

LINEAR TRANSFORMATIONS

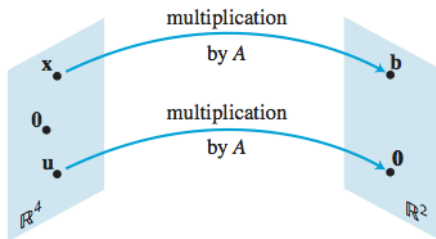
- Linear transformations
- Eigenvectors and eigenvalues

- Equation $\mathbf{Ax} = \mathbf{b}$ can be regarded as a function:

Matrix $\mathbf{A}$ *acts* on $\mathbf{x}$, producing a new vector $\mathbf{b}$
(analogous to an action of a function $y = f(x)$)

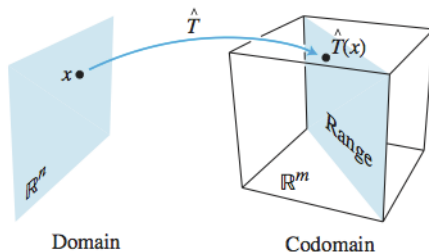
- So, left-multiplication by $\mathbf{A}$ *transforms* $\mathbf{x}$ into $\mathbf{b}$

The resulting correspondence between $\mathbf{x}$ and $\mathbf{b}$
is a *mapping* from one set of vectors to another



Definition: Transformation (mapping, function) $\hat{T}$ from V onto W is a rule assigning element $\hat{T}(\mathbf{x}) = \mathbf{y} \in W$ to each element $\mathbf{x} \in V$

- The usual notation is: $\hat{T} : V \mapsto W$
- V is called the **domain**, and W the **codomain** of $\hat{T}$
- Vector $\mathbf{y} = \hat{T}(\mathbf{x})$ is called the **image** of $\mathbf{x}$
- The set of all images $\{\hat{T}(\mathbf{x})\}$ is called the **range** of $\hat{T}$



Picture:

$$V = \mathbb{R}^n$$

$$W = \mathbb{R}^m$$

Definition:

Transformation $\hat{T}$ is **linear** if: $\forall \mathbf{u}, \mathbf{v}$ in the domain of $\hat{T}$

$$(i) \quad \hat{T}(\mathbf{u} + \mathbf{v}) = \hat{T}(\mathbf{u}) + \hat{T}(\mathbf{v})$$

$$(ii) \quad \hat{T}(c\mathbf{u}) = c\hat{T}(\mathbf{u}) \quad \forall c \in \mathbb{R}$$

Properties:

If $\hat{T}$ is a linear transformation, then

- $\hat{T}(\mathbf{0}) = \mathbf{0}$ (proof: $\hat{T}(\mathbf{0}) = \hat{T}(0 \cdot \mathbf{0}) = 0 \cdot \hat{T}(\mathbf{0}) = \mathbf{0}$)
- $\hat{T}(c\mathbf{u} + d\mathbf{v}) = c\hat{T}(\mathbf{u}) + d\hat{T}(\mathbf{v})$ (follows from (i) and (ii))

Note: Generally, a linear transformation is often called a linear operator

If $\mathbf{A}$ is an $m \times n$ matrix, $\hat{T}(\mathbf{x}) = \mathbf{A}\mathbf{x}$ is a linear transformation.

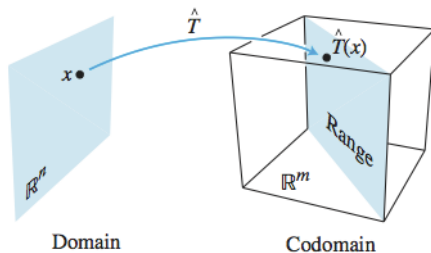
Proof: given that $\mathbf{A}\mathbf{x} = x_1\mathbf{a}_1 + \dots + x_n\mathbf{a}_n$

$$\begin{aligned}\hat{T}(\mathbf{x} + \mathbf{y}) &= (x_1 + y_1)\mathbf{a}_1 + \dots + (x_n + y_n)\mathbf{a}_n \\ &= x_1\mathbf{a}_1 + \dots + x_n\mathbf{a}_n + y_1\mathbf{a}_1 + \dots + y_n\mathbf{a}_n = \hat{T}(\mathbf{x}) + \hat{T}(\mathbf{y})\end{aligned}$$

$$\begin{aligned}\hat{T}(c\mathbf{x}) &= (cx_1)\mathbf{a}_1 + \dots + (cx_n)\mathbf{a}_n \\ &= c(x_1\mathbf{a}_1 + \dots + x_n\mathbf{a}_n) = c\hat{T}(\mathbf{x})\end{aligned}$$

Thus $\hat{T}(\mathbf{x} + \mathbf{y}) = \hat{T}(\mathbf{x}) + \hat{T}(\mathbf{y})$ and $\hat{T}(c\mathbf{x}) = c \cdot \hat{T}(\mathbf{x})$
so $\hat{T} = \mathbf{A}\mathbf{x}$ is a linear transformation, by definition.

- For $\mathbf{x} \in \mathbb{R}^n$, a linear transformation $\hat{T}(\mathbf{x})$ into $\mathbb{R}^m$ can be computed as $\mathbf{Ax}$ where $\mathbf{A}$ is an $m \times n$ matrix.
- If the domain of $\hat{T}$ is $\mathbb{R}^n$ then $\mathbf{A}$ has n columns, and if the codomain of $\hat{T}$ is $\mathbb{R}^m$ then $\mathbf{A}$ has m rows.
- The range of $\hat{T}$ is $\text{Span}\{\mathbf{a}_1 \dots \mathbf{a}_n\}$ and image of $\mathbf{x}$ is $\mathbf{Ax}$.



Example 1: image of $\mathbf{u}$ obtained with $\mathbf{A}$:

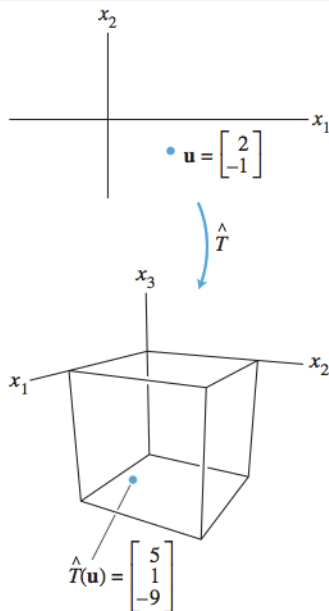
$$\mathbf{A} = \begin{bmatrix} 1 & -3 \\ 3 & 5 \\ -1 & 7 \end{bmatrix}, \quad \mathbf{u} = \begin{bmatrix} 2 \\ -1 \end{bmatrix}$$

This is a $\hat{T} : \mathbb{R}^2 \mapsto \mathbb{R}^3$ transformation:

$$\hat{T}(\mathbf{u}) = \mathbf{A}\mathbf{u} = \begin{bmatrix} 5 \\ 1 \\ -9 \end{bmatrix}$$

This can be also written in functional form:

$$\hat{T}(\mathbf{x}) = \begin{bmatrix} x_1 - 3x_2 \\ 3x_1 + 5x_2 \\ -x_1 + 7x_2 \end{bmatrix}$$



Example 2: Let $\hat{T}(x_1, x_2) = ((2x_1 - 3x_2); (x_1 + 4); (5x_2))$.

Show that the above $\hat{T}$ is *not a linear* transformation:

$$\hat{T}(x_1, x_2) = \begin{bmatrix} 2x_1 - 3x_2 \\ x_1 + 4 \\ 5x_2 \end{bmatrix} = \begin{bmatrix} 2 & -3 \\ 1 & 0 \\ 0 & 5 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 0 \\ 4 \\ 0 \end{bmatrix}$$

Thus $\hat{T}(\mathbf{x}) = \mathbf{Ax} + \mathbf{q}$ where

$$\mathbf{A} = \begin{bmatrix} 2 & -3 \\ 1 & 0 \\ 0 & 5 \end{bmatrix} \quad \text{and} \quad \mathbf{q} = \begin{bmatrix} 0 \\ 4 \\ 0 \end{bmatrix}$$

If $\hat{T}$ were a linear transformation, then $\hat{T}(\mathbf{0}) = \mathbf{0}$

However, here $\hat{T}(\mathbf{0}) = \mathbf{q} \neq \mathbf{0}$

Therefore, it is not a linear transformation.

Example 3: $\mathbf{T} = \begin{bmatrix} 1 & -3 \\ 3 & 5 \\ -1 & 7 \end{bmatrix}$, $\mathbf{b} = \begin{bmatrix} 3 \\ 2 \\ -5 \end{bmatrix}$, $\hat{T}(\mathbf{x}) = \mathbf{T}\mathbf{x}$.

To find $\mathbf{x}$ such that $\hat{T}(\mathbf{x}) = \mathbf{b}$ we need to solve the system:

$$\left[\begin{array}{cc|c} 1 & -3 & 3 \\ 3 & 5 & 2 \\ -1 & 7 & -5 \end{array} \right] \rightarrow \left[\begin{array}{cc|c} 1 & 0 & 3/2 \\ 0 & 1 & -1/2 \\ 0 & 0 & 0 \end{array} \right]$$

So $x_1 = \frac{3}{2}$, $x_2 = -\frac{1}{2}$ and thus $\mathbf{b}$ is the image of $\mathbf{x} = \begin{bmatrix} 1.5 \\ -0.5 \end{bmatrix}$

A unique solution implies only one $\mathbf{x}$ with the image $\mathbf{b}$.

We have also verified that $\mathbf{b}$ is in the range of $\hat{T}$.

Example 4: $\mathbf{T} = \begin{bmatrix} 1 & -3 \\ 3 & 5 \\ -1 & 7 \end{bmatrix}$, $\mathbf{c} = \begin{bmatrix} 3 \\ 2 \\ 5 \end{bmatrix}$, $\widehat{T}(\mathbf{x}) = \mathbf{T}\mathbf{x}$.

Determine whether or not $\mathbf{c}$ is in the range of transformation $\widehat{T}$.

Vector $\mathbf{c}$ is in the range of $\widehat{T}(\mathbf{x})$ if $\mathbf{c}$ is an image of some $\mathbf{x} \in \mathbb{R}^2$.

Solving the system $\mathbf{T}\mathbf{x} = \mathbf{c}$ gives

$$\left[\begin{array}{cc|c} 1 & -3 & 3 \\ 3 & 5 & 2 \\ -1 & 7 & 5 \end{array} \right] \rightarrow \left[\begin{array}{cc|c} 1 & -3 & 3 \\ 0 & 1 & 1/2 \\ 0 & 0 & 10 \end{array} \right]$$

The system is inconsistent and thus $\mathbf{c}$ is **not** in the range of $\widehat{T}$.

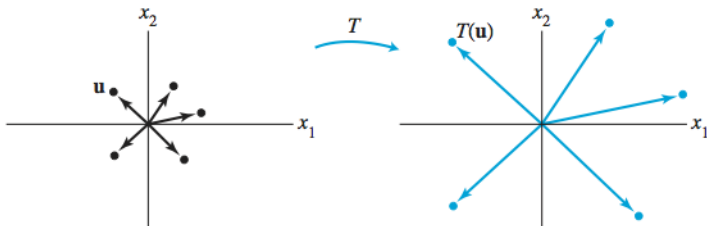
There are no vectors in $\mathbb{R}^2$ with an image $\mathbf{c}$ under $\widehat{T}$.

Example: Let $\hat{T} : \mathbb{R}^2 \mapsto \mathbb{R}^2$, $\hat{T}(\mathbf{x}) = r \mathbf{x}$, where $r \in \mathbb{R}$.

Show that this is a linear transformation:

$$\hat{T}(c \mathbf{u} + d \mathbf{v}) = r(c \mathbf{u} + d \mathbf{v}) = c(r \mathbf{u}) + d(r \mathbf{v}) = c \hat{T}(\mathbf{u}) + d \hat{T}(\mathbf{v}).$$

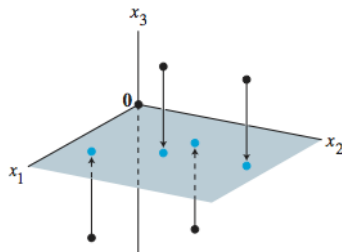
$\hat{T}$ is called a *scaling* (or dilation) transformation:



Example:

$$\mathbf{O}_{12} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

Action of this matrix on $\mathbf{x} \in \mathbb{R}^3$ is



$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \mapsto \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} x_1 \\ x_2 \\ 0 \end{bmatrix}$$

This transformation projects points of $\mathbb{R}^3$ onto a plane.

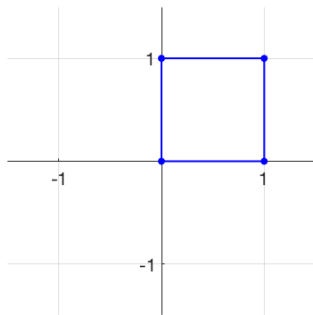
This is an example of *projection* transformation.

Note: this is still a $\mathbb{R}^3$ onto $\mathbb{R}^3$ transformation; its domain is $\mathbb{R}^3$ and codomain is $\mathbb{R}^3$, but the range is a plane within $\mathbb{R}^3$.

A convenient way to visualise transformations in $\mathbb{R}^2$ is to depict their action on a unit square: a square made by vectors

$$\begin{bmatrix} 0 \\ 1 \end{bmatrix} \quad \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

$$\begin{bmatrix} 0 \\ 0 \end{bmatrix} \quad \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

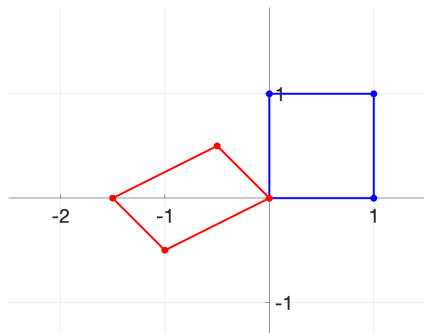


Plotting the resulting points and connecting these with lines (transformation is linear) shows how the shape is changed.

Example: illustrate linear transformation given by $\begin{bmatrix} -1 & -0.5 \\ -0.5 & 0.5 \end{bmatrix}$

$$\begin{bmatrix} -1 & -0.5 \\ -0.5 & 0.5 \end{bmatrix} \begin{bmatrix} 0 \\ 1 \end{bmatrix} = \begin{bmatrix} -0.5 \\ 0.5 \end{bmatrix}$$

$$\begin{bmatrix} -1 & -0.5 \\ -0.5 & 0.5 \end{bmatrix} \begin{bmatrix} 1 \\ 0 \end{bmatrix} = \begin{bmatrix} -1 \\ -0.5 \end{bmatrix}$$

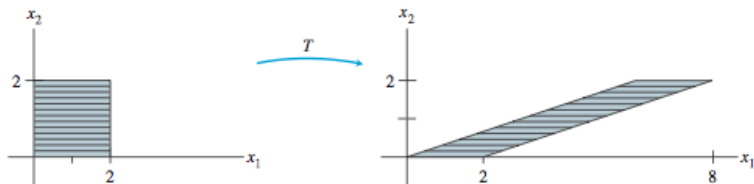


$$\begin{bmatrix} -1 & -0.5 \\ -0.5 & 0.5 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \end{bmatrix} \Rightarrow \begin{bmatrix} -1.5 \\ 0 \end{bmatrix} \Leftarrow \begin{bmatrix} -1 \\ -0.5 \end{bmatrix} + \begin{bmatrix} -0.5 \\ 0.5 \end{bmatrix}$$

Example: transformation with $\mathbf{T} = \begin{bmatrix} 1 & 3 \\ 0 & 1 \end{bmatrix}$ of a 2×2 square

$$\begin{bmatrix} 1 & 3 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 2 \\ 0 \end{bmatrix} = \begin{bmatrix} 2 \\ 0 \end{bmatrix}, \quad \begin{bmatrix} 1 & 3 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 2 \\ 2 \end{bmatrix} = \begin{bmatrix} 8 \\ 2 \end{bmatrix}$$

$$\begin{bmatrix} 1 & 3 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 0 \\ 2 \end{bmatrix} = \begin{bmatrix} 6 \\ 2 \end{bmatrix}, \quad \begin{bmatrix} 1 & 3 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$



This is an example of *shear* transformation (square to parallelogram)

- So far, we have seen how to visualise a given transformation
- But it is also important to design a desired transformation
- There is a straightforward algorithm: standard matrices

In $\mathbb{R}^2$, any $\mathbf{x} = x_1\mathbf{e}_1 + x_2\mathbf{e}_2$ where

$$\mathbf{e}_1 = \begin{bmatrix} 1 \\ 0 \end{bmatrix} \quad \text{and} \quad \mathbf{e}_2 = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

are called the *standard basis vectors* in $\mathbb{R}^2$.

Similarly, in $\mathbb{R}^3$, any $\mathbf{x} = x_1\mathbf{e}_1 + x_2\mathbf{e}_2 + x_3\mathbf{e}_3$ with the basis

$$\mathbf{e}_1 = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} \quad \text{and} \quad \mathbf{e}_2 = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} \quad \text{and} \quad \mathbf{e}_3 = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$$

Generally in $\mathbb{R}^n$ $\mathbf{x} = x_1\mathbf{e}_1 + \dots + x_n\mathbf{e}_n$ with $\mathbf{e}_n : \begin{cases} e_n^{(i=n)} = 1 \\ e_n^{(i \neq n)} = 0 \end{cases}$

For any linear transformation $\hat{T} : \mathbb{R}^2 \mapsto \mathbb{R}^2$ we can write

$$\hat{T}(\mathbf{x}) = \hat{T}(x_1\mathbf{e}_1 + x_2\mathbf{e}_2) = \hat{T}(x_1\mathbf{e}_1) + \hat{T}(x_2\mathbf{e}_2) = x_1\hat{T}(\mathbf{e}_1) + x_2\hat{T}(\mathbf{e}_2)$$

This can be written as $\hat{T}(\mathbf{x}) = \left[\hat{T}(\mathbf{e}_1) \mid \hat{T}(\mathbf{e}_2) \right] \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \equiv \mathbf{T}\mathbf{x}$

$\mathbf{T} = \left[\hat{T}(\mathbf{e}_1) \mid \hat{T}(\mathbf{e}_2) \right]$ is called the *standard matrix* of $\hat{T}$.

Similarly, for any linear transformation $\hat{T} : \mathbb{R}^n \mapsto \mathbb{R}^n$ we can write

$$\begin{aligned} \hat{T}(\mathbf{x}) &= \hat{T}(x_1\mathbf{e}_1 + \dots + x_n\mathbf{e}_n) = \hat{T}(x_1\mathbf{e}_1) + \dots + \hat{T}(x_n\mathbf{e}_n) \\ &= x_1\hat{T}(\mathbf{e}_1) + \dots + x_n\hat{T}(\mathbf{e}_n) = \mathbf{T}\mathbf{x} \end{aligned}$$

with the standard matrix $\mathbf{T} = \left[\hat{T}(\mathbf{e}_1) \mid \dots \mid \hat{T}(\mathbf{e}_n) \right]$.

Example: Find the standard matrix for scaling $\widehat{T}(\mathbf{x}) = r\mathbf{x}$

Action of this scaling on standard vectors is straightforward:

$$\widehat{T}(\mathbf{e}_1) = r\mathbf{e}_1 = r \begin{bmatrix} 1 \\ 0 \end{bmatrix} = \begin{bmatrix} r \\ 0 \end{bmatrix}$$

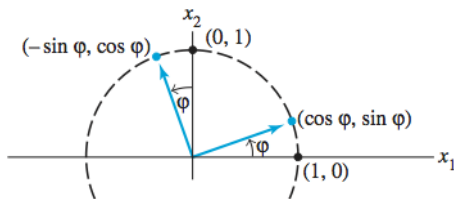
$$\widehat{T}(\mathbf{e}_2) = r\mathbf{e}_2 = r \begin{bmatrix} 0 \\ 1 \end{bmatrix} = \begin{bmatrix} 0 \\ r \end{bmatrix}$$

The standard matrix is therefore:

$$\mathbf{D}_r = \left[\widehat{T}(\mathbf{e}_1) \mid \widehat{T}(\mathbf{e}_2) \right] = \begin{bmatrix} r & 0 \\ 0 & r \end{bmatrix}$$

Find the standard matrix of a transformation that rotates any vector in $\mathbb{R}^2$ around the origin by an angle φ radians.

Consider the action of this rotation over the standard vectors:



$$\hat{T}(\mathbf{e}_1) = \begin{bmatrix} \cos \varphi \\ \sin \varphi \end{bmatrix} \quad \text{and} \quad \hat{T}(\mathbf{e}_2) = \begin{bmatrix} -\sin \varphi \\ \cos \varphi \end{bmatrix}$$

Therefore

$$\mathbf{R}_\varphi = \begin{bmatrix} \cos \varphi & -\sin \varphi \\ \sin \varphi & \cos \varphi \end{bmatrix}$$

Example: counterclockwise rotation by 90° about the origin

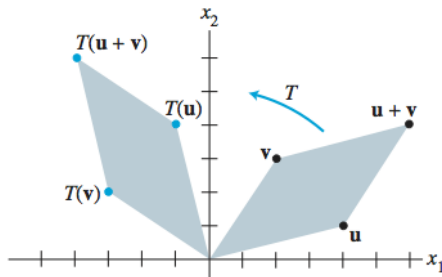
$$\mathbf{T} = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix} \quad \text{so} \quad \hat{T}(\mathbf{x}) = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} -x_2 \\ x_1 \end{bmatrix}$$

Find the images of: $\mathbf{u} = \begin{bmatrix} 4 \\ 1 \end{bmatrix}$, $\mathbf{v} = \begin{bmatrix} 2 \\ 3 \end{bmatrix}$, $\mathbf{u} + \mathbf{v} = \begin{bmatrix} 6 \\ 4 \end{bmatrix}$.

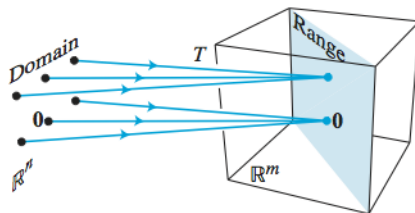
$$\hat{T}(\mathbf{u}) = \begin{bmatrix} -1 \\ 4 \end{bmatrix}$$

$$\hat{T}(\mathbf{v}) = \begin{bmatrix} -3 \\ 2 \end{bmatrix}$$

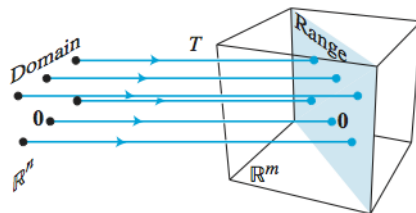
$$\hat{T}(\mathbf{u} + \mathbf{v}) = \begin{bmatrix} -4 \\ 6 \end{bmatrix}$$



Definition: Transformation $\hat{T} : V \mapsto W$ is called *one-to-one* if each $\mathbf{y} \in W$ is the image of at most one $\mathbf{v} \in V$



T is not one-to-one



T is one-to-one

Theorem: A linear transformation $\hat{T}$ is one-to-one if and only if the equation $\hat{T}(\mathbf{x}) = \mathbf{0}$ has only the trivial solution ($\mathbf{x} = \mathbf{0}$).

Equivalent **definition** for vector spaces:

Transformation $\hat{T} : \mathbb{R}^n \mapsto \mathbb{R}^m$ is a one-to-one linear transformation if $\forall \mathbf{b} \in \mathbb{R}^m$ equation $\mathbf{T}\mathbf{x} = \mathbf{b}$ (where $\mathbf{T}$ is the matrix of $\hat{T}$) has either a unique solution or no solutions.

Theorem: Let $\hat{T} : \mathbb{R}^n \mapsto \mathbb{R}^m$ be a linear transformation with the standard matrix $\mathbf{T}$. Then:

- (a) $\hat{T}$ maps $\mathbb{R}^n$ onto $\mathbb{R}^m$ if and only if the columns of $\mathbf{T}$ span $\mathbb{R}^m$
- (b) $\hat{T}$ is one-to-one if and only if the columns of $\mathbf{T}$ are linearly independent

- Isomorphism between linear spaces is established with a one-to-one linear transformation
- Coordinate mapping is a one-to-one linear transformation
- Change of basis is a one-to-one linear transformation (and change of basis matrix is the matrix of transformation)

Linearity of transformation ensures that coordinate vector of a linear combination of elements is a linear combinations of their coordinate vectors, taken with the same coefficients:

$$[c_1 \mathbf{u}_1 + \dots + c_n \mathbf{u}_n]_{\mathcal{B}} = c_1 [\mathbf{u}_1]_{\mathcal{B}} + \dots + c_n [\mathbf{u}_n]_{\mathcal{B}}$$

Example: Consider a transformation $\hat{T}$ with standard matrix

$$\mathbf{T} = \begin{bmatrix} 1 & -4 & 8 & 1 \\ 0 & 2 & -1 & 3 \\ 0 & 0 & 0 & 5 \end{bmatrix}$$

Check if this transformation is a one-to-one linear transformation, and specify the domain, codomain, and range of $\hat{T}$.

- $\hat{T}$ is presented as $\mathbf{T}\mathbf{x}$ so it is a linear transformation.
- The domain of $\hat{T}$ is $\mathbb{R}^4$ and the codomain is $\mathbb{R}^3$.
- There are three pivots in $\mathbf{T}$ so the columns of $\mathbf{T}$ span $\mathbb{R}^3$, thus the range of $\hat{T}$ is the entire $\mathbb{R}^3$.
- The columns of $\mathbf{T}$ are not linearly independent, therefore $\hat{T}$ is **not** one-to-one.

Example: Check if the transformation $\hat{T}(x_1, x_2) = \begin{bmatrix} 3x_1 + x_2 \\ 5x_1 + 7x_2 \\ x_1 + 3x_2 \end{bmatrix}$ is a one-to-one linear transformation, and find its range.

This transformation can be written in a matrix form:

$$\hat{T}(\mathbf{x}) = \begin{bmatrix} 3x_1 + x_2 \\ 5x_1 + 7x_2 \\ x_1 + 3x_2 \end{bmatrix} = \begin{bmatrix} 3 & 1 \\ 5 & 7 \\ 1 & 3 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \mathbf{T}\mathbf{x}$$

- The columns of $\mathbf{T}$ are linearly independent therefore $\hat{T}$ is a one-to-one linear transformation.
- $\mathbf{x} \in \mathbb{R}^2$ so domain of $\hat{T}$ is $\mathbb{R}^2$; $\mathbf{T}\mathbf{x} \in \mathbb{R}^3$ so codomain is $\mathbb{R}^3$.
- The two linearly independent columns of $\mathbf{T}$ span a plane within $\mathbb{R}^3$: this plane is the range of $\hat{T}$.

(this topic officially is a pre-requisite knowledge

— but there are some new details)

Definition: An *eigenvector* of a square matrix $\mathbf{A}$ is a nonzero vector $\mathbf{v}$ such that $\mathbf{A}\mathbf{v} = \lambda\mathbf{v}$ for some scalar λ .
A scalar λ is called an *eigenvalue* of $\mathbf{A}$ if there is a nontrivial solution $\mathbf{v}$ of $\mathbf{A}\mathbf{v} = \lambda\mathbf{v}$.
(then this $\mathbf{v}$ is an eigenvector *corresponding* to λ).

As a *linear transformation* $\mathbf{A}$ performs *scaling* of its eigenvectors

λ is an eigenvalue for $\mathbf{A}$ if and only there is a nontrivial solution to

$$(\mathbf{A} - \lambda\mathbf{I})\mathbf{v} = \mathbf{0}$$

Therefore, λ can be found by solving a *characteristic equation*:

$$\det(\mathbf{A} - \lambda\mathbf{I}) = 0$$

Note: there may be complex roots to the characteristic equation.

Example: Find eigenvalues and eigenvectors for $\mathbf{A} = \begin{bmatrix} 2 & 5 \\ 6 & 1 \end{bmatrix}$.

Solution: Construct characteristic equation $\det(\mathbf{A} - \lambda\mathbf{I}) = 0$:

$$\left| \begin{bmatrix} 2 & 5 \\ 6 & 1 \end{bmatrix} - \lambda \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \right| = \left| \begin{bmatrix} 2 - \lambda & 5 \\ 6 & 1 - \lambda \end{bmatrix} \right| = 0$$

$$(2 - \lambda)(1 - \lambda) - 30 = 0$$

$$\lambda^2 - 3\lambda - 28 = 0$$

which yields the eigenvalues as the solution:

$$\lambda_1 = 7 \quad \lambda_2 = -4$$

For each of these eigenvalues, we need to solve $(\mathbf{A} - \lambda\mathbf{I})\mathbf{x} = \mathbf{0}$.

Example: For $\mathbf{A} = \begin{bmatrix} 2 & 5 \\ 6 & 1 \end{bmatrix}$ we found $\lambda_1 = 7, \quad \lambda_2 = -4$

$$\begin{aligned}\mathbf{A} - 7\mathbf{I} &= \begin{bmatrix} 2 & 5 \\ 6 & 1 \end{bmatrix} - \begin{bmatrix} 7 & 0 \\ 0 & 7 \end{bmatrix} = \begin{bmatrix} -5 & 5 \\ 6 & -6 \end{bmatrix} \\ \rightarrow \quad \begin{bmatrix} 1 & -1 \\ 0 & 0 \end{bmatrix} &\Rightarrow \quad \mathbf{v}_1 = c \cdot \begin{bmatrix} 1 \\ 1 \end{bmatrix}\end{aligned}$$

$$\begin{aligned}\mathbf{A} + 4\mathbf{I} &= \begin{bmatrix} 2 & 5 \\ 6 & 1 \end{bmatrix} - \begin{bmatrix} -4 & 0 \\ 0 & -4 \end{bmatrix} = \begin{bmatrix} 6 & 5 \\ 6 & 5 \end{bmatrix} \\ \rightarrow \quad \begin{bmatrix} 6 & 5 \\ 0 & 0 \end{bmatrix} &\Rightarrow \quad \mathbf{v}_2 = c \cdot \begin{bmatrix} 5 \\ -6 \end{bmatrix}\end{aligned}$$

Example: Find eigenvalues and eigenvectors for $\mathbf{A} = \begin{bmatrix} 2 & 5 \\ 6 & 1 \end{bmatrix}$.

So the eigenvalues are: $\lambda_1 = 7$ and $\lambda_2 = -4$

and the corresponding eigenvectors are $\mathbf{v}_1 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$, $\mathbf{v}_2 = \begin{bmatrix} 5 \\ -6 \end{bmatrix}$

We can verify this back with the original matrix:

$$\mathbf{A}\mathbf{v}_1 = \begin{bmatrix} 2 & 5 \\ 6 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 7 \\ 7 \end{bmatrix} = 7 \cdot \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \lambda_1 \mathbf{v}_1$$

$$\mathbf{A}\mathbf{v}_2 = \begin{bmatrix} 2 & 5 \\ 6 & 1 \end{bmatrix} \begin{bmatrix} 5 \\ -6 \end{bmatrix} = \begin{bmatrix} -20 \\ 24 \end{bmatrix} = -4 \cdot \begin{bmatrix} 5 \\ -6 \end{bmatrix} = \lambda_2 \mathbf{v}_2$$

- 0 is an eigenvalue of $\mathbf{A}$ if and only if $\mathbf{A}$ is singular.
- All the eigenvectors of $\mathbf{A}$ corresponding to a given eigenvalue, span the corresponding *eigenspace*
- If $\mathbf{v}_1, \dots, \mathbf{v}_p$ are eigenvectors corresponding to different eigenvalues $\lambda_1, \dots, \lambda_p$, then the set $\{\mathbf{v}_1, \dots, \mathbf{v}_p\}$ is linearly independent.
- For a triangular matrix, eigenvalues are the diagonal entries:

$$\mathbf{A} = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ 0 & a_{22} & a_{23} \\ 0 & 0 & a_{33} \end{bmatrix} \Rightarrow \begin{cases} \lambda_1 = a_{11} \\ \lambda_2 = a_{22} \\ \lambda_3 = a_{33} \end{cases}$$

(because its determinant is the product of its main diagonal)

Example: for $\mathbf{A} = \begin{bmatrix} 4 & -1 & 6 \\ 2 & 1 & 6 \\ 2 & -1 & 8 \end{bmatrix}$ find bases for its eigenspaces.

Solution:

$$\det(\mathbf{A} - \lambda \mathbf{I}) = \left| \begin{bmatrix} 4 - \lambda & -1 & 6 \\ 2 & 1 - \lambda & 6 \\ 2 & -1 & 8 - \lambda \end{bmatrix} \right|$$

$$= (4 - \lambda)(1 - \lambda)(8 - \lambda) - 12 - 12 + 6(4 - \lambda) + 2(8 - \lambda) - 12(1 - \lambda)$$

$$= -\lambda^3 + 13\lambda^2 - 40\lambda + 36$$

$$\dots = \dots$$

$$= (9 - \lambda)(2 - \lambda)(2 - \lambda) = 0$$

so $\lambda_1 = 9$ and $\lambda_{2,3} = 2$.

Example: for $\mathbf{A} = \begin{bmatrix} 4 & -1 & 6 \\ 2 & 1 & 6 \\ 2 & -1 & 8 \end{bmatrix}$ find bases for its eigenspaces.

... so $\lambda_1 = 9$ and $\lambda_{2,3} = 2$; then we solve $(\mathbf{A} - \lambda \mathbf{I}) \mathbf{x} = \mathbf{0}$

$$\mathbf{A} - 9\mathbf{I} = \begin{bmatrix} -5 & -1 & 6 \\ 2 & -8 & 6 \\ 2 & -1 & -1 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & 0 & -1 \\ 0 & 1 & -1 \\ 0 & 0 & 0 \end{bmatrix} \Rightarrow \mathbf{x} = x_3 \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$$

$$\mathbf{A} - 2\mathbf{I} = \begin{bmatrix} 2 & -1 & 6 \\ 2 & -1 & 6 \\ 2 & -1 & 6 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & -\frac{1}{2} & 3 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \Rightarrow \mathbf{x} = x_2 \begin{bmatrix} 0.5 \\ 1 \\ 0 \end{bmatrix} + x_3 \begin{bmatrix} -3 \\ 0 \\ 1 \end{bmatrix}$$

So the bases are:

$$\left\{ \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \right\} \text{ for } \lambda_1 \quad \text{and} \quad \left\{ \begin{bmatrix} 1 \\ 2 \\ 0 \end{bmatrix}, \begin{bmatrix} -3 \\ 0 \\ 1 \end{bmatrix} \right\} \text{ for } \lambda_{2,3}$$

Dilation e.g. $\begin{bmatrix} 2 & 0 \\ 0 & 2 \end{bmatrix}$ we have $\lambda_{1,2} = 2$ and $\forall \mathbf{v} \in \mathbb{R}^2$

Shear e.g. $\begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}$ we have $\lambda_{1,2} = 1$ and $\mathbf{v} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$

Projection e.g. $\begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}$ we have $\lambda_1 = 1$ for $\mathbf{v} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$
and $\lambda_2 = 0$ for $\mathbf{v} = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$

Swap e.g. $\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$ we have $\lambda_{1,2} = \pm 1$ and $\mathbf{v} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$

Rotation e.g. $\begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix}$ we have $\lambda_{1,2} = \pm i$ and $\forall \mathbf{v} \in \mathbb{C}^2$

This week: quick test 5
(change of coordinates)

Next week: quick test 6
(linear transformations)