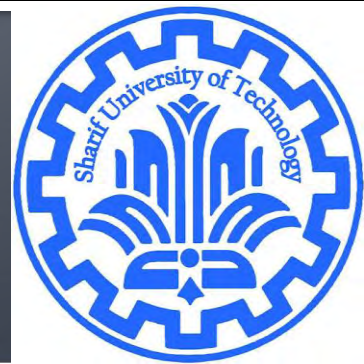


Matrix Transformation

CE40282-1: Linear Algebra
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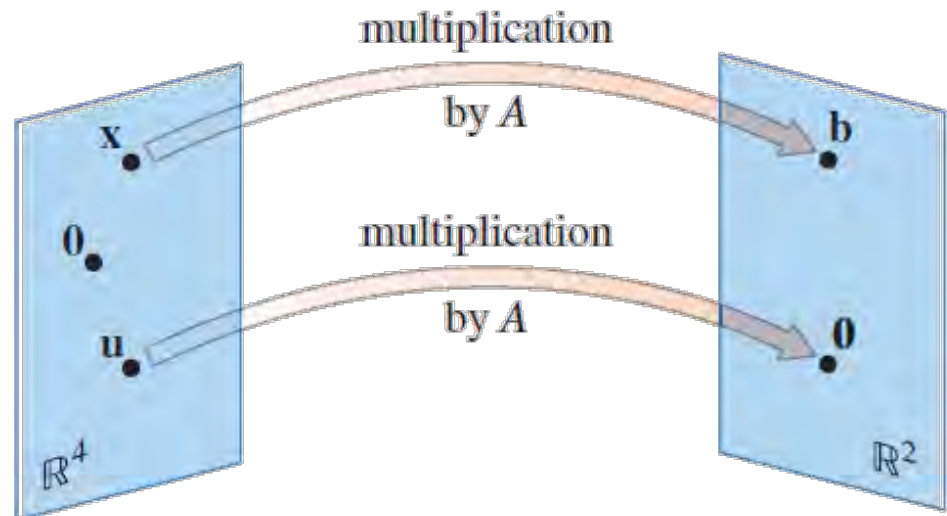
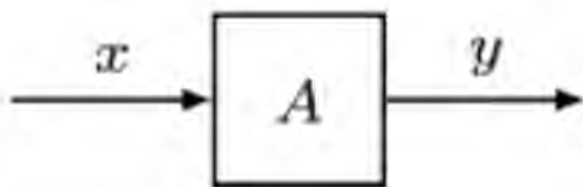
Linear Transformation

- Matrix is a linear transformation: map one vector to another vector

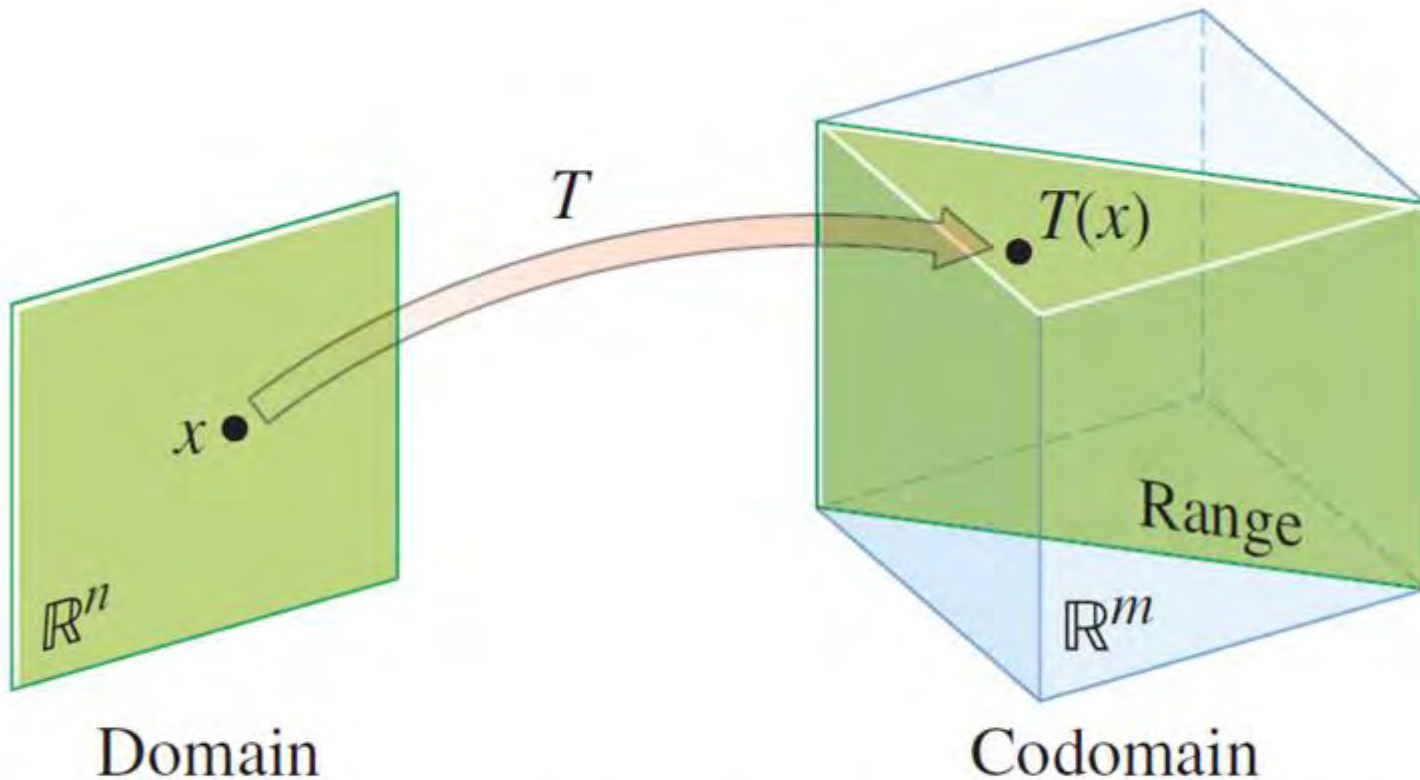
$$A \in \mathbb{R}^{m \times n}, x \in \mathbb{R}^n, y \in \mathbb{R}^m : \quad y_{m \times 1} = A_{m \times n} x_{n \times 1}$$

$$A : \mathbb{R}^n \longrightarrow \mathbb{R}^m$$

- Input-output



Linear Transformation



Domain, codomain, and range of $T : \mathbb{R}^n \rightarrow \mathbb{R}^m$

Linear Transformation

EXAMPLE 1 Let $A = \begin{bmatrix} 1 & -3 \\ 3 & 5 \\ -1 & 7 \end{bmatrix}$, $\mathbf{u} = \begin{bmatrix} 2 \\ -1 \end{bmatrix}$, $\mathbf{b} = \begin{bmatrix} 3 \\ 2 \\ -5 \end{bmatrix}$, $\mathbf{c} = \begin{bmatrix} 3 \\ 2 \\ 5 \end{bmatrix}$, and define a transformation $T : \mathbb{R}^2 \rightarrow \mathbb{R}^3$ by $T(\mathbf{x}) = A\mathbf{x}$, so that

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

- Find $T(\mathbf{u})$, the image of \mathbf{u} under the transformation T .
- Find an \mathbf{x} in \mathbb{R}^2 whose image under T is \mathbf{b} .
- Is there more than one \mathbf{x} whose image under T is \mathbf{b} ?
- Determine if \mathbf{c} is in the range of the transformation T .

Linear mapping

A linear transformation (or a linear map) is a function $\mathbf{T} : \mathbf{R}^n \rightarrow \mathbf{R}^m$ that satisfies the following properties:

1. $\mathbf{T}(\mathbf{x} + \mathbf{y}) = \mathbf{T}(\mathbf{x}) + \mathbf{T}(\mathbf{y})$
2. $\mathbf{T}(a\mathbf{x}) = a\mathbf{T}(\mathbf{x})$

for any vectors $\mathbf{x}, \mathbf{y} \in \mathbf{R}^n$ and any scalar $a \in \mathbf{R}$.

Linear mapping

- Example: which are linear mapping?
 - **zero** map $0 : V \rightarrow W$
 - **identity** map $I : V \rightarrow V$
 - Let $T : \mathcal{P}(\mathbb{F}) \rightarrow \mathcal{P}(\mathbb{F})$ be the **differentiation** map defined as $Tp(z) = p'(z)$.
 - Let $T : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ be the map given by $T(x, y) = (x - 2y, 3x + y)$
 - $T(x) = e^x$
 - $T : \mathbb{F} \rightarrow \mathbb{F}$ given by $T(x) = x - 1$

Linear mapping

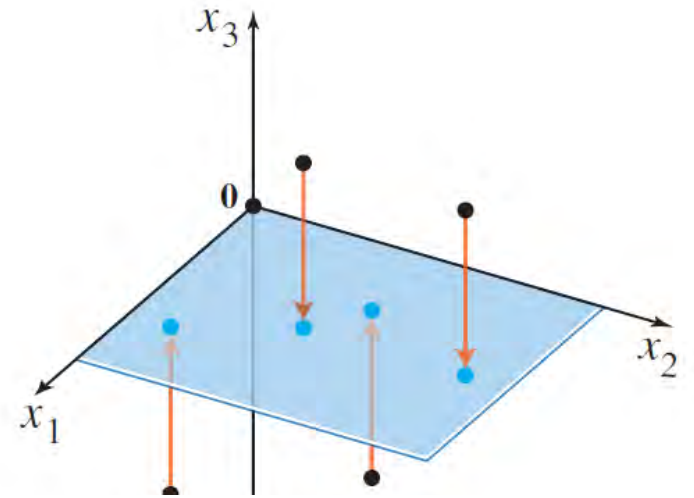
■ Theorem

Let (v_1, \dots, v_n) be a basis of V and (w_1, \dots, w_n) an arbitrary list of vectors in W . Then there exists a unique linear map

$$T : V \rightarrow W \quad \text{such that } T(v_i) = w_i.$$

Projection

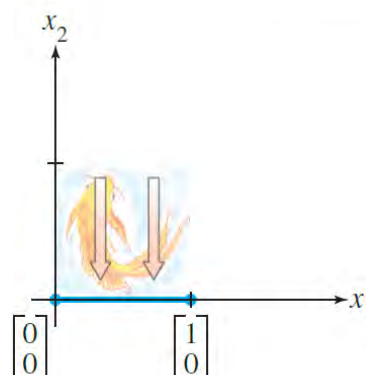
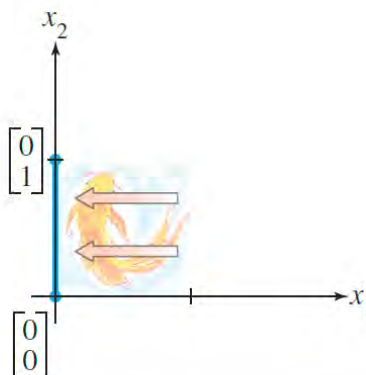
- Example:



If $A = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$, then the transformation $\mathbf{x} \mapsto A\mathbf{x}$ *projects* points in \mathbb{R}^3 onto the x_1x_2 -plane because

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

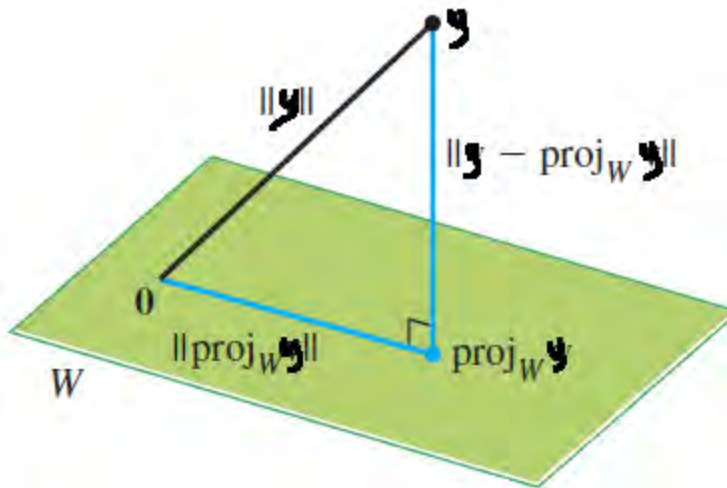
Projection

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

Projection

The **projection** of a vector $y \in \mathbb{R}^m$ onto the span of $\{x_1, \dots, x_n\}$ is the vector $v \in \text{span}(\{x_1, \dots, x_n\})$, such that v is as close as possible to y , as measured by the Euclidean norm $\|v - y\|_2$.

$$\text{Proj}(y; \{x_1, \dots, x_n\}) = \operatorname{argmin}_{v \in \text{span}(\{x_1, \dots, x_n\})} \|y - v\|_2.$$



Projection

Suppose that \mathcal{V} is a vector space and $P : \mathcal{V} \rightarrow \mathcal{V}$ is a linear transformation.

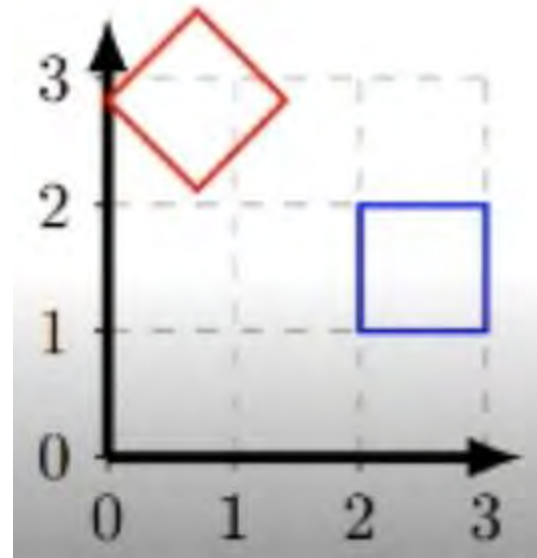
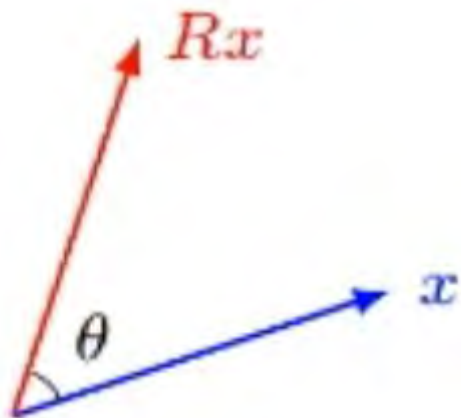
- a) If $P^2 = P$ then P is called a **projection**.
- b) If \mathcal{V} is an inner product space and $P^2 = P = P^*$ then P is called an **orthogonal projection**.

We furthermore say that P **projects onto** $\text{range}(P)$.

- Projection of vector v on:
 - Two orthogonal vectors
 - Two non-orthogonal vectors

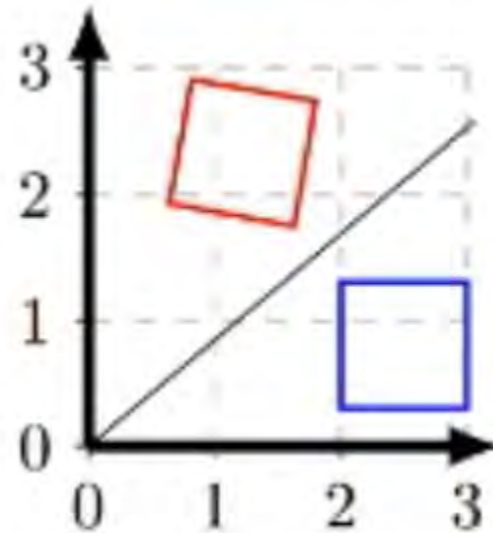
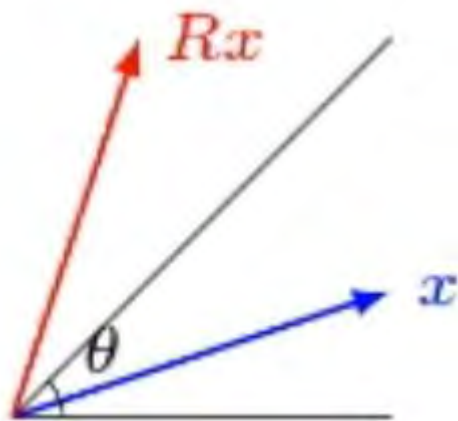
Rotation

- $R = \begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix}$



Reflection

- $R = \begin{bmatrix} \cos(2\theta) & \sin(2\theta) \\ \sin(2\theta) & -\cos(2\theta) \end{bmatrix}$

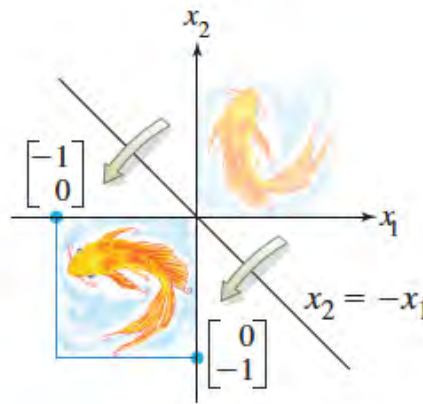


Reflection

Transformation	Image of the Unit Square	Standard Matrix
Reflection through the x_1 -axis	<p>A 2D coordinate system with axes x_1 and x_2. A unit square is shown in the first quadrant with vertices at $[0, 0]$, $[1, 0]$, $[1, 1]$, and $[0, 1]$. Its reflection through the x_1-axis is shown in the fourth quadrant with vertices at $[0, 0]$, $[1, 0]$, $[1, -1]$, and $[0, -1]$. The point $[1, 0]$ is labeled with a vector $\begin{bmatrix} 1 \\ 0 \end{bmatrix}$ and the point $[0, -1]$ is labeled with a vector $\begin{bmatrix} 0 \\ -1 \end{bmatrix}$.</p>	$\begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}$
Reflection through the x_2 -axis	<p>A 2D coordinate system with axes x_1 and x_2. A unit square is shown in the second quadrant with vertices at $[0, 0]$, $[-1, 0]$, $[-1, 1]$, and $[0, 1]$. The point $[-1, 0]$ is labeled with a vector $\begin{bmatrix} -1 \\ 0 \end{bmatrix}$ and the point $[0, 1]$ is labeled with a vector $\begin{bmatrix} 0 \\ 1 \end{bmatrix}$.</p>	$\begin{bmatrix} -1 & 0 \\ 0 & 1 \end{bmatrix}$
Reflection through the line $x_2 = x_1$	<p>A 2D coordinate system with axes x_1 and x_2. A line $x_2 = x_1$ is drawn. A unit square is shown in the first quadrant with vertices at $[0, 0]$, $[1, 0]$, $[1, 1]$, and $[0, 1]$. Its reflection across the line $x_2 = x_1$ is shown with vertices at $[0, 0]$, $[0, 1]$, $[1, 1]$, and $[1, 0]$. The point $[0, 1]$ is labeled with a vector $\begin{bmatrix} 0 \\ 1 \end{bmatrix}$ and the point $[1, 0]$ is labeled with a vector $\begin{bmatrix} 1 \\ 0 \end{bmatrix}$.</p>	$\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$

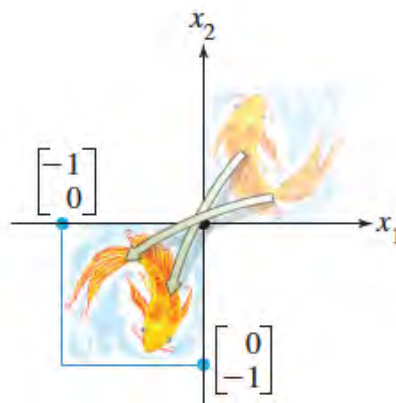
Reflection

Reflection through
the line $x_2 = -x_1$



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

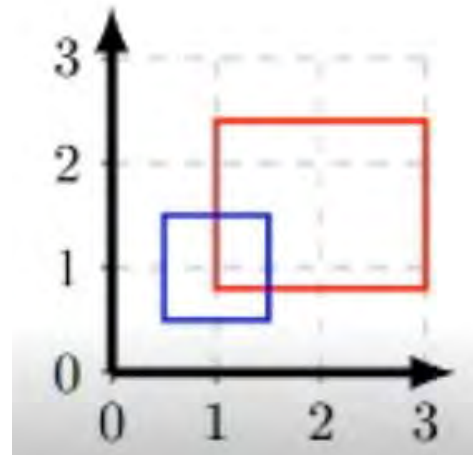
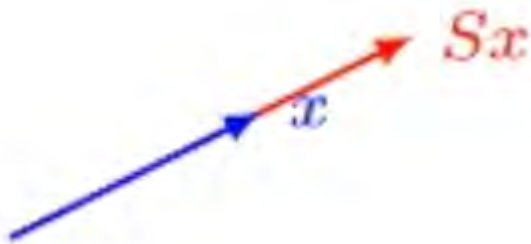
Reflection through
the origin



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

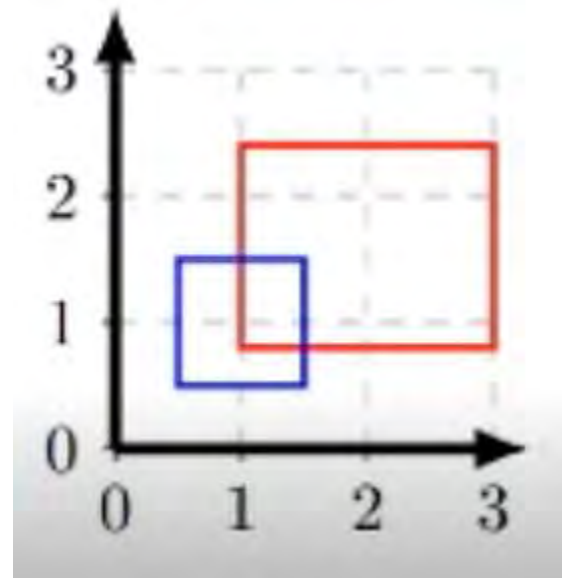
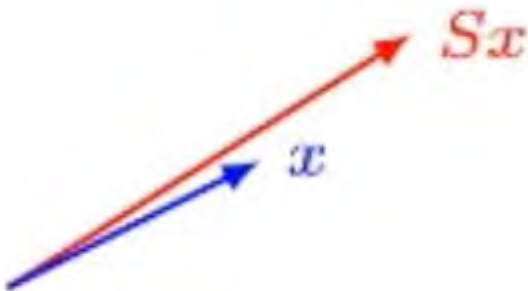
Uniform Scaling

- $S = sI = \begin{bmatrix} s & 0 \\ 0 & s \end{bmatrix}$



Non-uniform Scaling

$$\blacksquare S = \begin{bmatrix} s_x & 0 \\ 0 & s_y \end{bmatrix}$$



Shearing

■ Example

Let $A = \begin{bmatrix} 1 & 3 \\ 0 & 1 \end{bmatrix}$. The transformation $T : \mathbb{R}^2 \rightarrow \mathbb{R}^2$

A typical shear matrix is of the form

$$S = \begin{pmatrix} 1 & 0 & 0 & \lambda & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{pmatrix}.$$



sheep



sheared sheep

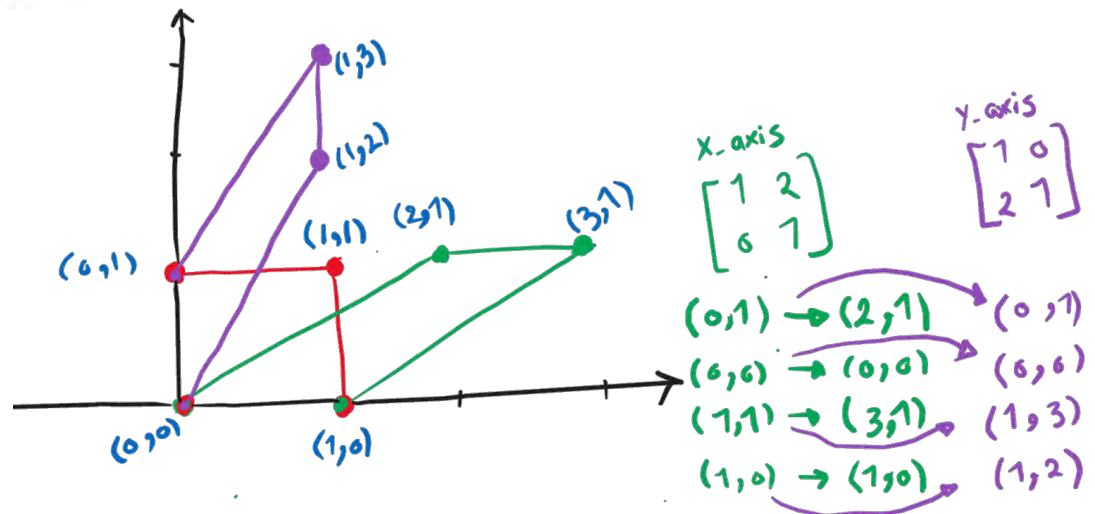
Shearing

A shear parallel to the x axis results in $x' = x + \lambda y$ and $y' = y$. In matrix form:

$$\begin{pmatrix} x' \\ y' \end{pmatrix} = \begin{pmatrix} 1 & \lambda \\ 0 & 1 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix}.$$

Similarly, a shear parallel to the y axis has $x' = x$ and $y' = y + \lambda x$. In matrix form:

$$\begin{pmatrix} x' \\ y' \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ \lambda & 1 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix}.$$



Difference Matrix

- $$D_{(n-1) \times n} = \begin{bmatrix} -1 & 1 & 0 & 0 & \cdots & 0 \\ 0 & -1 & 1 & 0 & \cdots & 0 \\ \vdots & & \ddots & \ddots & & \vdots \\ 0 & 0 & \cdots & -1 & 1 & 0 \\ 0 & 0 & \cdots & 0 & -1 & 1 \end{bmatrix}$$

$$D : \mathbb{R}^n \longrightarrow \mathbb{R}^{n-1} \quad \Rightarrow \quad D \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} = \begin{bmatrix} x_2 - x_1 \\ x_3 - x_2 \\ \vdots \\ x_n - x_{n-1} \end{bmatrix}$$

- Example

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

Selectors

- an $m \times n$ selector matrix: each row is a unit vector (transposed)

$$A = \begin{bmatrix} e_{k_1}^T \\ \vdots \\ e_{k_m}^T \end{bmatrix}$$

multiplying by A selects entries of x :

$$Ax = (x_{k_1}, x_{k_2}, \dots, x_{k_m})$$

- $A : \mathbb{R}^n \longrightarrow \mathbb{R}^m \quad \Rightarrow \quad A \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} = \begin{bmatrix} x_{k_1} \\ x_{k_2} \\ \vdots \\ x_{k_m} \end{bmatrix}$

Selectors

■ Example
$$\begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} -1 \\ 2 \\ 0 \\ -3 \end{bmatrix} = \begin{bmatrix} 2 \\ -3 \end{bmatrix}$$

- Selecting first and last elements of vector:
- Reversing the elements of vector:

Slicing

- Keeping m elements from r to s ($m=s-r+1$)

$$\begin{bmatrix} 0_{m \times (r-1)} & I_{m \times m} & 0_{m \times (n-s)} \end{bmatrix}$$

- Example: Slicing two first and one last elements:

$$\begin{bmatrix} -1 \\ 2 \\ 0 \\ -3 \\ 5 \end{bmatrix} = \begin{bmatrix} 0 \\ -3 \end{bmatrix}$$

Down Sampling

- Down sampling with k: selecting one sample in every k samples
- Example: k=2?

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ \vdots \end{bmatrix} = \begin{bmatrix} x_1 \\ x_3 \\ x_5 \\ \vdots \end{bmatrix}$$

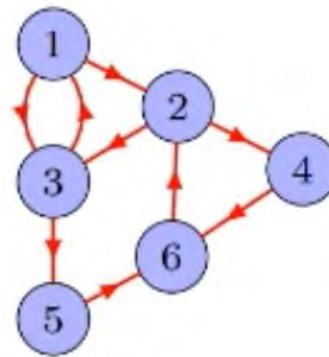
Applications

- Rotation matrix

(i) $\sin 2A = 2 \sin A \cos A$
 (ii) $\cos 2A = \cos^2 A - \sin^2 A$

$$R = \begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix} \Rightarrow R^n = \begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix}^n = \begin{bmatrix} \cos(n\theta) & -\sin(n\theta) \\ \sin(n\theta) & \cos(n\theta) \end{bmatrix}$$

- Adjacency matrix



$$A = \begin{matrix} & \begin{matrix} n1 & n2 & n3 & n4 & n5 & n6 \end{matrix} \\ \begin{matrix} n1 \\ n2 \\ n3 \\ n4 \\ n5 \\ n6 \end{matrix} & \begin{bmatrix} 0 & 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 1 \\ 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 0 \end{bmatrix} \end{matrix}$$

$$A^2 = \begin{bmatrix} 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 1 & 0 \\ 1 & 0 & 1 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & 0 & 1 \\ 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 & 0 & 0 \end{bmatrix}$$

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

Multiple Transformation

- $$x_{n \times 1} \xrightarrow{A_{m \times n}} y_{m \times 1} \xrightarrow{B_{p \times m}} z_{p \times 1} \Rightarrow \begin{cases} y = Ax \\ z = By \end{cases} \Rightarrow z = B(Ax) = BAx$$

- Example

- Difference Matrix

$$x = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix} \xrightarrow{4 \times 5} y = \begin{bmatrix} x_2 - x_1 \\ x_3 - x_2 \\ x_4 - x_3 \\ x_5 - x_4 \end{bmatrix} \xrightarrow{3 \times 4} z = \begin{bmatrix} x_3 - x_2 - (x_2 - x_1) \\ x_4 - x_3 - (x_3 - x_2) \\ x_5 - x_4 - (x_4 - x_3) \end{bmatrix} = \begin{bmatrix} x_3 - 2x_2 + x_1 \\ x_4 - 2x_3 + x_2 \\ x_5 - 2x_4 + x_3 \end{bmatrix}$$

$$x \rightarrow z \begin{bmatrix} 1 & -2 & 1 & 0 & 0 \\ 0 & 1 & -2 & 1 & 0 \\ 0 & 0 & 1 & -2 & 1 \end{bmatrix}_{3 \times 5}$$

$$x \rightarrow y \rightarrow z$$

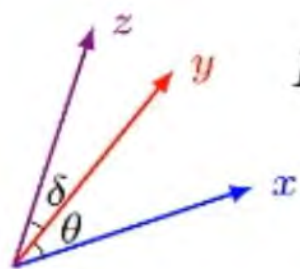
$$\begin{bmatrix} 1 & -1 & 0 & 0 \\ 0 & 1 & -1 & 0 \\ 0 & 0 & 1 & -1 \end{bmatrix}_{3 \times 4} \begin{bmatrix} 1 & -1 & 0 & 0 & 0 \\ 0 & 1 & -1 & 0 & 0 \\ 0 & 0 & 1 & -1 & 0 \\ 0 & 0 & 0 & 1 & -1 \end{bmatrix}_{4 \times 5} = \begin{bmatrix} 1 & -2 & 1 & 0 & 0 \\ 0 & 1 & -2 & 1 & 0 \\ 0 & 0 & 1 & -2 & 1 \end{bmatrix}$$

Multiple Transformation

- $$x_{n \times 1} \xrightarrow{A_{m \times n}} y_{m \times 1} \xrightarrow{B_{p \times m}} z_{p \times 1} \Rightarrow \begin{cases} y = Ax \\ z = By \end{cases} \Rightarrow z = B(Ax) = BAx$$

- Example

- Rotation



$$R_\theta = \begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix}$$

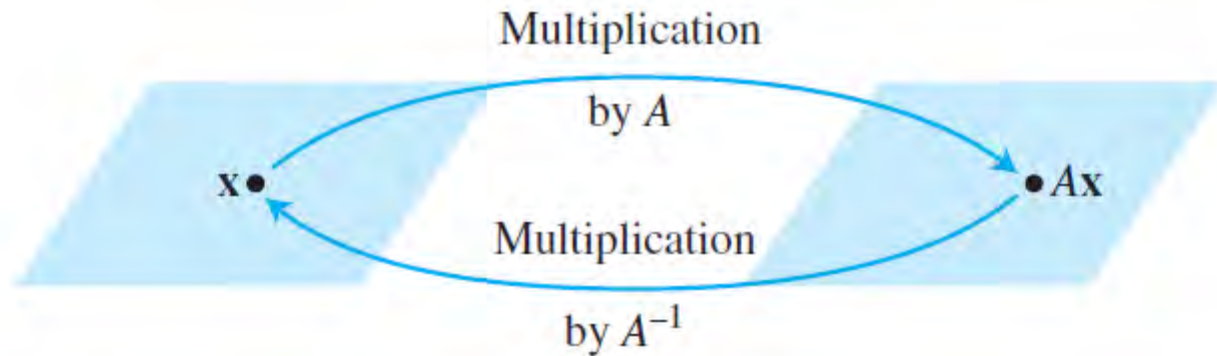
$$x \rightarrow z \quad z = R_{\delta+\theta} x \quad \begin{bmatrix} \cos(\delta + \theta) & -\sin(\delta + \theta) \\ \sin(\delta + \theta) & \cos(\delta + \theta) \end{bmatrix}$$

$$x \rightarrow y \rightarrow z \quad \begin{cases} y = R_\theta x \\ z = R_\delta y \end{cases} \Rightarrow z = R_\delta R_\theta x \quad \begin{bmatrix} \cos \delta & -\sin \delta \\ \sin \delta & \cos \delta \end{bmatrix} \begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix}$$

$$= \begin{bmatrix} \cos \delta \cos \theta - \sin \delta \sin \theta & -\cos \delta \sin \theta - \sin \delta \cos \theta \\ \sin \delta \cos \theta + \cos \delta \sin \theta & -\sin \delta \sin \theta + \cos \delta \cos \theta \end{bmatrix}$$

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

Invertible Linear Transformations



■ Definition:

A linear transformation $T : \mathbb{R}^n \rightarrow \mathbb{R}^n$ is said to be **invertible** if there exists a function $S : \mathbb{R}^n \rightarrow \mathbb{R}^n$ such that

$$S(T(\mathbf{x})) = \mathbf{x} \quad \text{for all } \mathbf{x} \text{ in } \mathbb{R}^n$$

$$T(S(\mathbf{x})) = \mathbf{x} \quad \text{for all } \mathbf{x} \text{ in } \mathbb{R}^n$$

Invertible Linear Transformations

■ Theorem:

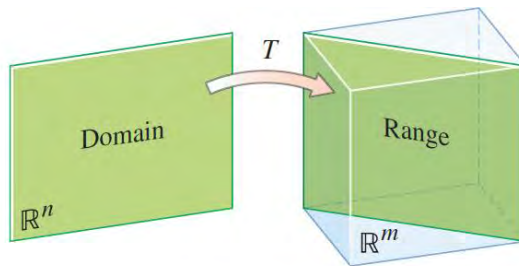
Let $T : \mathbb{R}^n \rightarrow \mathbb{R}^n$ be a linear transformation and let A be the standard matrix for T . Then T is invertible if and only if A is an invertible matrix. In that case, the linear transformation S given by $S(\mathbf{x}) = A^{-1}\mathbf{x}$ is the unique function satisfying

$$S(T(\mathbf{x})) = \mathbf{x} \quad \text{for all } \mathbf{x} \text{ in } \mathbb{R}^n$$

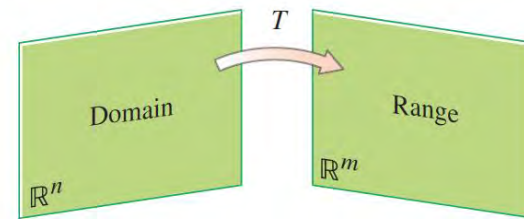
$$T(S(\mathbf{x})) = \mathbf{x} \quad \text{for all } \mathbf{x} \text{ in } \mathbb{R}^n$$

Mapping

A mapping $T : \mathbb{R}^n \rightarrow \mathbb{R}^m$ is said to be **onto** \mathbb{R}^m if each \mathbf{b} in \mathbb{R}^m is the image of *at least one* \mathbf{x} in \mathbb{R}^n .

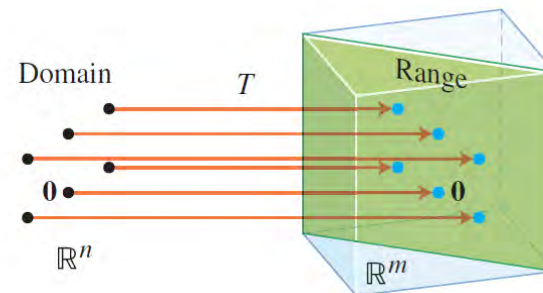
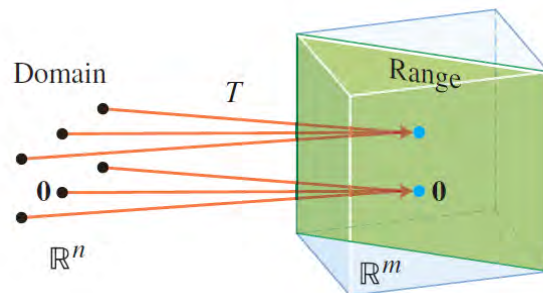


T is not onto \mathbb{R}^m



T is onto \mathbb{R}^m

A mapping $T : \mathbb{R}^n \rightarrow \mathbb{R}^m$ is said to be **one-to-one** if each \mathbf{b} in \mathbb{R}^m is the image of *at most one* \mathbf{x} in \mathbb{R}^n .

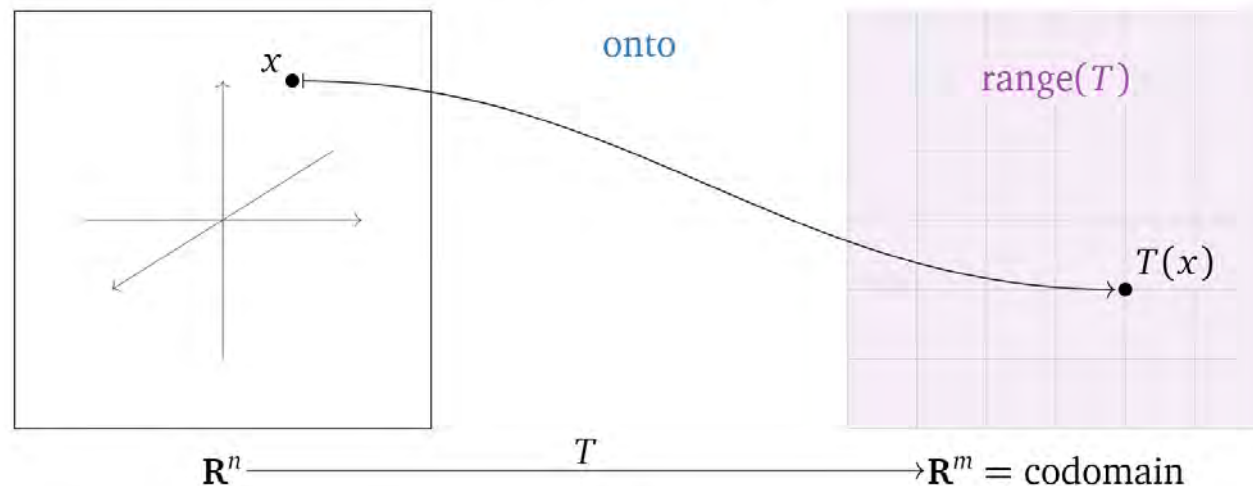


Onto (surjective) Transformations

Definition (Onto transformations). A transformation $T : \mathbb{R}^n \rightarrow \mathbb{R}^m$ is *onto* if, for every vector b in \mathbb{R}^m , the equation $T(x) = b$ has *at least one* solution x in \mathbb{R}^n .

Here are some equivalent ways of saying that T is onto:

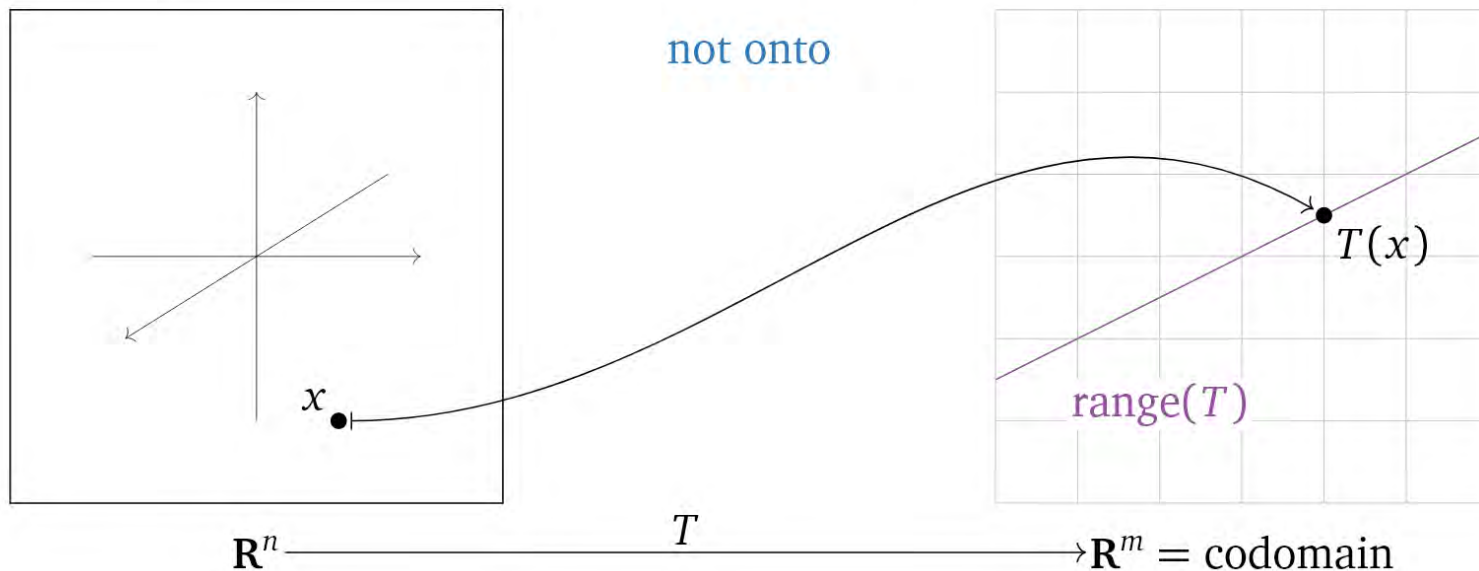
- The range of T is equal to the codomain of T .
- Every vector in the codomain is the output of some input vector.



Onto Transformations

Here are some equivalent ways of saying that T is not onto:

- The range of T is smaller than the codomain of T .
- There exists a vector b in \mathbf{R}^m such that the equation $T(x) = b$ does not have a solution.
- There is a vector in the codomain that is not the output of any input vector.



Onto Transformations

Theorem (Onto matrix transformations). *Let A be an $m \times n$ matrix, and let $T(x) = Ax$ be the associated matrix transformation. The following statements are equivalent:*

1. T is onto.
2. $T(x) = b$ has at least one solution for every b in \mathbf{R}^m .
3. $Ax = b$ is consistent for every b in \mathbf{R}^m .
4. The columns of A span \mathbf{R}^m .
5. A has a pivot in every row.
6. The range of T has dimension m .

Onto Transformations

Tall matrices do not have onto transformations. If $T : \mathbf{R}^n \rightarrow \mathbf{R}^m$ is an onto matrix transformation, what can we say about the relative sizes of n and m ?

The matrix associated to T has n columns and m rows. Each row and each column can only contain one pivot, so in order for A to have a pivot in every row, it must have *at least as many columns as rows*: $m \leq n$.

This says that, for instance, \mathbf{R}^2 is “too small” to admit an onto linear transformation to \mathbf{R}^3 .

Note that there exist wide matrices that are not onto: for example,

$$\begin{pmatrix} 1 & -1 & 2 \\ -2 & 2 & -4 \end{pmatrix}$$

does not have a pivot in every row.

Example

Let T be the linear transformation whose standard matrix is

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

Does T map \mathbb{R}^4 onto \mathbb{R}^3 ? Is T a one-to-one mapping?

One-to-One (injective) Linear Transformation

THEOREM

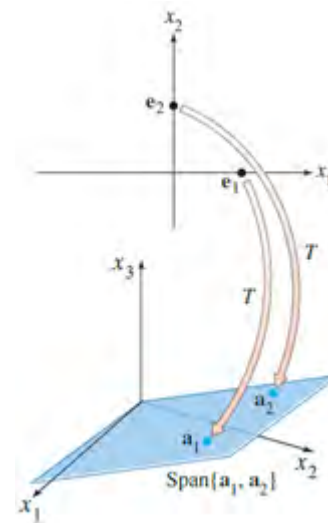
Let $T : \mathbb{R}^n \rightarrow \mathbb{R}^m$ be a linear transformation. Then T is one-to-one if and only if the equation $T(\mathbf{x}) = \mathbf{0}$ has only the trivial solution.

One-to-One Linear Transformation

- Let $T : \mathbb{R}^n \rightarrow \mathbb{R}^m$ be a linear transformation, and let A be the standard matrix for T . Then:
 - T maps \mathbb{R}^n onto \mathbb{R}^m if and only if the columns of A span \mathbb{R}^m ;
 - T is one-to-one if and only if the columns of A are linearly independent.

■ Example

Let $T(x_1, x_2) = (3x_1 + x_2, 5x_1 + 7x_2, x_1 + 3x_2)$. Show that T is a one-to-one linear transformation. Does T map \mathbb{R}^2 onto \mathbb{R}^3 ?



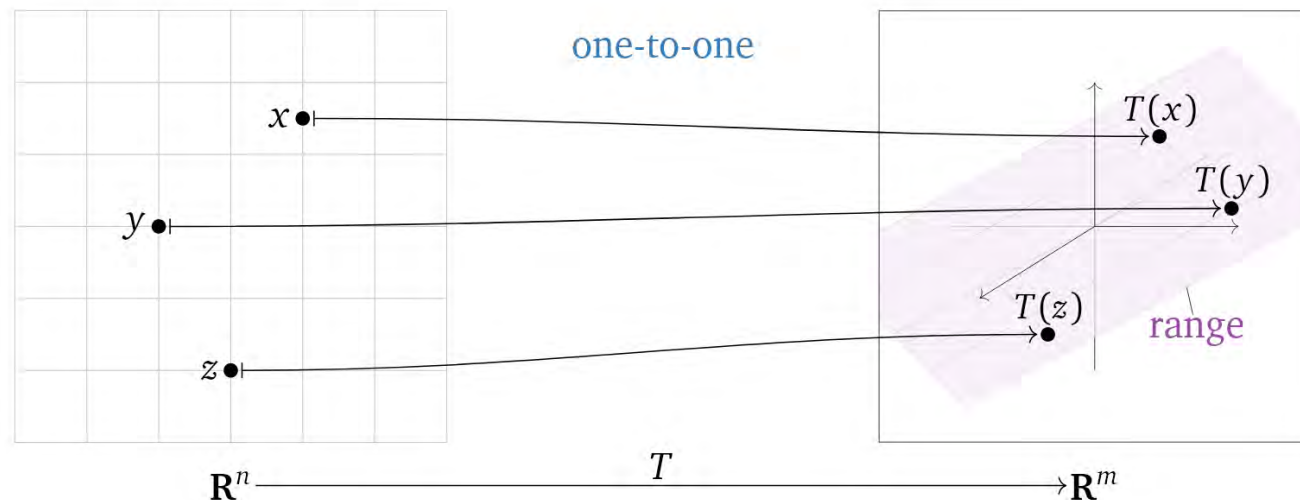
One-to-one Transformations

Definition (One-to-one transformations). A transformation $T: \mathbb{R}^n \rightarrow \mathbb{R}^m$ is *one-to-one* if, for every vector b in \mathbb{R}^m , the equation $T(x) = b$ has *at most one* solution x in \mathbb{R}^n .

Remark. ▼

Here are some equivalent ways of saying that T is one-to-one:

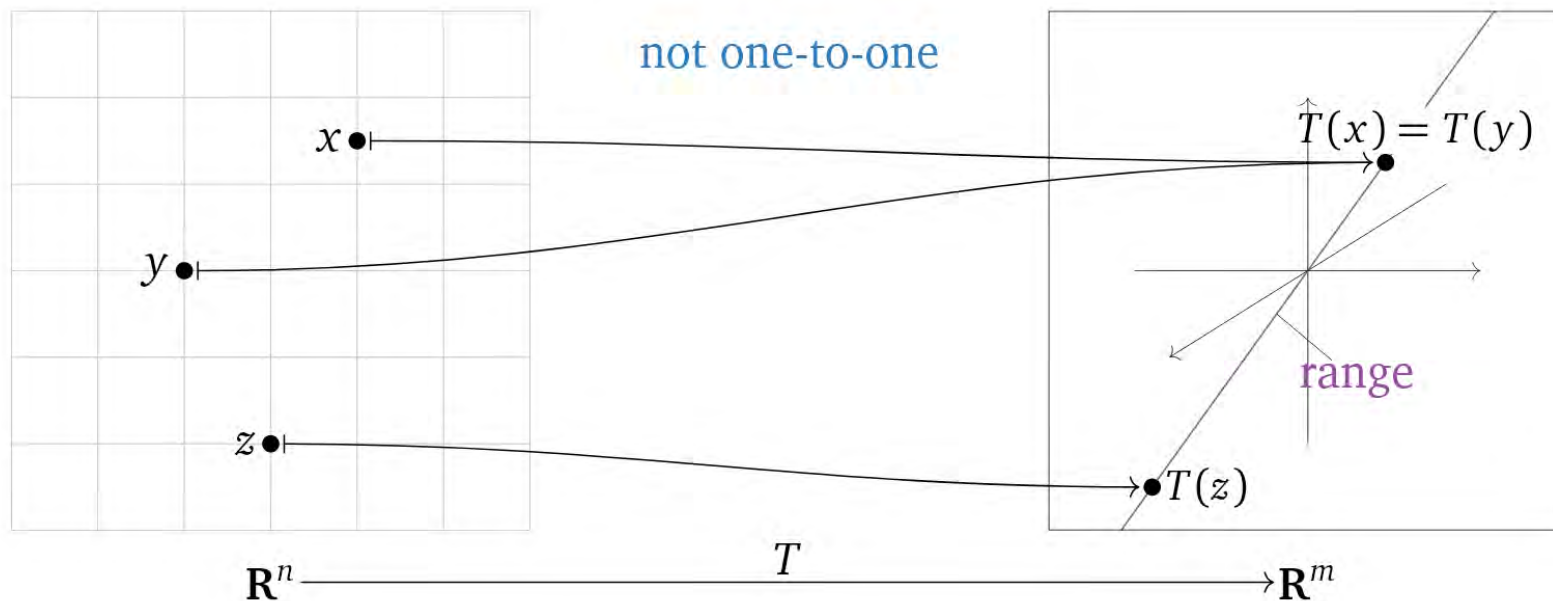
- For every vector b in \mathbb{R}^m , the equation $T(x) = b$ has *zero or one* solution x in \mathbb{R}^n .
- Different inputs of T have different outputs.
- If $T(u) = T(v)$ then $u = v$.



One-to-one Transformations

Here are some equivalent ways of saying that T is *not* one-to-one:

- There exists some vector b in \mathbf{R}^m such that the equation $T(x) = b$ has *more than one* solution x in \mathbf{R}^n .
- There are two different inputs of T with the same output.
- There exist vectors u, v such that $u \neq v$ but $T(u) = T(v)$.



One-to-one Transformations

Theorem (One-to-one matrix transformations). Let A be an $m \times n$ matrix, and let $T(x) = Ax$ be the associated matrix transformation. The following statements are equivalent:

1. T is one-to-one.
2. For every b in \mathbf{R}^m , the equation $T(x) = b$ has at most one solution.
3. For every b in \mathbf{R}^m , the equation $Ax = b$ has a unique solution or is inconsistent.
4. $Ax = 0$ has only the trivial solution.
5. The columns of A are linearly independent.
6. A has a pivot in every column.
7. The range of T has dimension n .

One-to-one Transformations

Wide matrices do not have one-to-one transformations. If $T : \mathbf{R}^n \rightarrow \mathbf{R}^m$ is a one-to-one matrix transformation, what can we say about the relative sizes of n and m ?

The matrix associated to T has n columns and m rows. Each row and each column can only contain one pivot, so in order for A to have a pivot in every column, it must have *at least as many rows as columns*: $n \leq m$.

This says that, for instance, \mathbf{R}^3 is “too big” to admit a one-to-one linear transformation into \mathbf{R}^2 .

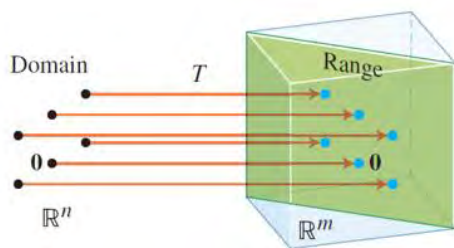
Note that there exist tall matrices that are not one-to-one: for example,

$$\begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}$$

does not have a pivot in every column.

Comparison

A is an $m \times n$ matrix, and $T: \mathbb{R}^n \rightarrow \mathbb{R}^m$ is the matrix transformation $T(x) = Ax$



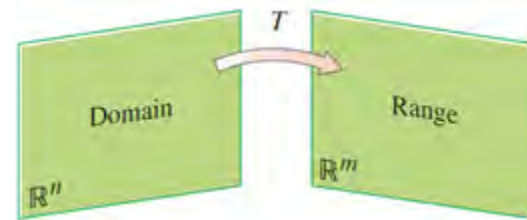
T is one-to-one

$T(x) = b$ has *at most one solution* for every b .

The columns of A are linearly independent.

A has a pivot in every column.

The range of T has dimension n .



T is onto

$T(x) = b$ has *at least one solution* for every b .

The columns of A span \mathbb{R}^m .

A has a pivot in every row.

The range of T has dimension m .

One-to-one and onto

One-to-one is the same as onto for square matrices. We observed in the previous [example](#) that a square matrix has a pivot in every row if and only if it has a pivot in every column. Therefore, a matrix transformation T from \mathbf{R}^n to itself is one-to-one if and only if it is onto: in this case, the two notions are equivalent.

Conversely, by this [note](#) and this [note](#), if a matrix transformation $T : \mathbf{R}^m \rightarrow \mathbf{R}^n$ is both one-to-one and onto, then $m = n$.

Note that in general, a transformation T is both one-to-one and onto if and only if $T(x) = b$ has *exactly one* solution for all b in \mathbf{R}^m .

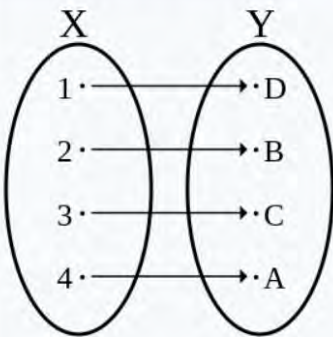
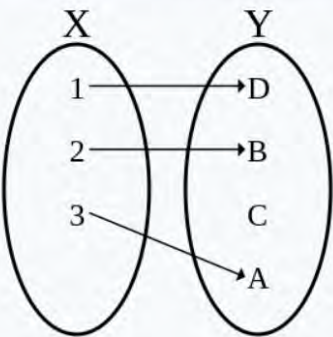
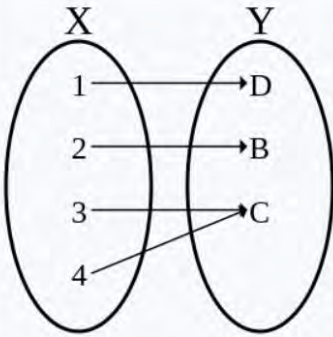
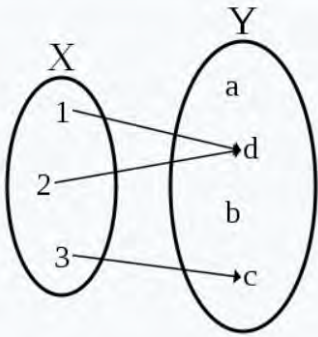
Bijjective

- one-to-one and onto
- if and only if every possible image is mapped to by exactly one argument

Conclusion

On to

One-to-One

	surjective	non-surjective
injective	 <p>bijjective</p>	 <p>injective-only</p>
non-injective	 <p>surjective-only</p>	 <p>general</p>

Machine Learning Application

- The central problem in machine learning and deep learning is to meaningfully transform data: in other words, to learn useful representations of the input data at hand — representations that get us closer to the expected output.

Inner Product

- $\langle Ax, y \rangle = \langle x, A^T y \rangle$
 - What about symmetric matrix?
- Show that unitary matrix preserves inner product. $\langle Ux, Uy \rangle = \langle x, y \rangle$

Introduction to change of basis

- $B = \{v_1, \dots, v_n\}$ are basis of R^n
- $C[a]_B = a$
- $C = [v_1 \quad v_2 \quad \dots \quad v_n]$

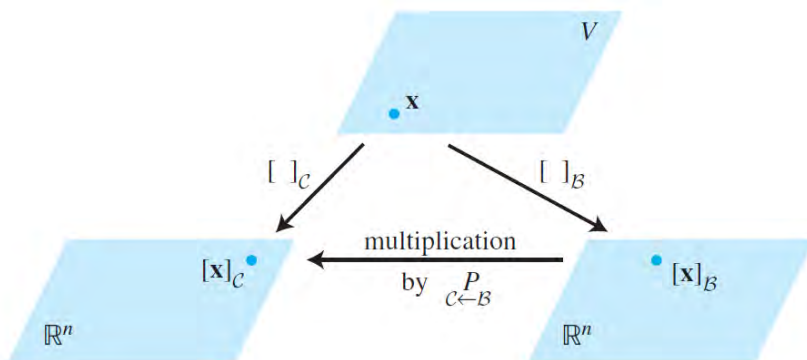
Change of Basis

Let $\mathcal{B} = \{\mathbf{b}_1, \dots, \mathbf{b}_n\}$ and $\mathcal{C} = \{\mathbf{c}_1, \dots, \mathbf{c}_n\}$ be bases of a vector space V . Then there is a unique $n \times n$ matrix ${}_{\mathcal{C} \leftarrow \mathcal{B}}P$ such that

$$[\mathbf{x}]_{\mathcal{C}} = {}_{\mathcal{C} \leftarrow \mathcal{B}}P [\mathbf{x}]_{\mathcal{B}} \quad (4)$$

The columns of ${}_{\mathcal{C} \leftarrow \mathcal{B}}P$ are the \mathcal{C} -coordinate vectors of the vectors in the basis \mathcal{B} . That is,

$${}_{\mathcal{C} \leftarrow \mathcal{B}}P = \begin{bmatrix} [\mathbf{b}_1]_{\mathcal{C}} & [\mathbf{b}_2]_{\mathcal{C}} & \cdots & [\mathbf{b}_n]_{\mathcal{C}} \end{bmatrix} \quad (5)$$



$$({}_{\mathcal{C} \leftarrow \mathcal{B}}P)^{-1} = {}_{\mathcal{B} \leftarrow \mathcal{C}}P$$

Change of Basis

■ Example

Let $\mathbf{b}_1 = \begin{bmatrix} 1 \\ -3 \end{bmatrix}$, $\mathbf{b}_2 = \begin{bmatrix} -2 \\ 4 \end{bmatrix}$, $\mathbf{c}_1 = \begin{bmatrix} -7 \\ 9 \end{bmatrix}$, $\mathbf{c}_2 = \begin{bmatrix} -5 \\ 7 \end{bmatrix}$,
the bases for \mathbb{R}^2 given by $\mathcal{B} = \{\mathbf{b}_1, \mathbf{b}_2\}$ and $\mathcal{C} = \{\mathbf{c}_1, \mathbf{c}_2\}$.

- Find the change-of-coordinates matrix from \mathcal{C} to \mathcal{B} .
- Find the change-of-coordinates matrix from \mathcal{B} to \mathcal{C} .

■ Final Review!

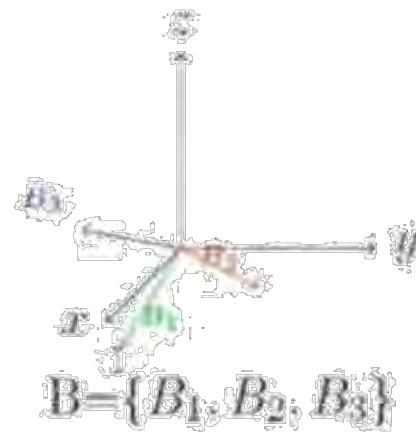
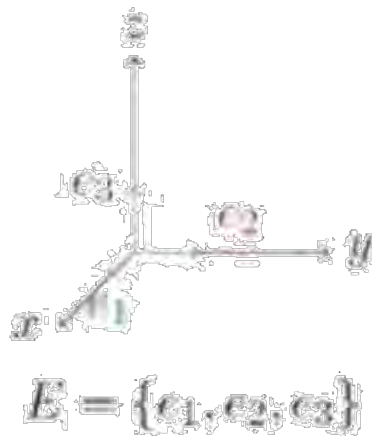
$$P_{\mathcal{B}}[\mathbf{x}]_{\mathcal{B}} = \mathbf{x}, \quad P_{\mathcal{C}}[\mathbf{x}]_{\mathcal{C}} = \mathbf{x}, \quad \text{and} \quad [\mathbf{x}]_{\mathcal{C}} = P_{\mathcal{C}}^{-1}\mathbf{x}$$

$$[\mathbf{x}]_{\mathcal{C}} = P_{\mathcal{C}}^{-1}\mathbf{x} = P_{\mathcal{C}}^{-1}P_{\mathcal{B}}[\mathbf{x}]_{\mathcal{B}}$$

Matrix Representation of Linear Function

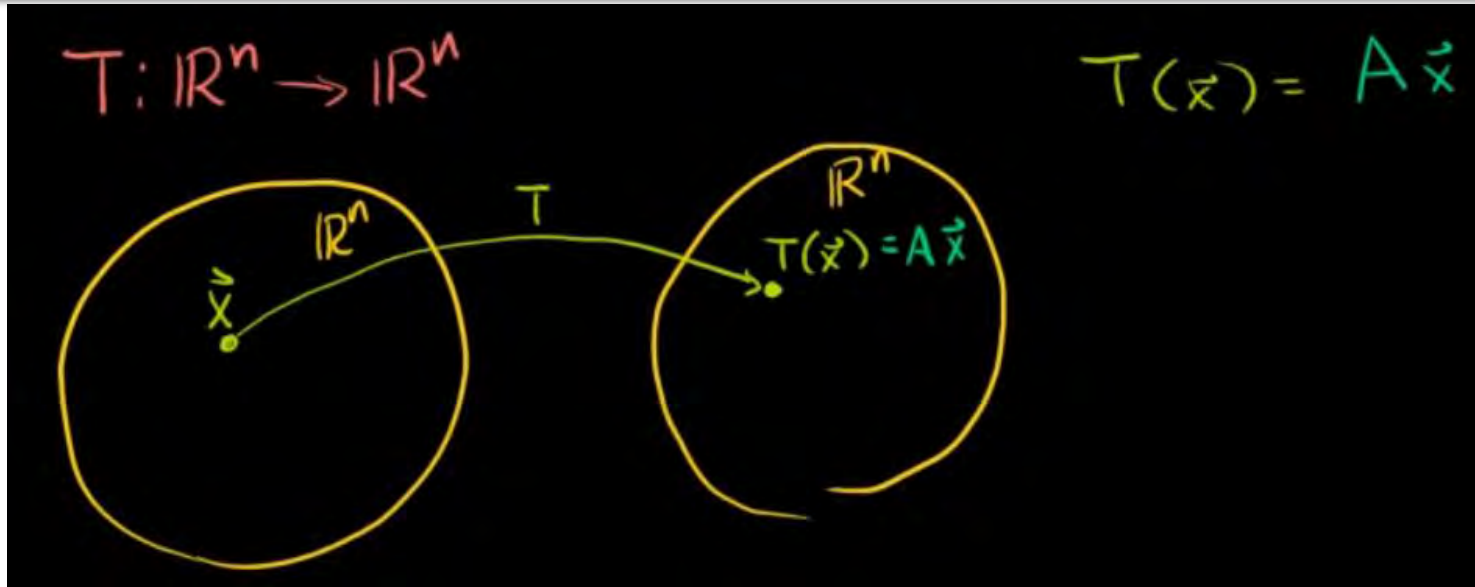
- Let $T: \mathbb{R}^n \rightarrow \mathbb{R}^n$ be a linear function and $u = \begin{bmatrix} u_1 \\ \vdots \\ u_n \end{bmatrix} \in \mathbb{R}^n$.

The matrix $\begin{bmatrix} T(e_1) & \cdots & T(e_n) \end{bmatrix}$ is called the matrix representation of linear function (transformation) T which is denoted by $[T]_E$.



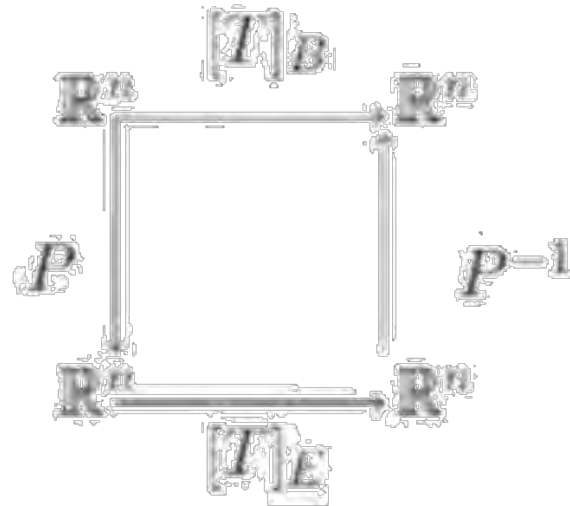
What is the relation between $[T]_B$ and $[T]_E$?

Transformation with Change of Basis



- $B = \{v_1, \dots, v_n\}$ are basis of R^n
- $C = [v_1 \quad v_2 \quad \dots \quad v_n]$
- $[T(x)]_B = C^{-1}AC[x]_B$

Change of Basis



$$[T]_B = P^{-1} [T]_E P$$

Example

- We have $B = \{x^3, x^2, x, 1\}$ and $B' = \{x^2, x, 1\}$ are bases for $P_3(x)$ and $P_2(x)$, respectively.

- Since $\begin{bmatrix} a_3 \\ a_2 \\ a_1 \\ a_0 \end{bmatrix}$ the vector representation of $a_3x^3 + a_2x^2 + a_1x + a_0 \in P_3(x)$, we have

$$\begin{aligned} \left[\frac{d}{dt} \right]_{\{B, B'\}} &= \begin{bmatrix} \frac{d}{dt}(x^3) & \frac{d}{dt}(x^2) & \frac{d}{dt}(x) & \frac{d}{dt}(1) \end{bmatrix} \\ &= \begin{bmatrix} 3 & 0 & 0 & 0 \\ 0 & 2 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \end{aligned}$$