row operation! See for yourself:

$$\begin{aligned} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & -5 \end{bmatrix} \begin{bmatrix} a & b & c \\ d & e & f \\ g & h & i \end{bmatrix} &= \begin{bmatrix} a & b & c \\ d & e & f \\ -5g & -5h & -5i \end{bmatrix} \\ \begin{bmatrix} 1 & 0 & 7 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} a & b & c \\ d & e & f \\ g & h & i \end{bmatrix} &= \begin{bmatrix} a+7g & b+7h & c+7i \\ d & e & f \\ g & h & i \end{bmatrix} \\ \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} a & b & c \\ d & e & f \\ g & h & i \end{bmatrix} &= \begin{bmatrix} d & e & f \\ a & b & c \\ g & h & i \end{bmatrix} \end{aligned}$$

As a refresher, the elementary row operations are

- multiply a row by a non-zero constant;
- add a multiple of one row to another; and
- swap to rows.

Each one of these operations can be undone, and so every elementary matrix is invertible. Not only that, but the inverse is another elementary matrix and is easy to come up with.

Example. Find the inverse of $E = \begin{bmatrix} 1 & 0 & 7 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$.

Since E corresponds to the row operation “add 7 times the last row to the first”, E^{-1} must correspond to the row operation “subtract 7 times the last row from the first”. Therefore,

$$E^{-1} = \begin{bmatrix} 1 & 0 & -7 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}.$$

Elementary Matrices and Inverses

For a matrix M to be invertible, we know that M must be square and $\text{nullity}(M) = 0$. That means, M is invertible if and only if $\text{rref}(M) = I$. In other words, there is a sequence of elementary row operations that turn M into I . Each one of these row operations can be represented by an elementary matrix, which gives us the following theorem.

Theorem. A matrix M is invertible if and only if there are elementary matrices E_1, \dots, E_k so that

$$E_k \cdots E_2 E_1 M = I.$$

Now, suppose M is invertible and let E_1, \dots, E_k be elementary matrices so that $E_k \cdots E_2 E_1 M = I$. We now know

$$E_k \cdots E_2 E_1 M = \underbrace{(E_k \cdots E_2 E_1)}_Q M = QM = I.$$

If we can argue that $MQ = I$, then Q will be the inverse of M !

Theorem. If A is a square matrix and $AB = I$ for some matrix B , then $BA = I$.

Proof. Suppose A is a square matrix and that $AB = I$. Since $AB = I$, B must also be square. Since $\text{null}(B) \subseteq \text{null}(AB)$, we know $\text{nullity}(B) \leq \text{nullity}(AB) = \text{nullity}(I) = 0$, and so B is invertible. Observe now that

$$A = AI = A(BB^{-1}) = (AB)B^{-1} = IB^{-1} = B^{-1},$$

and so $A = B^{-1}$. Finally, substituting B^{-1} for A shows

$$BA = BB^{-1} = I.$$

In light of this theorem, we now have a new algorithm for finding the inverse of a matrix—find elementary matrices that turn the matrix into the identity matrix and multiply those elementary matrices together to find the inverse. ■

Example. Let $A = \begin{bmatrix} 1 & 2 & 0 \\ 0 & 4 & 0 \\ 0 & -1 & 1 \end{bmatrix}$. Find A^{-1} using elementary matrices.

We can row-reduce A with the following steps:

$$\begin{bmatrix} 1 & 2 & 0 \\ 0 & 4 & 0 \\ 0 & -1 & 1 \end{bmatrix} \sim \begin{bmatrix} 1 & 2 & 0 \\ 0 & 1 & 0 \\ 0 & -1 & 1 \end{bmatrix} \sim \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & -1 & 1 \end{bmatrix} \sim \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

The elementary matrices corresponding to these steps are

$$E_1 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \frac{1}{4} & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad E_2 = \begin{bmatrix} 1 & -2 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad E_3 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 1 \end{bmatrix}.$$

And so we have

$$E_3 E_2 E_1 A = I.$$

Thus we obtain

$$A^{-1} = E_3 E_2 E_1 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 1 \end{bmatrix} \begin{bmatrix} 1 & -2 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & \frac{1}{4} & 0 \\ 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & -\frac{1}{2} & 0 \\ 0 & \frac{1}{4} & 0 \\ 0 & \frac{1}{4} & 1 \end{bmatrix}.$$

Decomposition into Elementary Matrices

If A is an invertible matrix, then the double-inverse of A (i.e., $(A^{-1})^{-1}$) is A itself.³⁷ This is easily proved. The definition of $(A^{-1})^{-1}$ is a matrix B so that $BA^{-1} = I$ and $A^{-1}B = I$. But $B = A$ already works!

Now, suppose M is an invertible matrix. Then, there exists a sequence of elementary matrices E_1, \dots, E_k so that $E_k \cdots E_2 E_1 M = I$ and

$$M^{-1} = E_k \cdots E_2 E_1.$$

Therefore

$$M = (M^{-1})^{-1} = (E_k \cdots E_2 E_1)^{-1}.$$

Thinking carefully about what $(E_k \cdots E_2 E_1)^{-1}$ should be, we see that

$$(E_1^{-1} E_2^{-1} \cdots E_k^{-1}) E_k \cdots E_2 E_1 = I \quad \text{and} \quad E_k \cdots E_2 E_1 (E_1^{-1} E_2^{-1} \cdots E_k^{-1}) = I,$$

and so

$$M = (E_k \cdots E_2 E_1)^{-1} = E_1^{-1} E_2^{-1} \cdots E_k^{-1}.$$

Each E_i^{-1} is also an elementary matrix, and so we have just shown that every invertible matrix can be written as the product of elementary matrices. This is actually an if and only if.

Theorem. A matrix M is invertible if and only if it can be written as the product of elementary matrices.

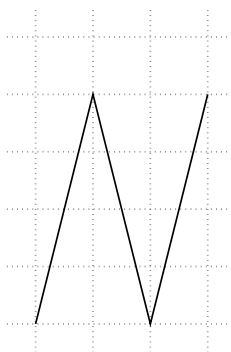
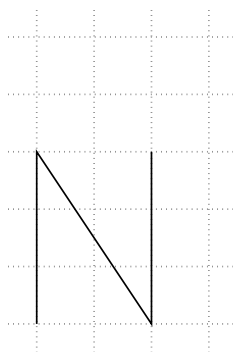
Proof. Suppose M is invertible. Then, there exists a sequence of elementary matrices E_1, \dots, E_k so that $E_k \cdots E_1 M = I$. It follows that

$$M = E_1^{-1} E_2^{-1} \cdots E_k^{-1}$$

is the product of elementary matrices. Conversely, since the product of invertible matrices is invertible and every elementary matrix is invertible, the product of elementary matrices must be invertible. Therefore, if M is not invertible, it *cannot* be written as the product of elementary matrices. ■

³⁷ Formally we say that the operation of taking a matrix inverse is an *involution*.

Task 2.4: Getting back N



Suppose that the “N” on the left is written in regular 12-point font. Find a matrix A that will transform the “N” into the letter on the right which is written in an italic 16-point font.

Two students—Pat and Jamie—explained their approach to the Italicizing N task as follows:

In order to find the matrix A , we are going to find a matrix that makes the “N” taller; find a matrix that italicizes the taller “N,” and a combination of those two matrices will give the desired matrix A .

Consider the new task: find a matrix C that transforms the “N” on the right to the “N” on the left.

1. Use any method you like to find C .
2. Use a method similar to Pat and Jamie’s method, only use it to find C instead of A .

- 56 56.1 Apply the row operation $R_3 \mapsto R_3 + 2R_1$ to the 3×3 identity matrix and call the result E_1 .
 56.2 Apply the row operation $R_3 \mapsto R_3 - 2R_1$ to the 3×3 identity matrix and call the result E_2 .

Elementary Matrix

DEF

A matrix is called an *elementary matrix* if it is an identity matrix with a single elementary row operation applied.

$$A = \begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \end{bmatrix}$$

- 56.3 Compute E_1A and E_2A . How do the resulting matrices relate to row operations?
 56.4 Without computing, what should the result of applying the row operation $R_3 \mapsto R_3 - 2R_1$ to E_1 be? Compute and verify.
 56.5 Without computing, what should E_2E_1 be? What about E_1E_2 ? Now compute and verify.

Matrix Inverse

DEF

The *inverse* of a matrix A is a matrix B such that $AB = I$ and $BA = I$. In this case, B is called the inverse of A and is notated by A^{-1} .

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Consider the matrices

$$A = \begin{bmatrix} 1 & 2 & 0 \\ 0 & 1 & 0 \\ -3 & -6 & 1 \end{bmatrix} \quad B = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \quad C = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix}$$
$$D = \begin{bmatrix} 1 & -2 & 0 \\ 0 & 1 & 0 \\ 3 & 0 & 1 \end{bmatrix} \quad E = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 1 & 1 \end{bmatrix} \quad F = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

57.1 Which pairs of matrices above are inverses of each other?

$$B = \begin{bmatrix} 1 & 4 \\ 0 & 2 \end{bmatrix}$$

- 58.1 Use two row operations to reduce B to $I_{2 \times 2}$ and write an elementary matrix E_1 corresponding to the first operation and E_2 corresponding to the second.
- 58.2 What is $E_2 E_1 B$?
- 58.3 Find B^{-1} .
- 58.4 Can you outline a procedure for finding the inverse of a matrix using elementary matrices?

$$A = \begin{bmatrix} 1 & 2 & -1 \\ 2 & 2 & 4 \\ 1 & 3 & -3 \end{bmatrix} \quad \vec{b} = \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix} \quad C = [A | \vec{b}] \quad A^{-1} = \begin{bmatrix} 9 & -3/2 & -5 \\ -5 & 1 & 3 \\ -2 & 1/2 & 1 \end{bmatrix}$$

- 59.1 What is $A^{-1}A$?
- 59.2 What is $\text{rref}(A)$?
- 59.3 What is $\text{rref}(C)$? (Hint, there is no need to actually do row reduction!)
- 59.4 Solve the system $A\vec{x} = \vec{b}$.

60

60.1 For two square matrices X, Y , should $(XY)^{-1} = X^{-1}Y^{-1}$?

60.2 If M is a matrix corresponding to a non-invertible linear transformation T , could M be invertible?

Change of Basis II

In this module you will learn

- How to create *change-of-basis* matrices.
- How to write a linear transformation in multiple bases.

Any basis for \mathbb{R}^n gives us a way to analyze vectors in \mathbb{R}^n by turning them in to lists of numbers (i.e., coordinates). Given a basis \mathcal{A} for \mathbb{R}^n , every vector $\vec{x} \in \mathbb{R}^n$ uniquely corresponds to the list of numbers $[\vec{x}]_{\mathcal{A}}$. In other words, the operation of writing a vector in a basis is *invertible*.

If we have two bases, \mathcal{A} and \mathcal{B} , for \mathbb{R}^n , we have two equally valid ways of representing a vector in coordinates.

XXX Figure (commutative diagram)

Not only that, but there must be a function that converts between $[\vec{x}]_{\mathcal{A}}$ and $[\vec{x}]_{\mathcal{B}}$. The function works as follows: input the list of numbers $[\vec{x}]_{\mathcal{A}}$, use those numbers as coefficients of the \mathcal{A} basis vectors to get the true vector \vec{x} , and then find the coordinates of that vector with respect to the \mathcal{B} basis.

Example. Let $\mathcal{A} = \{\vec{a}_1, \vec{a}_2\}$ where $\vec{a}_1 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}_{\mathcal{E}}$ and $\vec{a}_2 = \begin{bmatrix} 1 \\ -1 \end{bmatrix}_{\mathcal{E}}$ and let $\mathcal{B} = \{\vec{b}_1, \vec{b}_2\}$ where $\vec{b}_1 = \begin{bmatrix} 2 \\ 1 \end{bmatrix}_{\mathcal{E}}$ and $\vec{b}_2 = \begin{bmatrix} 5 \\ 3 \end{bmatrix}_{\mathcal{E}}$ be bases for \mathbb{R}^2 . Given that $[\vec{x}]_{\mathcal{A}} = \begin{bmatrix} 2 \\ -3 \end{bmatrix}$, find $[\vec{x}]_{\mathcal{B}}$.

XXX Finish

For a basis \mathcal{A} , the invertible function that takes a vector \vec{x} and generates the coordinates $[\vec{x}]_{\mathcal{A}}$ is a linear function. Therefore, for bases \mathcal{A} and \mathcal{B} , the function that converts $[\vec{x}]_{\mathcal{A}}$ to $[\vec{x}]_{\mathcal{B}}$ must have a matrix. This matrix is called the *change of basis* matrix.

Change of Basis Matrix. Let \mathcal{A} and \mathcal{B} be bases for \mathbb{R}^n . The matrix M is called a *change of basis* matrix converting from \mathcal{A} to \mathcal{B} if

$$M[\vec{x}]_{\mathcal{A}} = [\vec{x}]_{\mathcal{B}}$$

for all $\vec{x} \in \mathbb{R}^n$. Notationally, $[\mathcal{B} \leftarrow \mathcal{A}]$ stands for the change of basis matrix converting from \mathcal{A} to \mathcal{B} , and we may write $M = [\mathcal{B} \leftarrow \mathcal{A}]$.

Example. Let $\mathcal{A} = \{\vec{a}_1, \vec{a}_2\}$ where $\vec{a}_1 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}_{\mathcal{E}}$ and $\vec{a}_2 = \begin{bmatrix} 1 \\ -1 \end{bmatrix}_{\mathcal{E}}$ and let $\mathcal{B} = \{\vec{b}_1, \vec{b}_2\}$ where $\vec{b}_1 = \begin{bmatrix} 2 \\ 1 \end{bmatrix}_{\mathcal{E}}$ and $\vec{b}_2 = \begin{bmatrix} 5 \\ 3 \end{bmatrix}_{\mathcal{E}}$ be bases for \mathbb{R}^2 . Find the change of basis matrix $[\mathcal{B} \leftarrow \mathcal{A}]$.

XXX Finish

We can now enhance our diagram from earlier.

XXX Figure (commutative diagram with change of basis).

The notation $[\mathcal{B} \leftarrow \mathcal{A}]$ for the matrix that changes from the \mathcal{A} basis to the \mathcal{B} basis is suggestive. Suppose we have another basis \mathcal{C} . We can obtain $[\mathcal{C} \leftarrow \mathcal{A}]$ by multiplying $[\mathcal{B} \leftarrow \mathcal{A}]$ and $[\mathcal{C} \leftarrow \mathcal{B}]$. That is,

$$[\mathcal{C} \leftarrow \mathcal{A}] = [\mathcal{C} \leftarrow \mathcal{B}][\mathcal{B} \leftarrow \mathcal{A}].$$

The backwards arrow “ \leftarrow ” in the change-of-basis matrix notation comes because we multiply vectors on the *left* by matrices. So,

$$[\vec{x}]_{\mathcal{C}} = [\mathcal{C} \leftarrow \mathcal{A}][\vec{x}]_{\mathcal{A}} = [\mathcal{C} \leftarrow \mathcal{B}][\mathcal{B} \leftarrow \mathcal{A}][\vec{x}]_{\mathcal{A}}.$$

As such, the notation for the change of basis matrix chains, allowing you to figure out what’s going on without too much trouble.

Change of Basis Matrix in Detail

Let \mathcal{A} and \mathcal{B} be bases for \mathbb{R}^n and $M = [\mathcal{B} \leftarrow \mathcal{A}]$ be the matrix that changes from the \mathcal{A} to the \mathcal{B} basis. Since we can change vectors back from \mathcal{B} to \mathcal{A} , we know M is invertible and

$$M^{-1} = [\mathcal{A} \leftarrow \mathcal{B}]$$

Just playing with notation, we see

$$M^{-1}M = [\mathcal{A} \leftarrow \mathcal{B}][\mathcal{B} \leftarrow \mathcal{A}] = [\mathcal{A} \leftarrow \mathcal{A}] = I \quad MM^{-1} = [\mathcal{B} \leftarrow \mathcal{A}][\mathcal{A} \leftarrow \mathcal{B}] = [\mathcal{B} \leftarrow \mathcal{B}] = I,$$

which makes sense. The matrices $[\mathcal{A} \leftarrow \mathcal{A}]$ and $[\mathcal{B} \leftarrow \mathcal{B}]$ take vectors and rewrite them in the same basis, which is to say, they do nothing to the vectors.

The argument above shows that every change of basis matrix is invertible. The converse is also true.

Theorem. An $n \times n$ matrix is invertible if and only if it is a change of basis matrix.

Proof. Suppose $M = [\mathcal{B} \leftarrow \mathcal{A}]$ is a change-of-basis matrix. Then

$$M^{-1} = [\mathcal{A} \leftarrow \mathcal{B}].$$

Alternatively, suppose $M = [C_1 | C_2 | \cdots | C_n]$ is an invertible $n \times n$ matrix with columns C_1, \dots, C_n . Let $\vec{c}_i = [C_i]_{\mathcal{E}}$. That is, \vec{c}_i is the vector which comes from interpreting C_i as coordinates with respect to the standard basis.

Since M is invertible, $\text{rref}(M) = I$, and so $\{\vec{c}_1, \dots, \vec{c}_n\}$ is a linearly independent set of n vectors. Therefore $\mathcal{C} = \{\vec{c}_1, \dots, \vec{c}_n\}$ is a basis for \mathbb{R}^n . Now, observe

$$M[\vec{c}_i]_{\mathcal{C}} = C_i = [\vec{c}_i]_{\mathcal{E}}$$

for $i = 1, \dots, n$, and so $M = [\mathcal{E} \leftarrow \mathcal{C}]$ is a change-of-basis matrix. ■

The proof of the above theorem highlights something interesting. Let $\mathcal{A} = \{\vec{a}_1, \dots, \vec{a}_n\}$ be a basis for \mathbb{R}^n . It is always the case that

$$[\vec{a}_i]_{\mathcal{A}} = \begin{bmatrix} \vdots \\ 0 \\ 1 \\ 0 \\ 0 \\ \vdots \end{bmatrix}$$

has a 1 in the i th position and zeros elsewhere. Now, let $\mathcal{B} = \{\vec{b}_1, \dots, \vec{b}_n\}$ be another basis for \mathbb{R}^n and define the matrix $M = \begin{bmatrix} [\vec{a}_1]_{\mathcal{B}} & [\vec{a}_2]_{\mathcal{B}} & \cdots & [\vec{a}_n]_{\mathcal{B}} \end{bmatrix}$ to be the matrix with columns $[\vec{a}_1]_{\mathcal{B}}, \dots, [\vec{a}_n]_{\mathcal{B}}$. Since multiplying a matrix by $[\vec{a}_i]_{\mathcal{A}}$ will pick out the i th column, we have that

$$M[\vec{a}_i]_{\mathcal{A}} = [\vec{a}_i]_{\mathcal{B}}.$$

In other words,

$$M = [\mathcal{B} \leftarrow \mathcal{A}].$$

Transformations and Bases

A linear transformation $\mathcal{T} : \mathbb{R}^n \rightarrow \mathbb{R}^n$ always has a matrix associated with it. This matrix is defined as the matrix M so that

$$[\mathcal{T}\vec{x}]_{\mathcal{E}} = M[\vec{x}]_{\mathcal{E}}.$$

But, what if we swapped out \mathcal{E} for a different basis?

Linear Transformation in a Basis. Let $\mathcal{T} : \mathbb{R}^n \rightarrow \mathbb{R}^n$ be a linear transformation and let \mathcal{B} be a basis for \mathbb{R}^n . The **matrix for \mathcal{T} with respect to \mathcal{B}** , notated $[\mathcal{T}]_{\mathcal{B}}$, is the $n \times n$ matrix satisfying

$$[\mathcal{T}\vec{x}]_{\mathcal{B}} = [\mathcal{T}]_{\mathcal{B}}[\vec{x}]_{\mathcal{B}}.$$

In this case, we say the matrix $[\mathcal{T}]_{\mathcal{B}}$ is the representation of \mathcal{T} in the \mathcal{B} basis.

Just like there are many ways to write down coordinates for a vector—one per choice of basis—there are many ways to write down a matrix for a linear transformation. Up to this point, when we’ve said “ M is a matrix for \mathcal{T} ”, what we meant is “ $M = [\mathcal{T}]_{\mathcal{E}}$ ”. And, like with vectors, if we talk about a matrix for a linear transformation without specifying the basis, we mean the matrix for the transformation with respect to the standard basis.

Example. Let $\mathcal{B} = \{\vec{b}_1, \vec{b}_2\}$ where $\vec{b}_1 = \begin{bmatrix} 2 \\ -3 \end{bmatrix}_{\mathcal{E}}$ and $\vec{b}_2 = \begin{bmatrix} 5 \\ -7 \end{bmatrix}_{\mathcal{E}}$ be a basis for \mathbb{R}^2 and let $\mathcal{T} : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ be the transformation that stretches in the \vec{e}_1 direction by a factor of 2. Find $[\mathcal{T}]_{\mathcal{E}}$ and $[\mathcal{T}]_{\mathcal{B}}$.

XXX Finish

Similar Matrices

Just like some bases are better than others to represent particular vectors, some bases are better than others to represent a particular linear transformation.

Example. Let $\mathcal{B} = \{\vec{b}_1, \vec{b}_2\}$ where $\vec{b}_1 = \begin{bmatrix} 2 \\ -3 \end{bmatrix}_{\mathcal{E}}$ and $\vec{b}_2 = \begin{bmatrix} 5 \\ -7 \end{bmatrix}_{\mathcal{E}}$ be a basis for \mathbb{R}^2 and let $\mathcal{S} : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ be the transformation that stretches in the $2\vec{e}_1 - 3\vec{e}_3$ direction by a factor of 2. Find $[\mathcal{S}]_{\mathcal{E}}$ and $[\mathcal{S}]_{\mathcal{B}}$.

XXX Finish

In the example above, $[\mathcal{S}]_{\mathcal{B}}$ is a much nicer matrix than $[\mathcal{S}]_{\mathcal{E}}$. However, the two matrices relate to each other. After all,

$$[\mathcal{S}]_{\mathcal{B}} = [\mathcal{B} \leftarrow \mathcal{E}][\mathcal{S}]_{\mathcal{E}}[\mathcal{E} \leftarrow \mathcal{B}].$$

In this case, we call these matrices *similar*.³⁸

Similar Matrices. The matrices A and B are called *similar matrices*, denoted $A \sim B$, if A and B represent the same linear transformation but in possibly different bases. Equivalently, $A \sim B$ if there is an invertible matrix X so that

$$A = XBX^{-1}.$$

The X in the definition of similar matrices is always a change-of-basis matrix.

When studying a linear transformation, you can pick any basis to represent it in and study the resulting matrix. Different choices of basis will give you different perspectives on the linear transformation. It what's to follow, we will work to find the “best” basis in which to study a given linear transformation.³⁹

³⁸ Another commonly used term is *conjugate*.

³⁹ If you cannot wait, the “best” basis will turn out to be the *eigen basis* (provided it exists).

-
- 61 Let $\mathcal{B} = \{\vec{b}_1, \vec{b}_2\}$ where $\vec{b}_1 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$, $\vec{b}_2 = \begin{bmatrix} 1 \\ -1 \end{bmatrix}$ and let $X = [\vec{b}_1 | \vec{b}_2]$ be the matrix whose columns are \vec{b}_1 and \vec{b}_2 .
- 61.1 Compute $[\vec{e}_1]_{\mathcal{B}}$ and $[\vec{e}_2]_{\mathcal{B}}$.
- 61.2 Compute $X[\vec{e}_1]_{\mathcal{B}}$ and $X[\vec{e}_2]_{\mathcal{B}}$. What do you notice?
- 61.3 Find the matrix X^{-1} . How does X^{-1} relate to change of basis?

Let $\mathcal{E} = \{\vec{e}_1, \vec{e}_2, \dots, \vec{e}_n\}$ be the standard basis for \mathbb{R}^n . Given a basis $\mathcal{B} = \{\vec{b}_1, \vec{b}_2, \dots, \vec{b}_n\}$ for \mathbb{R}^n , the matrix $X = [\vec{b}_1 | \vec{b}_2 | \dots | \vec{b}_n]$ converts vectors from the \mathcal{B} basis into the standard basis. In other words,

$$X[\vec{v}]_{\mathcal{B}} = [\vec{v}]_{\mathcal{E}}.$$

62.1 Should X^{-1} exist? Explain.

62.2 Consider the equation

$$X^{-1}[\vec{v}]_{\mathcal{B}} = [\vec{v}]_{\mathcal{E}}.$$

Can you fill in the “?” symbols so that the equation makes sense?

62.3 What is $[\vec{b}_1]_{\mathcal{B}}$? How about $[\vec{b}_2]_{\mathcal{B}}$? Can you generalize to $[\vec{b}_i]_{\mathcal{B}}$?

Let $\vec{c}_1 = \begin{bmatrix} 2 \\ 1 \end{bmatrix}_{\mathcal{E}}$, $\vec{c}_2 = \begin{bmatrix} 5 \\ 3 \end{bmatrix}_{\mathcal{E}}$, $\mathcal{C} = \{\vec{c}_1, \vec{c}_2\}$, and $A = \begin{bmatrix} 2 & 5 \\ 1 & 3 \end{bmatrix}$. Note that $A^{-1} = \begin{bmatrix} 3 & -5 \\ -1 & 2 \end{bmatrix}$ and that A changes vectors from the \mathcal{C} basis to the standard basis and A^{-1} changes vectors from the standard basis to the \mathcal{C} basis.

63.1 Compute $[\vec{c}_1]_{\mathcal{C}}$ and $[\vec{c}_2]_{\mathcal{C}}$.

Let $T : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ be the linear transformation that stretches in the \vec{c}_1 direction by a factor of 2 and doesn't stretch in the \vec{c}_2 direction at all.

63.2 Compute $T \begin{bmatrix} 2 \\ 1 \end{bmatrix}_{\mathcal{E}}$ and $T \begin{bmatrix} 5 \\ 3 \end{bmatrix}_{\mathcal{E}}$.

63.3 Compute $[T\vec{c}_1]_{\mathcal{C}}$ and $[T\vec{c}_2]_{\mathcal{C}}$.

63.4 Compute the result of $T \begin{bmatrix} \alpha \\ \beta \end{bmatrix}_{\mathcal{C}}$ and express the result in the \mathcal{C} basis (i.e., as a vector of the form $\begin{bmatrix} ? \\ ? \end{bmatrix}_{\mathcal{C}}$).

63.5 Find $[T]_{\mathcal{C}}$, the matrix for T in the \mathcal{C} basis.

63.6 Find $[T]_{\mathcal{E}}$, the matrix for T in the standard basis.

Similar Matrices

DEFINITION

The matrices A and B are called *similar matrices*, denoted $A \sim B$, if A and B represent the same linear transformation but in possibly different bases. Equivalently, $A \sim B$ if there is an invertible matrix X so that

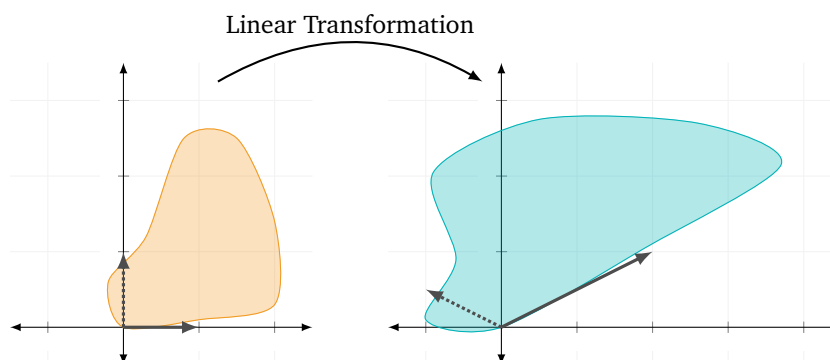
$$A = XBX^{-1}.$$

Determinants

In this module you will learn

- The definition of the determinant of a linear transformation and of a matrix.
- How to interpret the determinant as a change-of-volume factor.
- How to relate the determinant of $S \circ T$ to the determinant of S and of T .
- How to compute the determinants of elementary matrices and how to compute determinants of large matrices using row reduction.

Linear transformations transform vectors, but they also change *sets*.



It turns out to be particularly useful to track by how much a linear transformation changes area/volume. This number which is associated with a linear transformation with the same domain and codomain is called the *determinant*.⁴⁰

Volumes

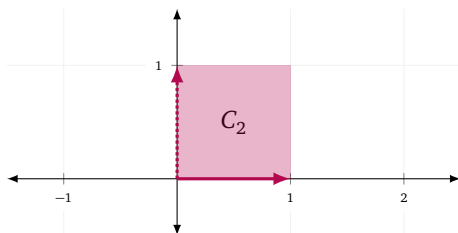
In this module, most examples will be in \mathbb{R}^2 because they're easier to draw. The definitions given will extend to \mathbb{R}^n for any n , however the English language will sometimes get in the way. In English, we say that a two-dimensional figure has an *area* and a three-and-up dimensional figure has a *volume*. In this section, we will use the term *volume* to also mean *area*.

To measure how volume changes, we will need to compare input volumes and output volumes. For this purpose, we will define notation for the *unit n -cube*.

Unit n -cube. The *unit n -cube* is the n -dimensional cube with sides given by the standard basis vectors and lower-left corner located at the origin. That is

$$C_n = \left\{ \vec{x} \in \mathbb{R}^n : \vec{x} = \sum_{i=1}^n \alpha_i \vec{e}_i \text{ for some } \alpha_1, \dots, \alpha_n \in [0, 1] \right\} = [0, 1]^n.$$

C_2 should look familiar as the unit square in \mathbb{R}^2 with lower-left corner at the origin.



C_n always has volume 1,⁴¹ and by analyzing the image of C_n under a linear transformation, we can see by how much a given transformation changes volume.

⁴⁰ This number is *almost* the determinant. The only difference is that the determinant might have a \pm in front.

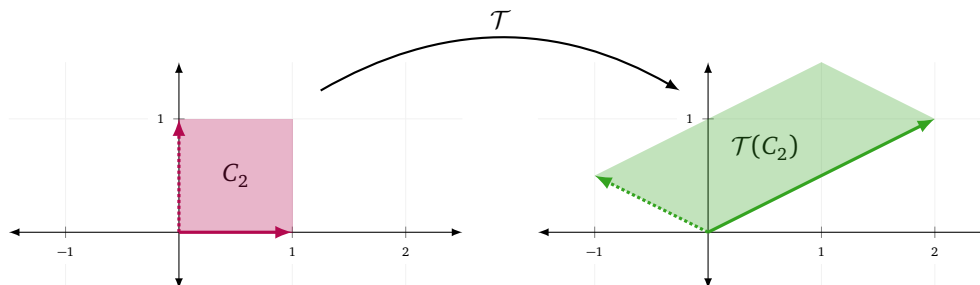
⁴¹ The fact that the volume of C_n is 1 is actually by definition.

Example. Let $\mathcal{T} : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ be defined by $\mathcal{T} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 2x + y \\ -x + \frac{1}{2}y \end{bmatrix}$. Find the volume of $\mathcal{T}(C_2)$.

Recall that C_2 is the unit square in \mathbb{R}^2 with sides given by $\vec{e}_1 = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$ and $\vec{e}_2 = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$. Applying the linear transformation \mathcal{T} to \vec{e}_1 and \vec{e}_2 , we obtain

$$\mathcal{T}(\vec{e}_1) = \begin{bmatrix} 2 \\ -1 \end{bmatrix} \quad \text{and} \quad \mathcal{T}(\vec{e}_2) = \begin{bmatrix} 1 \\ \frac{1}{2} \end{bmatrix}.$$

Plotting $\begin{bmatrix} 2 \\ -1 \end{bmatrix}$ and $\begin{bmatrix} 1 \\ \frac{1}{2} \end{bmatrix}$, we see $\mathcal{T}(C_2)$ is a parallelogram with base $\sqrt{5}$ and height $\frac{2\sqrt{5}}{5}$:



Therefore, the volume of $\mathcal{T}(C_2)$ is 2.

Let $\text{Vol}(X)$ stand for the volume of the set X . Given a linear transformation $S : \mathbb{R}^n \rightarrow \mathbb{R}^n$, we can define a number

$$\text{Vol Change}(S) = \frac{\text{Vol}(S(C_n))}{\text{Vol}(C_n)} = \frac{\text{Vol}(S(C_n))}{1} = \text{Vol}(S(C_n)).$$

A priori, $\text{Vol Change}(S)$ only describes how S changes the volume of C_n . However, because S is a linear transformation, $\text{Vol Change}(S)$ actually describes how S changes the volume of any figure.

Theorem. Let $\mathcal{T} : \mathbb{R}^n \rightarrow \mathbb{R}^n$ be a linear transformation and let $X \subseteq \mathbb{R}^n$ be a subset with volume α . Then the volume of $\mathcal{T}(X)$ is $\alpha \cdot \text{Vol Change}(\mathcal{T})$.

A full proof of the above theorem requires calculus and limits, but the linear algebra ideas are based on the following theorems.

Theorem. Suppose $\mathcal{T} : \mathbb{R}^n \rightarrow \mathbb{R}^n$ is a linear transformation and $X \subseteq \mathbb{R}^n$ is a subset and the volume of $\mathcal{T}(X)$ is α . Then for any $\vec{p} \in \mathbb{R}^n$, the volume of $\mathcal{T}(X + \{\vec{p}\})$ is α .

Proof. Fix $\mathcal{T} : \mathbb{R}^n \rightarrow \mathbb{R}^n$, $X \subseteq \mathbb{R}^n$, and $\vec{p} \in \mathbb{R}^n$. Combining linearity with the definition of set addition, we see

$$\mathcal{T}(X + \{\vec{p}\}) = \mathcal{T}(X) + \mathcal{T}(\{\vec{p}\}) = \mathcal{T}(X) + \{\mathcal{T}(\vec{p})\}$$

and so $\mathcal{T}(X + \{\vec{p}\})$ is just a translation of $\mathcal{T}(X)$. Since translations don't change volume, $\mathcal{T}(X + \{\vec{p}\})$ and $\mathcal{T}(X)$ must have the same volume. ■

Theorem. Fix k and let B_n be C_n scaled to have side lengths $\frac{1}{k}$ and let $\mathcal{T} : \mathbb{R}^n \rightarrow \mathbb{R}^n$ be a linear transformation. Then

$$\text{Vol Change}(\mathcal{T}) = \frac{\text{Vol}(\mathcal{T}(B_n))}{\text{Vol}(B_n)}.$$

Rather than giving a formal proof of the above theorem, let's make a motivating picture.

XXX Figure

The argument now goes: there are k^n copies of B_n in C_n and k^n copies of $\mathcal{T}(B_n)$ in $\mathcal{T}(C_n)$. Thus,

$$\text{Vol Change}(\mathcal{T}) = \frac{\text{Vol}(\mathcal{T}(C_n))}{\text{Vol}(C_n)} = \frac{k^n \text{Vol}(\mathcal{T}(B_n))}{k^n \text{Vol}(B_n)} = \frac{\text{Vol}(\mathcal{T}(B_n))}{\text{Vol}(B_n)}.$$

Now we can finally show that for a linear transformation $\mathcal{T} : \mathbb{R}^n \rightarrow \mathbb{R}^n$ the number “Vol Change(\mathcal{T})” actually corresponds to how much \mathcal{T} changes the volume of any figure.

The argument goes as follows: for a figure $X \subseteq \mathbb{R}^n$, we can fill it with shrunken and translated copies, B_n , of C_n . The same number of copies of $\mathcal{T}(B_n)$ fit inside $\mathcal{T}(X)$ as do B_n 's fit inside X . Therefore, the change in volume between $\mathcal{T}(X)$ and X must be the same as the change in volume between $\mathcal{T}(B_n)$ and B_n , which is VolChange(\mathcal{T}).

XXX Figure

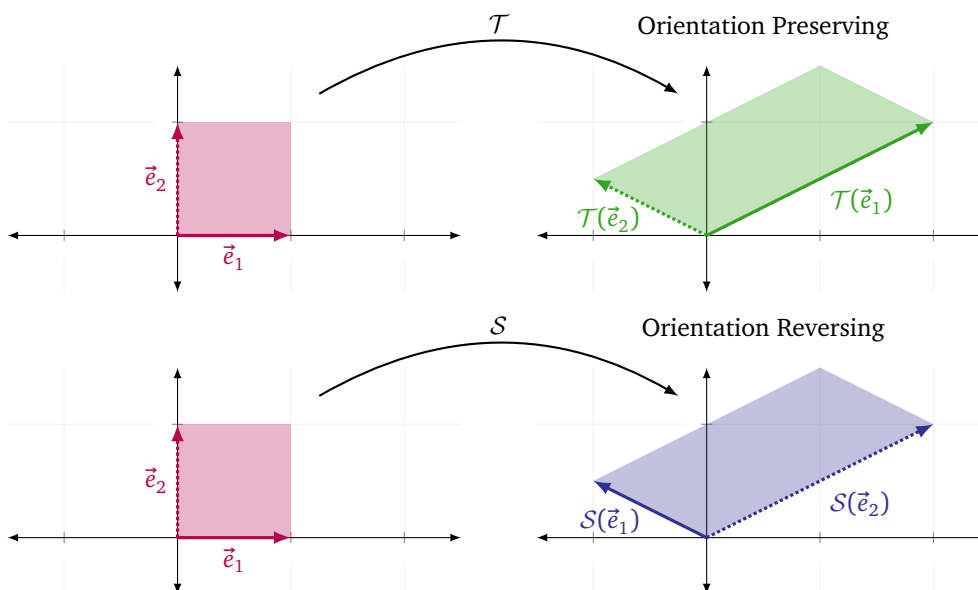
The Determinant

The determinant of a linear transformation $\mathcal{T} : \mathbb{R}^n \rightarrow \mathbb{R}^n$ is *almost* the same as VolChange(\mathcal{T}), but with one twist: *orientation*.

Determinant. The *determinant* of a linear transformation $X : \mathbb{R}^n \rightarrow \mathbb{R}^n$, denoted $\det(X)$ or $|X|$, is the oriented volume of the image of the unit n -cube. The determinant of a square matrix is the determinant of its induced transformation.

We've previously defined the orientation of a basis, and we can use the orientation of a basis to define whether a linear transformation is *orientation preserving* or *orientation reversing*.

Orientation Preserving Linear Transformation. Let $\mathcal{T} : \mathbb{R}^n \rightarrow \mathbb{R}^n$ be a linear transformation. We say \mathcal{T} is *orientation preserving* if the ordered basis $\{\mathcal{T}(\vec{e}_1), \dots, \mathcal{T}(\vec{e}_n)\}$ is a positively oriented and we say \mathcal{T} is *orientation reversing* if the ordered basis $\{\mathcal{T}(\vec{e}_1), \dots, \mathcal{T}(\vec{e}_n)\}$ is a negatively oriented. If $\{\mathcal{T}(\vec{e}_1), \dots, \mathcal{T}(\vec{e}_n)\}$ is not a basis for \mathbb{R}^n , then \mathcal{T} is neither orientation preserving nor orientation reversing.



In the figure above, \mathcal{T} is orientation preserving and S is orientation reversing.

Example. Let $\mathcal{T} : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ be defined by $\mathcal{T} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 2x + y \\ -x + \frac{1}{2}y \end{bmatrix}$. Find $\det(\mathcal{T})$.

Refer to the example from earlier, \mathcal{T} is orientation preserving. Therefore, $\det(\mathcal{T}) = 2$.

Example. Let $S : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ be defined by $S \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} -x + y \\ x + y \end{bmatrix}$. Find $\det(S)$.

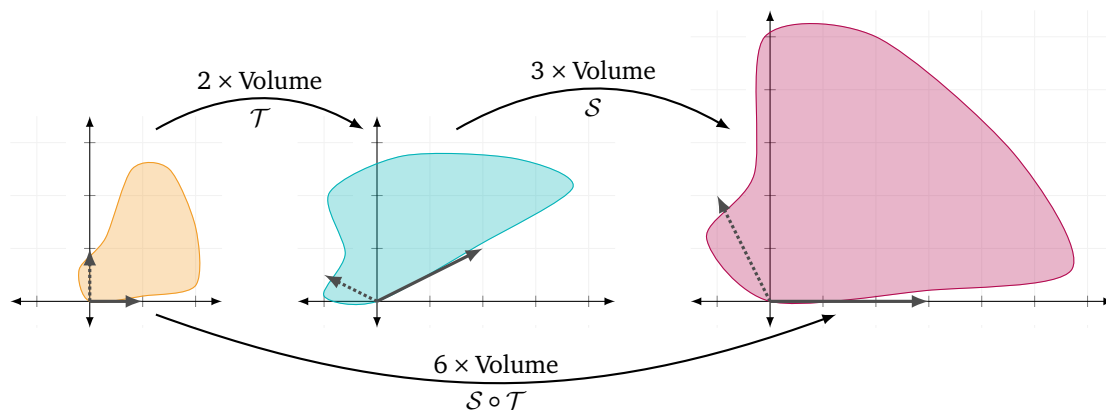
Similarly to the earlier example, we compute $S(\vec{e}_1) = \begin{bmatrix} -1 \\ 1 \end{bmatrix}$ and $S(\vec{e}_2) = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$. Plotting $S(\vec{e}_1)$ and $S(\vec{e}_2)$, we see that S is orientation reversing. Thus, $\det(S) = -\text{Vol}(S(C_2)) = -2$.

Example. Let $\mathcal{P} : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ be projection onto the line with equation $x + 2y = 4$. Find $\det(\mathcal{P})$.

Because \mathcal{P} projects everything to a line, we know $\mathcal{P}(C_2)$ must be a line segment, and therefore has no volume. Thus $\det(\mathcal{P}) = 0$.

Determinants of Composition

Volume changes are naturally multiplicative. If a linear transformation \mathcal{T} changes volume by a factor of α and \mathcal{S} changes volume by a factor of β , then $\mathcal{S} \circ \mathcal{T}$ changes volume by a factor of $\beta\alpha$. Thus, determinants are multiplicative.



Theorem. Let $\mathcal{T} : \mathbb{R}^n \rightarrow \mathbb{R}^n$ and $\mathcal{S} : \mathbb{R}^n \rightarrow \mathbb{R}^n$ be linear transformations. Then

$$\det(\mathcal{S} \circ \mathcal{T}) = \det(\mathcal{S}) \det(\mathcal{T}).$$

This means that we can compute the determinant of a complicated transformation by breaking it up into simpler ones and computing the determinant of each piece.

Determinants of Matrices

The determinant of a matrix is defined as the determinant of its induced transformation. That means, the determinant is multiplicative with respect to matrix multiplication (because it's multiplicative with respect to function composition).

Theorem. Let A and B be $n \times n$ matrices. Then

$$\det(AB) = \det(A) \det(B).$$

We will derive an algorithm for finding the determinant of a matrix by considering the determinant of elementary matrices. But first, consider the following theorem.

Theorem. (Volume Theorem I) For a square matrix M , $\det(M)$ is the oriented volume of the parallelepiped^a given by the column vectors.

^a A parallelepiped is the n -dimensional analog of a parallelogram.

Proof. Let M be an $n \times n$ matrix and let \mathcal{T}_M be its induced transformation. We know the sides of $\mathcal{T}_M(C_n)$ are given by $\{\mathcal{T}_M(\vec{e}_1), \dots, \mathcal{T}_M(\vec{e}_n)\}$. And, by definition,

$$[\mathcal{T}_M(\vec{e}_i)]_{\mathcal{E}} = M[\vec{e}_i]_{\mathcal{E}} = \text{ith column of } M.$$

Therefore $\mathcal{T}_M(C_n)$ is the parallelepiped whose sides are given by the columns of M . ■

This means we can think about the determinant of a matrix by considering its columns, and now we are ready to consider the determinants of the elementary matrices.

There are three types of elementary matrices corresponding to the three elementary row operations. For each one, we need to understand how the induced transformation changes volume.

Multiply a row by a non-zero constant α . Let E_m be such an elementary matrix. Scaling one row of I is equivalent to scaling one column of I , and so the columns of E_m specify a parallelepiped that is scaled by α in one direction.

For example, if

$$E_m = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & \alpha \end{bmatrix} \quad \text{then} \quad \{\vec{e}_1, \vec{e}_2, \vec{e}_3\} \mapsto \{\vec{e}_1, \vec{e}_2, \alpha\vec{e}_3\}.$$

Thus $\det(E_m) = \alpha$.

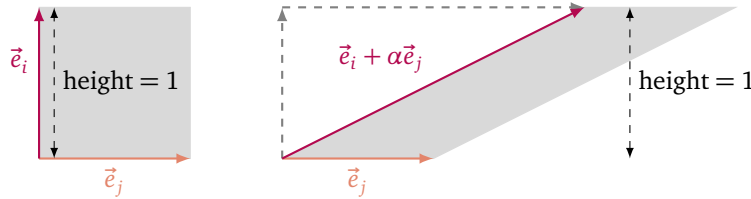
Swap two rows. Let E_s be such an elementary matrix. Swapping two rows of I is equivalent to swapping two columns of I , so E_s is I with two columns swapped. This reverses the orientation of the basis given by the columns.

For example, if

$$E_s = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad \text{then} \quad \{\vec{e}_1, \vec{e}_2, \vec{e}_3\} \mapsto \{\vec{e}_2, \vec{e}_1, \vec{e}_3\}.$$

Thus $\det(E_s) = -1$.

Add a multiple of one row to another. Let E_a be such an elementary matrix. The columns of E_a are the same as the columns of I except that one column where \vec{e}_i is replaced with $\vec{e}_i + \alpha\vec{e}_j$. This has the effect of *shearing* C_n in the \vec{e}_j direction.



Since C_n is sheared parallel to one of its other sides, its volume is not changed. Thus $\det(E_a) = 1$.

Takeaway. The determinants of elementary matrices are all easy to compute and the determinant of the most-used type of elementary matrix is 1.

Now, by decomposing a matrix into the product of elementary matrices, we can use the multiplicative property of the determinant and the formulas for the determinants of the different types of elementary matrices to compute the determinant of an invertible matrix.

Example. Use elementary matrices to find the determinant of $A = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix}$.

We can row-reduce A with the following steps:

$$\begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} \sim \begin{bmatrix} 1 & 2 \\ 0 & -2 \end{bmatrix} \sim \begin{bmatrix} 1 & 2 \\ 0 & 1 \end{bmatrix} \sim \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}.$$

The elementary matrices corresponding to these steps are

$$E_1 = \begin{bmatrix} 1 & 0 \\ -3 & 1 \end{bmatrix} \quad E_2 = \begin{bmatrix} 1 & 0 \\ 0 & -\frac{1}{2} \end{bmatrix} \quad \text{and} \quad E_3 = \begin{bmatrix} 1 & -2 \\ 0 & 1 \end{bmatrix},$$

and so $E_3 E_2 E_1 A = I$. Therefore

$$A = E_1^{-1} E_2^{-1} E_3^{-1} I = E_1^{-1} E_2^{-1} E_3^{-1} = \begin{bmatrix} 1 & 0 \\ 3 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & -2 \end{bmatrix} \begin{bmatrix} 1 & 2 \\ 0 & 1 \end{bmatrix}.$$

Using the fact that the determinant is multiplicative, we get

$$\begin{aligned} \det(A) &= \det\left(\begin{bmatrix} 1 & 0 \\ 3 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & -2 \end{bmatrix} \begin{bmatrix} 1 & 2 \\ 0 & 1 \end{bmatrix}\right) \\ &= \det\left(\begin{bmatrix} 1 & 0 \\ 3 & 1 \end{bmatrix}\right) \det\left(\begin{bmatrix} 1 & 0 \\ 0 & -2 \end{bmatrix}\right) \det\left(\begin{bmatrix} 1 & 2 \\ 0 & 1 \end{bmatrix}\right) \\ &= (1)(-2)(1) = -2. \end{aligned}$$

Determinants and Invertibility

We can use elementary matrices to compute the determinant of any invertible matrix by decomposing it into the product of elementary matrices. But, what about non-invertible matrices?

Let M be an $n \times n$ matrix that is *not* invertible. Then, we must have $\text{nullity}(M) > 0$ and $\text{col}(M) < n$. Geometrically, this means there is at least one line of vectors, $\text{null}(M)$, that gets collapsed to $\vec{0}$, and the column space of M must be “flattened” (i.e., have lost a dimension). Therefore, the volume of the parallelepiped given by the columns of M must be zero, and so $\det(M) = 0$.

Based on this argument, we have the following theorem.

Theorem. Let A be an $n \times n$ matrix. A is invertible if and only if $\det(A) \neq 0$.

Proof. If A is invertible, $A = E_1 \cdots E_k$, where E_1, \dots, E_k are elementary matrices, and so

$$\det(A) = \det(E_1 \cdots E_k) = \det(E_1) \cdots \det(E_k).$$

For every type of elementary matrix its determinant cannot be zero, and so $\det(A) \neq 0$.

Conversely, if A is not invertible, $\text{rank}(A) < n$, which means the parallelepiped given by the columns of A is “flattened” and has zero volume. ■

We now have another way to tell if a matrix is invertible! But, for an invertible matrix A , how do $\det(A)$ and $\det(A^{-1})$ relate? Well, by definition

$$AA^{-1} = I,$$

and so

$$\det(AA^{-1}) = \det(A) \det(A^{-1}) = \det(I) = 1$$

which gives

$$\det(A^{-1}) = \frac{1}{\det(A)}.$$

Determinants and Transposes

Somewhat mysteriously, we have the following theorem.

Theorem. (Volume Theorem II) The determinant of a square matrix A is equal to the oriented volume of the parallelepiped given by the rows of A .

Volume Theorem II can be concisely stated as $\det(A) = \det(A^T)$, and joins the ranks of other similarly strange properties of the transpose like $\text{rank}(A) = \text{rank}(A^T)$.

We can actually prove Volume Theorem II using elementary matrices.

Proof. Suppose A is not invertible. Then, neither is A^T and so $\det(A) = \det(A^T) = 0$.

Suppose A is invertible and $A = E_1 \cdots E_k$ where E_1, \dots, E_k are elementary matrices. We then have

$$A^T = E_k^T \cdots E_1^T.$$

However, for each E_i , we may observe that E_i^T is another elementary matrix of the same type and with the same determinant. Therefore,

$$\begin{aligned} \det(A^T) &= \det(E_k^T \cdots E_1^T) = \det(E_k^T) \cdots \det(E_1^T) \\ &= \det(E_k) \cdots \det(E_1) \\ &= \det(E_1) \cdots \det(E_k) = \det(E_1 \cdots E_k) = \det(A). \end{aligned}$$

The key observations for this proof are that (i) $\det(E_i^T) = \det(E_i)$ and (ii) since the $\det(E_i)$'s are just scalars, the order in which they are multiplied doesn't matter. ■

Determinants

Unit n -cube

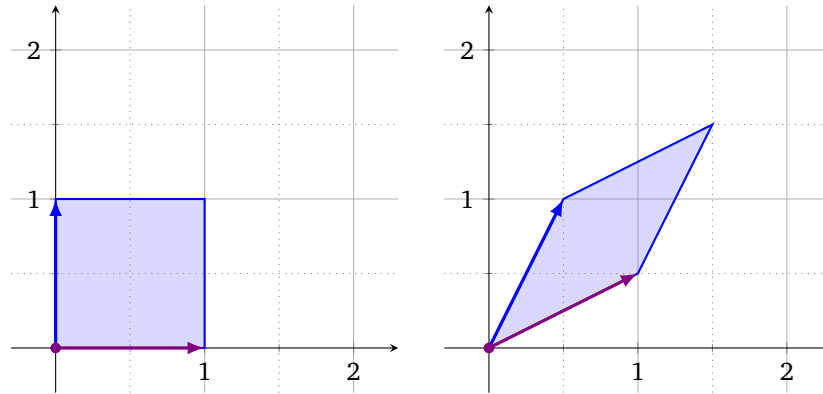
The **unit n -cube** is the n -dimensional cube with sides given by the standard basis vectors and lower-left corner located at the origin. That is

$$C_n = \left\{ \vec{x} \in \mathbb{R}^n : \vec{x} = \sum_{i=1}^n \alpha_i \vec{e}_i \text{ for some } \alpha_1, \dots, \alpha_n \in [0, 1] \right\} = [0, 1]^n.$$

The sides of the unit n -cube are always length 1 and its volume is always 1.

64

The picture shows what the linear transformation T does to the unit square (i.e., the unit 2-cube).



64.1 What is $T \begin{bmatrix} 1 \\ 0 \end{bmatrix}$, $T \begin{bmatrix} 0 \\ 1 \end{bmatrix}$, $T \begin{bmatrix} 1 \\ 1 \end{bmatrix}$?

64.2 Write down a matrix for T .

64.3 What is the volume of the image of the unit square (i.e., the volume of $T(C_2)$)? You may use trigonometry.

Determinant

The *determinant* of a linear transformation $X : \mathbb{R}^n \rightarrow \mathbb{R}^n$, denoted $\det(X)$ or $|X|$, is the oriented volume of the image of the unit n -cube. The determinant of a square matrix is the determinant of its induced transformation.

65

We know the following about the transformation A :

$$A \begin{bmatrix} 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 2 \\ 0 \end{bmatrix} \quad \text{and} \quad A \begin{bmatrix} 0 \\ 1 \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}.$$

65.1 Draw C_2 and $A(C_2)$, the image of the unit square under A .

65.2 Compute the area of $A(C_2)$.

65.3 Compute $\det(A)$.

66 Suppose R is a rotation counter-clockwise by 30° .

66.1 Draw C_2 and $R(C_2)$.

66.2 Compute the area of $R(C_2)$.

66.3 Compute $\det(R)$.

We know the following about the transformation F :

$$F \begin{bmatrix} 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \quad \text{and} \quad F \begin{bmatrix} 0 \\ 1 \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}.$$

67.1 What is $\det(F)$?

THM

Volume Theorem I

For a square matrix M , $\det(M)$ is the oriented volume of the parallelepiped (n -dimensional parallelogram) given by the column vectors of M .

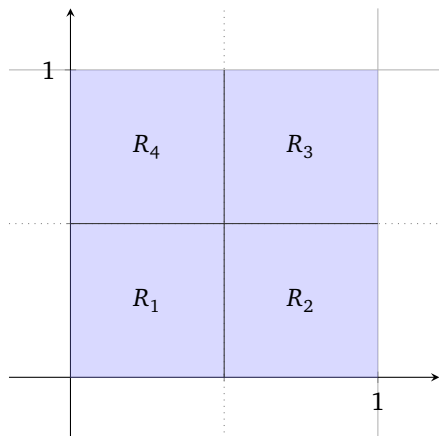
THM

Volume Theorem II

For a square matrix M , $\det(M)$ is the oriented volume of the parallelepiped (n -dimensional parallelogram) given by the row vectors of M .

68

- 68.1 Explain Volume Theorem I using the definition of determinant.
- 68.2 Based on Volume Theorems I and II, how should $\det(M)$ and $\det(M^T)$ relate for a square matrix M ?



Let $R = R_1 \cup R_2 \cup R_3 \cup R_4$. You know the following about the linear transformations M , T , and S .

$$M \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 2x \\ y \end{bmatrix}$$

$T : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ has determinant 2

$S : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ has determinant 3

- 69.1 Find the volumes (areas) of R_1 , R_2 , R_3 , R_4 , and R .
- 69.2 Compute the oriented volume of $M(R_1)$, $M(R_2)$, and $M(R)$.
- 69.3 Do you have enough information to compute the oriented volume of $T(R_2)$? What about the oriented volume of $T(R + \{\vec{e}_2\})$?
- 69.4 What is the oriented volume of $S \circ T(R)$? What is $\det(S \circ T)$?

- E_f is $I_{3 \times 3}$ with the first two rows swapped.
- E_m is $I_{3 \times 3}$ with the third row multiplied by 6.
- E_a is $I_{3 \times 3}$ with $R_1 \mapsto R_1 + 2R_2$ applied.

70.1 What is $\det(E_f)$?

70.2 What is $\det(E_m)$?

70.3 What is $\det(E_a)$?

70.4 What is $\det(E_f E_m)$?

70.5 What is $\det(4I_{3 \times 3})$?

70.6 What is $\det(W)$ where $W = E_f E_a E_f E_m E_m$?

71

$$U = \begin{bmatrix} 1 & 2 & 1 & 2 \\ 0 & 3 & -2 & 4 \\ 0 & 0 & -1 & 0 \\ 0 & 0 & 0 & 4 \end{bmatrix}$$

71.1 What is $\det(U)$?

71.2 V is a square matrix and $\text{rref}(V)$ has a row of zeros. What is $\det(V)$?

-
- 72 72.1 V is a square matrix whose columns are linearly dependent. What is $\det(V)$?
- 72.2 P is projection onto $\text{span}\left\{\begin{bmatrix} -1 \\ -1 \end{bmatrix}\right\}$. What is $\det(P)$?

-
- 73 Suppose you know $\det(X) = 4$.
- 73.1 What is $\det(X^{-1})$?
 - 73.2 Derive a relationship between $\det(Y)$ and $\det(Y^{-1})$ for an arbitrary matrix Y .
 - 73.3 Suppose Y is not invertible. What is $\det(Y)$?

Eigenvalues and Eigenvectors

In this module you will learn

- The definition of eigenvalues and eigenvectors.
- That eigenvectors give a particularly nice basis in which to study a linear transformation.
- How the characteristic polynomial relates to eigenvalues.

From here on out, we will only be considering linear transformations with the same domain and codomain (i.e., transformations $\mathcal{T} : \mathbb{R}^n \rightarrow \mathbb{R}^n$). Why? Because that will allow us to *compare* input and output vectors. From this perspective, a linear transformation $\mathcal{T} : \mathbb{R}^n \rightarrow \mathbb{R}^n$ may stretch, twist, shear, rotate, and project vectors.



It's the stretched vectors that we're most interested in now. If \mathcal{T} stretches the vector \vec{v} , then \mathcal{T} , in that direction, can be described by $\vec{v} \mapsto \alpha\vec{v}$, which is an easy-to-understand linear transformation. The “stretch” directions for a linear transformation have a special name—*eigen directions*—and the vectors that are stretched are called *eigenvectors*.

Eigenvector. Let X be a linear transformation or a matrix. An **eigenvector** for X is a non-zero vector that doesn't change directions when X is applied. That is, $\vec{v} \neq \vec{0}$ is an eigenvector for X if

$$X\vec{v} = \lambda\vec{v}$$

for some scalar λ . We call λ the **eigenvalue** of X corresponding to the eigenvector \vec{v} .

The word *eigen* is German for characteristic, representative, or intrinsic, and we will see that eigenvectors provide one of the best contexts in which to understand a linear transformation.

Example. Let $\mathcal{P} : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ be projection onto the line ℓ given by $y = x$. Find the eigenvectors and eigenvalues of \mathcal{P} .

We are looking for vectors $\vec{v} \neq \vec{0}$ such that $\mathcal{P}\vec{v} = \lambda\vec{v}$ for some λ . Since $\mathcal{P}(\ell) = \ell$, we know for any $\vec{v} \in \ell$

$$\mathcal{P}(\vec{v}) = 1\vec{v} = \vec{v}.$$

Therefore, any non-zero multiple of $\begin{bmatrix} 1 \\ 1 \end{bmatrix}$ is an eigenvector for \mathcal{P} with corresponding eigenvalue 1.

By considering the null space of \mathcal{P} , we see, for example,

$$\mathcal{P} \begin{bmatrix} 1 \\ -1 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} = 0 \begin{bmatrix} 1 \\ -1 \end{bmatrix},$$

and so $\begin{bmatrix} 1 \\ -1 \end{bmatrix}$ and all its non-zero multiples are eigenvectors of \mathcal{P} with corresponding eigenvalue 0.

Finding Eigenvectors

Sometimes you can find the eigenvectors/values of a linear transformation just by thinking about it. For example, for reflections, projections, and dilations eigenvectors, the eigen directions are geometrically clear. However, for an arbitrary matrix transformation, it may not be obvious.

Our goal now will be to see if we can leverage our other linear algebra knowledge to find eigenvectors/values, particularly for matrix transformations. So that we don't have to switch back and forth between thinking about linear transformations and thinking about matrices, let just think about matrices for now.

Let M be a square matrix. The vector $\vec{v} \neq \vec{0}$ is an eigenvector for M if and only if there exists a scalar λ so that

$$M\vec{v} = \lambda\vec{v}. \quad (11)$$

Put another way, $\vec{v} \neq \vec{0}$ is an eigenvector for M if and only if

$$M\vec{v} - \lambda\vec{v} = (M - \lambda I)\vec{v} = \vec{0}.$$

The middle equation provides a key insight. The operation $\vec{v} \mapsto M\vec{v} - \lambda\vec{v}$ can be achieved by multiplying \vec{v} by the single matrix $E_\lambda = M - \lambda I$.

Now we have that $\vec{v} \neq \vec{0}$ is an eigenvector for M if and only if

$$E_\lambda \vec{v} = (M - \lambda I)\vec{v} = M\vec{v} - \lambda\vec{v} = \vec{0},$$

or, phrased another way, \vec{v} is a non-zero vector satisfying $\vec{v} \in \text{null}(E_\lambda)$.

We've reduced the problem of finding eigenvectors/values of M to finding the null space of E_λ , a related matrix.

Characteristic Polynomial

Let M be an $n \times n$ matrix and define $E_\lambda = M - \lambda I$. Every eigenvector for M must be in the null space of E_λ for some λ . However, because eigenvectors must be non-zero, the only chance we have of finding an eigenvector is if $\text{null}(E_\lambda) \neq \{\vec{0}\}$. In other words, we would like to know when $\text{null}(E_\lambda)$ is *non-trivial*.

We're well equipped to answer this question. Because E_λ is an $n \times n$ matrix, we know E_λ has a non-trivial null space if and only if E_λ is not invertible which is true if and only if $\det(E_\lambda) = 0$. Every λ defines a different E_λ where eigenvectors could be hiding. By viewing $\det(E_\lambda)$ as a function of λ , we can use our mathematical knowledge of single-variable functions to figure out when $\det(E_\lambda) = 0$.

The quantity $\det(E_\lambda)$, view as a function of λ , has a special name—it's called the *characteristic polynomial*.⁴²

Characteristic Polynomial.

For a matrix A , the *characteristic polynomial* of A is

$$\text{char}(A) = \det(A - \lambda I).$$

Example. Find the characteristic polynomial of $A = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix}$.

By the definition of the characteristic polynomial of A , we have

$$\begin{aligned} \text{char}(A) &= \det(A - \lambda I) \\ &= \det\left(\begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} - \begin{bmatrix} \lambda & 0 \\ 0 & \lambda \end{bmatrix}\right) = \det\left(\begin{bmatrix} 1-\lambda & 2 \\ 3 & 4-\lambda \end{bmatrix}\right) \\ &= (1-\lambda)(4-\lambda) - 6 = \lambda^2 - 5\lambda - 2. \end{aligned}$$

For an $n \times n$ matrix A , $\text{char}(A)$ has some nice properties.

- $\text{char}(A)$ is a polynomial.⁴³
- $\text{char}(A)$ has degree n .
- The coefficient of the λ^n term in $\text{char}(A)$ is ± 1 .
- $\text{char}(A)$ evaluated at $\lambda = 0$ is $\det(A)$.
- The roots of $\text{char}(A)$ are precisely the eigenvalues of A .

We will just accept these properties as facts, but each of them can be proved with the tools we've developed.

Using the Characteristic Polynomial to find Eigenvalues

With the characteristic polynomial in hand, finding eigenvectors/values becomes easier.

Example. Find the eigenvectors/values of $A = \begin{bmatrix} 1 & 2 \\ 3 & 2 \end{bmatrix}$.

Similarly to the above example, we first determinate $\text{char}(A)$:

$$\begin{aligned} \text{char}(A) &= \det\left(\begin{bmatrix} 1-\lambda & 2 \\ 3 & 2-\lambda \end{bmatrix}\right) \\ &= (1-\lambda)(2-\lambda) - 6 = \lambda^2 - 3\lambda - 4 = (4-\lambda)(-1-\lambda) \end{aligned}$$

⁴² This time the term is traditionally given the English name, rather than being called the *eigenpolynomial*.

⁴³ A priori, it's not obvious that $\det(A - \lambda I)$ should be a polynomial as opposed to some other type of function.

Next, we set the $\text{char}(A) = 0$ to find eigenvalues, which are $\lambda_1 = -1$ and $\lambda_2 = 4$. Based on the previous discussion, we know non-zero vectors in $\text{null}(A - \lambda_1 I)$ are eigenvectors with eigenvalue -1 . Computing,

$$\text{null}(A - \lambda_1 I) = \text{null}\left(\begin{bmatrix} 2 & 2 \\ 3 & 3 \end{bmatrix}\right) = \text{span}\left\{\begin{bmatrix} 1 \\ -1 \end{bmatrix}\right\}.$$

The vector $\begin{bmatrix} 1 \\ -1 \end{bmatrix}$ can be found by using row reduction to solve $\begin{bmatrix} 2 & 2 \\ 3 & 3 \end{bmatrix} \vec{x} = \vec{0}$.

We conclude, one eigenvector of A with eigenvalue $\lambda_1 = -1$ is $\begin{bmatrix} 1 \\ -1 \end{bmatrix}$. More generally, vectors $\vec{v} = k \begin{bmatrix} 1 \\ -1 \end{bmatrix}$ where $k \neq 0$ are eigenvectors of A with eigenvalue -1 .

Similarly,

$$\text{null}(A - \lambda_2 I) = \text{null}\left(\begin{bmatrix} -3 & 2 \\ 3 & -2 \end{bmatrix}\right) = \text{span}\left\{\begin{bmatrix} 2 \\ 3 \end{bmatrix}\right\},$$

and so the eigenvectors with eigenvalue 4 are $\vec{v}_2 = k \begin{bmatrix} 2 \\ 3 \end{bmatrix}$ where $k \neq 0$.

Using the characteristic polynomial, we can show that every eigenvalue for a matrix is a root of some polynomial (the characteristic polynomial). In general, finding roots of polynomials is a hard problem,⁴⁴ and it's not one we will focus on. However, it's handy to have the quadratic formula in your back pocket for factoring particularly stubborn polynomials.

Example. Find the eigenvectors/values of $A = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix}$.

First, find the roots of $\text{char}(A)$ by setting it to 0.

$$\begin{aligned} \text{char}(A) &= \det\left(\begin{bmatrix} 1-\lambda & 2 \\ 3 & 4-\lambda \end{bmatrix}\right) \\ &= (1-\lambda)(4-\lambda) - 6 = \lambda^2 - 5\lambda - 2 = 0 \end{aligned}$$

By the quadratic formula,⁴⁵ we find that

$$\lambda_1 = \frac{5 - \sqrt{33}}{2} \quad \lambda_2 = \frac{5 + \sqrt{33}}{2}$$

are the roots of $\text{char}(A)$.

Following the procedure outlined above, we need to find $\text{null}(A - \lambda_1 I)$ and $\text{null}(A - \lambda_2 I)$.

We will start by applying row reduction to $A - \lambda_1 I$.

$$\begin{aligned} \begin{bmatrix} 1 - \frac{5 - \sqrt{33}}{2} & 2 \\ 3 & 4 - \frac{5 - \sqrt{33}}{2} \end{bmatrix} &\sim \begin{bmatrix} \frac{-3 + \sqrt{33}}{2} & 2 \\ 3 & \frac{3 + \sqrt{33}}{2} \end{bmatrix} \sim \begin{bmatrix} 1 & \frac{4}{-3 + \sqrt{33}} \\ 1 & \frac{3 + \sqrt{33}}{6} \end{bmatrix} \\ &\sim \begin{bmatrix} 1 & \frac{4(3 + \sqrt{33})}{(-3 + \sqrt{33})(3 + \sqrt{33})} \\ 1 & \frac{3 + \sqrt{33}}{6} \end{bmatrix} \sim \begin{bmatrix} 1 & \frac{3 + \sqrt{33}}{6} \\ 1 & \frac{3 + \sqrt{33}}{6} \end{bmatrix} \\ &\sim \begin{bmatrix} 1 & \frac{3 + \sqrt{33}}{6} \\ 0 & 0 \end{bmatrix} \end{aligned}$$

Thus, we conclude that $\vec{v}_1 = \begin{bmatrix} \frac{3 + \sqrt{33}}{6} \\ -1 \end{bmatrix}$ is an eigenvector with eigenvalue $\frac{5 - \sqrt{33}}{2}$. Similarly, $\vec{v}_2 = \begin{bmatrix} \frac{3 - \sqrt{33}}{6} \\ -1 \end{bmatrix}$ is an eigenvector with eigenvalue $\lambda_2 = \frac{5 + \sqrt{33}}{2}$.

Transformations without Eigenvectors

Are there linear transformations without eigenvectors? Well, it depends on exactly what you mean. Let $\mathcal{R} : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ be rotation counter-clockwise by 90° . Are there any non-zero vectors that don't change direction when \mathcal{R} is applied? Certainly not.

⁴⁴ In fact, numerically approximating eigenvalues turns out to be easier than finding roots of a polynomial, so many numerical root finding algorithms actually create a matrix with an appropriate characteristic polynomial and use numerical linear algebra to approximate its roots.

⁴⁵ Recall that the roots of $ax^2 + bx + c$ are given by $\frac{-b \pm \sqrt{b^2 - 4ac}}{2a}$.

Let's examine further. We know $R = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}$ is a matrix for \mathcal{R} , and

$$\text{char}(R) = \lambda^2 + 1.$$

The polynomial $\lambda^2 + 1$ has no real roots, which means that R (and \mathcal{R}) have no real eigenvalues. However, $\lambda^2 + 1$ does have *complex* roots of $\pm i$. So far, we've always thought of scalars as real numbers, but if we allow complex numbers as scalars and view \mathcal{R} as a transformation from $\mathbb{C}^2 \rightarrow \mathbb{C}^2$, it would have eigenvalues and eigenvectors.

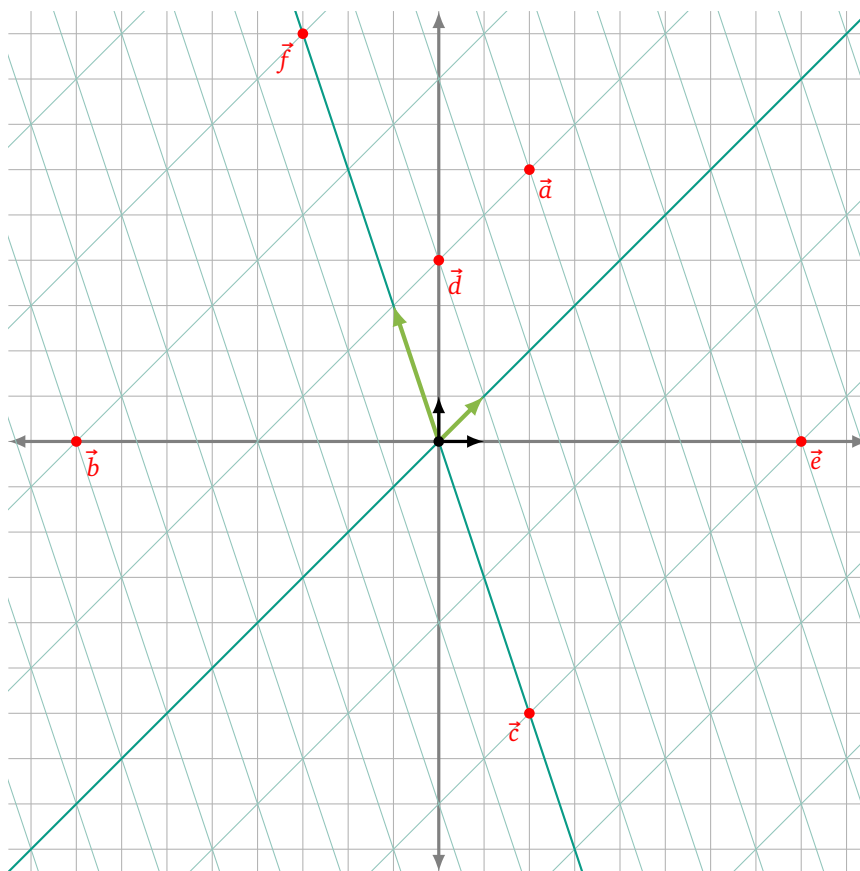
Complex numbers play an invaluable role in advanced linear algebra and applications of linear algebra to physics. We will leave the following theorem as food for thought.⁴⁶

Theorem. If A is a square matrix, then A always has an eigenvalue provided complex eigenvalues are permitted.

⁴⁶ The theorem is a direct corollary of the fundamental theorem of algebra.

Task 3.1: The Green and the Black

Consider the following two bases for \mathbb{R}^2 : the green basis $\mathcal{G} = \{\vec{g}_1, \vec{g}_2\}$ and the black basis $\mathcal{B} = \{\vec{e}_1, \vec{e}_2\}$.



1. Write each point above in both the green and the black bases.
2. Find a change-of-basis matrix X that converts vectors from a green basis representation to a black basis representation. Find another matrix Y that converts vectors from a black basis representation to a green basis representation.
3. Let $T : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ be the linear transformation that stretches in the $y = -3x$ direction by a factor of 2 and leaves vectors in the $y = x$ direction fixed.

Describe what happens to the vectors \vec{u} , \vec{v} , and \vec{w} when T is applied given that

$$[\vec{u}]_{\mathcal{G}} = \begin{bmatrix} 6 \\ 1 \end{bmatrix} \quad [\vec{v}]_{\mathcal{G}} = \begin{bmatrix} 4 \\ -3 \end{bmatrix} \quad [\vec{w}]_{\mathcal{B}} = \begin{bmatrix} -8 \\ -7 \end{bmatrix}.$$

4. When working with the transformation T , which basis do you prefer vectors be represented in?

Eigenvectors

Eigenvector

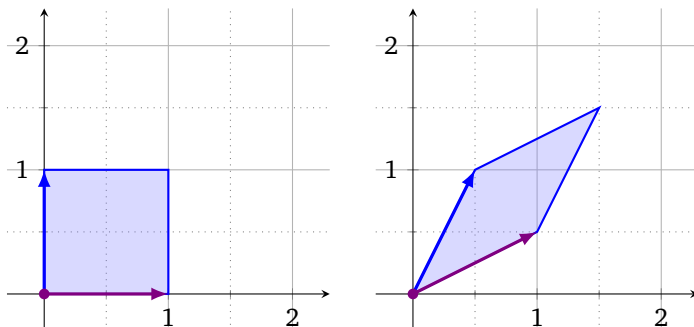
Let X be a linear transformation or a matrix. An **eigenvector** for X is a non-zero vector that doesn't change directions when X is applied. That is, $\vec{v} \neq \vec{0}$ is an eigenvector for X if

$$X\vec{v} = \lambda\vec{v}$$

for some scalar λ . We call λ the **eigenvalue** of X corresponding to the eigenvector \vec{v} .

74

The picture shows what the linear transformation T does to the unit square (i.e., the unit 2-cube).



74.1 Give an eigenvector for T . What is the eigenvalue?

74.2 Can you give another?

For some matrix A ,

$$A \begin{bmatrix} 3 \\ 3 \\ 1 \end{bmatrix} = \begin{bmatrix} 2 \\ 2 \\ 2/3 \end{bmatrix} \quad \text{and} \quad B = A - \frac{2}{3}I.$$

75.1 Give an eigenvector and a corresponding eigenvalue for A .

75.2 What is $B \begin{bmatrix} 3 \\ 3 \\ 1 \end{bmatrix}$?

75.3 What is the dimension of $\text{null}(B)$?

75.4 What is $\det(B)$?

76

Let $C = \begin{bmatrix} -1 & 2 \\ 1 & 0 \end{bmatrix}$ and $E_\lambda = C - \lambda I$.

- 76.1 For what values of λ does E_λ have a non-trivial null space?
- 76.2 What are the eigenvalues of C ?
- 76.3 Find the eigenvectors of C .

Characteristic Polynomial

DEF

For a matrix A , the *characteristic polynomial* of A is

$$\text{char}(A) = \det(A - \lambda I).$$

77

Let $D = \begin{bmatrix} 1 & 2 \\ 3 & 0 \end{bmatrix}$.

77.1 Compute $\text{char}(D)$.

77.2 Find the eigenvalues of D .

78 Suppose $\text{char}(E) = -\lambda(2 - \lambda)(-3 - \lambda)$ for some unknown 3×3 matrix E .

78.1 What are the eigenvalues of E ?

78.2 Is E invertible?

78.3 What can you say about $\text{nullity}(E)$, $\text{nullity}(E - 3I)$, $\text{nullity}(E + 3I)$?

Diagonalization

In this module you will learn

- How to diagonalize a matrix.
- When a matrix can and cannot be diagonalized.

Suppose \mathcal{T} is a linear transformation and \vec{v}_1 and \vec{v}_2 are eigenvectors with eigenvalues λ_1 and λ_2 . With this setup, for any $\vec{a} \in \text{span}\{\vec{v}_1, \vec{v}_2\}$, we can compute $\mathcal{T}(\vec{a})$ with minimal effort.

Let's get specific. Define $\mathcal{T} : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ to be the linear transformation with matrix $M = \begin{bmatrix} 1 & 2 \\ 3 & 2 \end{bmatrix}$. Let $\vec{v}_1 = \begin{bmatrix} -1 \\ 1 \end{bmatrix}$ and $\vec{v}_2 = \begin{bmatrix} 2 \\ 3 \end{bmatrix}$, and notice that \vec{v}_1 is an eigenvector for \mathcal{T} with eigenvalue -1 and that \vec{v}_2 is an eigenvector for \mathcal{T} with eigenvalue 4 . Let $\vec{a} = \vec{v}_1 + \vec{v}_2$.

Now,

$$\mathcal{T}(\vec{a}) = \mathcal{T}(\vec{v}_1 + \vec{v}_2) = \mathcal{T}(\vec{v}_1) + \mathcal{T}(\vec{v}_2) = -\vec{v}_1 + 4\vec{v}_2.$$

We didn't need to refer to the entries of M to compute $\mathcal{T}(\vec{a})$.

Let's explore further. Let $\mathcal{V} = \{\vec{v}_1, \vec{v}_2\}$ and notice that \mathcal{V} is a basis for \mathbb{R}^2 . By definition $[\vec{a}]_{\mathcal{V}} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$, and so we just computed

$$\mathcal{T} \begin{bmatrix} 1 \\ 1 \end{bmatrix}_{\mathcal{V}} = \begin{bmatrix} -1 \\ 4 \end{bmatrix}_{\mathcal{V}}.$$

When represented in the \mathcal{V} basis, computing \mathcal{T} is easy. In general,

$$\mathcal{T}(\alpha\vec{v}_1 + \beta\vec{v}_2) = \alpha\mathcal{T}(\vec{v}_1) + \beta\mathcal{T}(\vec{v}_2) = -\alpha\vec{v}_1 + 4\beta\vec{v}_2,$$

and so

$$\mathcal{T} \begin{bmatrix} \alpha \\ \beta \end{bmatrix}_{\mathcal{V}} = \begin{bmatrix} -\alpha \\ 4\beta \end{bmatrix}_{\mathcal{V}}.$$

In other words, \mathcal{T} , when acting on vectors written in the \mathcal{V} basis, just multiplies each coordinate by an eigenvalue. This is enough information to determine the matrix for \mathcal{T} in the \mathcal{V} basis:

$$[\mathcal{T}]_{\mathcal{V}} = \begin{bmatrix} -1 & 0 \\ 0 & 4 \end{bmatrix}.$$

The matrix representations $[\mathcal{T}]_{\mathcal{E}} = \begin{bmatrix} 1 & 2 \\ 3 & 2 \end{bmatrix}$ and $[\mathcal{T}]_{\mathcal{V}} = \begin{bmatrix} -1 & 0 \\ 0 & 4 \end{bmatrix}$ are equally valid, but writing \mathcal{T} in the \mathcal{V} basis gives a very simple matrix!

Diagonalization

Recall that two matrices are similar if they represent the same transformation but in possibly different bases. The process of *diagonalizing* a matrix A is that of finding a diagonal matrix that is similar to A , and you can bet that this process is closely related to eigenvectors/values.

Let $\mathcal{T} : \mathbb{R}^n \rightarrow \mathbb{R}^n$ be a linear transformation and suppose that $\mathcal{B} = \{\vec{b}_1, \dots, \vec{b}_n\}$ is a basis so that

$$[\mathcal{T}]_{\mathcal{B}} = \begin{bmatrix} \alpha_1 & 0 & \cdots & 0 \\ 0 & \alpha_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \alpha_n \end{bmatrix}$$

is a diagonal matrix. This means that $\vec{b}_1, \dots, \vec{b}_n$ are eigenvectors for \mathcal{T} ! The proof goes as follows:

$$[\mathcal{T}]_{\mathcal{B}}[\vec{b}_1]_{\mathcal{B}} = \begin{bmatrix} \alpha_1 & 0 & \cdots & 0 \\ 0 & \alpha_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \alpha_n \end{bmatrix} \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ 0 \\ \vdots \\ 0 \end{bmatrix} = \alpha_1[\vec{b}_1]_{\mathcal{B}} = [\alpha_1\vec{b}_1]_{\mathcal{B}},$$

and in general

$$[\mathcal{T}]_{\mathcal{B}}[\vec{b}_i]_{\mathcal{B}} = \alpha_i[\vec{b}_i]_{\mathcal{B}} = [\alpha_i \vec{b}_i]_{\mathcal{B}}.$$

Therefore, for $i = 1, \dots, n$, we have

$$\mathcal{T}\vec{b}_i = \alpha_i \vec{b}_i.$$

Since \mathcal{B} is a basis, $\vec{b}_i \neq \vec{0}$ for any i , and so each \vec{b}_i is an eigenvector for \mathcal{T} with corresponding eigenvalue α_i .

We've just shown that if a linear transformation $\mathcal{T} : \mathbb{R}^n \rightarrow \mathbb{R}^n$ can be represented by a diagonal matrix, then there must be a basis for \mathbb{R}^n consisting of eigenvectors for \mathcal{T} . The converse is also true.

Suppose again that $\mathcal{T} : \mathbb{R}^n \rightarrow \mathbb{R}^n$ is a linear transformation and that $\mathcal{B} = \{\vec{b}_1, \dots, \vec{b}_n\}$ is a basis of eigenvectors for \mathcal{T} with corresponding eigenvalues $\alpha_1, \dots, \alpha_n$. By definition,

$$\mathcal{T}(k\vec{b}_i) = k\mathcal{T}(\vec{b}_i) = \alpha_i k\vec{b}_i,$$

and so

$$\mathcal{T} \begin{bmatrix} k_1 \\ k_2 \\ \vdots \\ k_n \end{bmatrix}_{\mathcal{B}} = \begin{bmatrix} \alpha_1 k_1 \\ \alpha_2 k_2 \\ \vdots \\ \alpha_n k_n \end{bmatrix}_{\mathcal{B}} \quad \text{which is equivalent to} \quad [\mathcal{T}]_{\mathcal{B}} \begin{bmatrix} k_1 \\ k_2 \\ \vdots \\ k_n \end{bmatrix} = \begin{bmatrix} \alpha_1 k_1 \\ \alpha_2 k_2 \\ \vdots \\ \alpha_n k_n \end{bmatrix}.$$

The only matrix that does this is

$$[\mathcal{T}]_{\mathcal{B}} = \begin{bmatrix} \alpha_1 & 0 & \cdots & 0 \\ 0 & \alpha_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \alpha_n \end{bmatrix},$$

which is a diagonal matrix.

What we've shown is summarized by the following theorem.

Theorem. A linear transformation $\mathcal{T} : \mathbb{R}^n \rightarrow \mathbb{R}^n$ can be represented by a diagonal matrix if and only if there exists a basis for \mathbb{R}^n consisting of eigenvectors for \mathcal{T} . If \mathcal{B} is such a basis, then $[\mathcal{T}]_{\mathcal{B}}$ is a diagonal matrix.

Now that we have a handle on representing a linear transformation by a diagonal matrix, let's tackle the problem of diagonalizing a matrix itself.

Diagonalizable. A matrix is *diagonalizable* if it is similar to a diagonal matrix.

Suppose A is an $n \times n$ matrix. A induces some transformation $\mathcal{T}_A : \mathbb{R}^n \rightarrow \mathbb{R}^n$. By definition, this means $A = [\mathcal{T}_A]_{\mathcal{E}}$. The matrix B is similar to A if there is some basis \mathcal{V} so that $B = [\mathcal{T}_A]_{\mathcal{V}}$. Using change-of-basis matrices, we see

$$A = [\mathcal{E} \leftarrow \mathcal{V}][\mathcal{T}_A]_{\mathcal{V}}[\mathcal{V} \leftarrow \mathcal{E}] = [\mathcal{E} \leftarrow \mathcal{V}]B[\mathcal{V} \leftarrow \mathcal{E}].$$

In other words, A and B are similar if there is some invertible change-of-basis matrix P so

$$A = PBP^{-1}.$$

Based on our earlier discussion, B will be a diagonal matrix if and only if P is the change-of-basis matrix for a basis of eigenvectors. In this case, we know B will be the diagonal matrix with eigenvalues along the diagonal (in the proper order).

Example. Let $A = \begin{bmatrix} 1 & 2 & 5 \\ -11 & 14 & 5 \\ -3 & 2 & 9 \end{bmatrix}$ be a matrix and notice that $\vec{v}_1 = \begin{bmatrix} 5 \\ 5 \\ 1 \end{bmatrix}$, $\vec{v}_2 = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$, and $\vec{v}_3 = \begin{bmatrix} 1 \\ 3 \\ 1 \end{bmatrix}$ are eigenvectors for A . Diagonalize A .

XXX Finish (eigenvalues are 4,8,12)

Non-diagonalizable Matrices

Is every matrix diagonalizable? Unfortunately the world is not that sweet. But, we have a tool to tell if a matrix is diagonalizable—checking to see if there is a basis of eigenvectors.

Example. Is the matrix $R = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}$ diagonalizable?

Computing, $\text{char}(R) = \lambda^2 + 1$ which has no real roots. Therefore, R has no real eigenvalues. Consequently, R has no real eigenvectors, and so R is not diagonalizable.⁴⁷

Example. Is the matrix $D = \begin{bmatrix} 5 & 0 \\ 0 & 5 \end{bmatrix}$ diagonalizable?

For every vector $\vec{v} \in \mathbb{R}^2$, we have $D\vec{v} = 5\vec{v}$, and so every non-zero vector in \mathbb{R}^2 is an eigenvector for D . Thus, $\mathcal{E} = \{\vec{e}_1, \vec{e}_2\}$ is a basis of eigenvectors for \mathbb{R}^2 , and so D is diagonalizable.⁴⁸

Example. Is the matrix $J = \begin{bmatrix} 5 & 1 \\ 0 & 5 \end{bmatrix}$ diagonalizable?

XXX Finish

Example. Is the matrix $K = \begin{bmatrix} 5 & 1 \\ 0 & 2 \end{bmatrix}$ diagonalizable?

XXX Finish

Takeaway. Not all matrices are diagonalizable, but you can check if an $n \times n$ matrix is diagonalizable by determining whether there is a basis of eigenvectors for \mathbb{R}^n .

Geometric and Algebraic Multiplicities

When analyzing linear transformations or matrices, we're often interested in studying the subspaces where vectors are stretched by only one eigenvalue. These are called the *eigenspaces*.

Eigenspace. Let A be an $n \times n$ matrix with eigenvalues $\lambda_1, \dots, \lambda_m$. The *eigenspace* of A corresponding to the eigenvalue λ_i is the null space of $A - \lambda_i I$. That is, it is the space spanned by all eigenvectors that have the eigenvalue λ_i .

The *geometric multiplicity* of an eigenvalue λ_i is the dimension of the corresponding eigenspace. The *algebraic multiplicity* of λ_i is the number of times λ_i occurs as a root of the characteristic polynomial of A (i.e., the number of times $x - \lambda_i$ occurs as a factor).

Now is the time when linear algebra and regular algebra (the solving of non-linear equations) combine. We know, every root of the characteristic polynomial of a matrix gives an eigenvalue for that matrix. Since the degree of the characteristic polynomial of an $n \times n$ matrix is always n , the fundamental theorem of algebra tells us exactly how many roots to expect.

Recall that the *multiplicity* of a root of a polynomial is the power of that root in the factored polynomial. So, for example $p(x) = (4 - x)^3(5 - x)$ has a root of 4 with multiplicity 3 and a root of 5 with multiplicity 1.

Example. Let $R = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}$ and find the geometric and algebraic multiplicity of each eigenvalue of R .

XXX Finish

Example. Let $D = \begin{bmatrix} 5 & 0 \\ 0 & 5 \end{bmatrix}$ and find the geometric and algebraic multiplicity of each eigenvalue of D .

XXX Finish

Example. Let $J = \begin{bmatrix} 5 & 1 \\ 0 & 5 \end{bmatrix}$ and find the geometric and algebraic multiplicity of each eigenvalue of J .

XXX Finish

Example. Let $K = \begin{bmatrix} 5 & 1 \\ 0 & 2 \end{bmatrix}$ and find the geometric and algebraic multiplicity of each eigenvalue of K .

XXX Finish

Consider the following two theorems.

Theorem. (Fundamental Theorem of Algebra) Let p be a polynomial of degree n . Then, if complex roots are allowed, the sum of the multiplicities of the roots of p is n .

⁴⁷ If we allow complex eigenvalues, then R is diagonalizable and is similar to the matrix $\begin{bmatrix} i & 0 \\ 0 & -i \end{bmatrix}$. So, to be more precise, we might say R is not *real* diagonalizable.

⁴⁸ Of course, every square matrix is similar to itself and D is already diagonal, so of course it's diagonalizable.

Theorem. Let λ be an eigenvalue of the matrix A . Then

$$\text{geometric mult}(\lambda) \leq \text{algebraic mult}(\lambda).$$

We can now deduce the following.

Theorem. An $n \times n$ matrix A is diagonalizable if and only if the sum of its geometric multiplicities is equal to n . Further, provided complex eigenvalues are permitted, A is diagonalizable if and only if all its geometric multiplicities equal its algebraic multiplicities.

Proof. XXX Finish ■

$$A = \begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & 1 \\ 1 & 1 & 0 \end{bmatrix} \quad \vec{v}_1 = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \quad \vec{v}_2 = \begin{bmatrix} 1 \\ 1 \\ -2 \end{bmatrix} \quad \vec{v}_3 = \begin{bmatrix} -1 \\ 1 \\ 0 \end{bmatrix}$$

and notice that $\vec{v}_1, \vec{v}_2, \vec{v}_3$ are eigenvectors for A . Let T_A be the transformation induced by A .

79.1 Find the eigenvalues of T_A .

79.2 Find the characteristic polynomial of T_A .

79.3 Compute $T_A \vec{w}$ where $w = 2\vec{v}_1 - \vec{v}_2$.

79.4 Compute $T_A \vec{u}$ where $\vec{u} = a\vec{v}_1 + b\vec{v}_2 + c\vec{v}_3$ for unknown scalar coefficients a, b, c .

Notice that $\mathcal{V} = \{\vec{v}_1, \vec{v}_2, \vec{v}_3\}$ is a basis for \mathbb{R}^3 .

79.5 If $[\vec{x}]_{\mathcal{V}} = \begin{bmatrix} 1 \\ 3 \\ 4 \end{bmatrix}$ is \vec{x} written in the \mathcal{V} basis, compute $T_A \vec{x}$ in the \mathcal{V} basis.

80 The matrix P^{-1} takes vectors in the standard basis and outputs vectors in their \mathcal{V} -basis representation. Here, A , T_A , and \mathcal{V} come from Problem 79.

80.1 Describe in words what P does.

80.2 Describe how you can use P and P^{-1} to compute $T_A \vec{y}$ for any $\vec{y} \in \mathbb{R}^3$.

80.3 Can you find a matrix D so that

$$PDP^{-1} = A?$$

80.4 $[\vec{x}]_{\mathcal{V}} = \begin{bmatrix} 1 \\ 3 \\ 4 \end{bmatrix}$. Compute $T_A^{100} \vec{x}$. Express your answer in both the \mathcal{V} basis and the standard basis.

Diagonalizable

DEF

A matrix is *diagonalizable* if it is similar to a diagonal matrix.

- 81 Let B be an $n \times n$ matrix and let T_B be the induced transformation. Suppose T_B has eigenvectors $\vec{v}_1, \dots, \vec{v}_n$ which form a basis for \mathbb{R}^n , and let $\lambda_1, \dots, \lambda_n$ be the corresponding eigenvalues.
- 81.1 How do the eigenvalues and eigenvectors of B and T_B relate?
- 81.2 Is B diagonalizable (i.e., similar to a diagonal matrix)? If so, explain how to obtain its diagonalized form.
- 81.3 What if one of the eigenvalues of T_B is zero? Would B be diagonalizable?
- 81.4 What if the eigenvectors of T_B did not form a basis for \mathbb{R}^n . Would B be diagonalizable?

Eigenspace

Let A be an $n \times n$ matrix with eigenvalues $\lambda_1, \dots, \lambda_m$. The **eigenspace** of A corresponding to the eigenvalue λ_i is the null space of $A - \lambda_i I$. That is, it is the space spanned by all eigenvectors that have the eigenvalue λ_i .

The **geometric multiplicity** of an eigenvalue λ_i is the dimension of the corresponding eigenspace. The **algebraic multiplicity** of λ_i is the number of times λ_i occurs as a root of the characteristic polynomial of A (i.e., the number of times $x - \lambda_i$ occurs as a factor).

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Let $F = \begin{bmatrix} 3 & 1 \\ 0 & 3 \end{bmatrix}$ and $G = \begin{bmatrix} 3 & 0 \\ 0 & 3 \end{bmatrix}$.

- 82.1 Is F diagonalizable? Why or why not?
- 82.2 Is G diagonalizable? Why or why not?
- 82.3 What are the geometric and algebraic multiplicities of each eigenvalue of F ? What about the multiplicities for each eigenvalue of G ?
- 82.4 Suppose A is a matrix where the geometric multiplicity of one of its eigenvalues is smaller than the algebraic multiplicity of the same eigenvalue. Is A diagonalizable? What if all the geometric and algebraic multiplicities match?