Matrix Algebra

Geometric Algorithms
Lecture 9

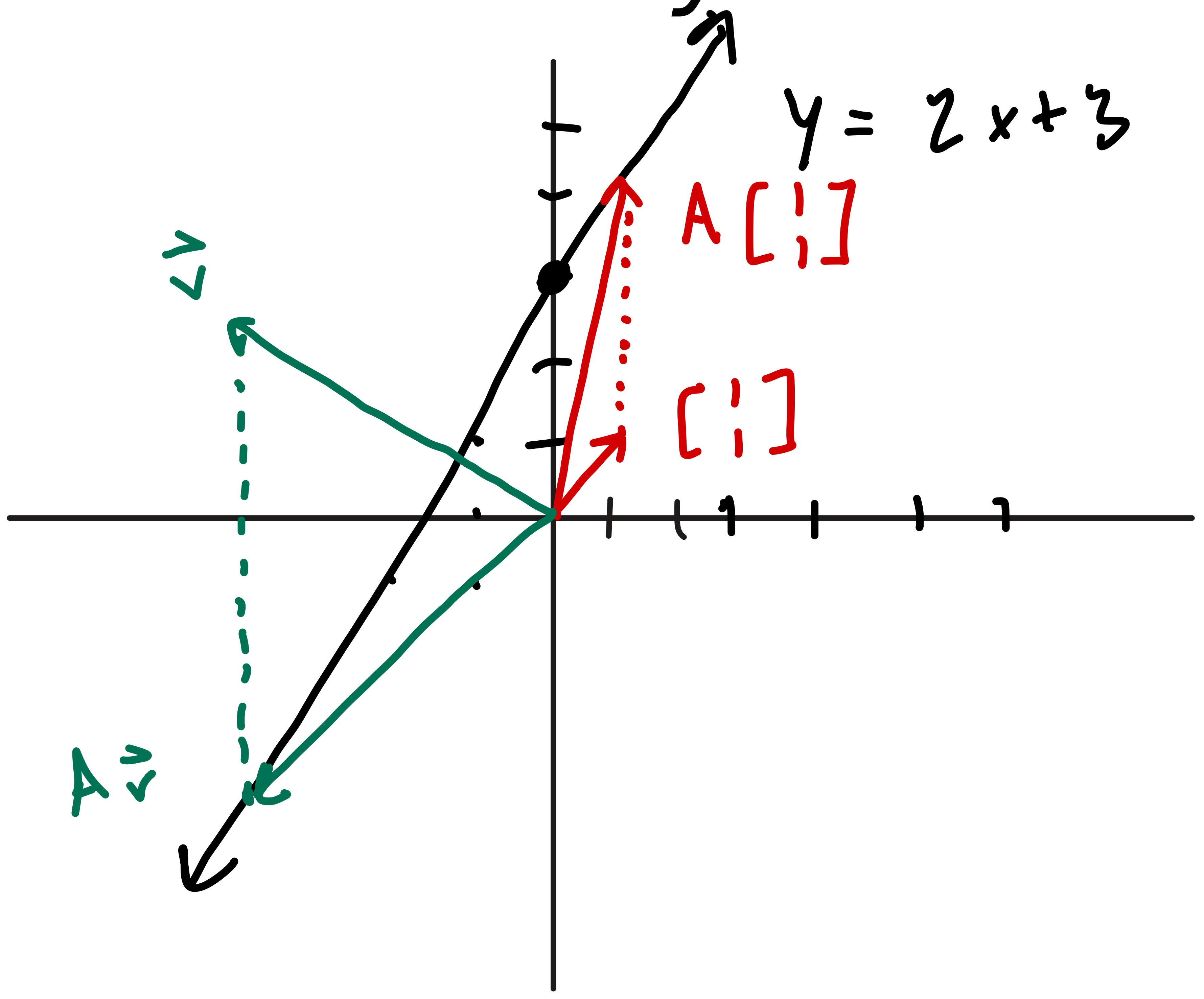
CAS CS 132

Practice Problem

PROBLEM: THIS IS NOT LINEAR

Write the matrix for the transformation which projects vectors in $\mathbb{R}^2$ *vertically onto the line* $y = 2x + 3$ *in* $\mathbb{R}^2$

$$T\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}\right) = \begin{bmatrix} 0 \\ 3 \end{bmatrix}$$

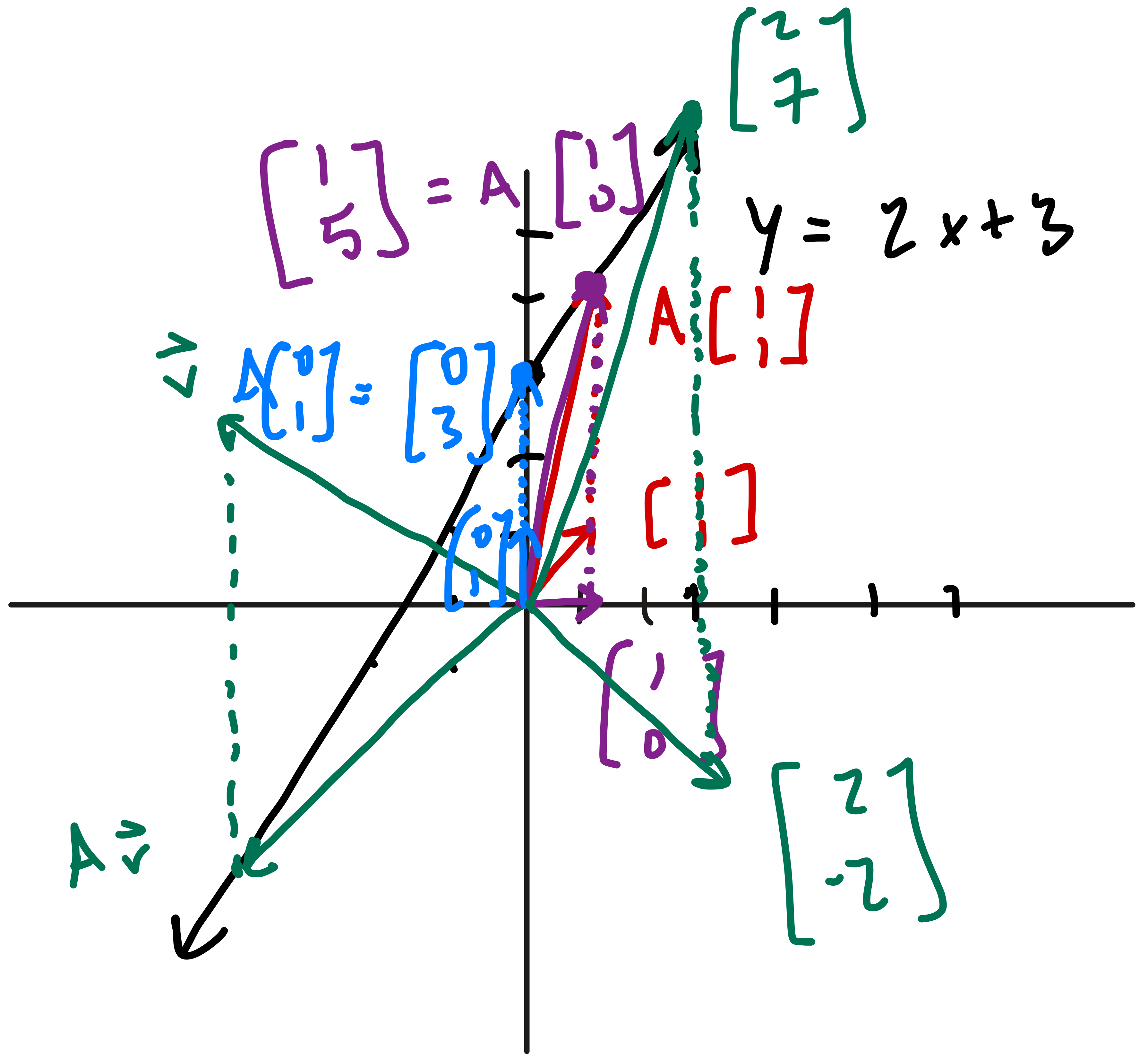


Answer

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

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

$$\cancel{\begin{bmatrix} 2 \\ 10 \end{bmatrix} + \begin{bmatrix} 0 \\ -6 \end{bmatrix} = \begin{bmatrix} 2 \\ 4 \end{bmatrix}}$$

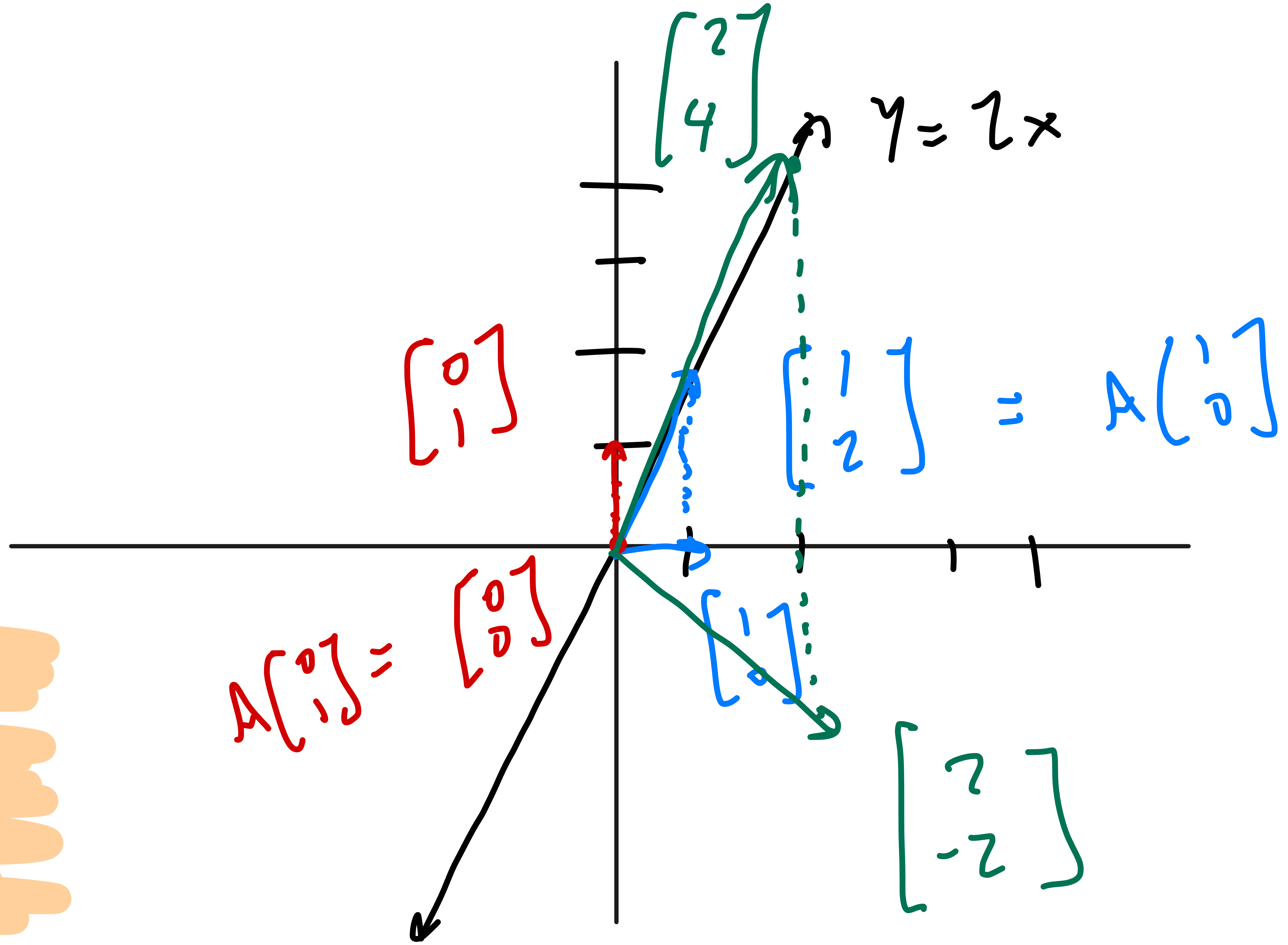


Answer

$$y = 2x$$

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

$$2\begin{bmatrix}1\\ 2\end{bmatrix} - 2\begin{bmatrix}0\\ 0\end{bmatrix} = \begin{bmatrix}2\\ 4\end{bmatrix}$$

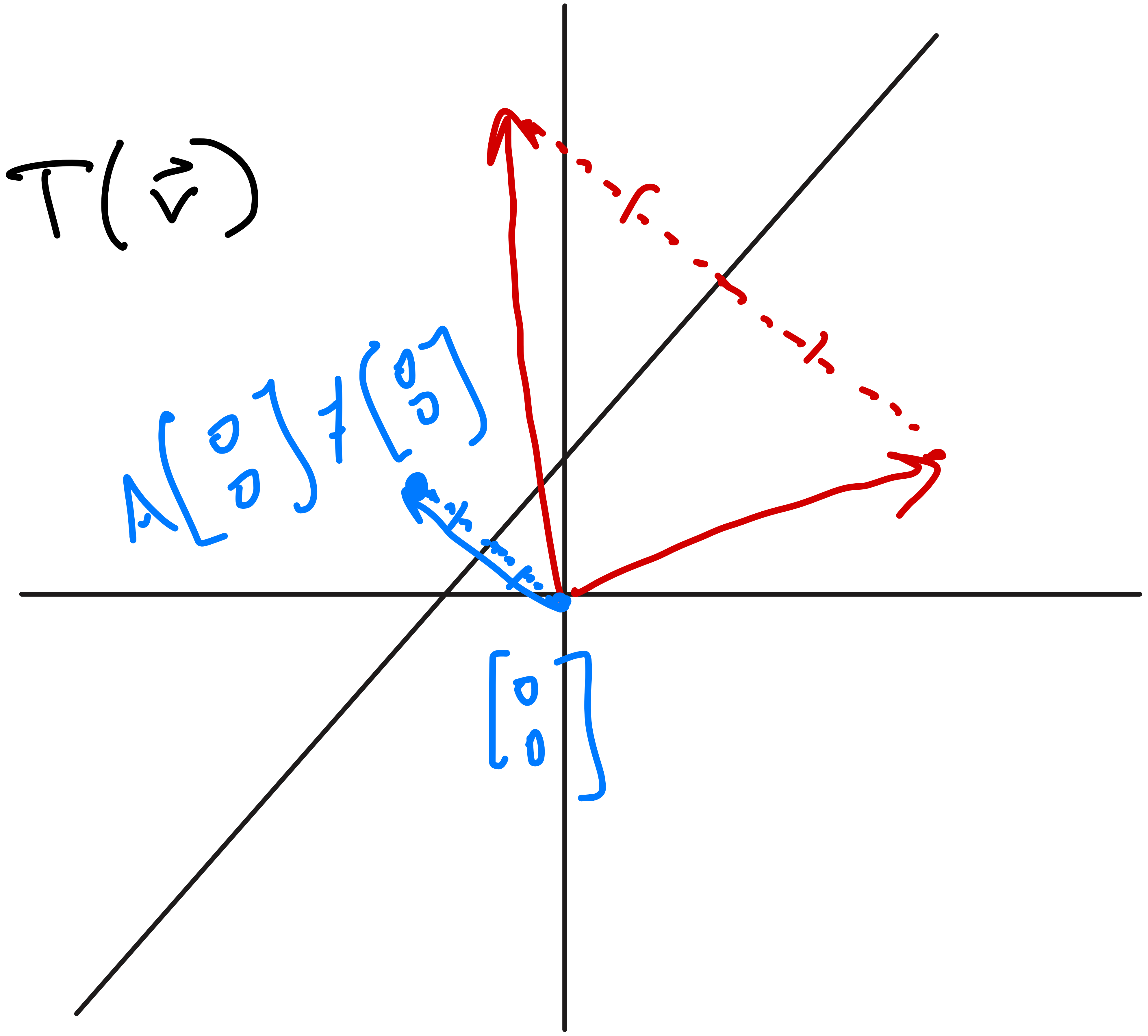


Answer

① $T(\vec{u}+\vec{v}) = T(\vec{u}) + T(\vec{v})$

② $T(c\vec{v}) = c\,T(\vec{v})$

$$T(\vec{0}) = T\left(0\begin{bmatrix}1\\1\end{bmatrix}\right) = 0\,T\left(\begin{bmatrix}1\\1\end{bmatrix}\right) = \begin{bmatrix}0\\0\end{bmatrix}$$



Objectives

- Connect questions about **matrix equations** and **linear transformations**
- Motivate **matrix multiplication**
- Define matrix multiplication
- Look at the **algebra** of matrix multiplication

Keywords

one-to-one transformation

onto transformation

matrix multiplication

row-column rule

matrix addition and scaling

non-commutativity

Recap: Geometry of Linear Transformations

Recall: Matrices as Transformations

Matrices allow us to *transform* vectors

The transformed vector lies in the span of its columns

$$\mathbf{x} \mapsto A\mathbf{x}$$

map a vector $\mathbf{x}$ to the vector $A\mathbf{v}$

Recall: Motivating Questions

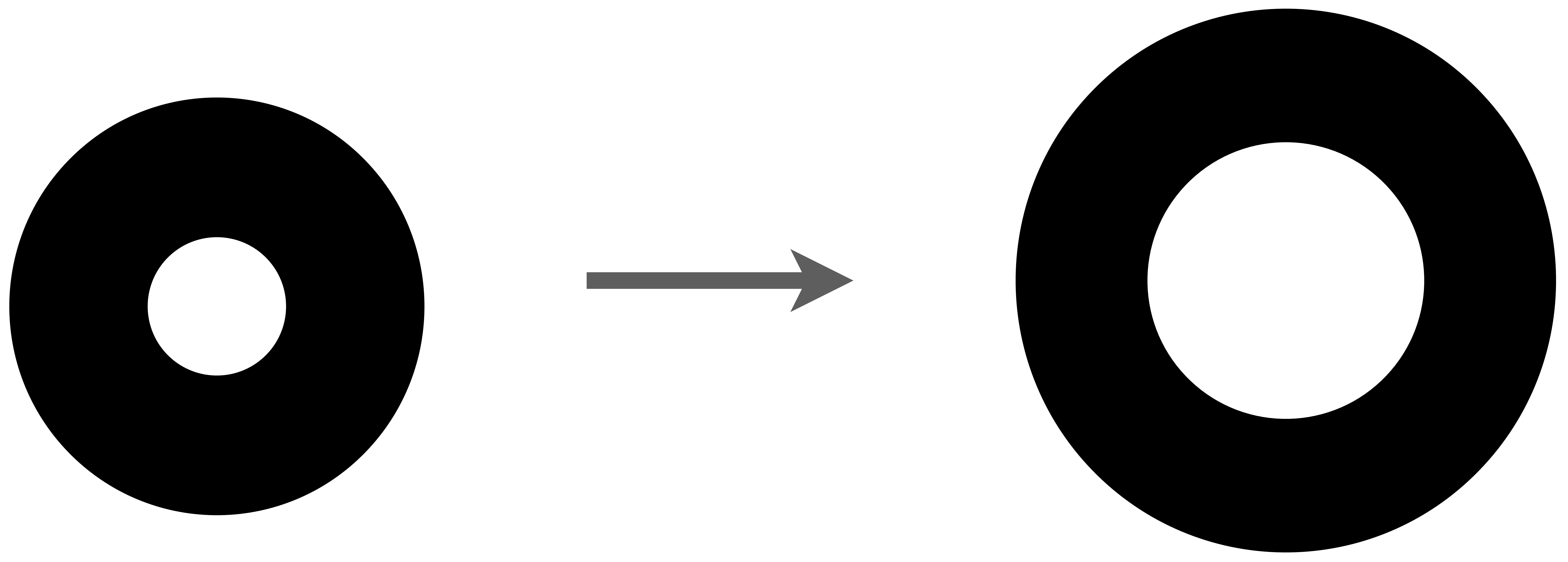
What kind of functions can we define in this way?

How do we interpret what the transformation does to a set of vectors?

How does this relate back to matrix equations?

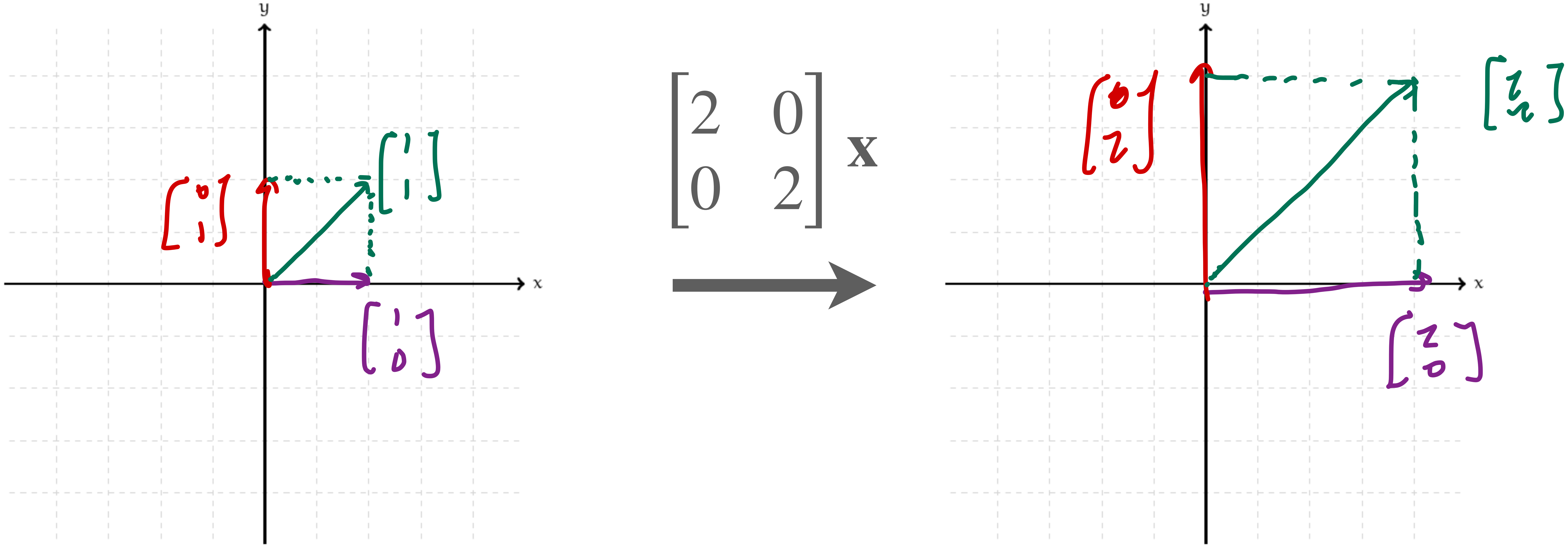
Matrix transformations change the "shape" of a set of set of vectors (points)

Example: Dilation



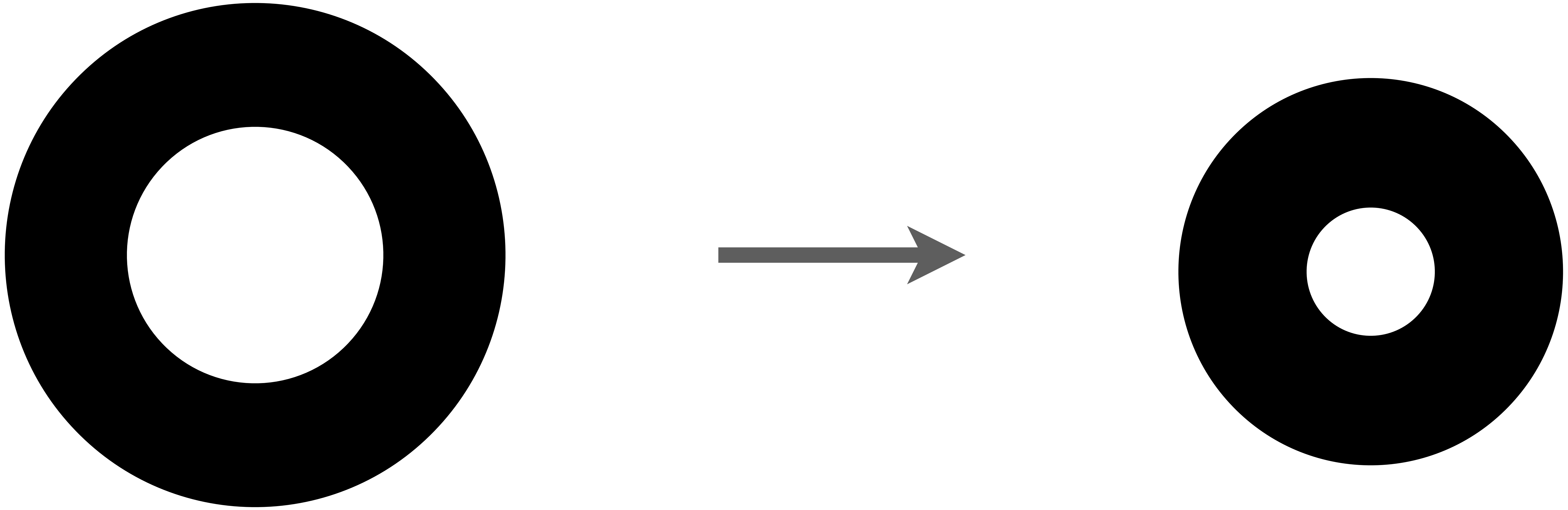
Example: Dilation

$$\begin{bmatrix} r & 0 \\ 0 & r \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} rx_1 \\ rx_2 \end{bmatrix}$$



if $r > 1$, then the transformation pushes points away from the origin

Example: Contraction



Example: Contraction

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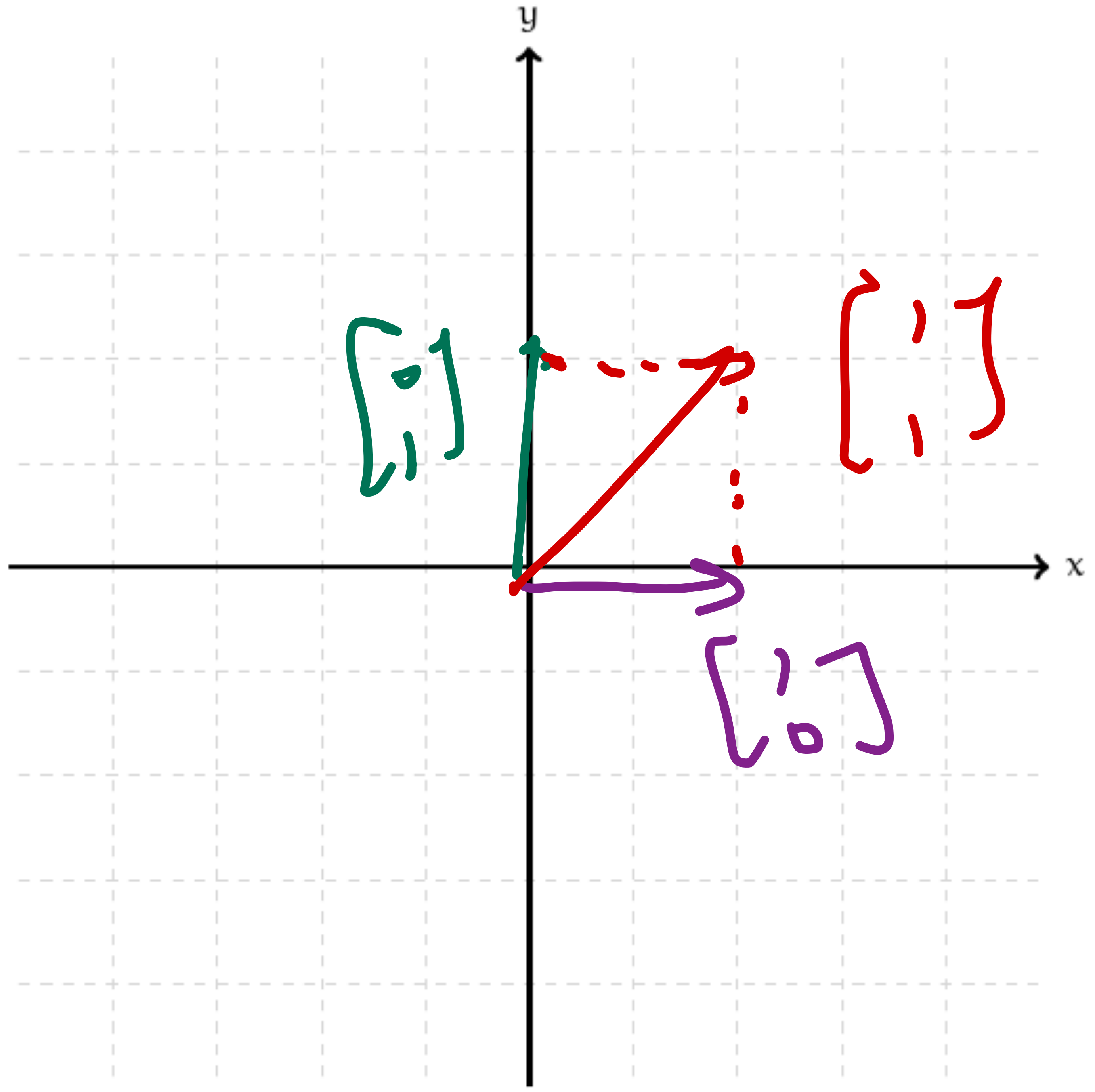
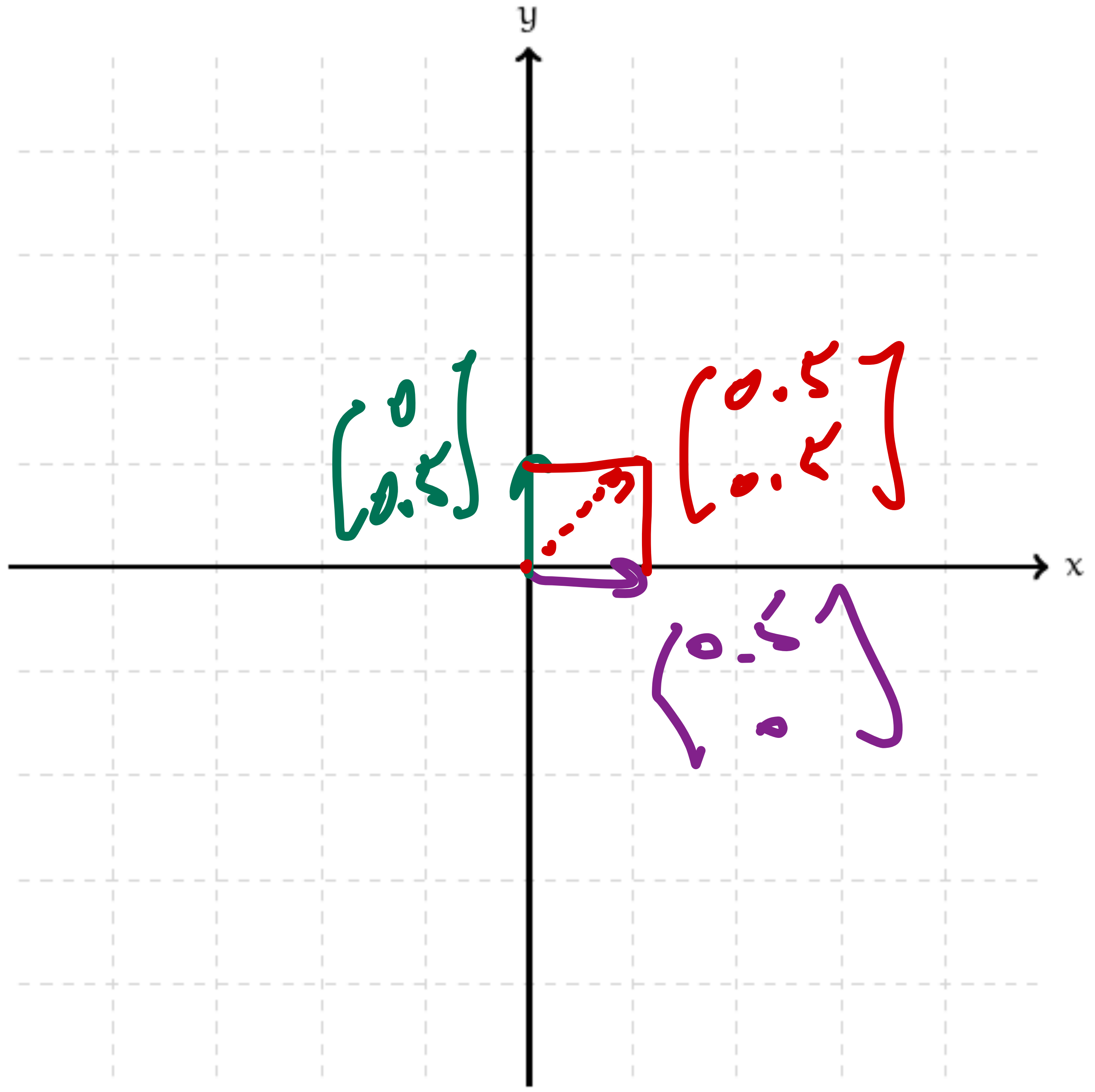


$$\begin{bmatrix} 0.5 & 0 \\ 0 & 0.5 \end{bmatrix} \mathbf{x}$$

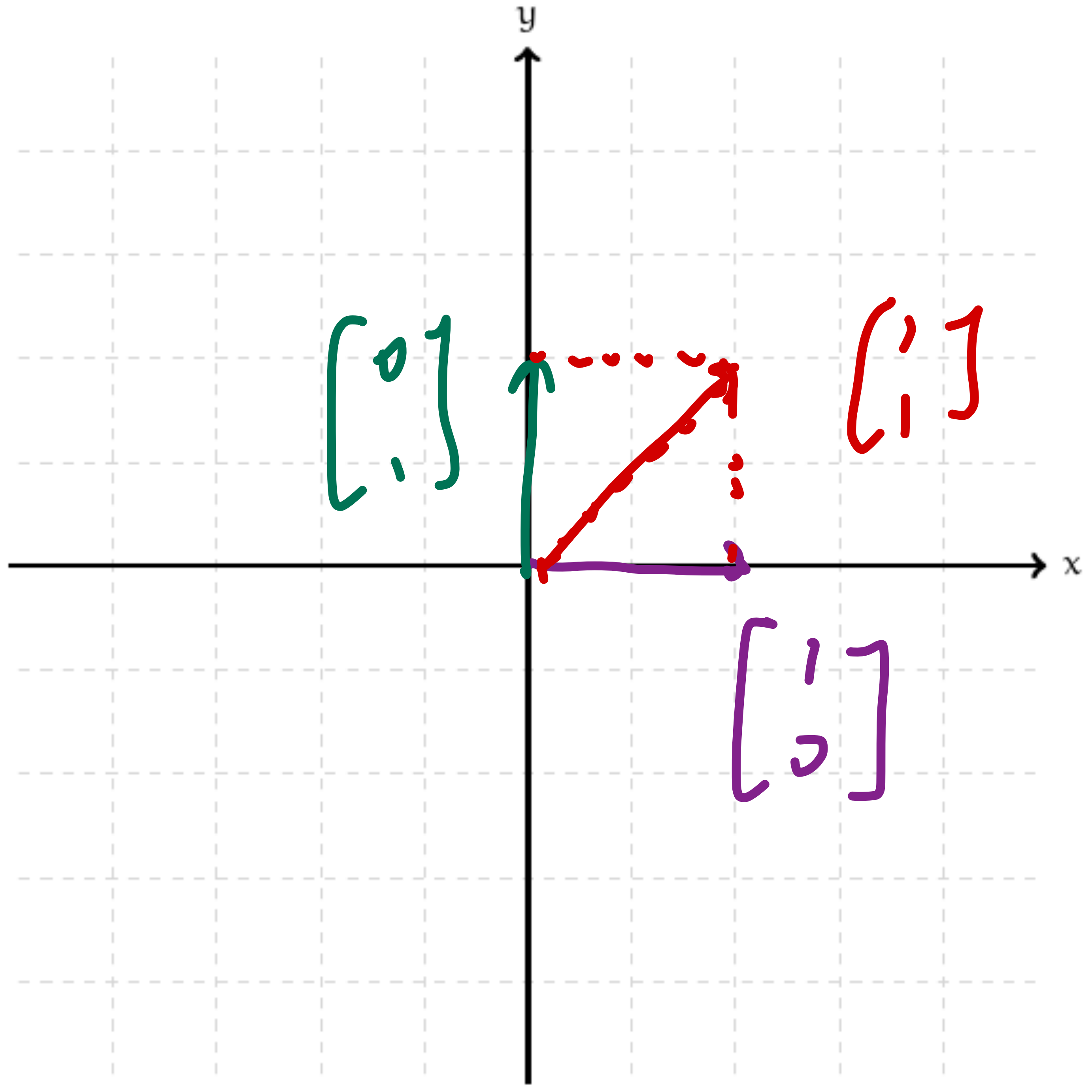


if $0 \leq r \leq 1$, then the transformation pulls points towards the origin

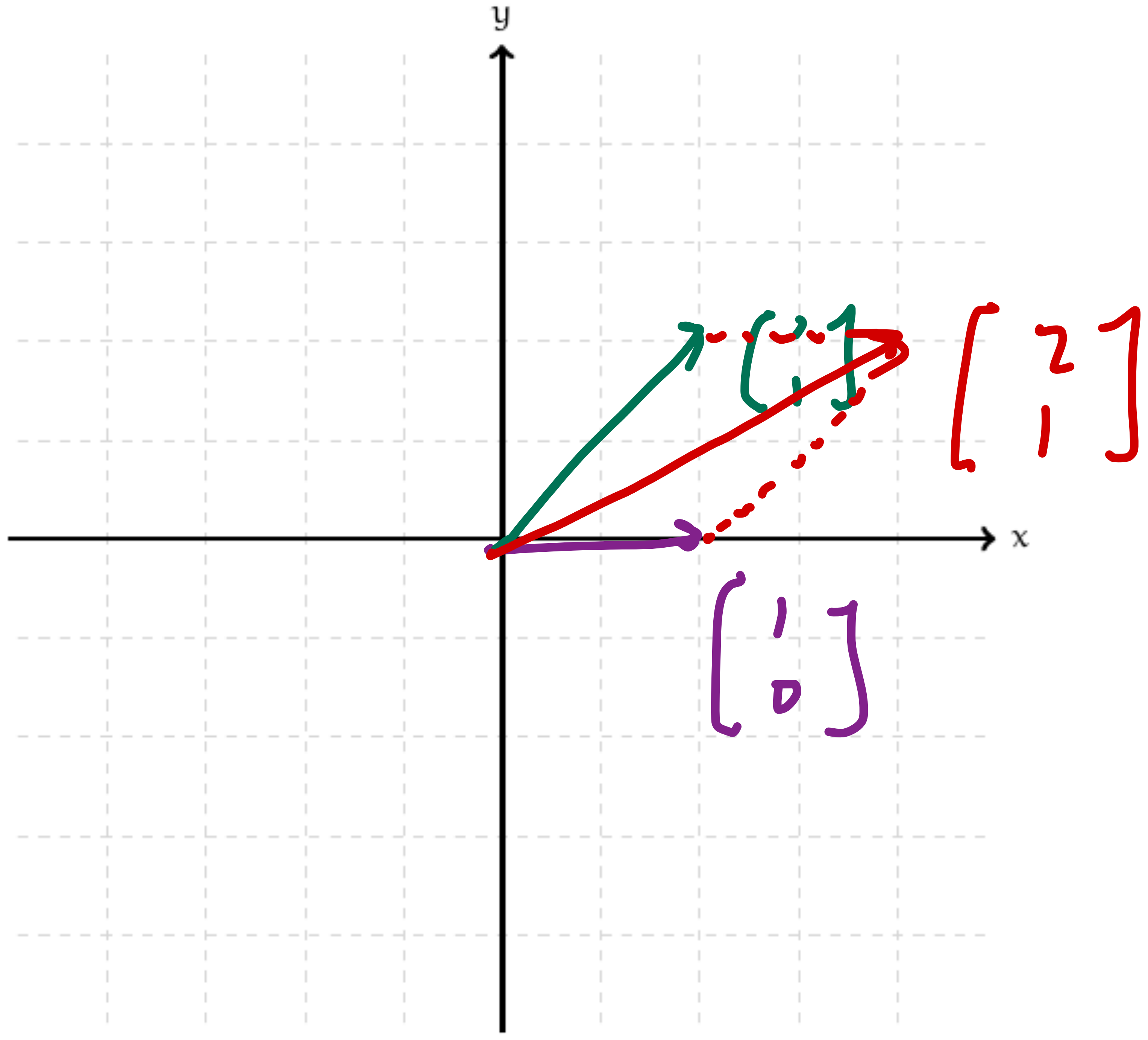
Example: Shearing

Example: Shearing

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

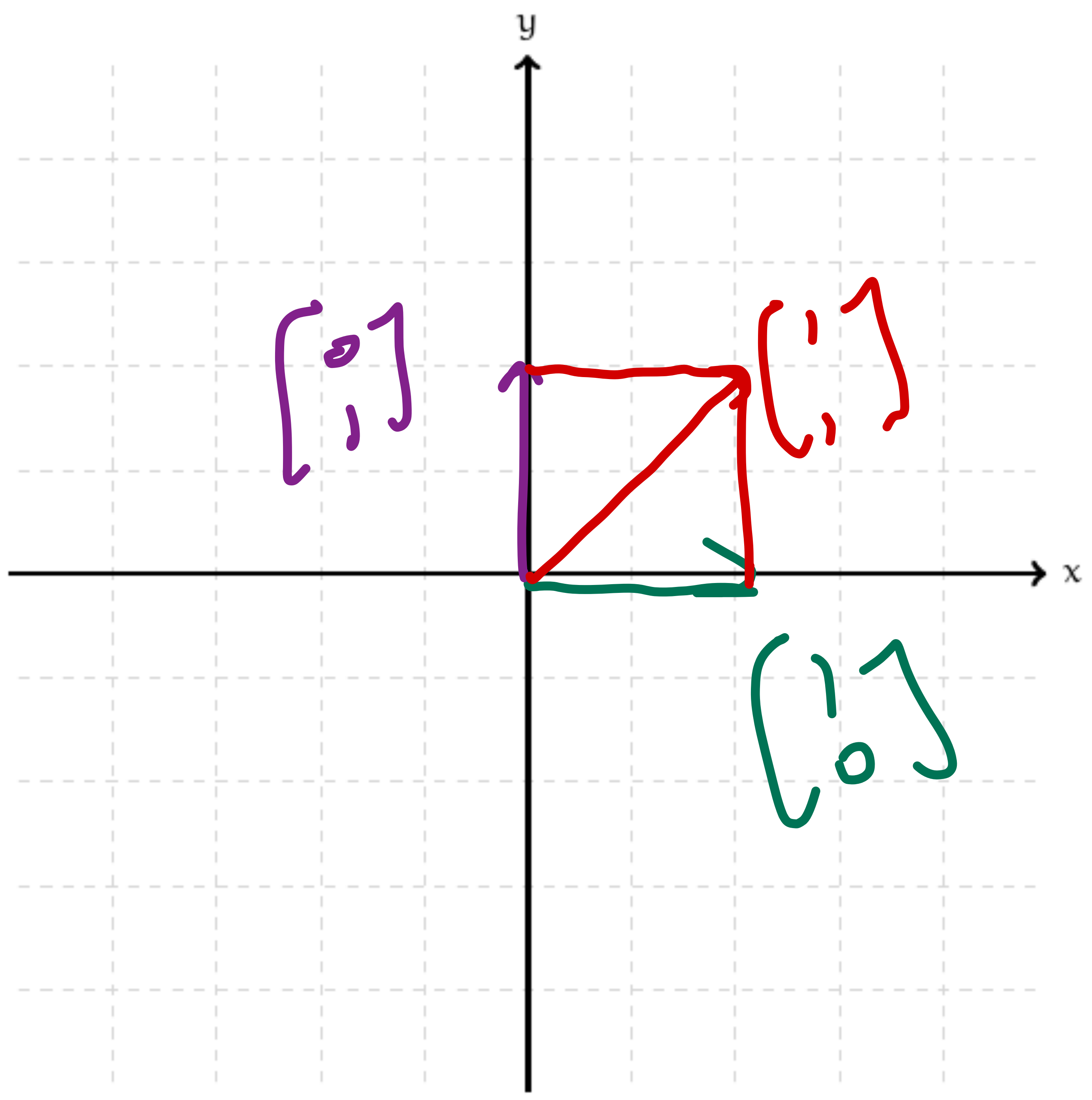


$$\begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \mathbf{x}$$

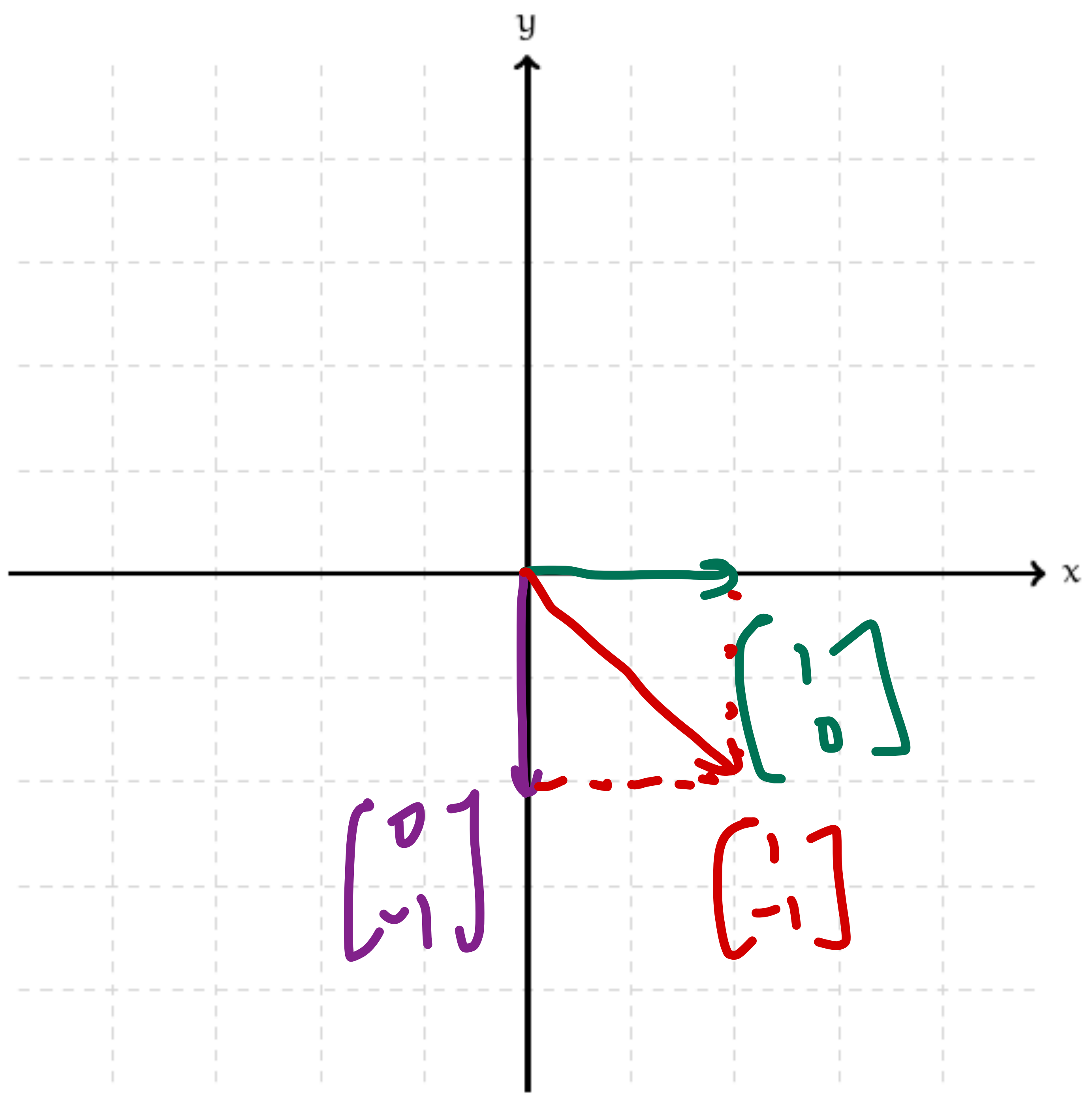


Imagine shearing like with rocks or metal

Example: Reflection

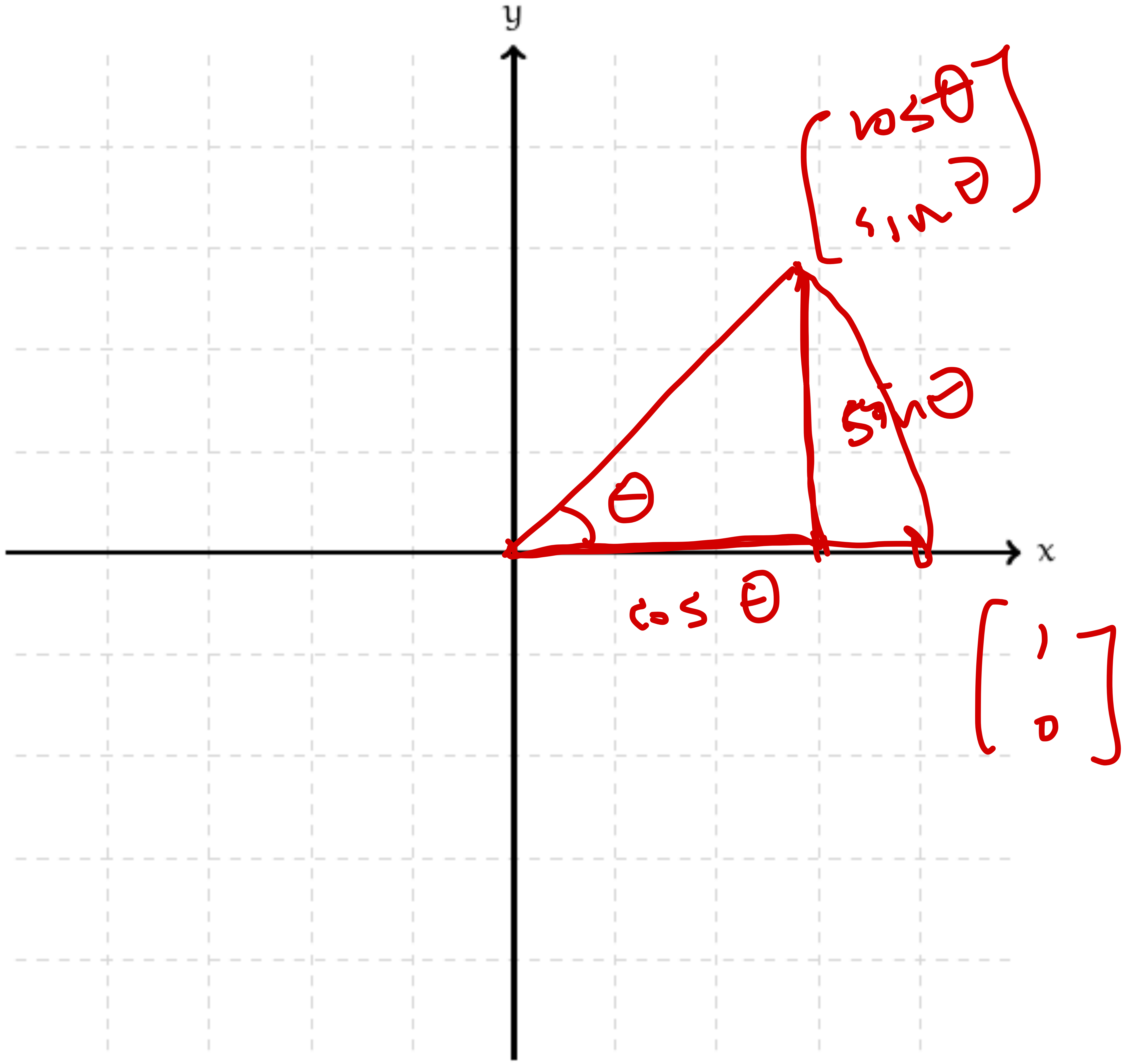


$$\begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} \mathbf{x}$$

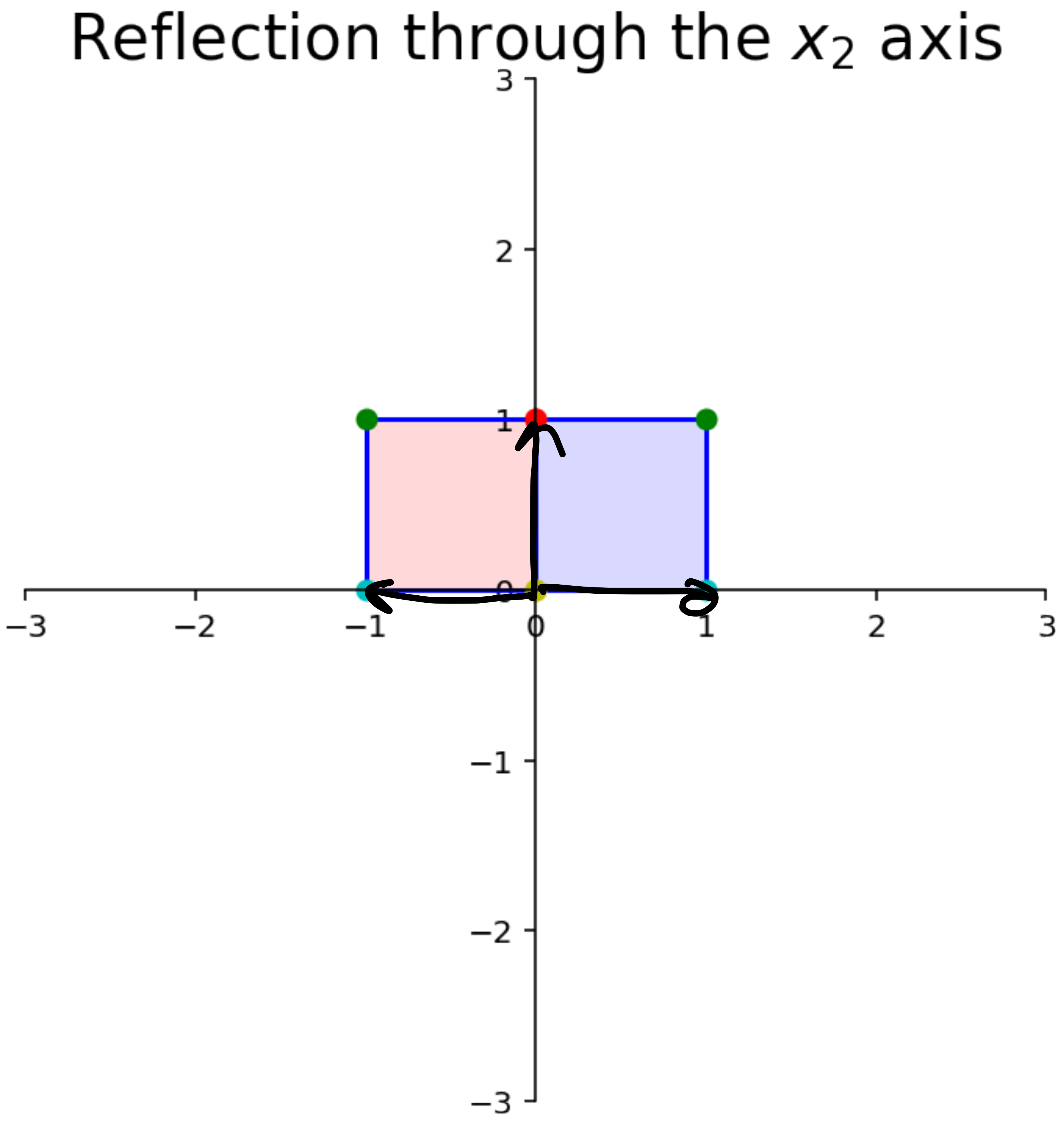


General Rotation

$$\begin{bmatrix} \boxed{\begin{matrix}\cos\theta \\ \sin\theta\end{matrix}} & \begin{matrix}-\sin\theta \\ \cos\theta\end{matrix} \end{bmatrix}$$



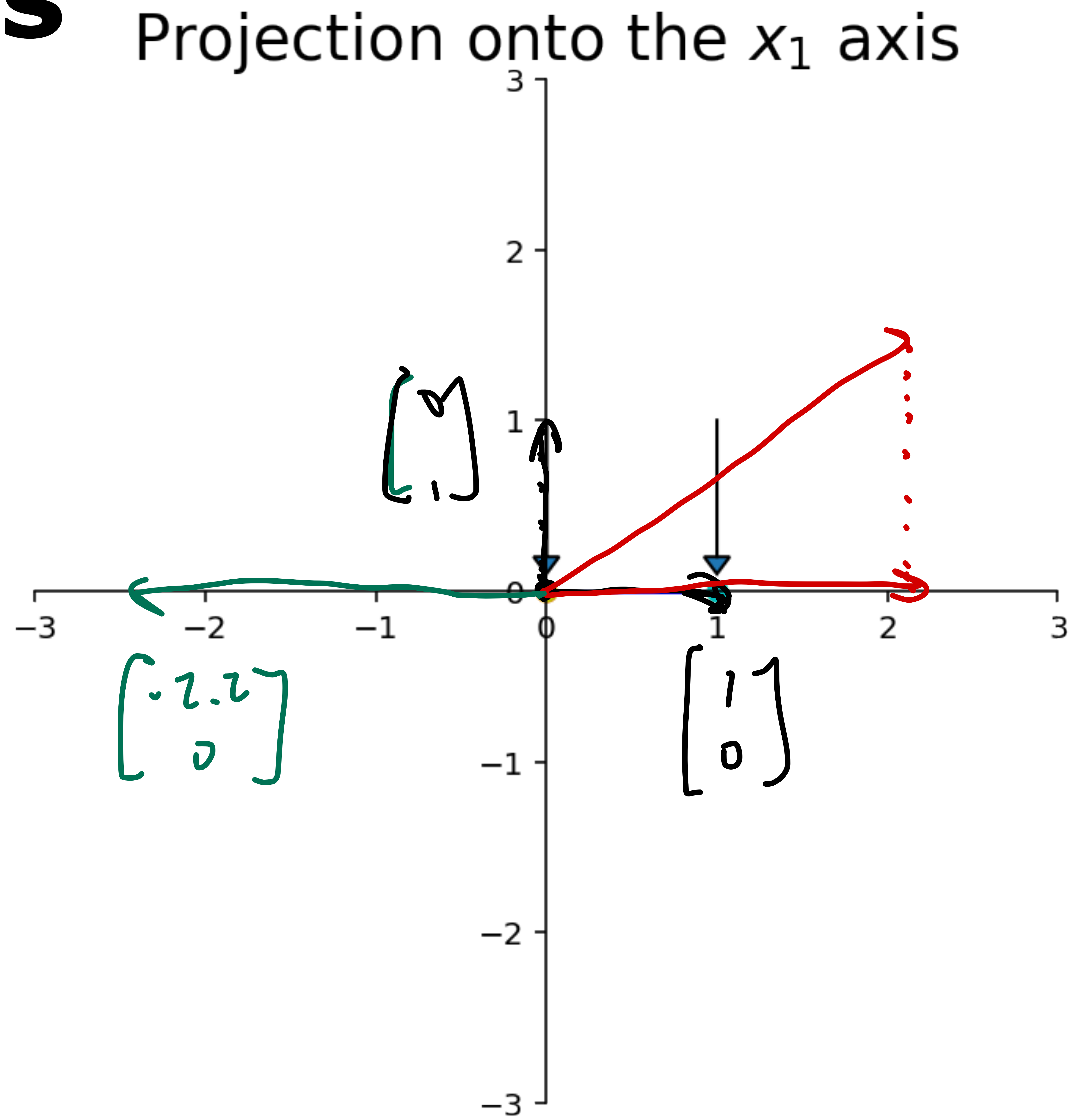
Example: Reflection through the x_2-axis



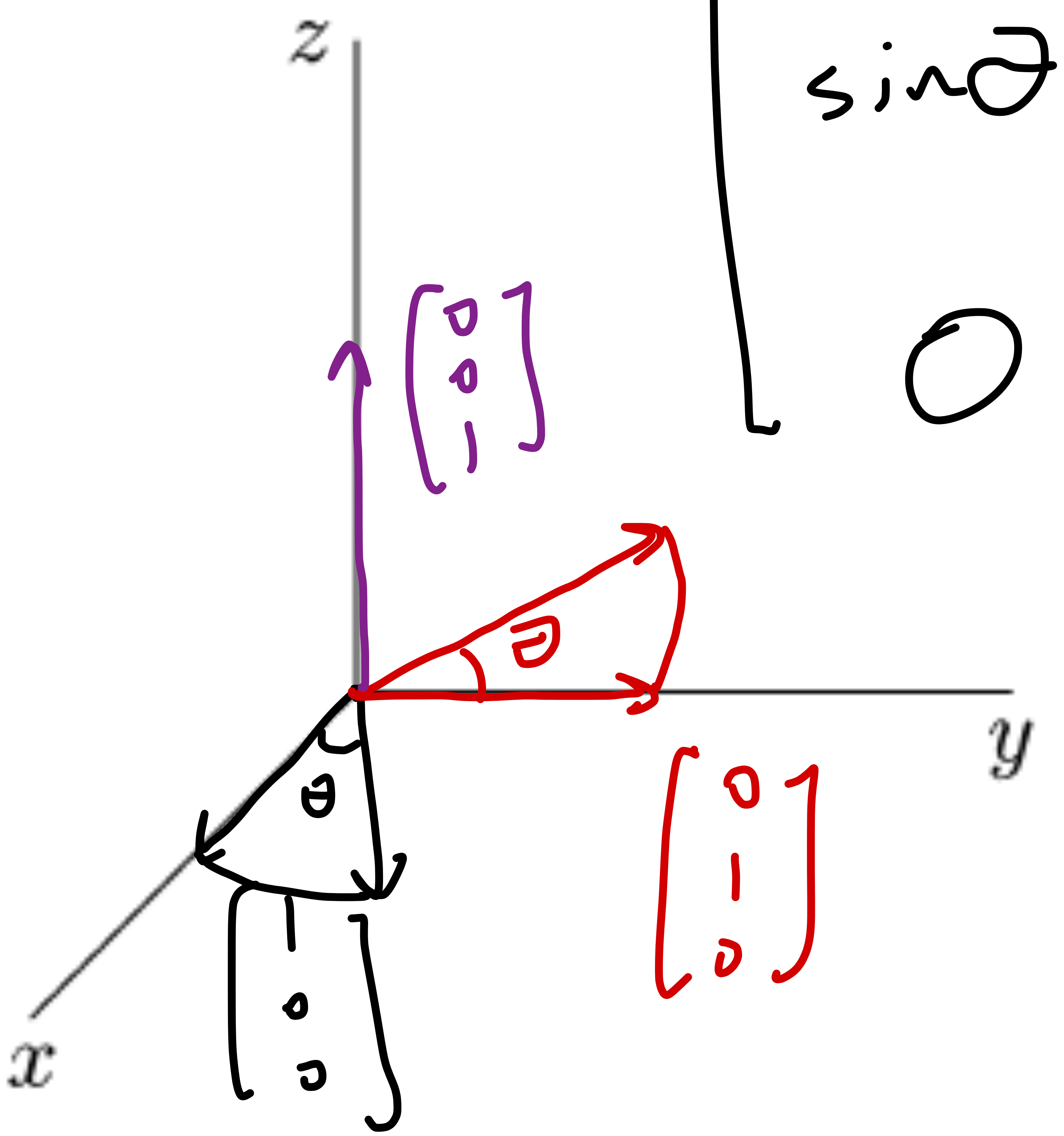
$$\begin{bmatrix} -1 & 0 \\ 0 & 1 \end{bmatrix}$$

Example: Projections

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



3D Example: Rotation about the x_3-Axis (z-Axis)



$$\begin{bmatrix} \cos\theta & -\sin\theta & 0 \\ \sin\theta & \cos\theta & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

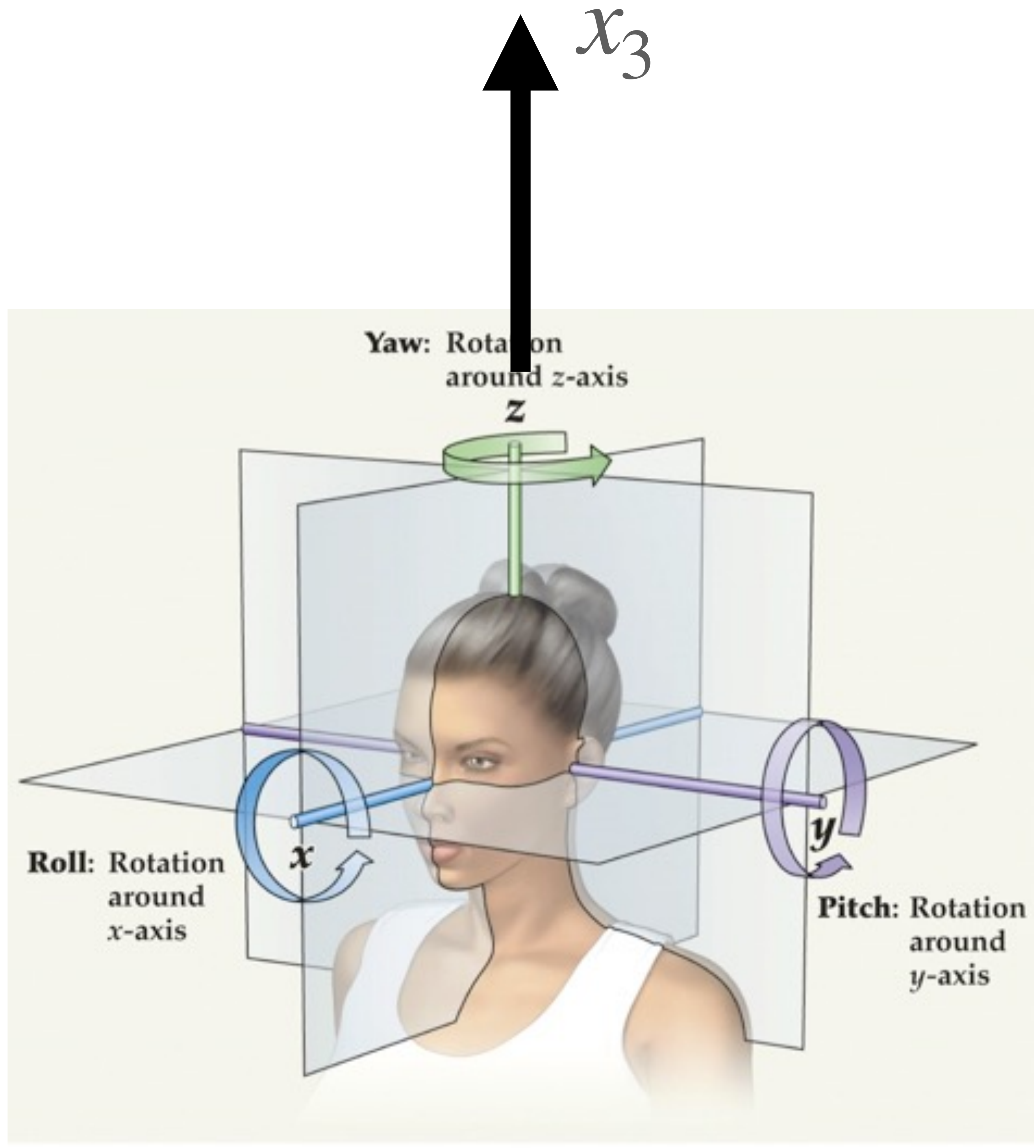
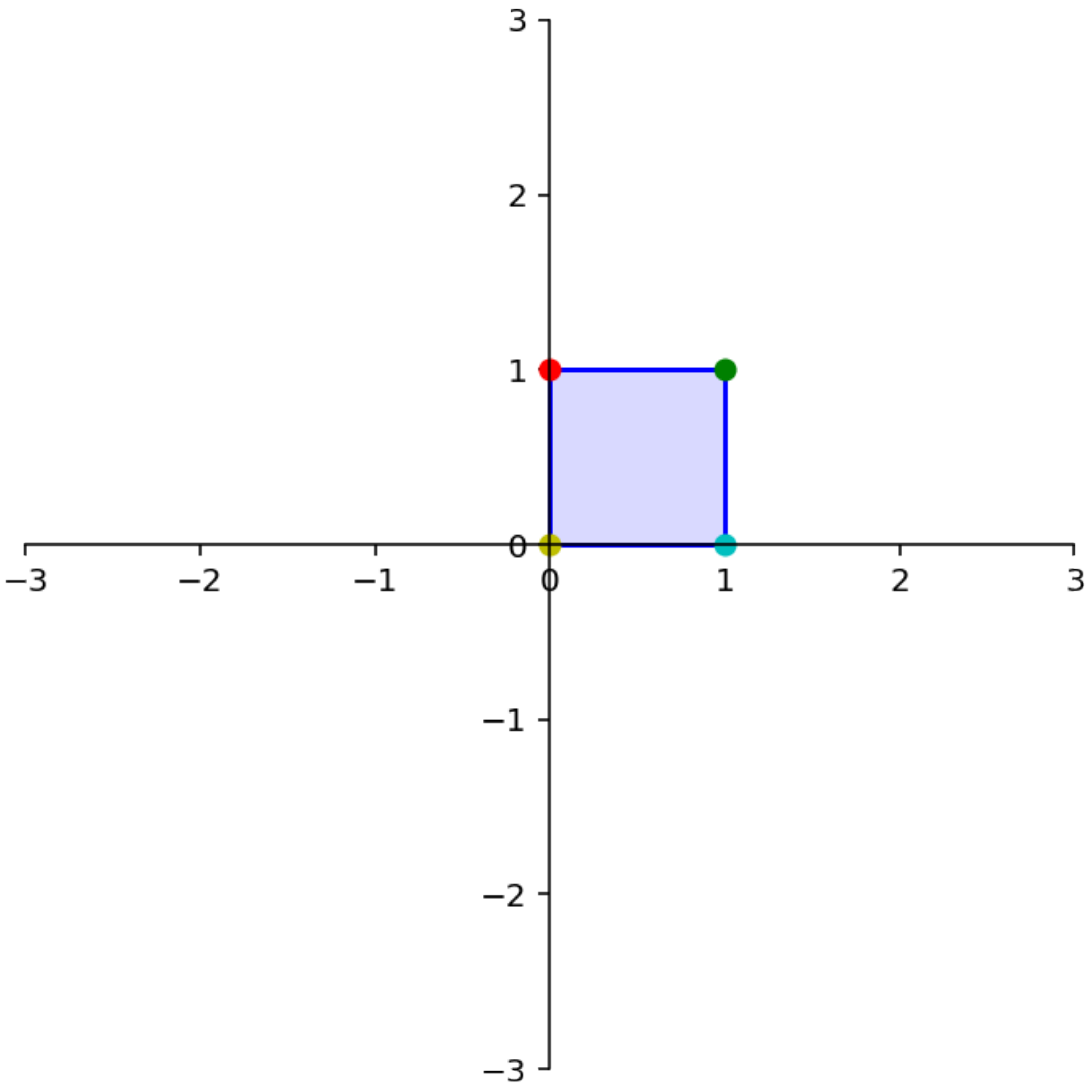


image source

The Unit Square

The ***unit square*** is the
enclosed by the points



How To: The Unit Square and Matrices

How To: The Unit Square and Matrices

Question. Find the matrix which implements the linear transformation which is represented geometrically in the following picture

How To: The Unit Square and Matrices

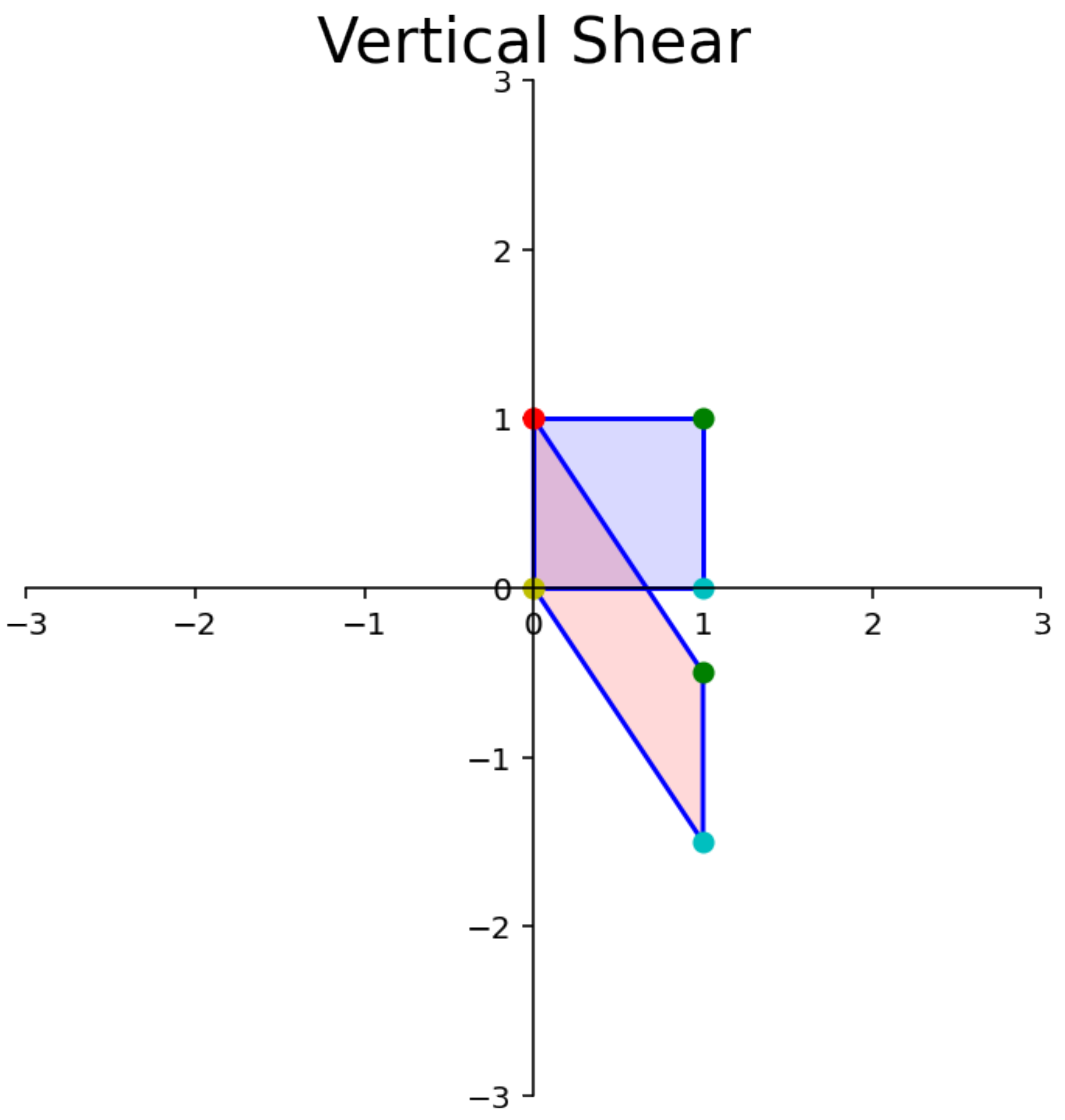
Question. Find the matrix which implements the linear transformation which is represented geometrically in the following picture

Solution. Find where the standard basis vectors go

Example

Write down the matrix for the following shearing operation using this method

Exercise:



You need to know these matrices, but you don't need to memorize them

Remember: What does this matrix do to the unit square? Then build the matrix from there

List of Important 2D Linear Transformations

- dilation, contraction
- reflections
- projections
- horizontal/vertical contractions
- horizontal/vertical shearing

Look through the notes for a comprehensive collection of pictures or... (demo)

One-to-One and Onto

Recall: Motivating Questions

What kind of functions can we define in this way?

How do we interpret what the transformation does to a set of vectors?

How does this relate back to matrix equations?

Recall: A New Interpretation of the Matrix Equation

$A\mathbf{x} = \mathbf{b}$?	$\equiv$	is there a vector which A transforms into $\mathbf{b}$?
Solve $A\mathbf{x} = \mathbf{b}$	$\equiv$	find a vector which A transforms into $\mathbf{b}$

Recall: A New Interpretation of the Matrix Equation

$A\mathbf{x} = \mathbf{b}$? $\equiv$ is there a vector which A transforms into $\mathbf{b}$?

Solve $A\mathbf{x} = \mathbf{b}$ $\equiv$ find a vector which A transforms into $\mathbf{b}$

What about other questions?

Other Questions Like...

Does $A\mathbf{x} = \mathbf{b}$ have a solution for any choice of $\mathbf{b}$?

Does $A\mathbf{x} = \mathbf{0}$ have a unique solution?

Other Questions Like...

Does $A\mathbf{x} = \mathbf{b}$ have at least one solution for any choice of $\mathbf{b}$?

Does $A\mathbf{x} = \mathbf{b}$ have at most one solution for any choice of $\mathbf{b}$?

Wait

$A\mathbf{x} = \mathbf{0}$ has a unique solution $\equiv$ $A\mathbf{x} = \mathbf{b}$ has at most one solution

why?:

$A\vec{v}_1 = \vec{b}$

$A\vec{v}_2 = \vec{b}$

$\vec{v}_1 \neq \vec{v}_2$

$A(\vec{v}_1 - \vec{v}_2) = A\vec{v}_1 - A\vec{v}_2 = \vec{b} - \vec{b} = \vec{0}$

Onto Transformations

Onto Transformations

Definition. A transformation $T : \mathbb{R}^n \to \mathbb{R}^m$ is ***onto*** if any vector $\mathbf{b}$ in $\mathbb{R}^m$ is the image of at least one vector $\mathbf{v}$ in $\mathbb{R}^n$ (where $T(\mathbf{v}) = \mathbf{b}$)

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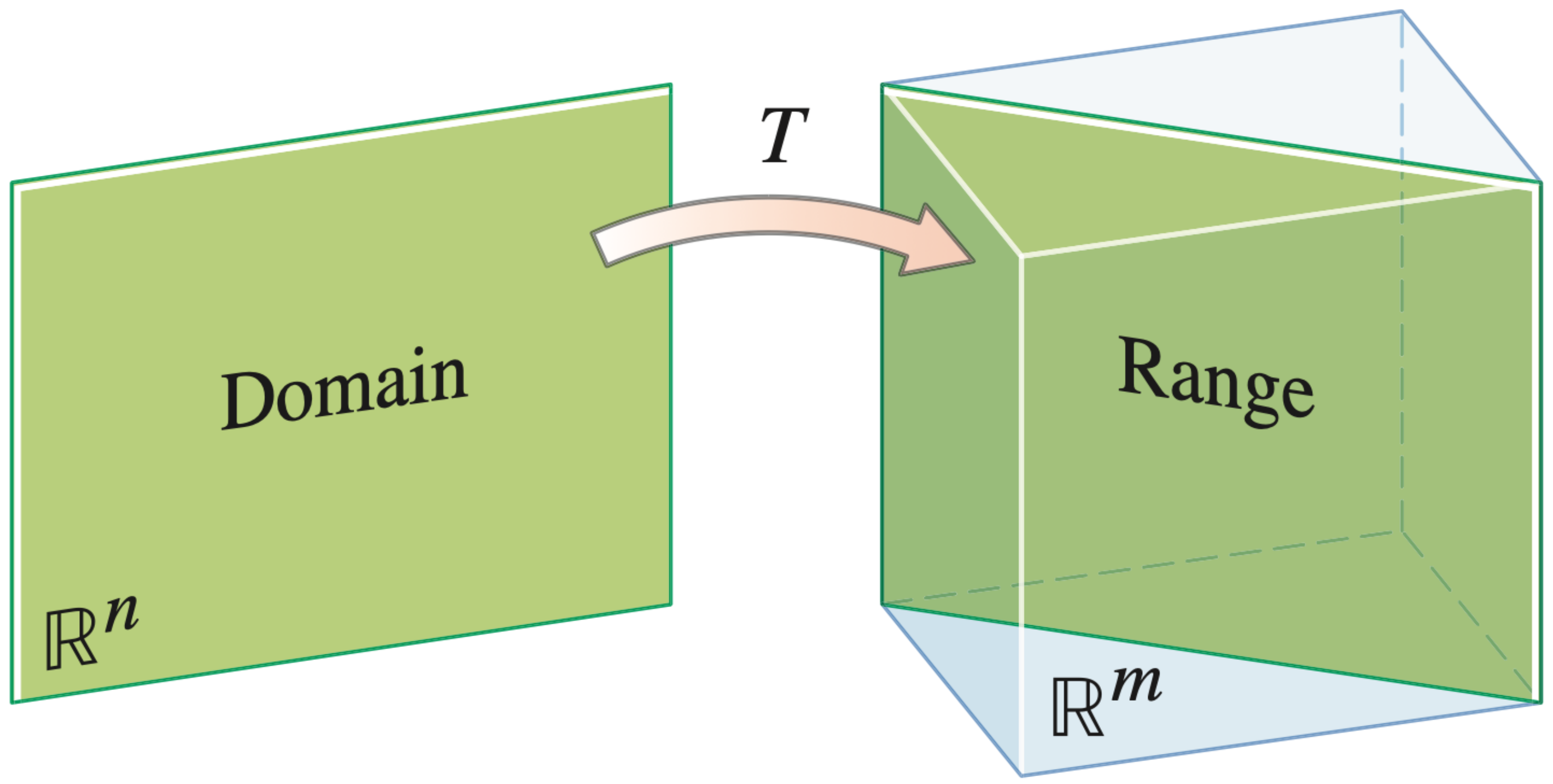
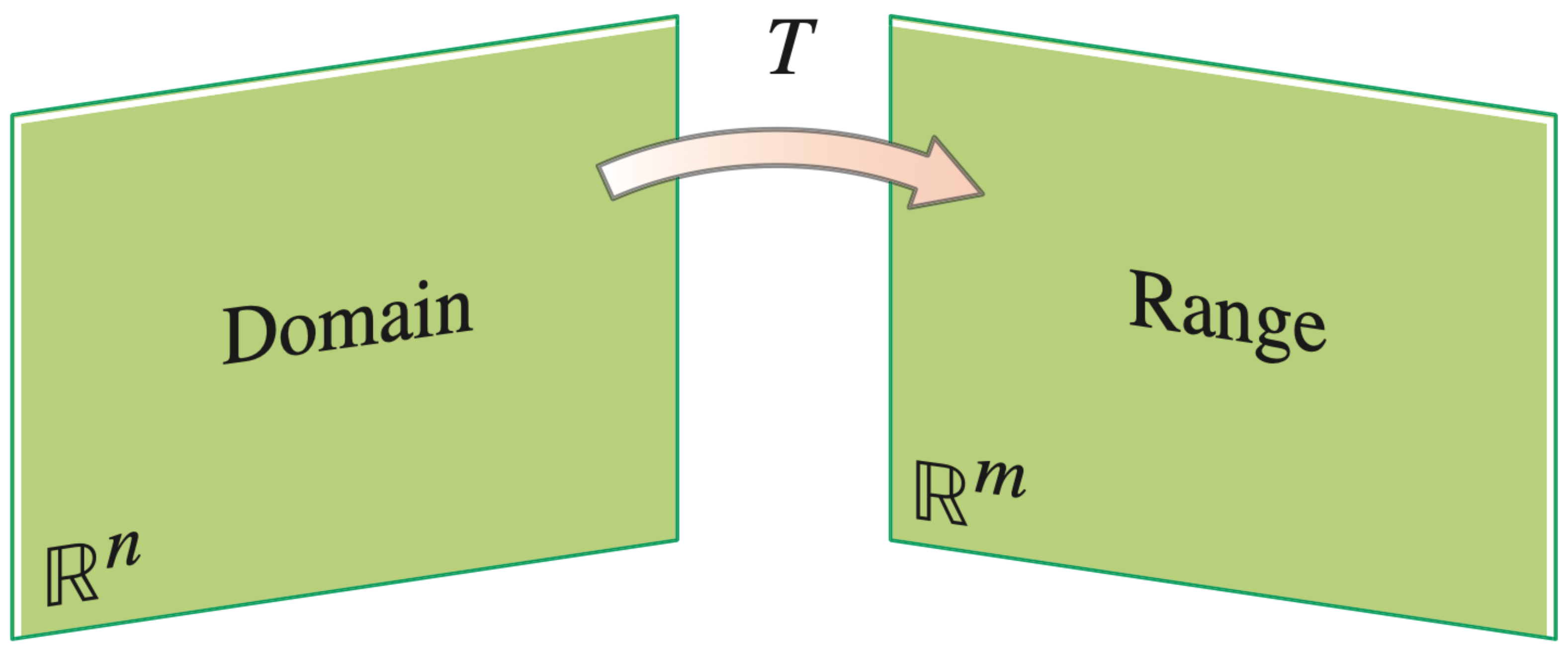


T is *not* onto $\mathbb{R}^m$



T is onto $\mathbb{R}^m$

image source: Linear Algebra and its Applications. Lay, Lay, and McDonald

Onto Transformations

(surjective)

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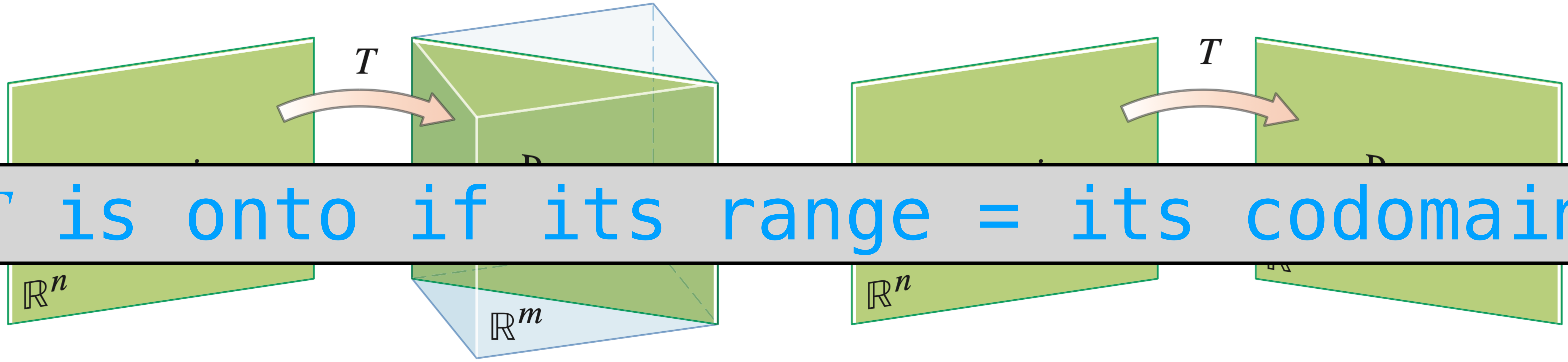

T is onto if its range = its codomain

T is *not* onto $\mathbb{R}^m$ T is onto $\mathbb{R}^m$

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One-to-one Transformations

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Definition. A transformation $T:\mathbb{R}^n \to \mathbb{R}^m$ is ***one-to-one*** if any vector $\mathbf{b}$ in $\mathbb{R}^m$ is the image of at most one vector $\mathbf{v}$ in $\mathbb{R}^n$ (where $T(\mathbf{v}) = \mathbf{b}$)

One-to-one Transformations

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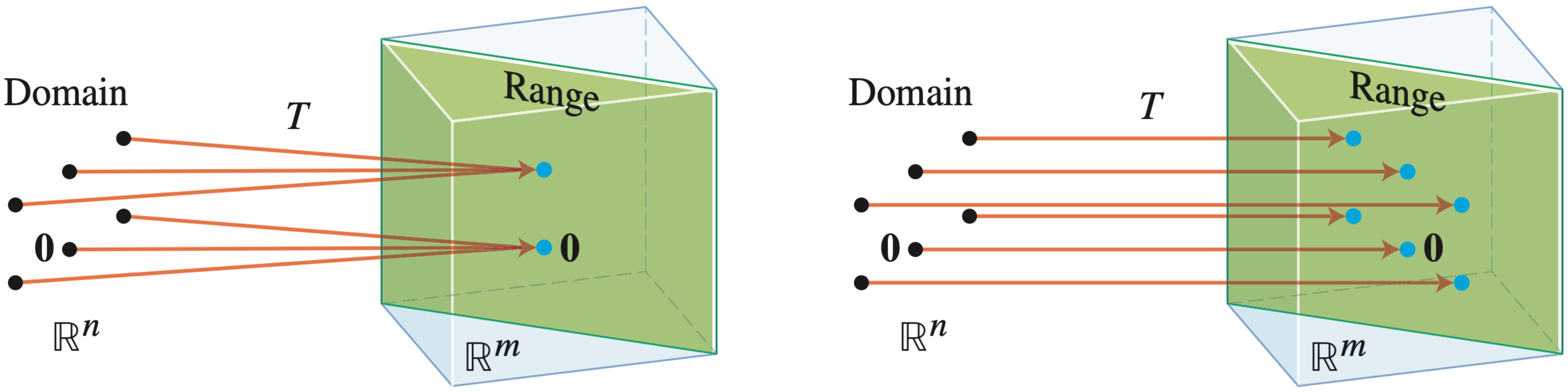
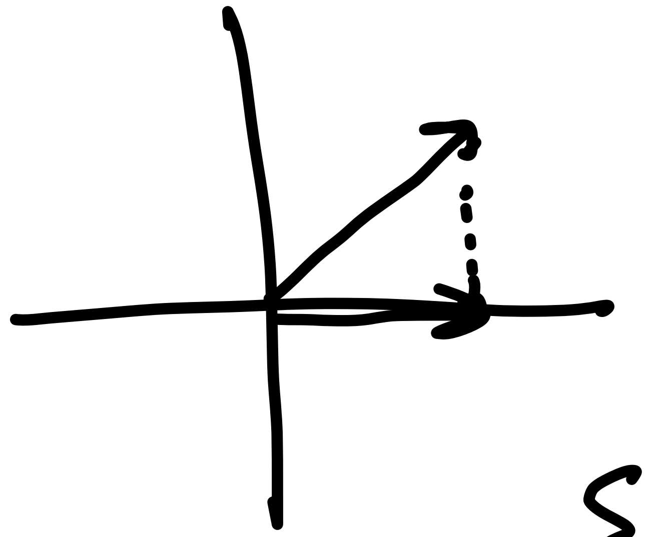


T is *not* one-to-one

T is one-to-one

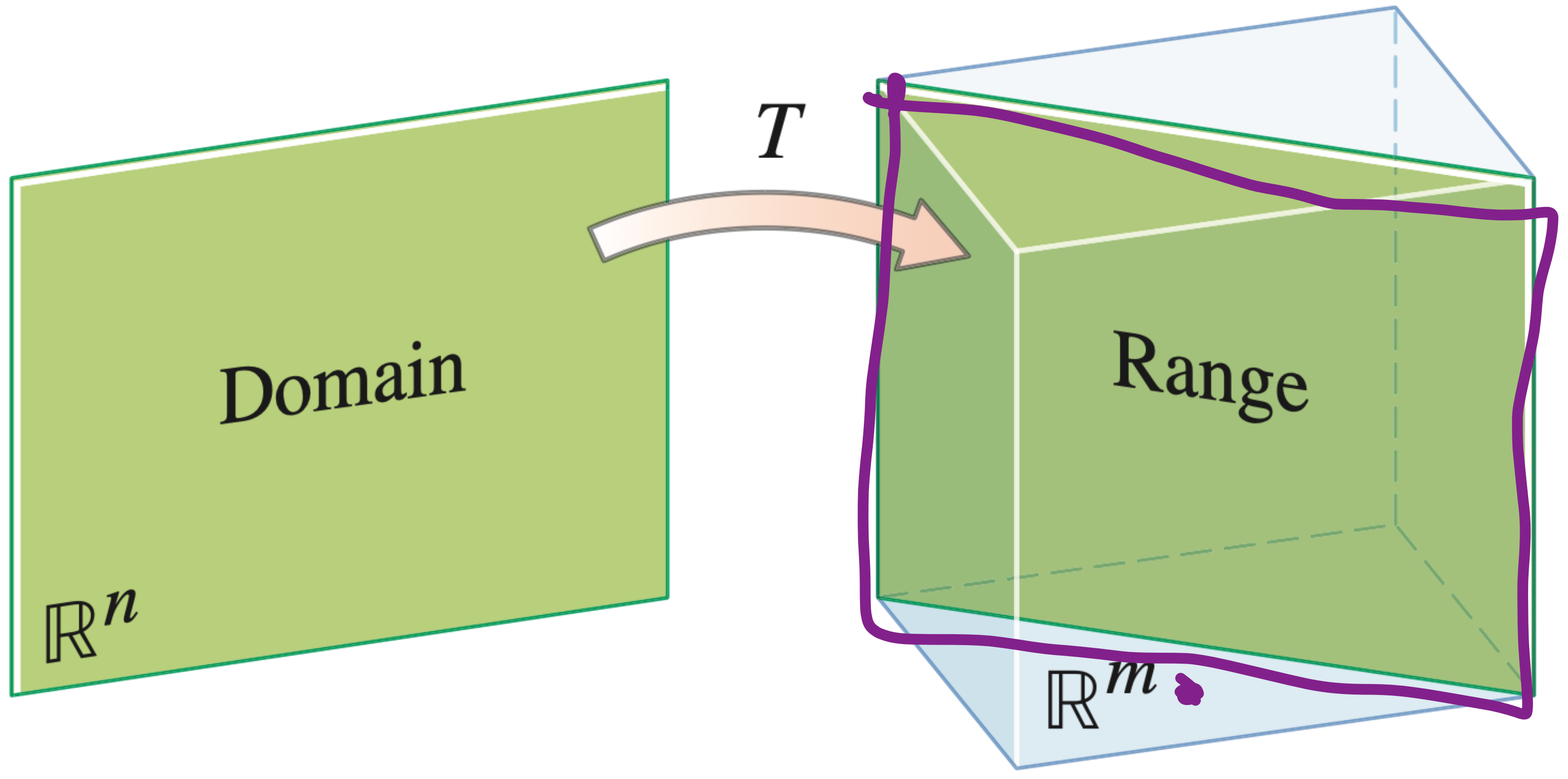
image source: Linear Algebra and its Applications. Lay, Lay, and McDonald

Comparing Pictures

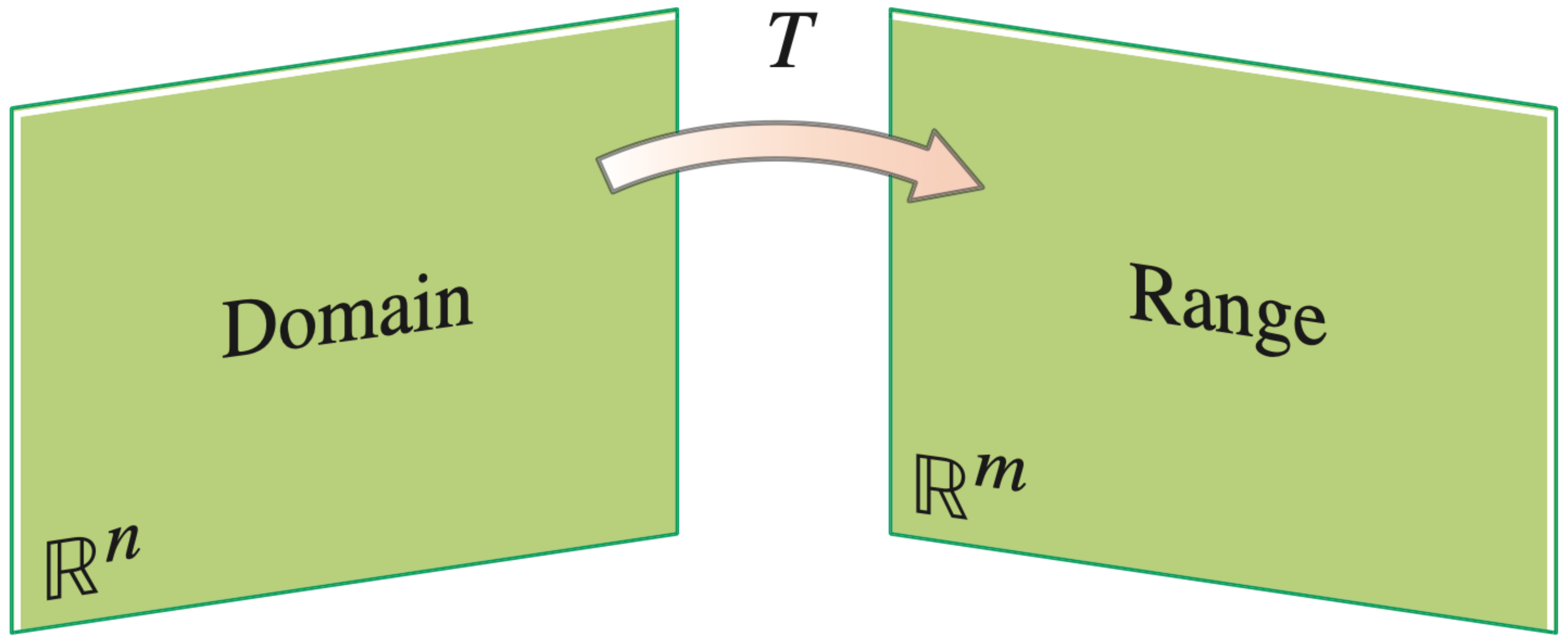


$\operatorname{ran}(T) = \{T(\vec{v}) : v \in \operatorname{dom}(T)\}$

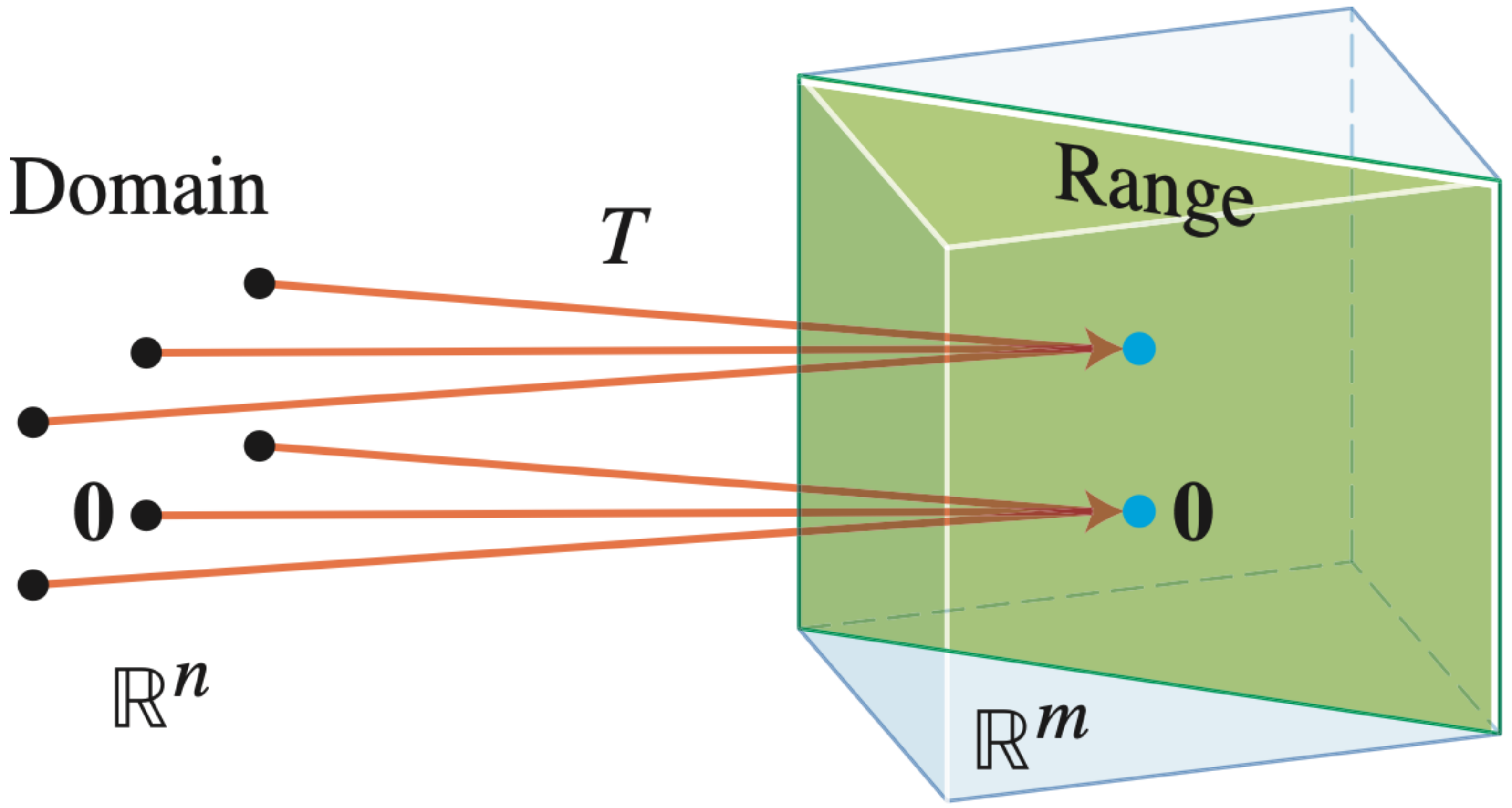
$\subseteq \mathbb{R}^m$



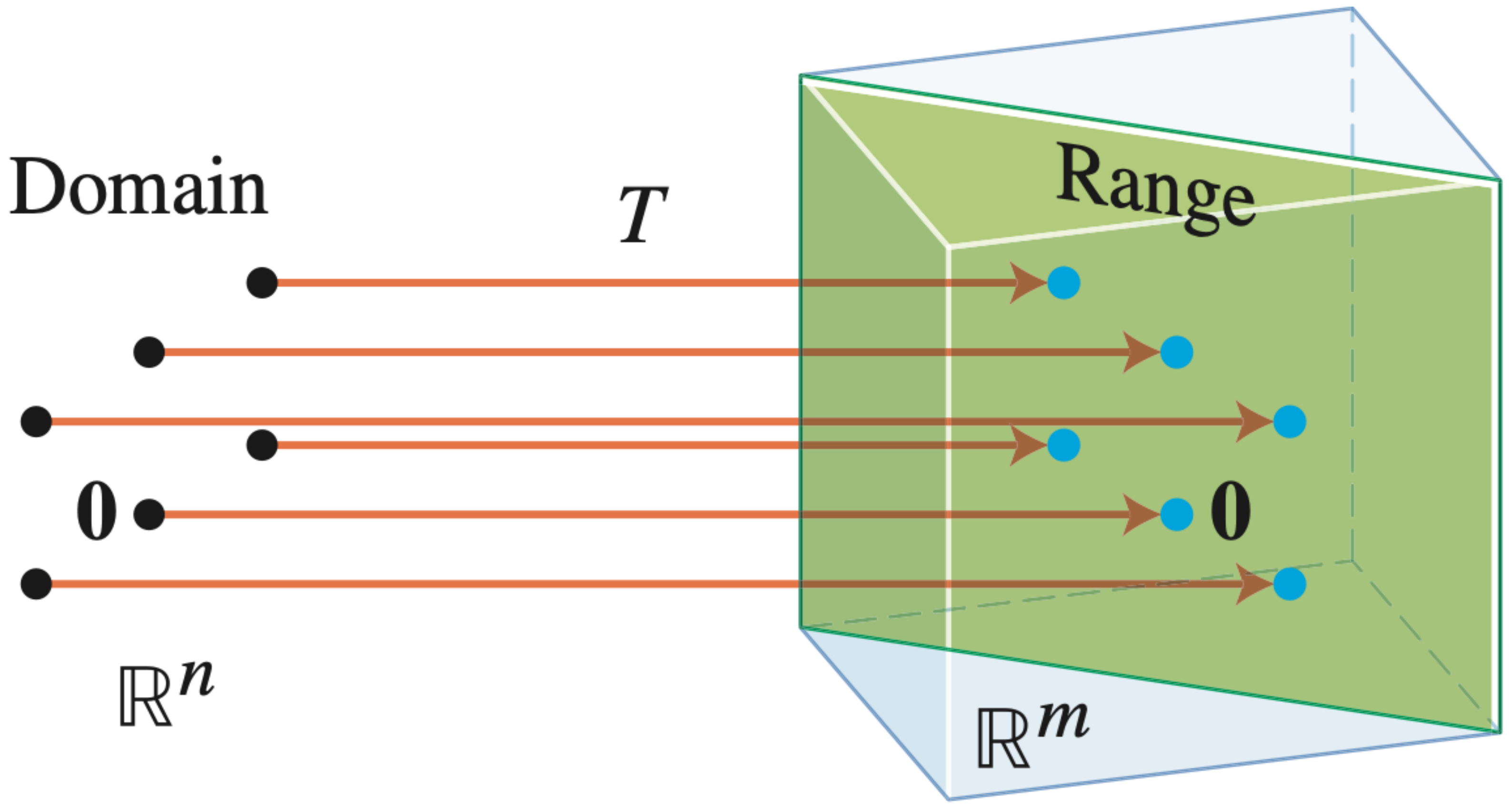
T is *not* onto $\mathbb{R}^m$



T is onto $\mathbb{R}^m$



T is *not* one-to-one



T is one-to-one

$$\text{range}(T) = \underbrace{\{}_{\text{the set of all}}\ \underbrace{T(\vec{v})}_{\text{output of } T \text{ on } \vec{v}}\ \underbrace{:}_{\text{such that}}\ \underbrace{\vec{v} \in \text{dom}(T)\}}_{\vec{v} \text{ is in the domain of } T}$$

$$T\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}\right) \in \text{ran}(T)$$

$$T\left(\begin{bmatrix} 1 \\ 2 \end{bmatrix}\right) \in \text{ran}(T)$$

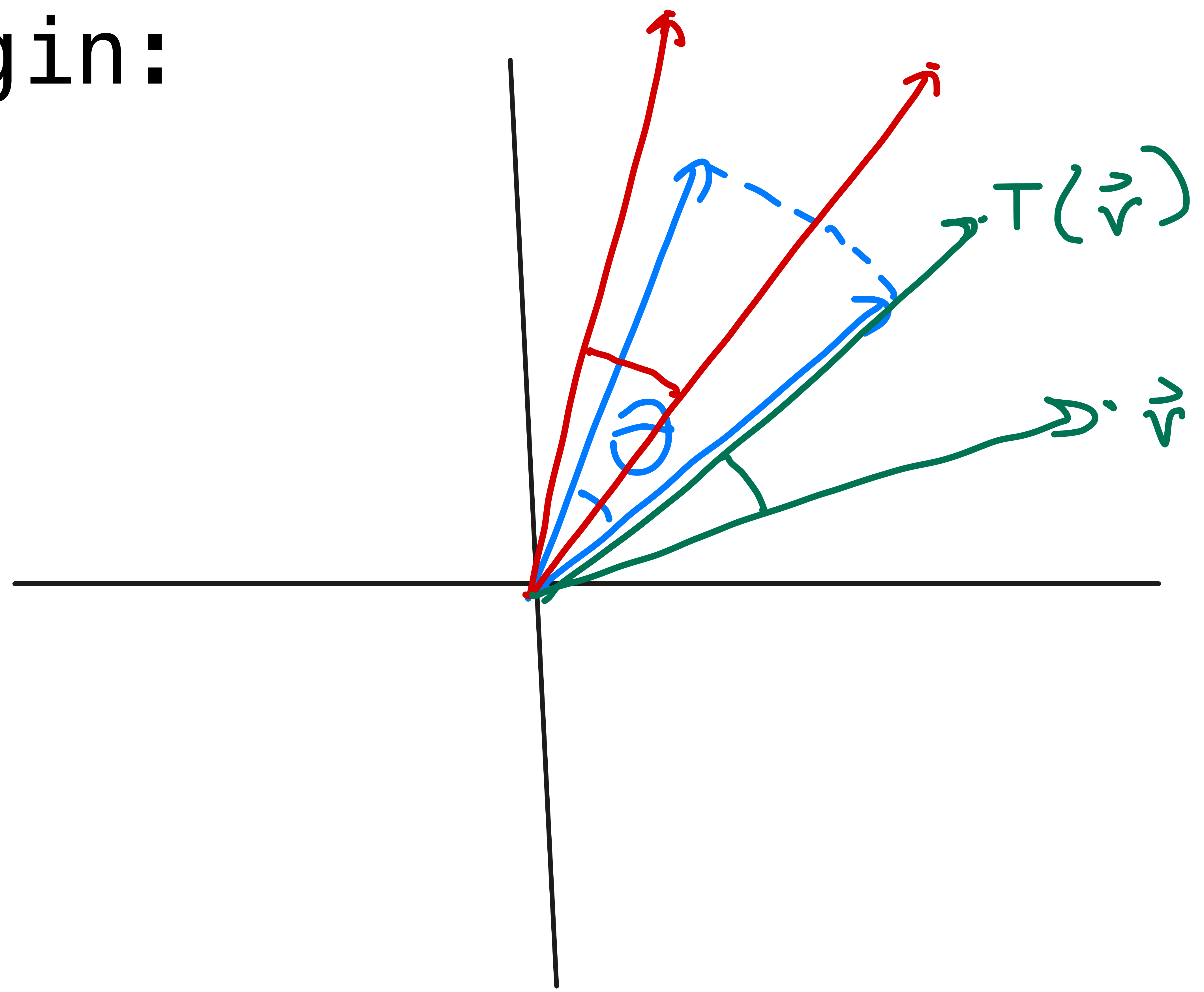
set of <u>all</u> images of T

Example: both 1-1 and onto

Rotation about the origin:

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

why?:



Example: 1-1, not onto

Lifting:

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \mapsto \begin{bmatrix} x_1 \\ x_2 \\ x_1 + x_2 \end{bmatrix}$$

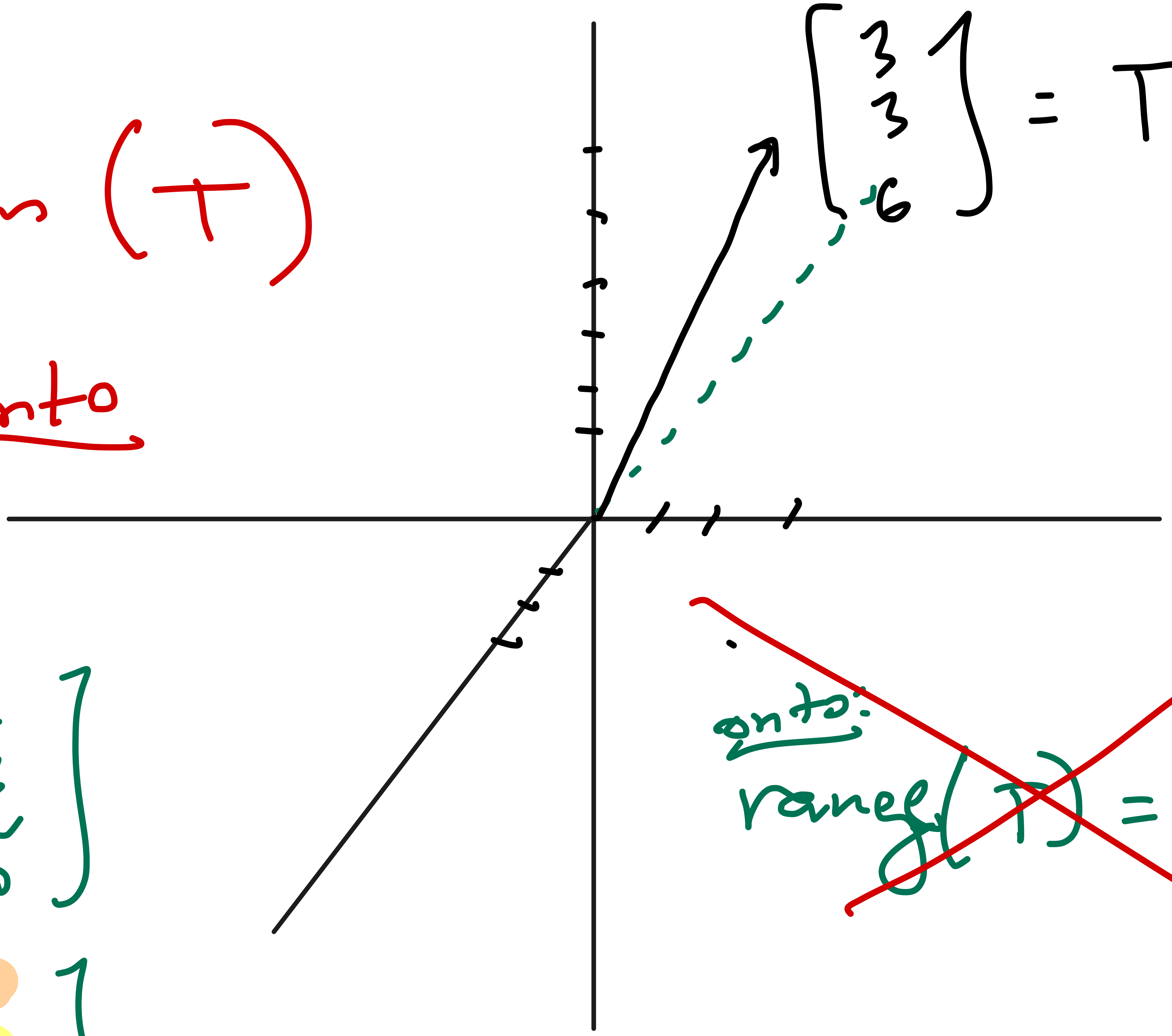
$\begin{bmatrix} 1 \\ 2 \\ 4 \end{bmatrix} \notin \operatorname{ran}(T)$

not onto

why?:

$\begin{bmatrix} 2 \\ 3 \end{bmatrix} \mapsto \begin{bmatrix} 2 \\ 3 \\ 5 \end{bmatrix}$

$\begin{bmatrix} 3 \\ 2 \end{bmatrix} \mapsto \begin{bmatrix} 3 \\ 2 \\ 5 \end{bmatrix}$



$\begin{bmatrix} 3 \\ 3 \\ 6 \end{bmatrix} = T\left(\begin{bmatrix} 3 \\ 3 \end{bmatrix}\right)$

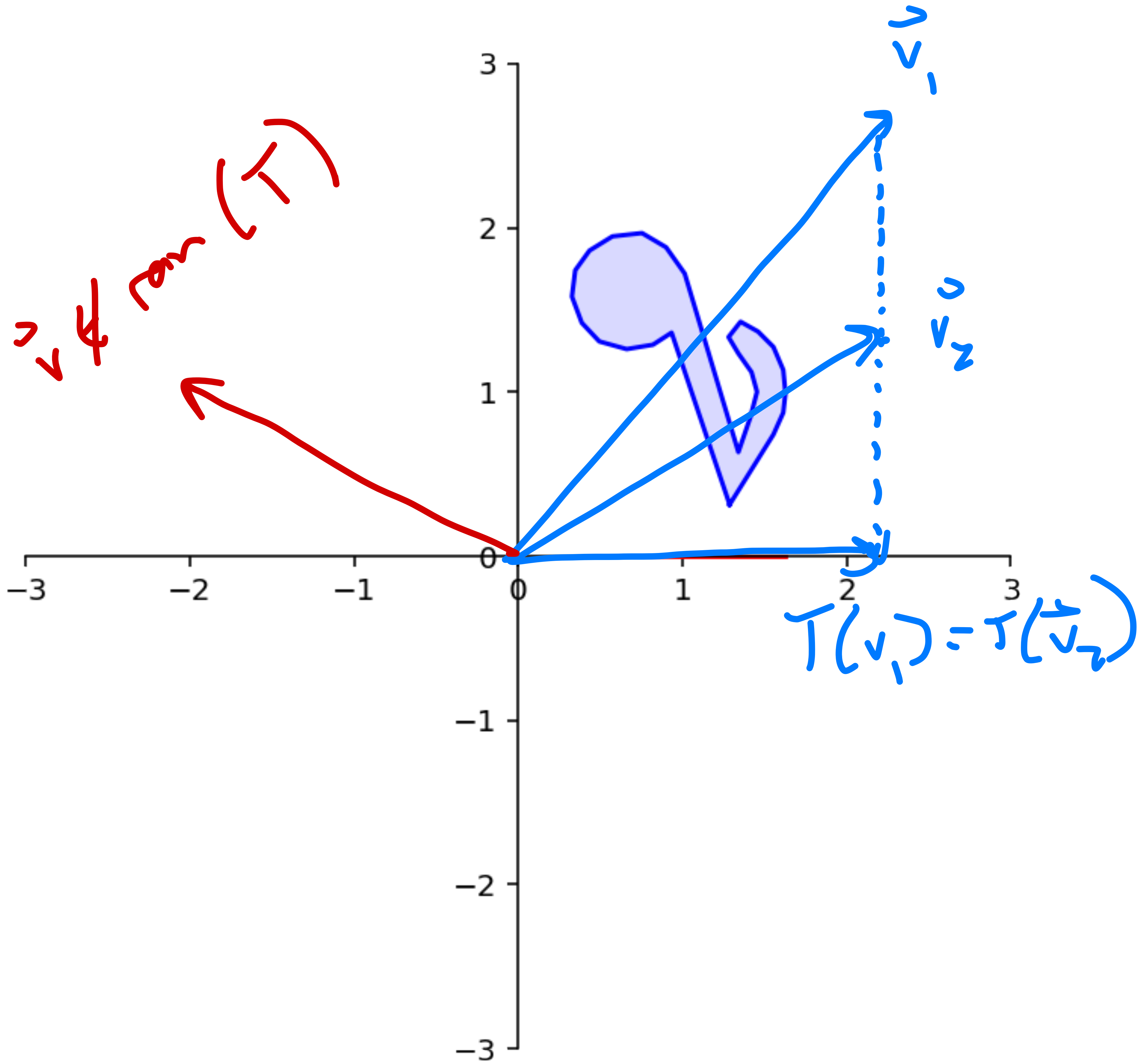
~~onto: range(T) = $\mathbb{R}^3$~~

Example: not 1-1, not onto

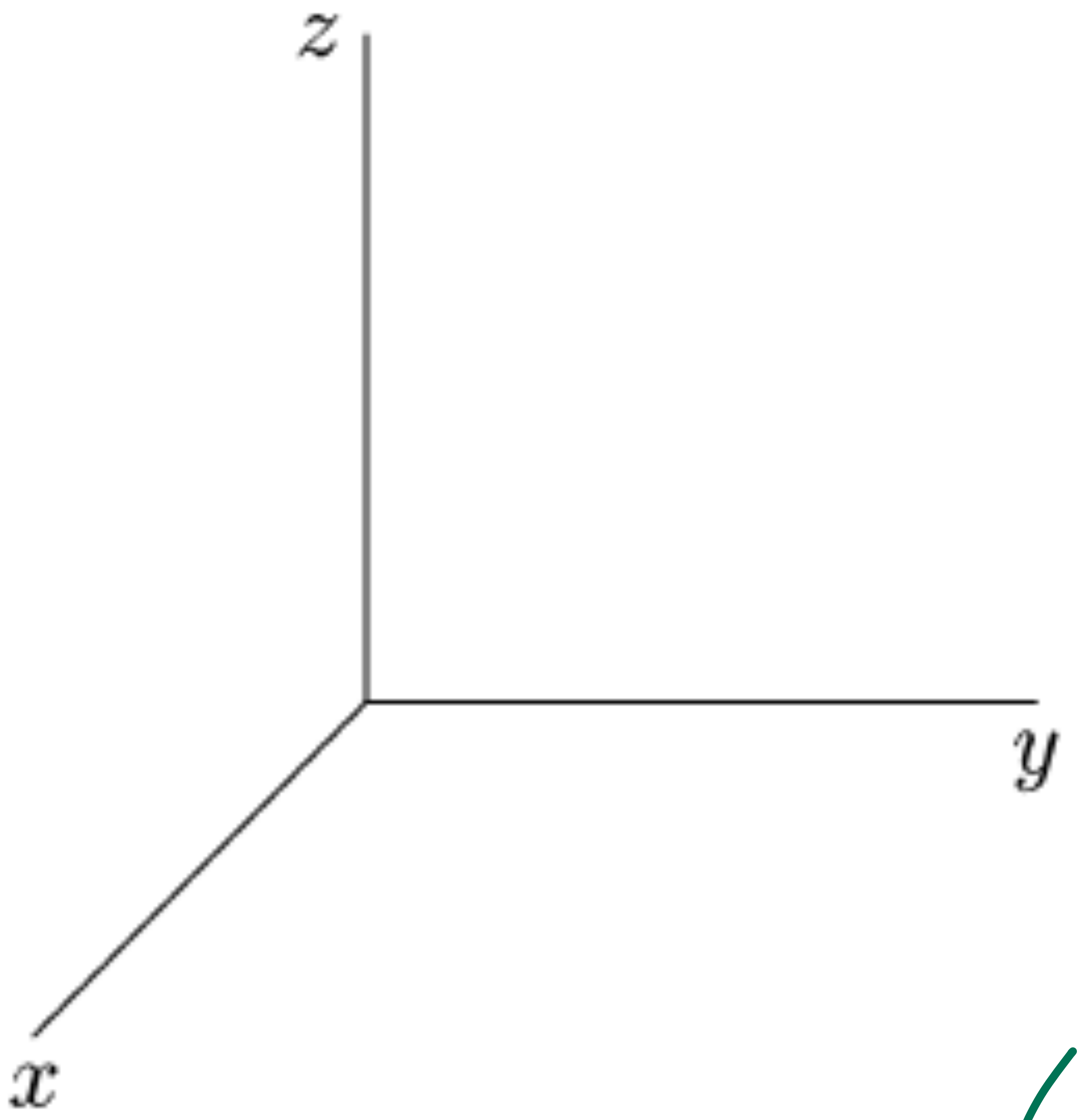
Projection onto the x_1 axis:

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

why?:



Example: onto, not 1-1



Projection from $\mathbb{R}^3$ to $\mathbb{R}^2$.

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \mapsto \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \qquad T\left(\begin{bmatrix} x \\ y \\ 0 \end{bmatrix}\right) = \begin{bmatrix} x \\ y \end{bmatrix}$$

onto ✓

why?:

$$T\left(\begin{bmatrix} x \\ y \\ 1 \end{bmatrix}\right) = \begin{bmatrix} x \\ y \end{bmatrix} \qquad \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \neq \begin{bmatrix} x \\ y \\ 0 \end{bmatrix}$$

not 1-1 ✓

Taking Stock: Onto

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Theorem. The following are logically equivalent for the linear transformation $T : \mathbb{R}^n \to \mathbb{R}^m$ implemented by the matrix A

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- » T is onto
- » $A\mathbf{x} = \mathbf{b}$ has a solution for any choice of $\mathbf{b}$

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- T is onto
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- $\text{range}(T) = \text{codomain}(T)$

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» the columns of A span $\mathbb{R}^m$ codomain
» A has a pivot position in every row

Taking Stock: One-to-One

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» T is one–to–one
» $A\mathbf{x} = \mathbf{b}$ has at most one solution for any $\mathbf{b}$

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Theorem. The following are logically equivalent for the linear transformation $T : \mathbb{R}^n \to \mathbb{R}^m$ implemented by the matrix A

» T is one-to-one
» $A\mathbf{x} = \mathbf{b}$ has at most one solution for any $\mathbf{b}$
» $A\mathbf{x} = \mathbf{0}$ has only the trivial solution

Taking Stock: One-to-One

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- » $A\mathbf{x} = \mathbf{0}$ has only the trivial solution
- » The columns of A are linearly independent
- » A has a pivot position in every <u>column</u>

How To: One-to-One and Onto

Question. Show that the linear transformation T is one-to-one/onto

Solution. (one approach) Find the matrix which implements T and see if it has a pivot in every column/row

Warning: this is not the only way. Always try to think if you can solve it using *any* of the perspectives

Example: both 1-1 and onto

Rotation about the origin:

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

why?:

Example: 1-1, not onto

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

Lifting:

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \mapsto \begin{bmatrix} x_1 \\ x_2 \\ x_1 + x_2 \end{bmatrix}$$

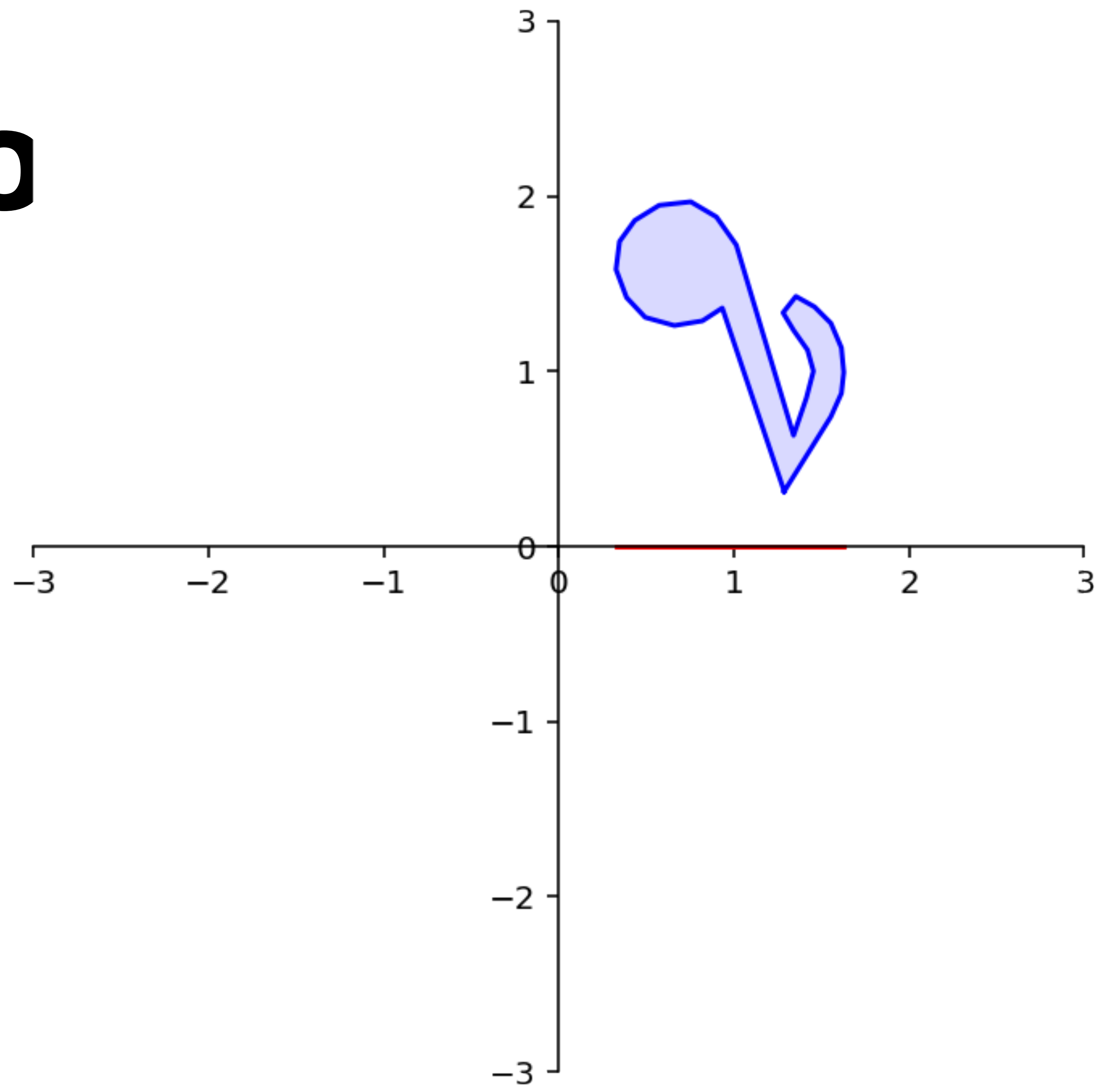
why?:

Example: not 1-1, not o

Projection onto the x_1 axis:

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

why?:

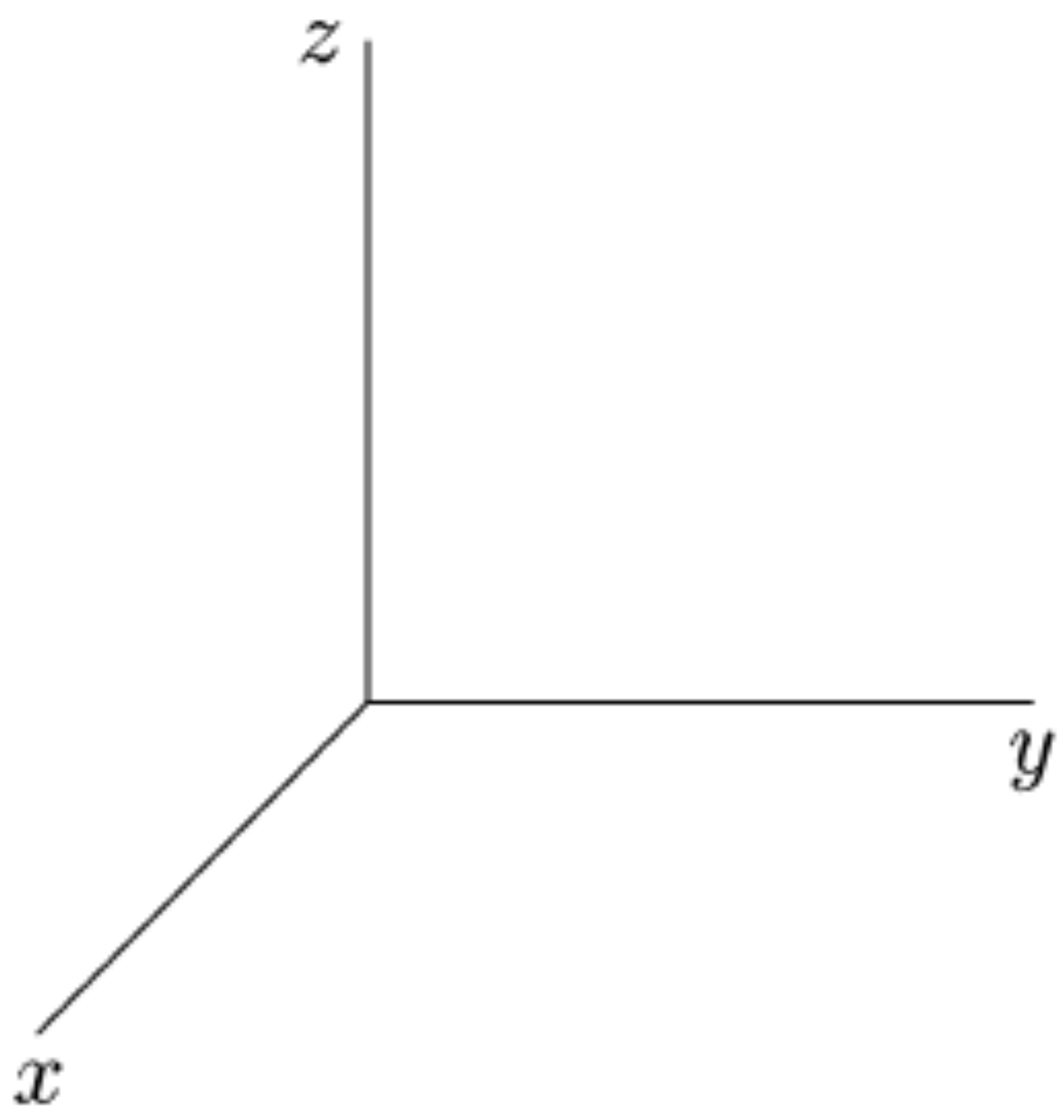


Example: onto, not 1-1

Projection from $\mathbb{R}^3$ to $\mathbb{R}^2$.

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \mapsto \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

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

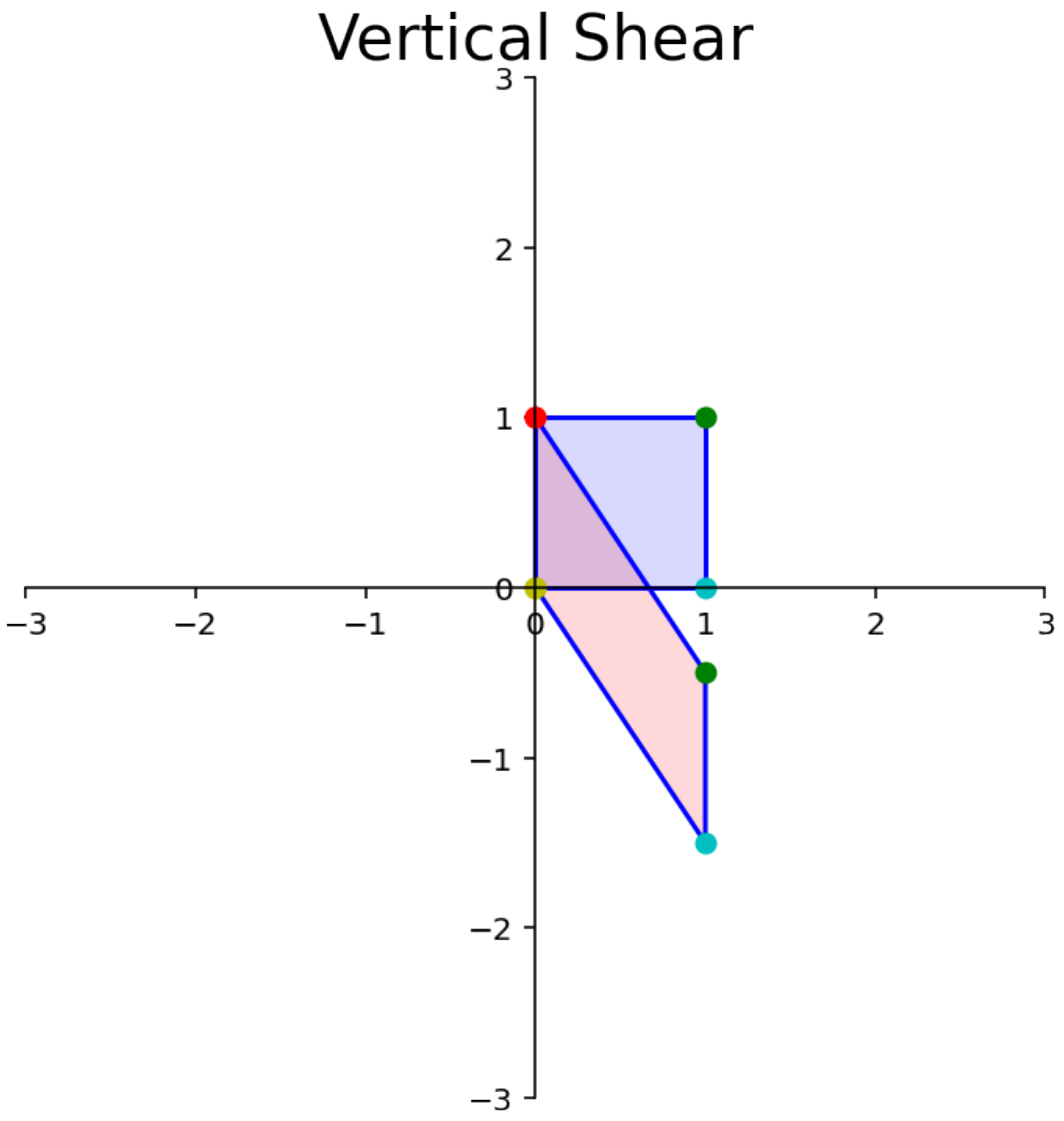


why?:

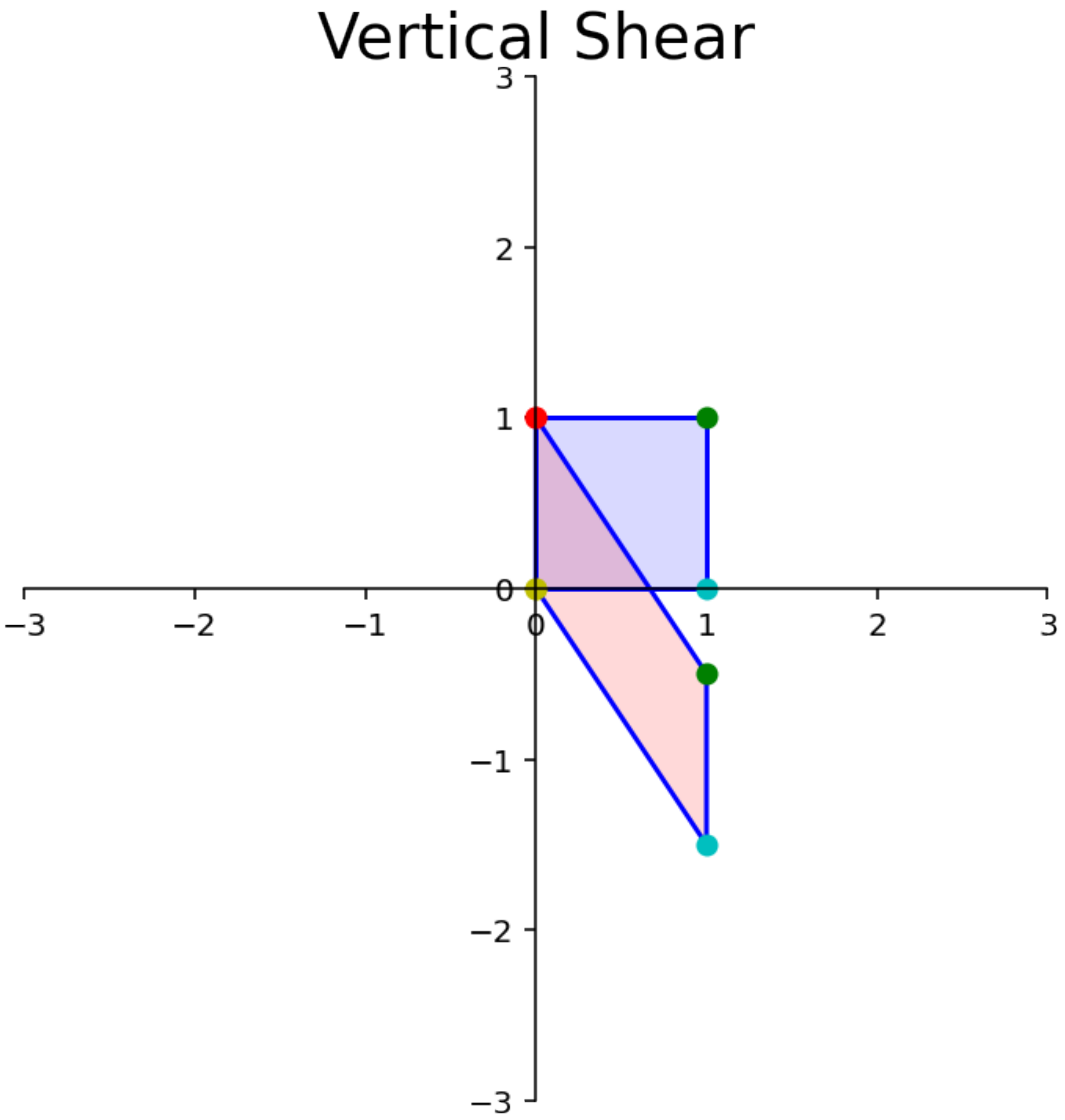
Question

Is vertical shearing a 1–1 transformation? Justify your answer

Exercise:

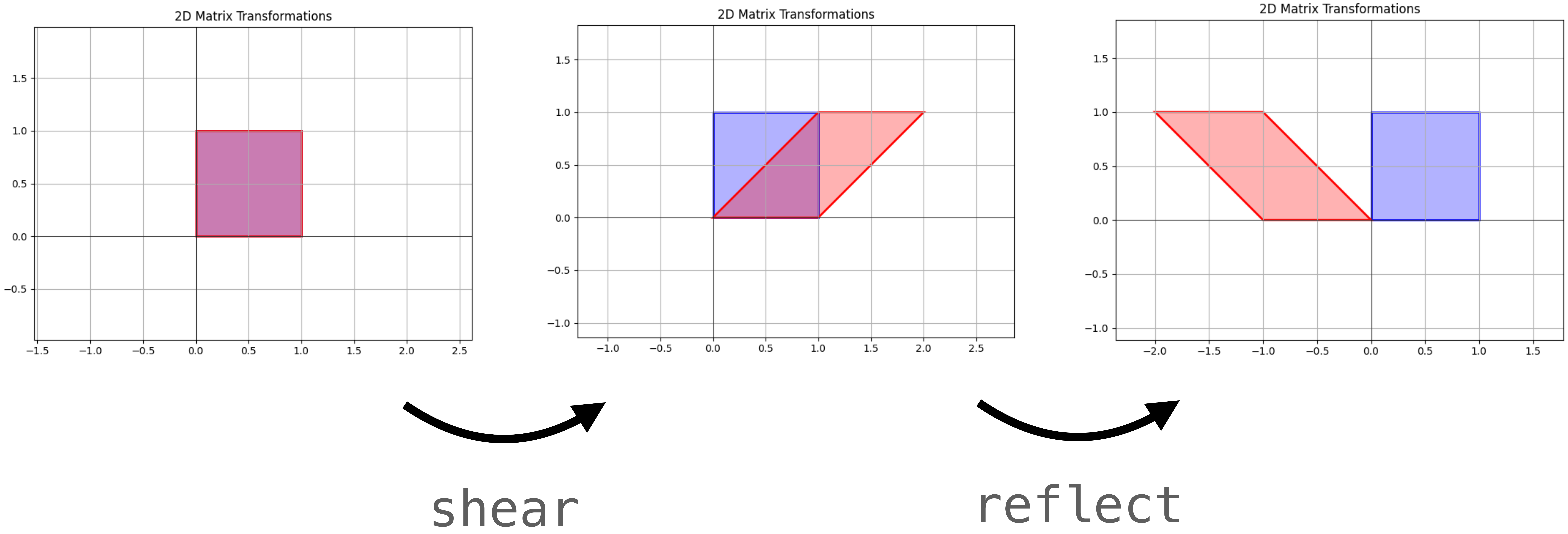


Answer: Yes



Composing Linear Transformations

Shearing and Reflecting (Geometrically)

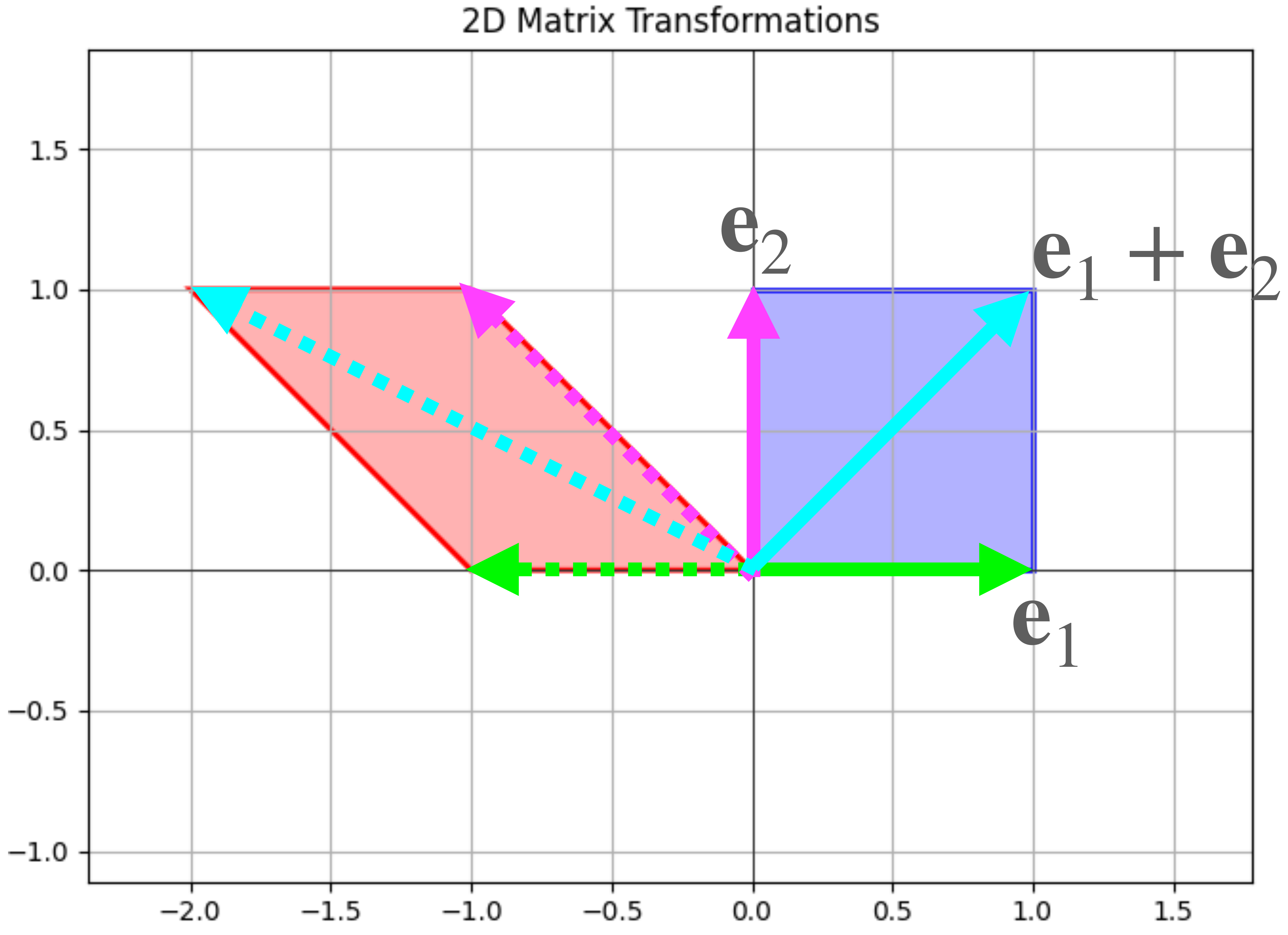


Shearing and Reflecting Matrix

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

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

$$\begin{bmatrix} 1 \\ 1 \end{bmatrix} \mapsto$$



Shearing and Reflecting (Algebraically)

$$\underbrace{\begin{bmatrix} -1 & 0 \\ 0 & 1 \end{bmatrix}}_{\texttt{reflect}} \left(\underbrace{\begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}}_{\texttt{shear}} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \right)$$

First multiply by shear matrix, then multiply by reflection matrix

Shearing and Reflecting (Algebraically)

$$\underbrace{\begin{bmatrix} -1 & 0 \\ 0 & 1 \end{bmatrix}}_{\text{reflect}} \left(\underbrace{\begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}}_{\text{shear}} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \right)$$

First multiply by shear matrix, then multiply by reflection matrix

This gives us the same transformation

Shearing and Reflecting

$$\begin{bmatrix} -1 & -1 \\ 0 & 1 \end{bmatrix} \mathbf{x} = \begin{bmatrix} -1 & 0 \\ 0 & 1 \end{bmatrix} \left(\begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \mathbf{x} \right)$$

The Key Fact

The Key Fact

Fact. The composition of two linear transformation is a linear transformation

The Key Fact

Fact. The composition of two linear transformation is a linear transformation

Verify:

The Key Fact

Fact. The composition of two linear transformation is a linear transformation

Verify:

This means the composition of two matrix transformations can be represented as a *single* matrix

The Key Question

Given two linear transformations, how to we compute the matrix which implements their composition?

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Given two linear transformations, how to we compute the matrix which implements their composition?

Matrix Multiplication

Matrix Multiplication

Shearing and Reflecting

$$\begin{bmatrix} -1 & 0 \\ 0 & 1 \end{bmatrix} \left(\begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \right) =$$

General Composition (2D)

$$A\left(\begin{bmatrix}\mathbf{b}_1 & \mathbf{b}_2\end{bmatrix}\begin{bmatrix}x_1 \\ x_2\end{bmatrix}\right) =$$

Matrix Multiplication

Definition. For a $m \times n$ matrix A and a $n \times p$ matrix B with columns $\mathbf{b}_1, \mathbf{b}_2, \ldots, \mathbf{b}_p$ the product AB is the $m \times p$ matrix given by

$$AB = A \begin{bmatrix} \mathbf{b}_1 & \mathbf{b}_2 & \ldots & \mathbf{b}_p \end{bmatrix} = \begin{bmatrix} A\mathbf{b}_1 & A\mathbf{b}_2 & \ldots & A\mathbf{b}_p \end{bmatrix}$$

Replace each column of B with A multiplied by that column

Tracking Dimensions

This only works if the number of columns of the left matrix matches the number of rows of the right matrix

$$
\begin{array}{cc} & n \\ m & \begin{bmatrix} * & * & * \\ * & * & * \\ * & * & * \\ * & * & * \\ * & * & * \end{bmatrix} \end{array}
\begin{array}{cc} & k \\ n & \begin{bmatrix} * & * & * & * \\ * & * & * & * \\ * & * & * & * \end{bmatrix} \end{array}
=
\begin{array}{cc} & k \\ m & \begin{bmatrix} * & * & * & * \\ * & * & * & * \\ * & * & * & * \\ * & * & * & * \\ * & * & * & * \end{bmatrix} \end{array}
$$

$(m \times n)$ $(n \times k)$ $(m \times k)$

Important Note

Even if AB is defined, it may be that BA is <u>not</u> defined

Non-Example

$$\begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix} \begin{bmatrix} 1 \\ 3 \end{bmatrix} \begin{bmatrix} 2 \\ 4 \end{bmatrix} = \left[\begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix} \begin{bmatrix} 1 \\ 3 \end{bmatrix} \quad \begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix} \begin{bmatrix} 2 \\ 4 \end{bmatrix} \right]$$

Non-Example

$$\begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix} \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} = \begin{bmatrix} \cancel{\begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix} \begin{bmatrix} 1 \\ 3 \end{bmatrix}} & \cancel{\begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix} \begin{bmatrix} 2 \\ 4 \end{bmatrix}} \end{bmatrix}$$

These are not defined.

Example

$$\begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} \begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix} = \left[\begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} \begin{bmatrix} 1 \\ 4 \end{bmatrix} \quad \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} \begin{bmatrix} 2 \\ 5 \end{bmatrix} \quad \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} \begin{bmatrix} 3 \\ 6 \end{bmatrix} \right]$$

The Key Fact (Restated)

For any matrices A and B (such that AB is defined) and any vector $\mathbf{v}$

$$A(B\mathbf{v}) = (AB)\mathbf{v}$$

The matrix implementing the composition is the product of the two underlying matrices

Row-Column Rule

$$(AB)_{ij} = \sum_{k=1}^{n} A_{ik} B_{kj}$$

Given a $m \times n$ matrix A and a $n \times p$ matrix B, the entry in row i and column j of AB is defined above

Example

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

Row-Column Rule (Pictorially)

$$\begin{bmatrix} * & * & * \\ * & * & * \\ * & * & * \\ * & * & * \\ * & * & * \end{bmatrix} \begin{bmatrix} * & * & * & * \\ * & * & * & * \\ * & * & * & * \end{bmatrix} = \begin{bmatrix} * & * & * & * \\ * & * & * & * \\ * & * & * & * \\ * & * & * & * \\ * & * & * & * \end{bmatrix}$$

$$(AB)_{ij} = \sum_{k=1}^{n} A_{ik} B_{kj}$$

Row-Column Rule (Pictorially)

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$$\begin{bmatrix} * & * & * \\ \boxed{* \quad * \quad *} \\ * & * & * \\ * & * & * \\ * & * & * \end{bmatrix} \begin{bmatrix} * & * & * & * \\ * & * & * & * \\ * & * & * & * \end{bmatrix} = \begin{bmatrix} * & * & * & * \\ * & * & \boxed{*} & * \\ * & * & * & * \\ * & * & * & * \\ * & * & * & * \end{bmatrix}$$

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$$(AB)_{ij} = \sum_{k=1}^{n} A_{ik} B_{kj}$$

Question

Compute $\begin{bmatrix} 1 & 0 & -1 \\ 0 & 1 & 1 \end{bmatrix} \begin{bmatrix} 1 & 1 \\ 2 & 0 \\ -1 & 2 \end{bmatrix}$

short version: What is the entry in the 2nd row and 2nd column?

Answer

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

Matrix Operations

Connection with Matrix-Vector Multiplication

Connection with Matrix-Vector Multiplication

What about when the right matrix is a single column?

Connection with Matrix-Vector Multiplication

What about when the right matrix is a single column?

$$A[\mathbf{b}_1] = [A\mathbf{b}_1] = A\mathbf{b}_1$$

Connection with Matrix-Vector Multiplication

What about when the right matrix is a single column?

$$A[\mathbf{b}_1] = [A\mathbf{b}_1] = A\mathbf{b}_1$$

This is just vector multiplication

Connection with Matrix-Vector Multiplication

What about when the right matrix is a single column?

$$A[\mathbf{b}_1] = [A\mathbf{b}_1] = A\mathbf{b}_1$$

This is just vector multiplication

We can think of $\begin{bmatrix} A\mathbf{b}_1 & A\mathbf{b}_2 & \dots & A\mathbf{b}_p \end{bmatrix}$ as collection of simultaneous matrix–vector multiplications

Matrix "Interface"

multiplication	what does AB mean when A and B are matrices?
addition	what does $A+B$ mean when A and B are matrices?
scaling	what does cA mean when A is matrix and c is a real number?

Matrix "Interface"

multiplication	what does AB mean when A and B are matrices?
addition	what does $A+B$ mean when A and B are matrices?
scaling	what does cA mean when A is matrix and c is a real number?

These should be consistent with matrix-vector interface and vector interface

Matrix Addition

$$[\mathbf{a}_1 \quad \dots \quad \mathbf{a}_n] + \left[\mathbf{b}_1 \dots \quad \mathbf{b}_n\right] = \left[(\mathbf{a}_1 + \mathbf{b}_1) \quad \dots \quad (\mathbf{a}_n + \mathbf{b}_n)\right]$$

Addition is done column-wise (or equivalently, element-wise)

e.g. $\begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} + \begin{bmatrix} 2 & 3 \\ -2 & -3 \end{bmatrix} = \begin{bmatrix} (1+2) & (2+3) \\ (3-2) & (4-3) \end{bmatrix} = \begin{bmatrix} 3 & 5 \\ 1 & 1 \end{bmatrix}$

Matrix Addition

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This is exactly the same as vector addition, but for matrices

Matrix Addition and Scaling

$$c\,[\mathbf{a}_1 \quad \mathbf{a}_2 \quad \cdots \quad \mathbf{a}_n] = [c\mathbf{a}_1 \quad c\mathbf{a}_2 \quad \cdots \quad c\mathbf{a}_n]$$

Scaling and adding happen element-wise (or, equivalently, column-wise)

e.g. $2\begin{bmatrix} 1 & 2 \\ -1 & 3 \end{bmatrix} = \begin{bmatrix} 2(1) & 2(2) \\ 2(-1) & 2(3) \end{bmatrix} = \begin{bmatrix} 2 & 4 \\ -2 & 6 \end{bmatrix}$

Matrix Addition and Scaling

$$c\,[\mathbf{a}_1 \quad \mathbf{a}_2 \quad \cdots \quad \mathbf{a}_n] = [c\mathbf{a}_1 \quad c\mathbf{a}_2 \quad \cdots \quad c\mathbf{a}_n]$$

Scaling and adding happen element-wise (or, equivalently, column-wise)

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This is exactly the same as vector scaling, but for matrices

Algebraic Properties (Addition and Scaling)

$A + B = B + A$

$(A + B) + C = A + (B + C)$

$A + 0 = A$

$r(A + B) = rA + rB$

$(r + s)A = rA + sA$

$r(sA) = (rs)A$

In these properties A, B, and C are matrices of the same size and r and s are scalars ($\mathbb{R}$)

We need to know/memorize these

Algebraic Properties (Addition and Scaling)

$$A(BC) = (AB)C$$

$$A(B + C) = AB + AC$$

$$(B + C)A = BC + CA$$

$$r(AB) = (rA)B = A(rB)$$

$$I_m A = A = AI_n$$

In these properties A, B, and C are matrices of the appropriate size so that everything is defined, and r is a scalar

We need to know/memorize these

Matrix Multiplication is not Commutative

Important. AB may not be the same as BA

(it may not even be defined)

Question (Conceptual)

Find a pair of 2D linear transformations T_1 and T_2 such that T_1 followed by T_2 is not the same as T_2 followed by T_1

(also find a pair where they are the same)

Answer: Rotation and Reflection

Computational Aspects of Matrix Multiplication

Matrix Operations in Numpy

Let a and b be 2D numpy arrays and let c be a floating point number

» a @ b   (matrix multiplication)

» a + b   (matrix addition)

» c * a   (matrix scaling)

We've seen these, we've used them a bit, we'll use them much more

Analyzing Linear Algebra Algorithms

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We will not use $O(\cdot)$ notation!

Analyzing Linear Algebra Algorithms

We will not use $O(\cdot)$ notation!

For numerics, we care about number of **FL**oating-oint **OP**erations (FLOPs):

>> addition
>> subtraction
>> multiplication
>> division
>> square root

Analyzing Linear Algebra Algorithms

We will not use $O(\cdot)$ notation!

For numerics, we care about number of **FL**oating-oint **OP**erations (FLOPs):

>> addition
>> subtraction
>> multiplication
>> division
>> square root

$2n$ vs. n is very different when $n \sim 10^{20}$

Dominant Terms

Dominant Terms

`that said, we don't care about` *`exact`* `bounds`

Dominant Terms

that said, we don't care about *exact* bounds

A function $f(n)$ is ***asymptotically equivalent*** to $g(n)$ if

$$\lim_{i \to \infty} \frac{f(i)}{g(i)} = 1$$

Dominant Terms

that said, we don't care about *exact* bounds

A function $f(n)$ is ***asymptotically equivalent*** to $g(n)$ if

$$\lim_{i \to \infty} \frac{f(i)}{g(i)} = 1$$

for polynomials, they are equivalent to their dominant term

Dominant Terms

the dominant term of a polynomial is the monomial with the highest degree

$$\lim_{i \to \infty} \frac{3x^3 + 100000x^2}{3x^3} = 1$$

$3x^3$ dominates the function even though the coefficient for x^2 is so large

A Note on Complexity

$$(AB)_{ij} = \sum_{k=1}^{n} A_{ik}B_{kj}$$

Suppose A and B are $n \times n$ matrices

This operations takes n multiplications and n divisions ($2n$ FLOPS total)

Repeating for each entry gives $\sim 2n^3$ FLOPS

A Note on Parallelization

$$(AB)_{ij} = \sum_{k=1}^{n} A_{ik} B_{kj}$$

`The main part of this procedure is highly parallelizable`

A Note on Parallelization

```
a = np.array(...)
b = np.array(...)
prod = np.zeros([a.shape[0], b.shape[1]])
for i in range(a.shape[0]):
    for j in range(b.shape[1]):
        prod[i, j] = np.dot(a[i], b[:,j])
```

The main part of this procedure is highly parallelizable

One processor per entry gets you to $\sim 2n$ FLOPS

A Note on Libraries

There are a lot of other considerations for doing linear algebra on computers

Best leave it to experts (or do research in the area)

LAPACK is the state of the art library for matrix operations

numpy uses LAPACK

Summary

We can reason about matrix equations by reasoning directly about properties of linear transformations

Matrix multiplication coincides with composition of linear transformations

There is an algebra of matrices which is consistent with the algebra of vectors