1.8-1.9 Matrices and Linear Transformations

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Linear Transformations and Matrices

If A is an $n \times m$ matrix, and x is any vector in $\mathbf{R}^m$, then Ax is a vector in $\mathbf{R}^n$.

So we can define a function $T : \mathbf{R}^m \to \mathbf{R}^n$ by

$$T(x) = Ax.$$

For example if

$$A = \begin{bmatrix} 0 & -4 \\ 4 & 1 \\ 3 & 3 \end{bmatrix} \text{ and } v = \begin{bmatrix} x \\ y \end{bmatrix}$$

then

$$T(v) = Av = \begin{bmatrix} -4y \\ 4x + y \\ 3x + 3y \end{bmatrix}$$

Function terminology

In general if $f : X \to Y$ is a function then f is a "rule" that associates exactly one element $y \in Y$ to each element $x \in X$. The y corresponding to x is called $f(x)$. Furthermore:

- X is called the domain of f
- Y is called the codomain of f
- the set of $y \in Y$ so that there is an $x \in X$ with $f(x) = y$ is called the *range* of f.
- if $f(x) = y$, then y is called the *image* of x under f.

If A is an $n \times m$ matrix, then the domain of $f(x) = Ax$ is $\mathbf{R}^m$ and the codomain is $\mathbf{R}^n$.

Examples of matrix transformations

If

$$A = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

then

$$A \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} x \\ y \\ 0 \end{bmatrix}$$

is called a *projection*, in this case onto the xy-plane.

Rotations in 2d

If

$$A(\theta) = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix}$$

then

$$A(\theta) \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} x\cos\theta - y\sin\theta \\ x\sin\theta + y\cos\theta \end{bmatrix}$$

rotates the vector (x, y) through an angle θ counterclockwise.

To see this, write $x = r\cos\phi$ and $y = r\sin\phi$. Then:

$$\begin{aligned} r\cos\phi\cos\theta - r\sin\phi\sin\theta &= r\cos(\phi+\theta) \\ r\cos\phi\sin\theta + r\sin\phi\cos\theta &= r\sin(\phi+\theta) \end{aligned}$$

Linear Transformations

Let $T : \mathbf{R}^m \to \mathbf{R}^n$ be a function. Then T is called a *linear transformation* if

- $T(ax) = aT(x)$ for every scalar a, and
- $T(x+y) = T(x) + T(y)$ for any two vectors $x, y \in \mathbf{R}^m$.

Any matrix transformation $T(x) = Ax$, where A is $n \times m$, is linear.

If T is linear, then $T(0) = 0$ (because $T(0x) = 0T(x) = 0$.)

Linear Transformations

Let

$$T(x) = \begin{bmatrix} 1 & 0 & -2 \\ -2 & 1 & 6 \\ 3 & -2 & -5 \end{bmatrix} x.$$

Find a vector x so that $T(x) = b$ and determine if this x is unique.

Hint: The rref form for the augmented matrix $[A \quad b]$ is

$$\begin{bmatrix} 1 & 0 & 0 & 3 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 2 \end{bmatrix}$$

Another problem

Let

$$T(x) = \begin{bmatrix} 1 & -2 & 1 \\ 3 & -4 & 5 \\ 0 & 1 & 1 \\ -3 & 5 & -4 \end{bmatrix} x.$$

Find a vector x so that $T(x) = b$ and determine if this x is unique.

Hint: The rref form for the augmented matrix $[A \quad b]$ is

$$\begin{bmatrix} 1 & 0 & 3 & 7 \\ 0 & 1 & 1 & 3 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

Linear Transformations

If $T : \mathbf{R}^m \to \mathbf{R}^n$\$ is linear, and $v_1, \ldots, v_k$ are vectors in $\mathbf{R}^m$, then if you know

$$T(v_1), \ldots, T(v_k)$$

you know

$$T(a_1 v_1 + \cdots + a_k v_k)$$

for any constants a_i. In other words, you can compute T for any vector in the span of $v_1, \ldots, v_k$.

Linear Transformations

In particular if

$$T(\begin{bmatrix} 1 \\ 0 \end{bmatrix}) = \begin{bmatrix} a \\ b \end{bmatrix}$$

and

$$T(\begin{bmatrix} 0 \\ 1 \end{bmatrix}) = \begin{bmatrix} c \\ d \end{bmatrix}$$

then

$$T(\begin{bmatrix} x \\ y \end{bmatrix}) = T(x \begin{bmatrix} 1 \\ 0 \end{bmatrix} + y \begin{bmatrix} 0 \\ 1 \end{bmatrix}) = xT(\begin{bmatrix} 1 \\ 0 \end{bmatrix}) + yT(\begin{bmatrix} 0 \\ 1 \end{bmatrix}) = \begin{bmatrix} ax + cy \\ bx + dy \end{bmatrix}$$

and $T(x) = Ax$ where

$$A = \begin{bmatrix} a & c \\ b & d \end{bmatrix}$$

Matrices and Linear Transformations

We have seen that, given a matrix A, then $T(x) = Ax$ is a linear transformation.

Now suppose $T : \mathbf{R}^m \to \mathbf{R}^n$ is a linear transformation.

Let $e_i \in \mathbf{R}^m$ be the vector

$$e_i = \begin{bmatrix} 0 \\ \vdots \\ 1 \\ \vdots \\ 0 \end{bmatrix}$$

where the 1 is in row i of e_i.

Matrices and Linear Transformations

Let

$$A(T) = [T(e_1) \quad T(e_2) \cdots T(e_m))]$$

whose columns are the $T(e_i)$. This is an $n \times m$ matrix because each $T(e_i) \in \mathbf{R}^n$.

Notice that $Ae_i = T(e_i)$ for $i = 1, \ldots, m$. As a result, by linearlity, $Av = T(v)$ for any vector $v \in \mathbf{R}^m$.

Therefore *every linear transformation comes from multiplication by a matrix.*

The identity map

The map $T : \mathbf{R}^m \to \mathbf{R}^m$ given by $Tx = x$ is called the identity map.

Since $T(e_i) = e_i$ for $i = 1, \dots, m$ the matrix of T is the $m \times m$ matrix with 1's on the diagonal and zeros elsewhere.

$$\begin{bmatrix} 1 & 0 & 0 & \cdots & 0 \\ 0 & 1 & 0 & \cdots & 0 \\ 0 & 0 & \ddots & 1 & 0 \\ 0 & 0 & \cdots & 0 & 1 \end{bmatrix}$$

Matrices and Linear Transformations

If $T : \mathbf{R}^m \to \mathbf{R}^n$ is linear, then T is determined by what it does to the standard basis vectors e_i.

For example, if $m = n = 2$, and T is the reflection map $T(x, y) = (y, x)$, then $T(e_1) = e_2$ and $T(e_2) = e_1$ and therefore $Tx = Ax$ where

$$A = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}.$$

Reflections

TABLE 1 Reflections

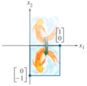
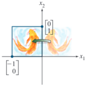
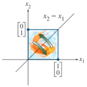
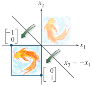
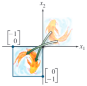
Transformation	Image of the Unit Square	Standard Matrix
Reflection through the x_1-axis		$\begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}$
Reflection through the x_2-axis		$\begin{bmatrix} -1 & 0 \\ 0 & 1 \end{bmatrix}$
Reflection through the line $x_2 = x_1$		$\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$
Reflection through the line $x_2 = -x_1$		$\begin{bmatrix} 0 & -1 \\ -1 & 0 \end{bmatrix}$
Reflection through the origin		$\begin{bmatrix} -1 & 0 \\ 0 & -1 \end{bmatrix}$

Figure 1: reflections

Shears

TABLE 3 Shears

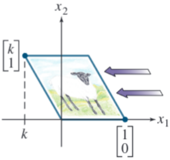
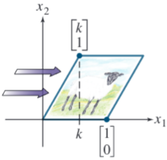
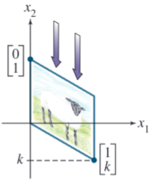
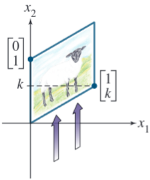
Transformation	Image of the Unit Square		Standard Matrix
Horizontal shear	 $k < 0$	 $k > 0$	$\begin{bmatrix} 1 & k \\ 0 & 1 \end{bmatrix}$
Vertical shear	 $k < 0$	 $k > 0$	$\begin{bmatrix} 1 & 0 \\ k & 1 \end{bmatrix}$

Figure 2: shears

Contractions/Expansions

TABLE 2 Contractions and Expansions

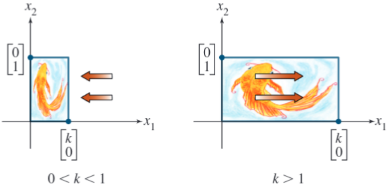
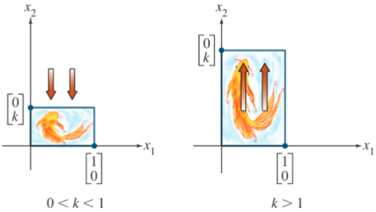
<table>
<tr><th>Transformation</th><th>Image of the Unit Square</th><th>Standard Matrix</th></tr>
<tr><td>Horizontal contraction and expansion</td><td>
</td><td>$\begin{bmatrix} k & 0 \\ 0 & 1 \end{bmatrix}$</td></tr>
<tr><td>Vertical contraction and expansion</td><td>
</td><td>$\begin{bmatrix} 1 & 0 \\ 0 & k \end{bmatrix}$</td></tr>
</table>

Figure 3: contractions and expansions

Projections

TABLE 4 **Projections**

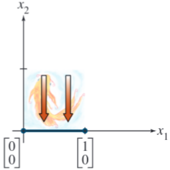
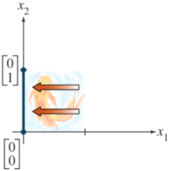
Transformation	Image of the Unit Square	Standard Matrix
Projection onto the x_1-axis		$\begin{bmatrix}1 & 0\\0 & 0\end{bmatrix}$
Projection onto the x_2-axis		$\begin{bmatrix}0 & 0\\0 & 1\end{bmatrix}$

Figure 4: projections

One-to-one and onto maps

A function $T : A \to B$ is *one-to-one* if the only way that $T(x) = T(y)$ is if $x = y$.

Eg the function $f(x) = x^2$ is *not* one-to-one, because $f(-1) = f(1)$ even though $-1 \neq 1$. But the function $f(x) = 3x$ is one-to-one, because if $3x = 3y$ then x and y must be equal.

A function $T : A \to B$ is *onto* if, for any $b \in B$, there is an $a \in A$ so that $T(a) = b$.

The function $f(x) = x^2$ is not *onto*, because the equation $-1 = x^2$ does not have a solution (at least in real numbers.) The function $f(x) = 3x$ is *onto*, because the equation $y = 3x$ always has a solution ($x = y/3$).

One-to-one linear maps

If T is linear, then $T(x) = T(y)$ if and only if $T(x) - T(y) = T(x - y) = 0$. So T is one-to-one if the only solution to $T(v) = 0$ is $v = 0$.

Since T comes from a matrix A, the map is one-to-one if and only if the matrix equation $Ax = 0$ has only zero as its solution.

This happens if and only if *the columns of A are linearly independent.*

Onto linear maps

If $T : \mathbf{R}^m \to \mathbf{R}^n$ is linear, then $T(x)$ is onto if only if $T(x) = b$ has a solution for any $b \in \mathbf{R}^n$. This means that the matrix equation

$$Ax = b$$

has a solution for any $b \in \mathbf{R}^n$.

Since Ax is a linear combination of the columns of A, every equation $Ax = b$ has a solution only if every b is a linear combination of the columns of A. In other words, A is onto if and only if the columns of A span $\mathbf{R}^n$.

Theorem 12

Theorem 12 in the book summarizes these two key facts.

Theorem: Let $T(x) = Ax$ be a linear map from $\mathbf{R}^m$ to $\mathbf{R}^n$, where A is an $n \times m$ matrix.

1. T is one-to-one if and only if the columns of A are linearly independent vectors in $\mathbf{R}^n$.
2. T is onto if and only if the columns of A span $\mathbf{R}^n$.

Algebraic version

Algebraically:

1. $T(x) = Ax$ is one-to-one if and only if the rref of A has no free variables - in other words, if every column has a pivot.
2. $T(x) = Ax$ is onto if and only if every row of A has a pivot.

Note that if A is an $n \times m$ matrix, then:

- if $m > n$, the map cannot be one-to-one.
- if $n > m$, the map cannot be onto.