

# Announcements

Wednesday, September 20

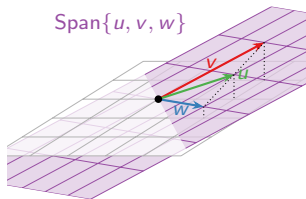
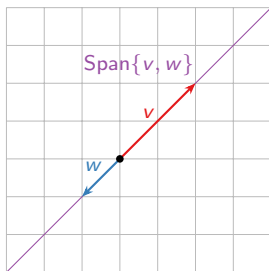
- ▶ **Quiz 3:** Come forward to pick up your exam
  
  
  
  
  
  
  
  
  
  
- ▶ **First time I was away of home:** Masters in Montreal
  - ▶ Life on campus was too expensive for me
  - ▶ I couldn't find people that I felt comfortable with (cultural clash)
  - ▶ School was ok, though I only took two courses
  - ▶ I didn't know how to ask my family for more attention
- ▶ Don't hesitate to **use the resources** on campus

# Section 1.7

## Linear Independence

# Motivation

Sometimes the *span* of a set of vectors “*is smaller*” than you expect from the number of vectors.



This “means” you *don't need so many vectors* to express the same set of vectors.

Today we will formalize this idea in the concept of *linear (in)dependence*.

# Linear Independence

## Definition

A set of vectors  $\{v_1, v_2, \dots, v_p\}$  in  $\mathbf{R}^n$  is **linearly independent** if the vector equation

$$x_1 v_1 + x_2 v_2 + \dots + x_p v_p = 0$$

has **only the trivial solution**  $x_1 = x_2 = \dots = x_p = 0$ .

The opposite:

The set  $\{v_1, v_2, \dots, v_p\}$  is *linearly dependent* if there exist numbers  $x_1, x_2, \dots, x_p$ , not all equal to zero, such that

$$x_1 v_1 + x_2 v_2 + \dots + x_p v_p = 0.$$

This is called a *linear dependence relation*.

# Linear Independence

## Definition

A set of vectors  $\{v_1, v_2, \dots, v_p\}$  in  $\mathbf{R}^n$  is **linearly independent** if the vector equation

$$x_1 v_1 + x_2 v_2 + \dots + x_p v_p = 0$$

has only the trivial solution  $x_1 = x_2 = \dots = x_p = 0$ . The set  $\{v_1, v_2, \dots, v_p\}$  is **linearly dependent** otherwise.

The notion of linear (in)dependence *applies to a collection of vectors*, not to a single vector, or to one vector in the presence of some others.

## Checking Linear Independence

Question: Is  $\left\{ \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}, \begin{pmatrix} 1 \\ -1 \\ 2 \end{pmatrix}, \begin{pmatrix} 3 \\ 1 \\ 4 \end{pmatrix} \right\}$  linearly independent?

## Checking Linear Independence

Question: Is  $\left\{ \begin{pmatrix} 1 \\ 1 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 \\ -1 \\ 2 \end{pmatrix}, \begin{pmatrix} 3 \\ 1 \\ 4 \end{pmatrix} \right\}$  linearly independent?

## Linear Independence and Matrix Columns

By definition,  $\{v_1, v_2, \dots, v_p\}$  is *linearly independent* if and only if the vector equation

$$x_1 v_1 + x_2 v_2 + \dots + x_p v_p = 0$$

has only the trivial solution. This holds *if and only if* the matrix equation

$$Ax = 0$$

has only the trivial solution, where  $A$  is the *matrix with columns*  $v_1, v_2, \dots, v_p$ :

$$A = \left( \begin{array}{c|c|c|c} | & | & & | \\ v_1 & v_2 & \cdots & v_p \\ | & | & & | \end{array} \right).$$

This is true if and only if the matrix  $A$  has *a pivot in each column*.



# Linear Dependence

## Criterion

If one of the vectors  $\{v_1, v_2, \dots, v_p\}$  is a linear combination of the other ones:

$$v_3 = 2v_1 - \frac{1}{2}v_2 + 6v_4$$

Then the vectors are linearly *dependent*:

Conversely, if the vectors are linearly dependent

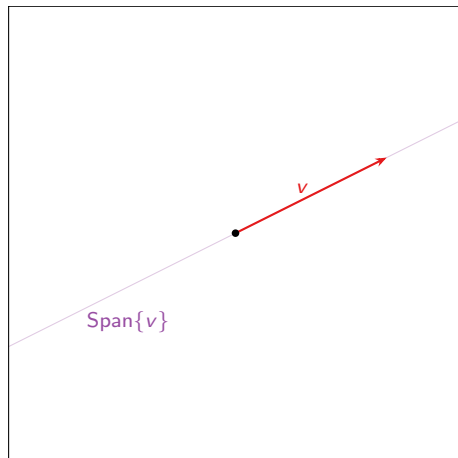
$$2v_1 - \frac{1}{2}v_2 + 6v_4 = 0,$$

## Theorem

A set of vectors  $\{v_1, v_2, \dots, v_p\}$  is **linearly dependent** if and only if *one* of the vectors is *in the span of the other* ones.

# Linear Independence

Pictures in  $\mathbb{R}^2$



In this picture

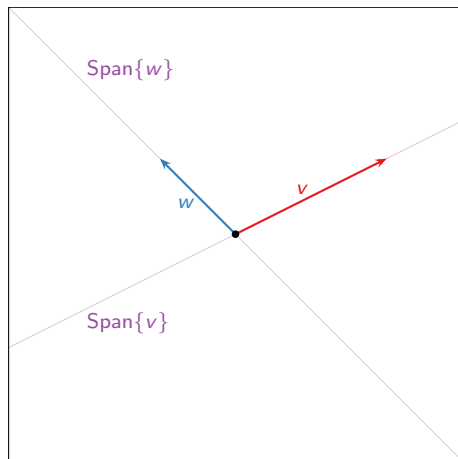
---

One vector  $\{v\}$ :

Linearly independent **if**  $v \neq 0$ .

# Linear Independence

Pictures in  $\mathbb{R}^2$



In this picture

---

One vector  $\{v\}$ :

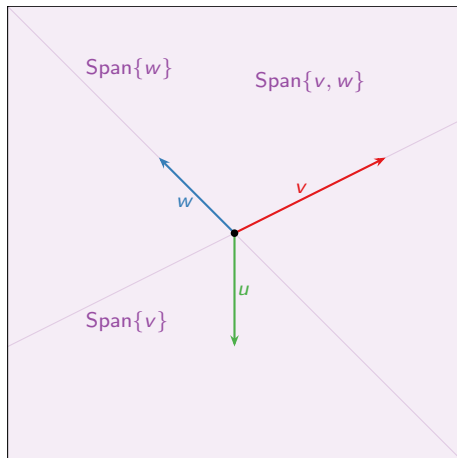
Linearly independent **if**  $v \neq 0$ .

Two vectors  $\{v, w\}$ :

Linearly independent: neither is in the span of the other.

# Linear Independence

Pictures in  $\mathbb{R}^2$



In this picture

---

One vector  $\{v\}$ :

Linearly independent **if**  $v \neq 0$ .

Two vectors  $\{v, w\}$ :

Linearly independent: neither is in the span of the other.

Three vectors  $\{v, w, u\}$ :

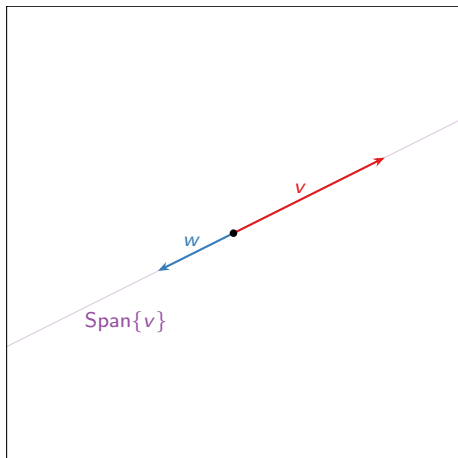
Linearly dependent:  $u$  is in  $\text{Span}\{v, w\}$ .

Also

$v$  is in  $\text{Span}\{u, w\}$  and  
 $w$  is in  $\text{Span}\{u, v\}$ .

# Linear Independence

Pictures in  $\mathbb{R}^2$

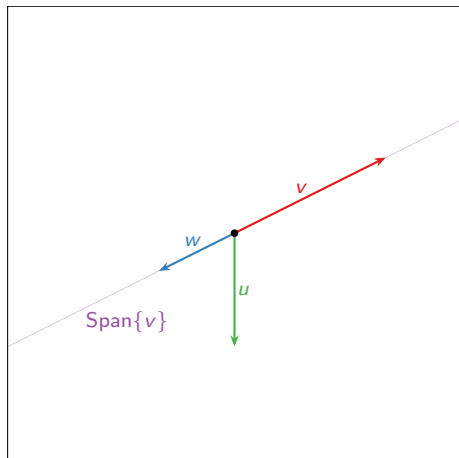


Two collinear vectors  $\{v, w\}$ :  
Linearly dependent:  $w$  is in  $\text{Span}\{v\}$  (and vice-versa).

- ▶ Two *vectors* are linearly **dependent** if and only if they are *collinear*.

# Linear Independence

Pictures in  $\mathbb{R}^2$



Two collinear vectors  $\{v, w\}$ :  
Linearly dependent:  $w$  is in  $\text{Span}\{v\}$  (and vice-versa).

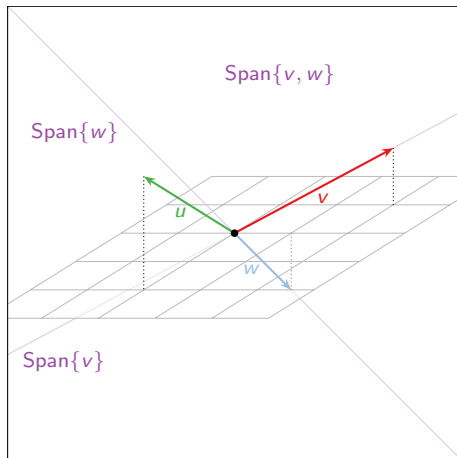
- ▶ Two *vectors* are linearly **dependent** if and only if they are *collinear*.

Three vectors  $\{v, w, u\}$ :  
Linearly dependent:  $w$  is in  $\text{Span}\{v\}$  (and vice-versa).

- ▶ If a *set of vectors* is linearly **dependent**, then so is *any larger set* of vectors!

# Linear Independence

Pictures in  $\mathbb{R}^3$



In this picture

---

Two vectors  $\{v, w\}$ :

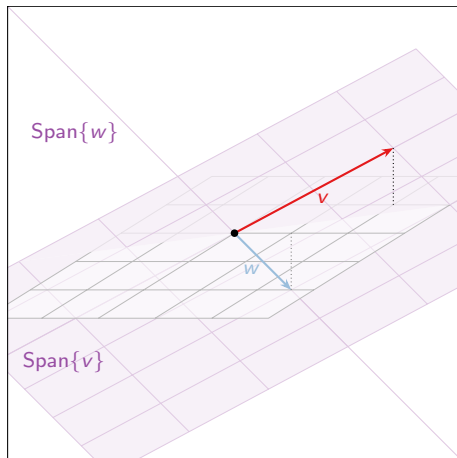
Linearly independent: neither is in the span of the other.

Three vectors  $\{v, w, u\}$ :

Linearly independent: no one is in the span of the other two.

# Linear Independence

Pictures in  $\mathbb{R}^3$



In this picture

---

Two vectors  $\{v, w\}$ :

Linearly independent: neither is in the span of the other.

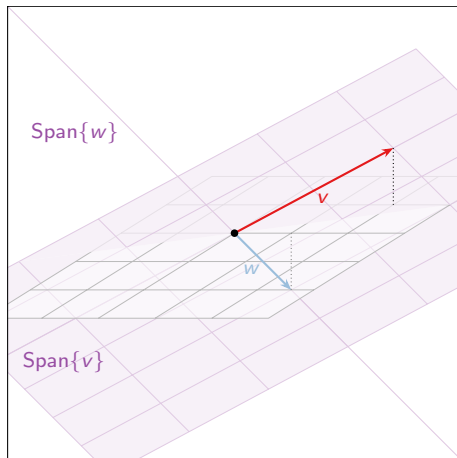
Three vectors  $\{v, w, x\}$ :

Linearly dependent:  $x$  is in  $\text{Span}\{v, w\}$ .



# Linear Independence

Pictures in  $\mathbb{R}^3$



In this picture

---

Two vectors  $\{v, w\}$ :

Linearly independent: neither is in the span of the other.

Three vectors  $\{v, w, x\}$ :

Linearly dependent:  $x$  is in  $\text{Span}\{v, w\}$ .

Which subsets are linearly dependent?

# Linear Dependence

## Stronger criterion

Suppose a set of vectors  $\{v_1, v_2, \dots, v_p\}$  is *linearly dependent*.

Take the **largest**  $j$  such that  $v_j$  *is in the span* of the others.

Is  $v_j$  is in the *span* of  $v_1, v_2, \dots, v_{j-1}$ ?

For example,  $j = 3$  and

$$v_3 = 2v_1 - \frac{1}{2}v_2 + 6v_4$$

Rearrange:

## Better Theorem

A set of vectors  $\{v_1, v_2, \dots, v_p\}$  is **linearly dependent** if and only if there is some  $j$  such that  $v_j$  *is in Span* $\{v_1, v_2, \dots, v_{j-1}\}$ .

# Linear Independence

## Increasing span criterion

If the vector  $v_j$  **is not in**  $\text{Span}\{v_1, v_2, \dots, v_{j-1}\}$ ,

it means  $\text{Span}\{v_1, v_2, \dots, v_j\}$  *is bigger* than  $\text{Span}\{v_1, v_2, \dots, v_{j-1}\}$ .

If true for all  $j$

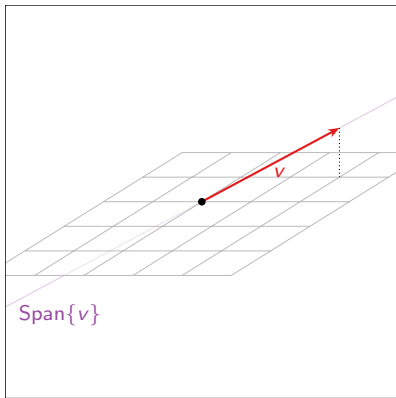
A set of vectors is linearly independent if and only if, every time *you add another vector* to the set, the *span gets bigger*.

# Linear Independence

Increasing span criterion: pictures

## Theorem

A set of vectors  $\{v_1, v_2, \dots, v_p\}$  is **linearly independent** if and only if, *for every*  $j$ , the *span of  $v_1, v_2, \dots, v_j$  is strictly larger* than the span of  $v_1, v_2, \dots, v_{j-1}$ .



One vector  $\{v\}$ :

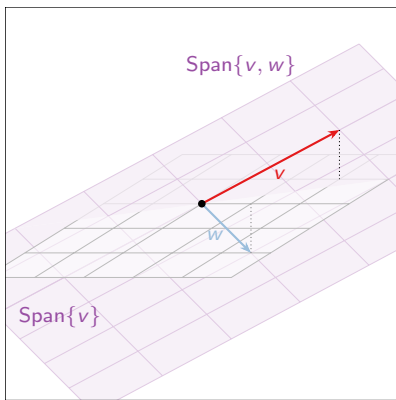
Linearly independent: span got bigger (than  $\{0\}$ ).

# Linear Independence

Increasing span criterion: pictures

## Theorem

A set of vectors  $\{v_1, v_2, \dots, v_p\}$  is **linearly independent** if and only if, *for every  $j$ , the span of  $v_1, v_2, \dots, v_j$  is strictly larger* than the span of  $v_1, v_2, \dots, v_{j-1}$ .



One vector  $\{v\}$ :

Linearly independent: span got bigger (than  $\{0\}$ ).

Two vectors  $\{v, w\}$ :

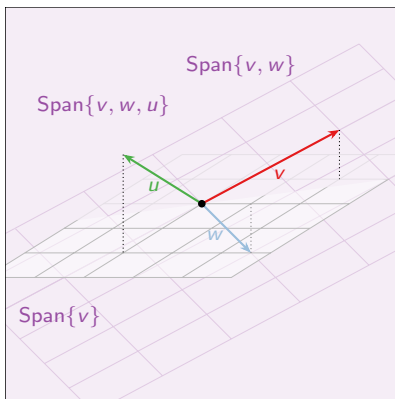
Linearly independent: span got bigger.

# Linear Independence

Increasing span criterion: pictures

## Theorem

A set of vectors  $\{v_1, v_2, \dots, v_p\}$  is **linearly independent** if and only if, *for every  $j$ , the **span of  $v_1, v_2, \dots, v_j$  is strictly larger** than the span of  $v_1, v_2, \dots, v_{j-1}$ .*



One vector  $\{v\}$ :

Linearly independent: span got bigger (than  $\{0\}$ ).

Two vectors  $\{v, w\}$ :

Linearly independent: span got bigger.

Three vectors  $\{v, w, u\}$ :

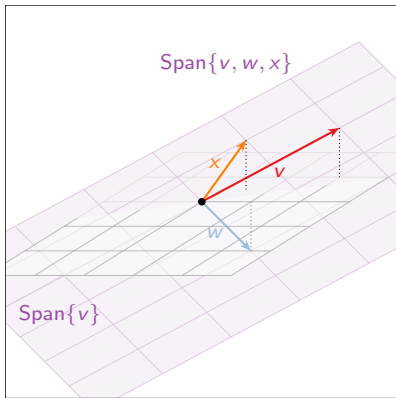
Linearly independent: span got bigger.

# Linear Independence

Increasing span criterion: pictures

## Theorem

A set of vectors  $\{v_1, v_2, \dots, v_p\}$  is **linearly independent** if and only if, *for every  $j$ , the span of  $v_1, v_2, \dots, v_j$  is strictly larger* than the span of  $v_1, v_2, \dots, v_{j-1}$ .



One vector  $\{v\}$ :

Linearly independent: span got bigger (than  $\{0\}$ ).

Two vectors  $\{v, w\}$ :

Linearly independent: span got bigger.

Three vectors  $\{v, w, x\}$ :

Linearly dependent: span didn't get bigger.



## Extra: Linear Independence

Two more facts

**Fact 1:** Say  $v_1, v_2, \dots, v_n$  are in  $\mathbf{R}^m$ . If  $n > m$  then  $\{v_1, v_2, \dots, v_n\}$  is *linearly dependent*.

A wide matrix can't have linearly independent columns.

**Fact 2:** If *one* of  $v_1, v_2, \dots, v_n$  *is zero*, then  $\{v_1, v_2, \dots, v_n\}$  is *linearly dependent*.

A set containing the zero vector is linearly dependent.

# Section 1.8

## Introduction to Linear Transformations

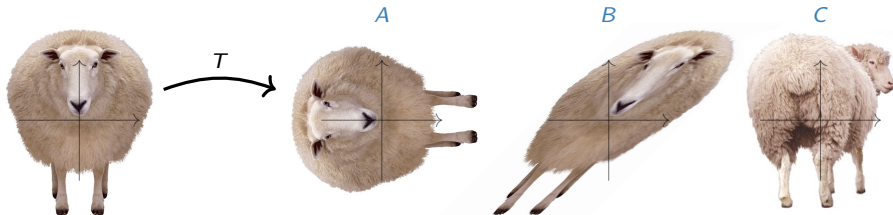
# Motivation

Let  $A$  be an  $m \times n$  matrix. For  $Ax = b$  we can describe

- ▶ the **solution set**: all  $x$  in  $\mathbf{R}^n$  making the **equation true**.
- ▶ the *column span*: the set of all  $b$  in  $\mathbf{R}^m$  making the *equation consistent*.

It turns out these two sets are *very closely related* to each other.

**Geometry matrices**: *linear transformation* from  $\mathbf{R}^n$  to  $\mathbf{R}^m$ .



# Transformations

## Definition

A **transformation** (or **function** or **map**) from  $\mathbf{R}^n$  to  $\mathbf{R}^m$  is a rule  $T$  that assigns to each vector  $x$  in  $\mathbf{R}^n$  a vector  $T(x)$  in  $\mathbf{R}^m$ .

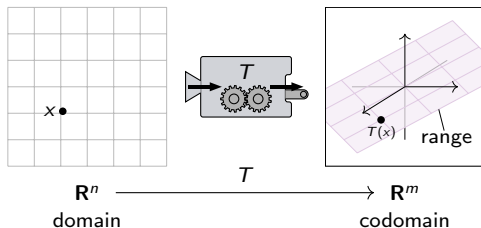
- ▶ For  $x$  in  $\mathbf{R}^n$ , the vector  $T(x)$  in  $\mathbf{R}^m$  is the **image** of  $x$  under  $T$ .

**Notation:**  $x \mapsto T(x)$ .

- ▶ The set of all images  $\{T(x) \mid x \text{ in } \mathbf{R}^n\}$  is the **range** of  $T$ .

**Notation:**

$T: \mathbf{R}^n \longrightarrow \mathbf{R}^m$  means  $T$  is a transformation from  $\mathbf{R}^n$  to  $\mathbf{R}^m$ .



Think of  $T$  as a *“machine”*

- ▶ takes  $x$  as an input
- ▶ *gives you*  $T(x)$  as the output.

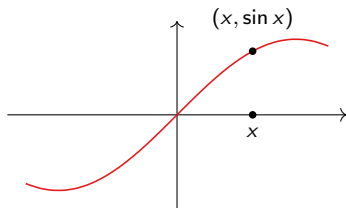
# Functions from Calculus

Many of the functions you know have domain and codomain  $\mathbf{R}$ .

$$\text{For example, } f: \mathbf{R} \longrightarrow \mathbf{R} \quad f(x) = x^2$$

Often times *we omit the name  $f(x)$  of the function “ $x^2$ ”*.

You may be used to thinking of a function in terms of its graph. E.g.,



The horizontal axis is the *domain*, and the vertical axis is the *codomain*.

This is fine when the domain and codomain are  $\mathbf{R}$ , but **it's hard to do when they're  $\mathbf{R}^2$  and  $\mathbf{R}^3$ !**

# Matrix Transformations

## Definition

Let  $A$  be an  $m \times n$  matrix. The **matrix transformation** associated to  $A$  is the transformation

$$T: \mathbf{R}^n \longrightarrow \mathbf{R}^m \quad \text{defined by} \quad T(x) = Ax.$$

In other words,  $T$  takes the vector  $x$  in  $\mathbf{R}^n$  to the vector  $Ax$  in  $\mathbf{R}^m$ .

- ▶ The **domain** of  $T$  is  $\mathbf{R}^n$ , which is the number of **columns** of  $A$ .
- ▶ The **codomain** of  $T$  is  $\mathbf{R}^m$ , which is the number of **rows** of  $A$ .
- ▶ The **range** of  $T$  is the set of all images of  $T$ :

$$T(x) = Ax = \begin{pmatrix} | & | & & | \\ v_1 & v_2 & \cdots & v_n \\ | & | & & | \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix} = x_1 v_1 + x_2 v_2 + \cdots + x_n v_n.$$

This is the **column span of  $A$** . It is a *span of vectors in the codomain*.

# Matrix Transformations

## Example

Let  $A = \begin{pmatrix} 1 & 1 \\ 0 & 1 \\ 1 & 1 \end{pmatrix}$  and let  $T(x) = Ax$ , so  $T: \mathbf{R}^2 \rightarrow \mathbf{R}^3$ .

► If  $u = \begin{pmatrix} 3 \\ 4 \end{pmatrix}$  then  $T(u) =$

► Let  $b = \begin{pmatrix} 7 \\ 5 \\ 7 \end{pmatrix}$ . Find  $v$  in  $\mathbf{R}^2$  such that  $T(v) = b$ . Is there more than one?

# Matrix Transformations

Example, continued

Let  $A = \begin{pmatrix} 1 & 1 \\ 0 & 1 \\ 1 & 1 \end{pmatrix}$  and let  $T(x) = Ax$ , so  $T: \mathbf{R}^2 \rightarrow \mathbf{R}^3$ .

- ▶ Is there any  $c$  in  $\mathbf{R}^3$  such that there is more than one  $v$  in  $\mathbf{R}^2$  with  $T(v) = c$ ?
- ▶ Find  $c$  such that there is *no*  $v$  with  $T(v) = c$ .



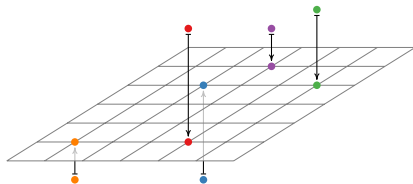
# Matrix Transformations

## Projection

Let  $A = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{pmatrix}$  and let  $T(x) = Ax$ , so  $T: \mathbf{R}^3 \rightarrow \mathbf{R}^3$ . Then

$$T \begin{pmatrix} x \\ y \\ z \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} x \\ y \\ z \end{pmatrix} = \begin{pmatrix} x \\ y \\ 0 \end{pmatrix}.$$

This is *projection onto the  $xy$ -axis*. Picture:



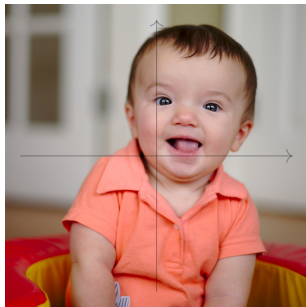
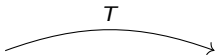
# Matrix Transformations

## Reflection

Let  $A = \begin{pmatrix} -1 & 0 \\ 0 & 1 \end{pmatrix}$  and let  $T(x) = Ax$ , so  $T: \mathbf{R}^2 \rightarrow \mathbf{R}^2$ . Then

$$T \begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} -1 & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} -x \\ y \end{pmatrix}.$$

This is *reflection over the y-axis*. Picture:



Let  $A = \begin{pmatrix} 1 & 1 \\ 0 & 1 \end{pmatrix}$  and let  $T(x) = Ax$ , so  $T: \mathbf{R}^2 \rightarrow \mathbf{R}^2$ . ( $T$  is called a **shear**.)

# Linear Transformations

**Recall:** If  $A$  is a matrix,  $u, v$  are vectors, and  $c$  is a scalar, then

$$A(u + v) = Au + Av \quad A(cv) = cAv.$$

So if  $T(x) = Ax$  is a matrix transformation then,

$$T(u + v) = T(u) + T(v) \quad T(cv) = cT(v).$$

## Definition

A transformation  $T: \mathbf{R}^n \rightarrow \mathbf{R}^m$  is **linear** if it satisfies the above equations for *all vectors*  $u, v$  in  $\mathbf{R}^n$  and *all scalars*  $c$ .

In other words,  $T$  **“respects” addition and scalar multiplication.**

More generally, (in engineering this is called **superposition**)

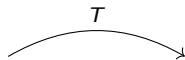
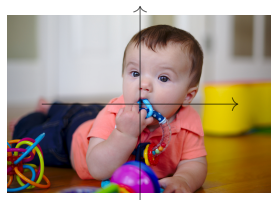
$$T(c_1 v_1 + c_2 v_2 + \cdots + c_n v_n) = c_1 T(v_1) + c_2 T(v_2) + \cdots + c_n T(v_n).$$

# Linear Transformations

## Dilation

Define  $T: \mathbf{R}^2 \rightarrow \mathbf{R}^2$  by  $T(x) = 1.5x$ . Is  $T$  linear?

This is called **dilation** or **scaling** (by a factor of 1.5). Picture:



# Linear Transformations

## Rotation

Define  $T: \mathbf{R}^2 \rightarrow \mathbf{R}^2$  by  $T \begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} -y \\ x \end{pmatrix}$ . Is  $T$  linear?

This is called **rotation** (by  $90^\circ$ ). Picture:

$$T \begin{pmatrix} 1 \\ 2 \end{pmatrix} = \begin{pmatrix} -2 \\ 1 \end{pmatrix}$$

$$T \begin{pmatrix} -1 \\ 1 \end{pmatrix} = \begin{pmatrix} -1 \\ -1 \end{pmatrix}$$

$$T \begin{pmatrix} 0 \\ -2 \end{pmatrix} = \begin{pmatrix} 2 \\ 0 \end{pmatrix}$$

