

Course 1

Linear

Algebra

Week 1 - Systems of linear Equations

Linear Algebra and Machine Learning

→ Linear Regression $\xrightarrow{\text{is}}$ Supervised Machine Learning : It means that we have some Inputs and the Output and we want to find the relation between Inputs and the Output.

System of sentences

Assume that we only have 1 dog and 1 cat and they're both of only 1 color.

We are given some information and our goal is to try to figure out the color of each of the animals.

1

The dog is black.

The cat is orange.

2

The dog is black

The dog is black.

3

The dog is black.

The dog is white.

2 sentences and 2 pieces
of information

2 sentences that
they're exactly the same

the sentences
contradict each other

Complete System

Redundant System

Contradictory System

//

Non-Singular System

//

Singular System

▷

Singular System

■ In a nutshell (= summarize) :

- Non-Singular System : is a system that carries as many pieces of information as sentences. So It's the most informative system can be. So we can find a unique solution.
- Singular System : is less informative than a non-singular one. Because the system doesn't carry enough information, the system has infinitely many solutions. / or no solution if the system is contradictory and singular.

■ What is a Linear Equation ?

→ visualized as lines

- Linear : A Linear Equation is a equation that can have as many variables as we want , and we can multiply the variable by scalars and then add them or subtract them and then add a constant.

Ex: $a + b = 10$ / $2a + 3b - 15 = 0$ / $3.4a + 8b - 2.2c = 122.5$

- Non-Linear : is a equation that can have squares , things like Sin / Cos , powers , multiply variables , divided variables, log and etc .

Ex: $a^2 + b^2 = 10$ / $\sin(a) + b^3 = 15$ / $ab^2 + \frac{b}{a} - \log(c) = 4^9$

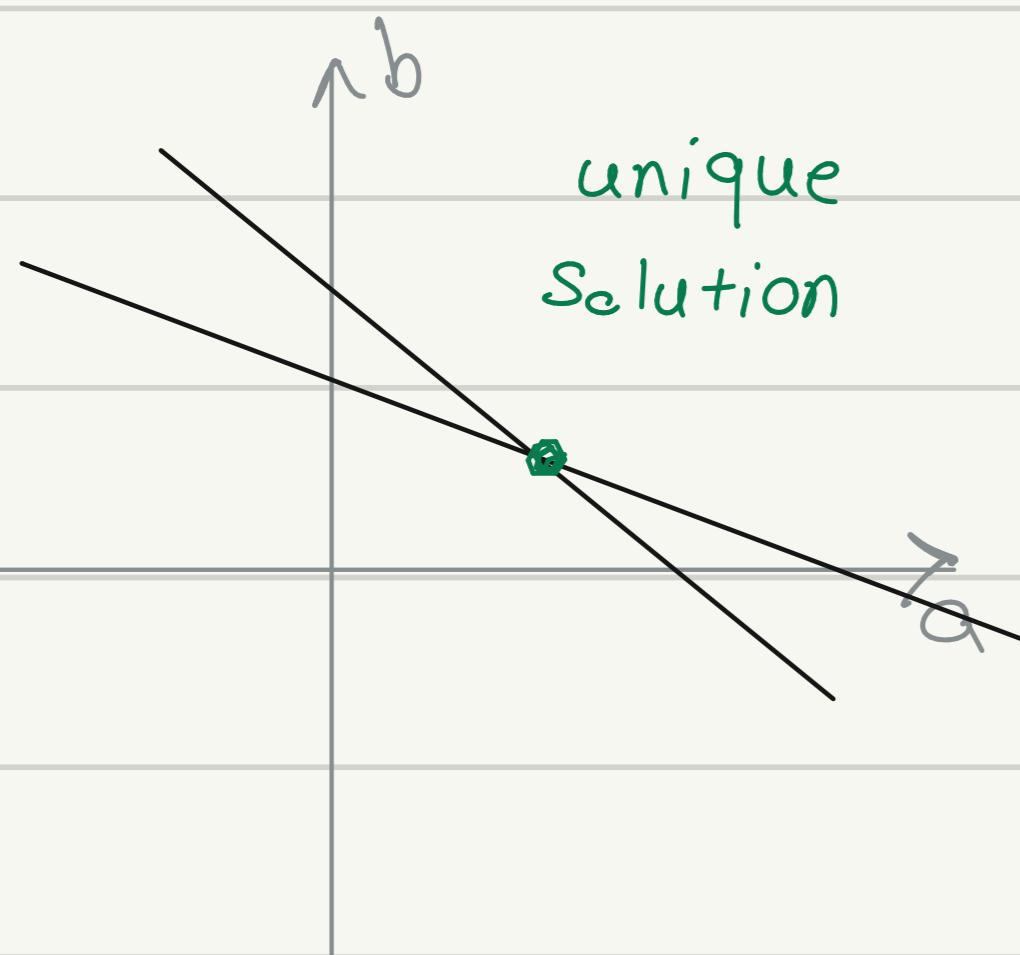
System of equations as lines

Example:

System 1

$$a+b=10$$

$$a+2b=12$$



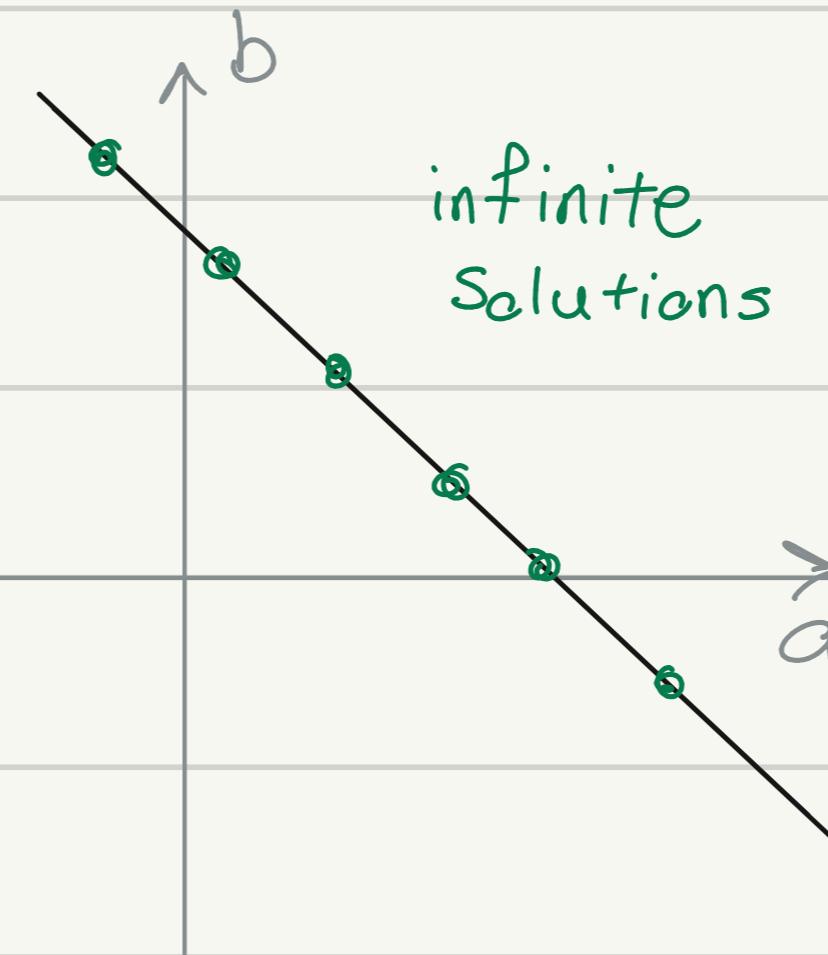
Complete

Non-Singular

System 2

$$a+b=10$$

$$2a+2b=20$$



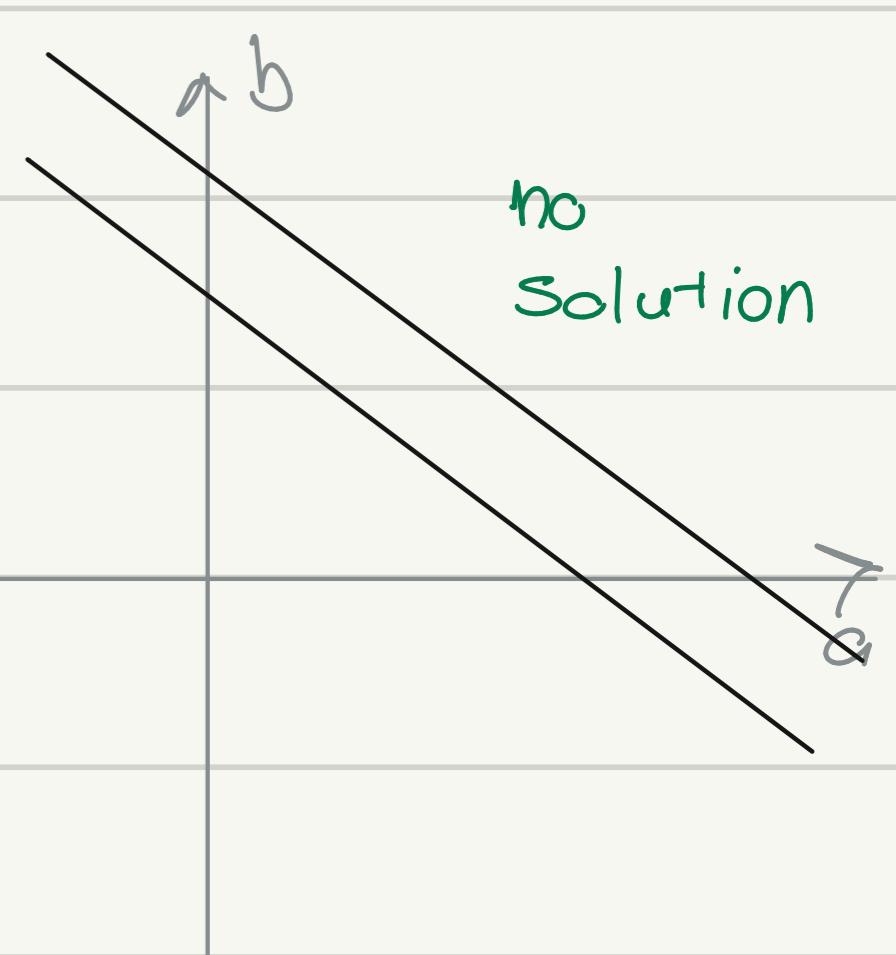
Redundant

Singular

System 3

$$a+b=10$$

$$2a+2b=24$$



Contradictory

Singular

* Note that Constants don't matter for Singularity.

Changing Example:

System 1

$$a+b=0$$

$$a+2b=0$$

System 2

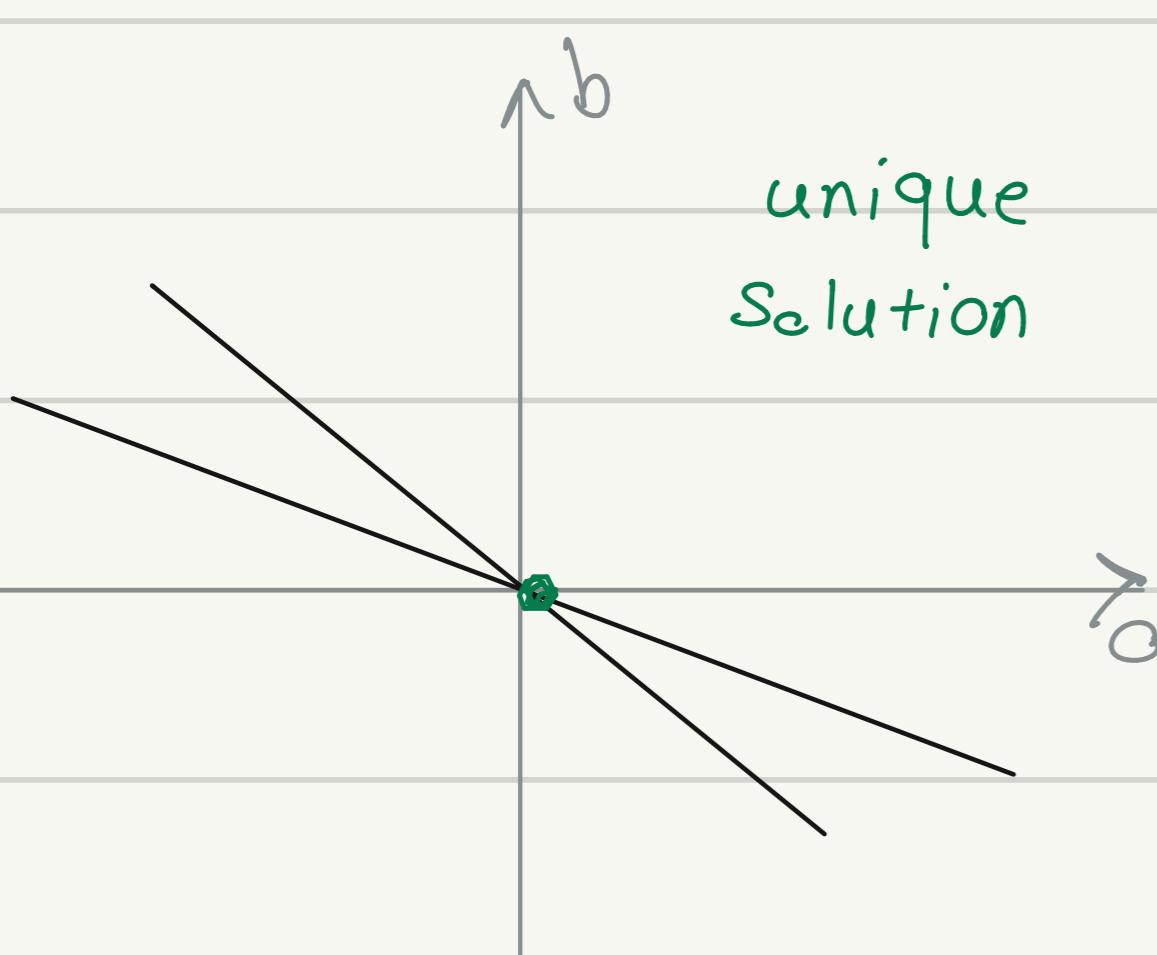
$$a+b=0$$

$$2a+2b=0$$

System 3

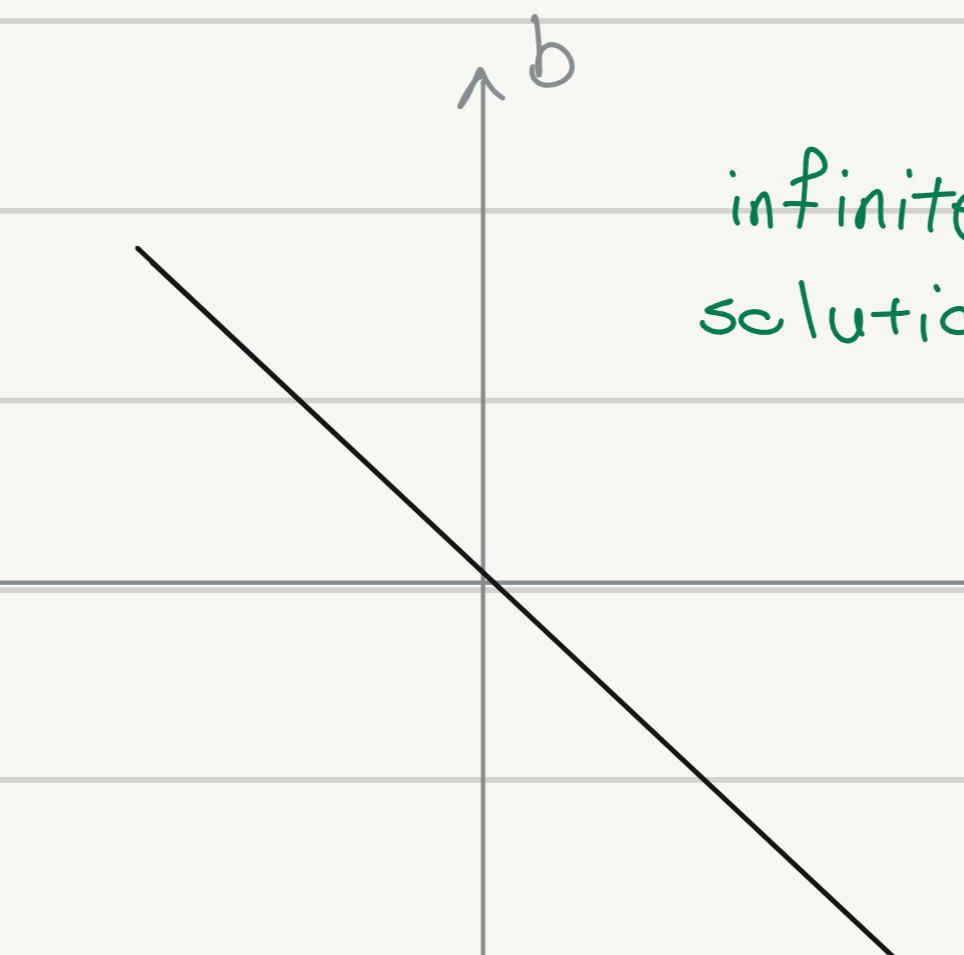
$$a+b=0$$

$$2a+2b=0$$



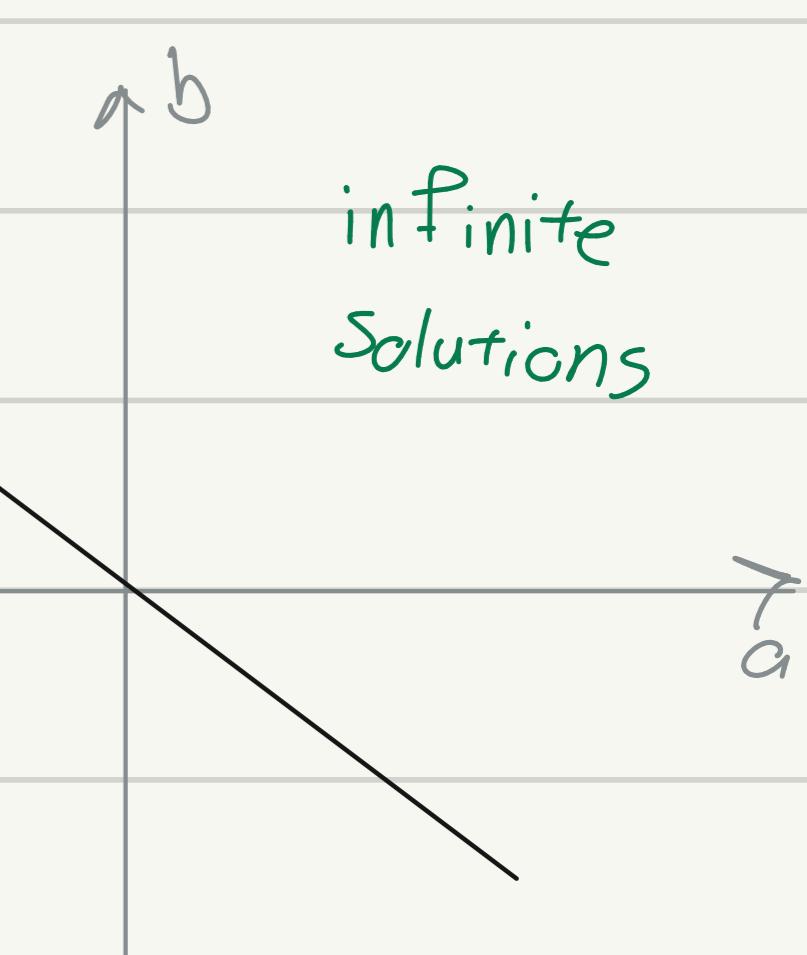
Complete

Non-Singular



Redundant

Singular



Redundant +

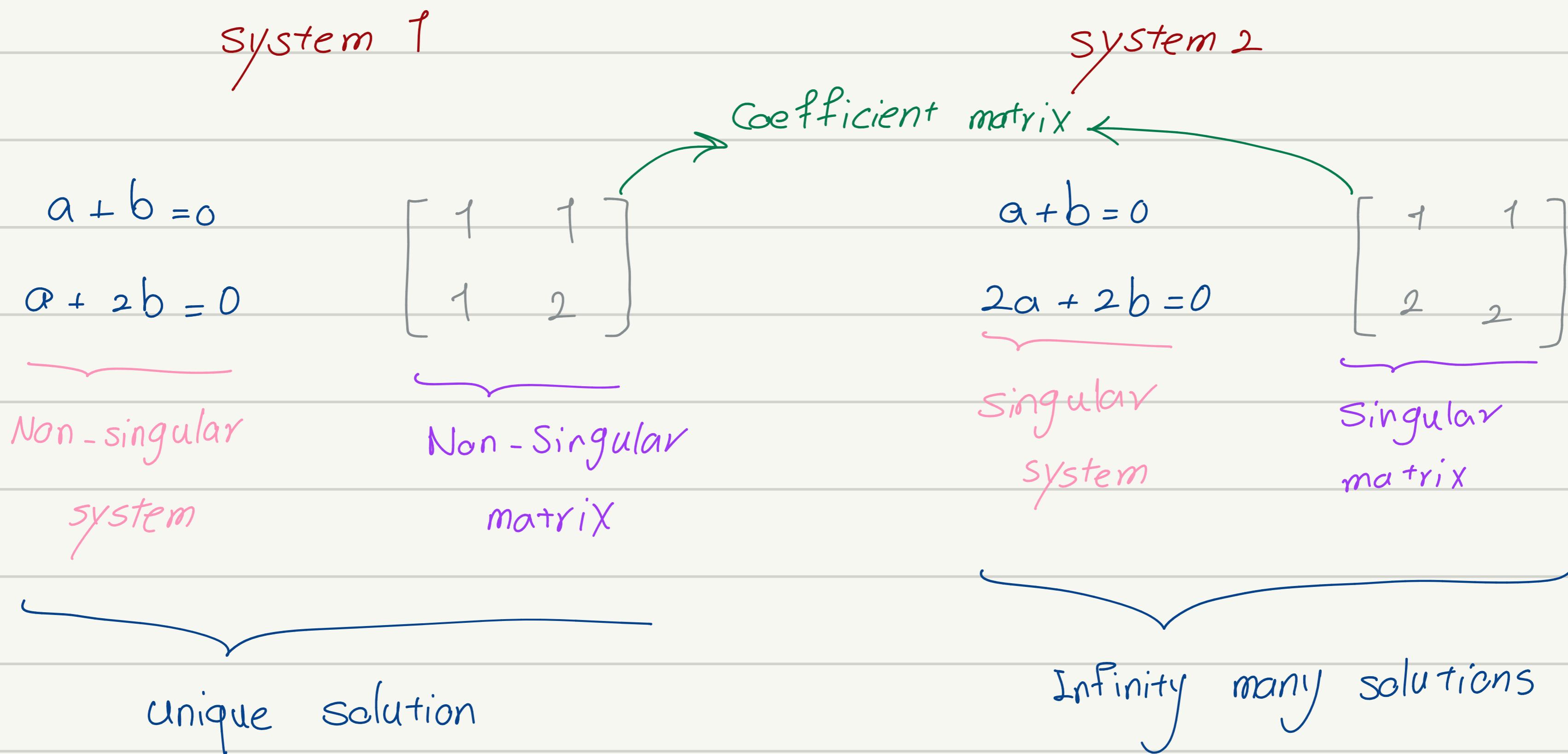
Singular

Constants matter for the reason of singularity: Redundant / contradictory / ...

Singular vs Non-Singular Matrices

- Coefficient Matrix:** is a Matrix consisting of the coefficients of the variables in a set of linear equations.

Example:



Linear Dependence and Independence

In above example:

$$\text{System 1} \quad \begin{bmatrix} 1 & 1 \\ 1 & 2 \end{bmatrix} \xrightarrow{x?}$$

$$\text{System 2} \quad \begin{bmatrix} 1 & 1 \\ 2 & 2 \end{bmatrix} \xrightarrow{x2}$$

- * In system 2 we can reach the second row with multiplying first row to 2. So in system 2 rows are linearly dependent but in system 1 rows are linearly independent.

- Linearly Dependent:** IF between the rows of a matrix exist any relations.

■ The Determinant : a much faster way to tell if a matrix is Singular or Non-Singular.

- A Singular matrix:

$$\begin{bmatrix} a & b \\ c & d \end{bmatrix} \xrightarrow{\text{singular if}} [a \ b] * k = [c \ d]$$

$$ak = c \quad \text{and} \quad bk = d$$

$$\frac{c}{a} = k \quad \text{and} \quad \frac{d}{b} = k$$

$$\frac{c}{a} = \frac{d}{b} \quad \text{So} \quad \underline{\underline{ad = bc}}$$

or

Determinant $\leftarrow ad - bc = 0$

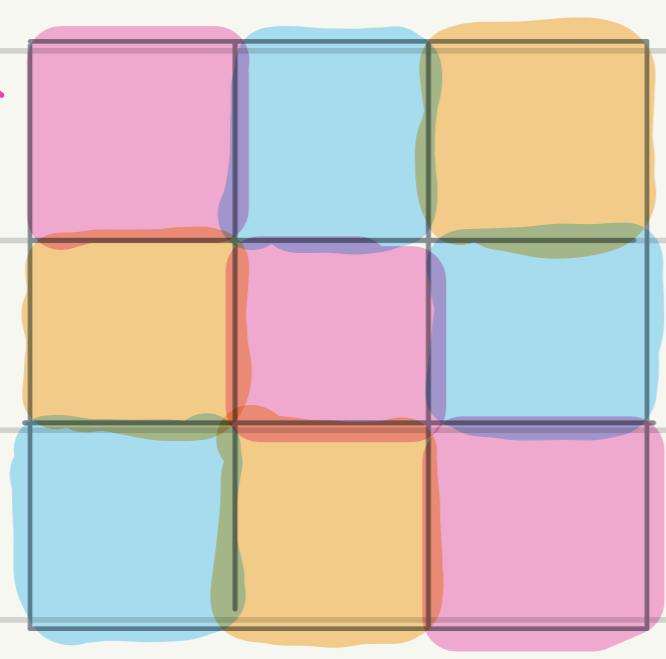
is zero : The matrix is Singular

- If Determinant is not zero: The matrix is Non-Singular

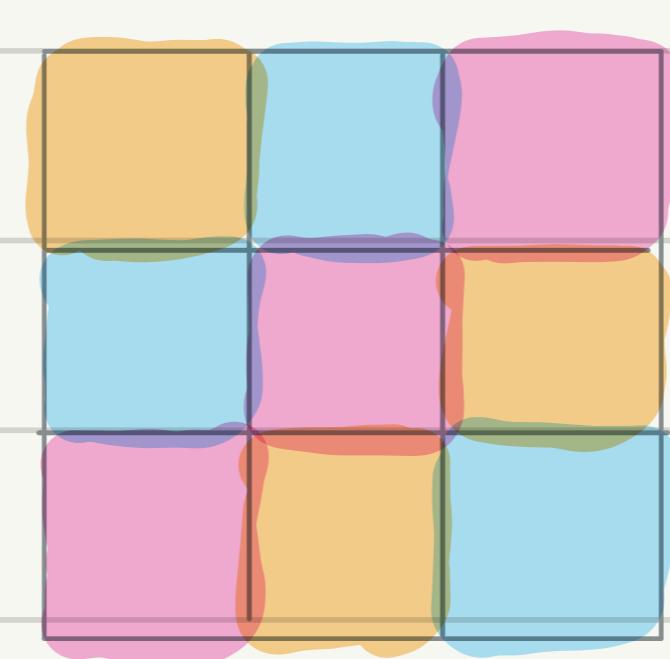
• Determinant for 2×2 matrix: the product of the numbers in the main diagonal minus the product of the numbers in the antidiagonal.

■ The Determinant : 3×3 Matrix

Diagonals
in 3×3
matrix



ADD +



SUBTRACT = DETERMINANT

Ex:

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

$$1 + 2 + 1 - (1 + 1 + 2) = 1$$

* Note : Whenever you have a matrix where anything underneath the diagonal is zero, the determinant is going to be the product of the elements in the main diagonal.

a	b	c
0	b	c
0	0	c

$$\text{Determinant} = a * b * c$$

→ Read Lab 1 (Introduction to numpy arrays) and Lab 2 (Solving linear systems - 2 variables).

② Week 2 - Solving Systems of Linear Equations ②

Manipulating Equations
(For non-Singular system)

Swapping equations
Adding "",
subtracting "",
Multiplying equations by a constant

Matrix Row Reduction

Matrix row reduction, also called Gaussian Elimination, consists of applying the exact same manipulations to the rows of a matrix.

Example:

original system	Intermediate System	Solved system
$5a + b = 17$	$a + 0.2b = 3.4$	$a = 3$
$4a + 3b = 6$	$b = 2$	$b = 2$

original matrix	upper diagonal matrix	Diagonal matrix
$\begin{bmatrix} 5 & 1 \\ 4 & -3 \end{bmatrix}$	$\begin{bmatrix} 1 & 0.2 \\ 0 & 1 \end{bmatrix}$	$\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$

Coefficient matrices

Row echelon form

reduced row echelon form

Row Echelon Form

Looks like:

1	*	*	*	*	*
0	1	*	*	*	*
0	0	1	*	*	*
0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0

- On the main diagonal, we have a bunch of ones followed by perhaps a bunch of zeros. (could have all ones or zeros) .
- Below the diagonal, everything is a zero.
- To the right of the ones, any number is allowed.
- To the right of the zeros, everything must be zero.

2x2
matrices

$$\textcircled{1} \quad \begin{bmatrix} 1 & * \\ 0 & 1 \end{bmatrix}$$

$$\textcircled{2} \quad \begin{bmatrix} 1 & * \\ 0 & 0 \end{bmatrix}$$

$$\textcircled{3} \quad \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$$

two 1s in the diagonal one 1 in the diagonal two 0s in the diagonal

Row Operations that preserve Singularity

The same manipulations that we use to solve systems of linear equations, can be used in matrices. These are called row operations in a matrix.

- * A very important property that they have is that they **preserve the Singularity of a matrix**.

1) Switching Rows:

Ex: $\begin{bmatrix} 5 & 1 \\ 4 & 3 \end{bmatrix}$ switch rows $\rightarrow \begin{bmatrix} 4 & 3 \\ 5 & 1 \end{bmatrix}$

$$\det = 15 - 4 = 11$$



non-singular

$$\det = 4 - 15 = -11$$



non-singular

2) Multiplying a row by a (non-zero) scalar:

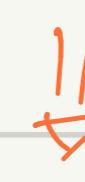
Ex: $\begin{bmatrix} 5 & 1 \\ 4 & 3 \end{bmatrix} \xrightarrow{[5 \ 1] * 10 = [50 \ 10]} \begin{bmatrix} 50 & 10 \\ 4 & 3 \end{bmatrix}$

$$\det = 15 - 4 = 11$$



non-Singular

$$\det = 150 - 40 = 110$$



non-Singular

3) Adding a row to another row:

Ex: $\begin{bmatrix} 5 & 1 \\ 4 & 3 \end{bmatrix} \xrightarrow{+ \begin{bmatrix} 5 & 1 \\ 4 & 3 \end{bmatrix}} \begin{bmatrix} 9 & 4 \\ 4 & 3 \end{bmatrix}$

$$\det = 11$$



non-Singular

$$\det = 27 - 16 = 11$$



non-Singular

Rank of a Matrix → application = Image compression

Example:

System 1

$$a + b = 0$$

$$a + 2b = 0$$

two equations
two pieces of info



$$\text{Rank} = 2$$

System 2

$$a + b = 0$$

$$2a + 2b = 0$$

two equations
one piece of info



$$\text{Rank} = 1$$

System 3

$$0a + 0b = 0$$

$$0a + 0b = 0$$

two equation
zero piece of info



$$\text{Rank} = 0$$

Rank and Solutions to the system

System 1

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

$$\text{Rank} = 2$$

System 2

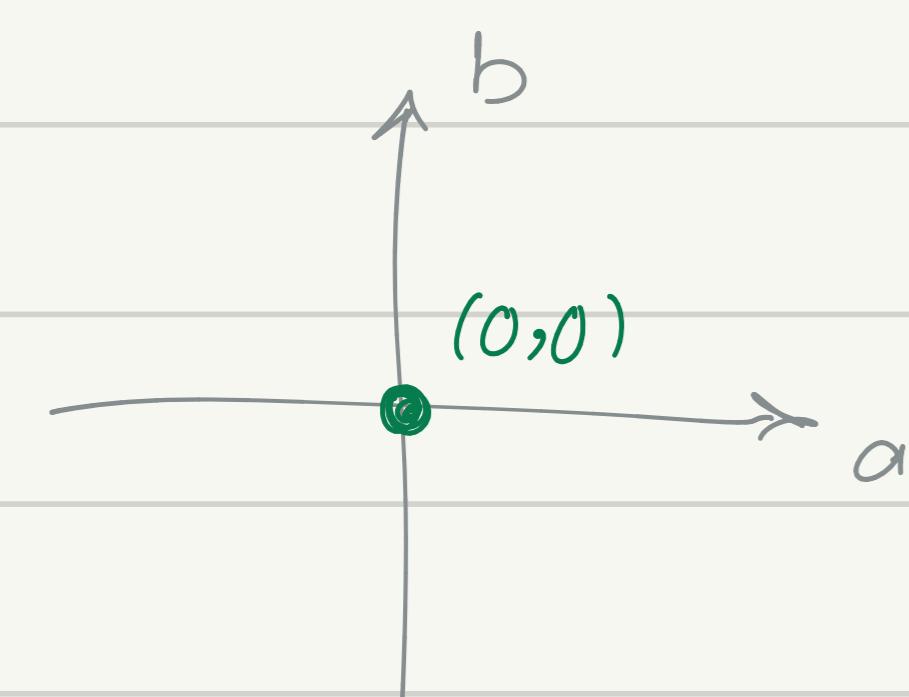
$$\begin{bmatrix} 1 & 1 \\ 2 & 2 \end{bmatrix}$$

$$\text{Rank} = 1$$

System 3

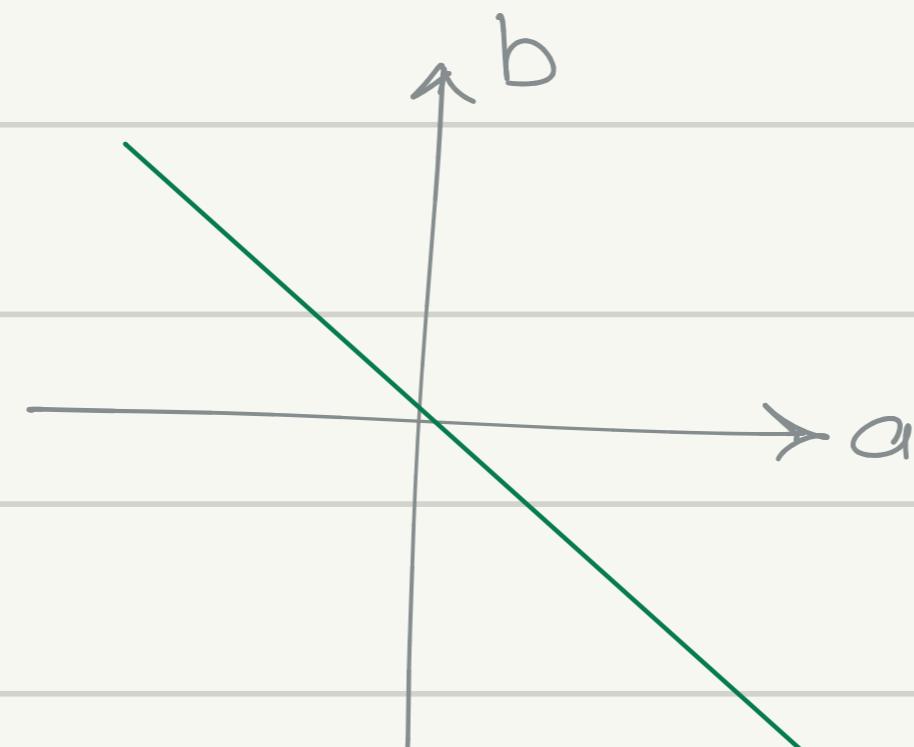
$$\begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$$

$$\text{Rank} = 0$$



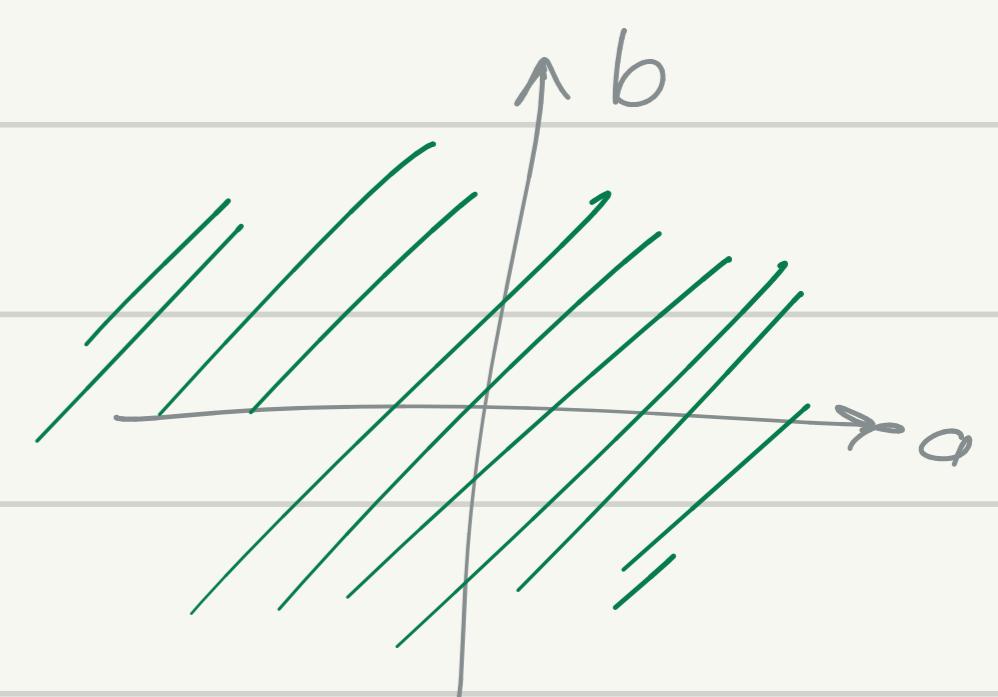
$$\text{Dimension of solution space} = 0$$

* non-singular



$$= 1$$

Singular



$$= 2$$

Singular

So, for 2×2 Matrices:

$$\text{Rank} = 2 - (\text{Dimension of solution Space})$$

* A matrix is non-singular if and only if it has full rank. (rank = number of rows)

Rank of a Matrix : General Case

- Question: Is there an easier way to calculate the rank?
- Answer: Yes! As before, it is the number of ones in the diagonal of the reduced row echelon form of the matrix.

Row Echelon Form

Ex 1:

original Matrix

$$\begin{bmatrix} 5 & 1 \\ 4 & -3 \end{bmatrix}$$

Divide each row by the leftmost coefficient

$$\begin{bmatrix} 1 & 0.2 \\ 1 & -0.75 \end{bmatrix}$$

$$\begin{array}{r} [1 \ -0.75] \\ - [1 \ 0.2] \\ \hline [0 \ -0.95] \end{array}$$

$$\begin{bmatrix} 1 & 0.2 \\ 0 & -0.95 \end{bmatrix}$$

Row Echelon Form

$$\begin{bmatrix} 1 & 0.2 \\ 0 & 1 \end{bmatrix}$$

Divide the second row by the leftmost non-zero coefficient

- This matrix has 2 ones in the diagonal of the row echelon form, so it has Rank = 2.

Ex 2. System 1

2	*	*	*
0	1	*	*
0	0	3	*
0	0	0	-5

Rank = 4

3	*	*	*
0	0	1	*
0	0	0	0
0	0	0	0

Rank = 2

- Zero rows at the bottom

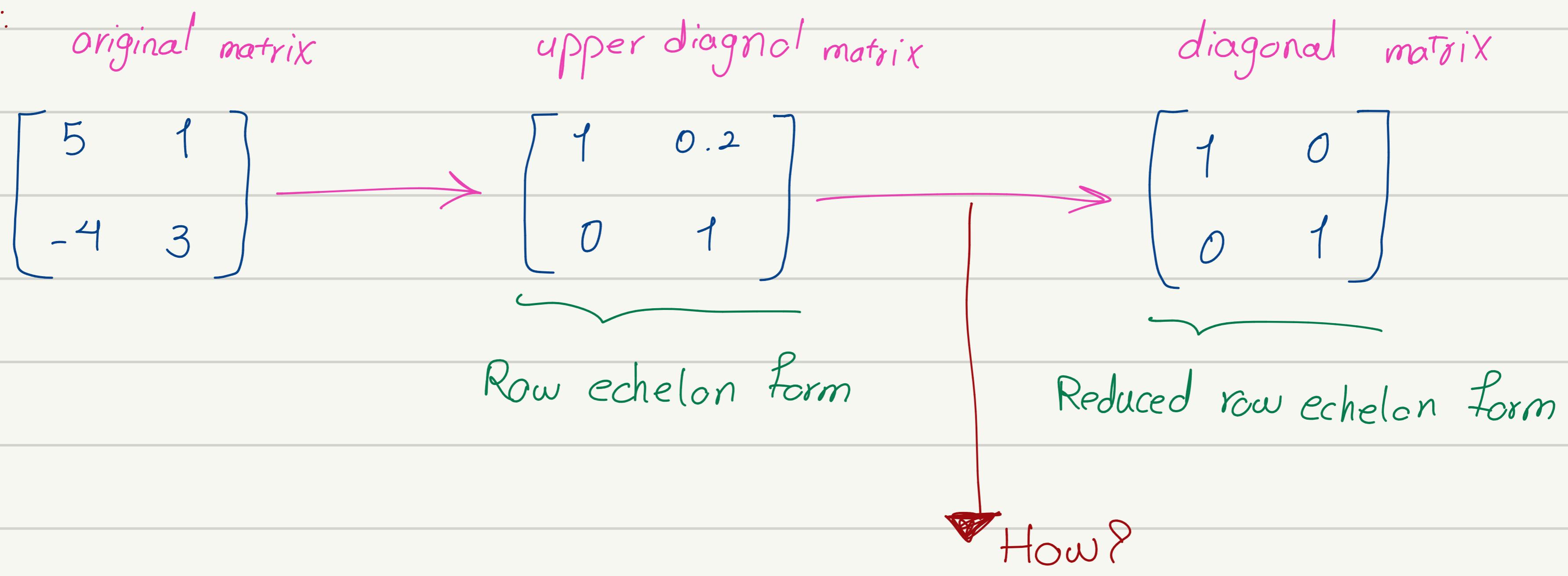
- Each row has a pivot (leftmost non-zero entry)

- Each pivot is to the right of the pivots one the rows above.

- Rank of the matrix is the number of pivots.

Reduced Row Echelon Form

Ex:



Answer:

$$\begin{array}{c}
 \begin{bmatrix} 1 & 0.2 \\ 0 & 1 \end{bmatrix} \xrightarrow{\textcircled{1}} \begin{bmatrix} 0 & 1 \\ 0 & 0.2 \end{bmatrix} \xrightarrow{\textcircled{2}} \begin{bmatrix} 1 & 0.2 \\ 0 & 0.2 \end{bmatrix} \xrightarrow{\textcircled{3}} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \\
 \text{row echelon form} \qquad \qquad \qquad \text{reduced row echelon form}
 \end{array}$$

Reduced Row Echelon Form : In General

1)

(1)	(0)	(0)	(0)	(0)
0	(1)	(0)	(0)	(0)
0	0	(1)	(0)	(0)
0	0	0	(1)	(0)
0	0	0	0	(1)

Rank = 5

2)

(1)	*	(0)	(0)	*
0	0	(1)	(0)	*
0	0	0	(1)	*
0	0	0	0	(1)
0	0	0	0	0

Rank = 3

Rules: • Is in row echelon form

• Each pivot is a $\underline{\underline{1}}$

• Any number above a pivot is $\underline{0}$

• Rank of the matrix is the number of pivots

* A General method to go from a row echelon form matrix to a reduced row echelon form:

We can just divide each row by the leading coefficient.

Ex 1:

Row echelon Form

3	*	*	*	*	*
0	0	2	*	*	
0	0	0	-4	*	
0	0	0	0	0	
0	0	0	0	0	

1	*	*	*	*	*
0	0	1	*	*	
0	0	0	1	*	
0	0	0	0	0	
0	0	0	0	0	

Reduced row echelon Form

1	*	0	0	*
0	0	1	0	*
0	0	0	1	*
0	0	0	0	0
0	0	0	0	0

divide each row by
the value of the pivot

Turn anything above
a pivot to 0

Ex 2:

Row echelon Form

Reduced row echelon Form

1	2	3
0	1	4
0	0	1

1	0	-5
0	1	4
0	0	1

1	0	0
0	1	4
0	0	1

1	0	0
0	1	0
0	0	1

Subtract 2 times
the second row
from the first
One.

Add 5 times
the third row
to the first
One.

Subtract 4 times
the third row
from the second
One.

The Gaussian Elimination Algorithm

① **Augmented Matrix**: is a matrix formed by combining the columns of two matrices to form a new matrix.

Ex:

$$2a - b + c = 1$$

$$2a + 2b + 4c = -2$$

$$4a + b = -1$$



R_1	2	-1	1	1
R_2	2	2	4	-2
R_3	4	1	0	-1

Coefficient matrix

Constant values

+

Augmented Matrix

Let's solve the equations:

① **Pivoting**: turn the pivot from first row into a $\underline{\underline{1}}$.

$$R_1 \leftarrow \frac{1}{2} R_1 \Rightarrow R_1 [1 \ -\frac{1}{2} \ \frac{1}{2} \ \frac{1}{2}] \text{ updated row } \underline{\underline{1}}$$

② Set all the values below the pivot to $\underline{\underline{0}}$: using row operations

$$\begin{aligned} 1) R_2 &\leftarrow R_2 - 2R_1 \xrightarrow{\text{updated row}} R_2 [2 \ 2 \ 4 \ -2] \\ &\quad - 2R_1 [2 \ -1 \ 1 \ 1] \\ &\quad \hline \text{new } R_2 [0 \ 3 \ 3 \ -3] \text{ updated row } \underline{\underline{2}} \end{aligned}$$

$$\begin{aligned} 2) R_3 &\leftarrow R_3 - 4R_1 \xrightarrow{\text{updated row } \underline{\underline{3}}} R_3 [4 \ 1 \ 0 \ -1] \\ &\quad - 4R_1 [4 \ -2 \ 2 \ 2] \\ &\quad \hline \text{new } R_3 [0 \ 3 \ -2 \ -3] \text{ updated row } \underline{\underline{3}} \end{aligned}$$

updated Matrix:

R_1	1	$-\frac{1}{2}$	$\frac{1}{2}$	$\frac{1}{2}$
R_2	0	3	3	-3
R_3	0	3	-2	2

③ Pivoting : turn the pivot from second row into a $\underline{\underline{1}}$.

$$R_2 \leftarrow \frac{1}{3} R_2 \quad \Rightarrow \quad R_2 \begin{bmatrix} 0 & 1 & 1 & -1 \end{bmatrix} \text{ updated row } 2 =$$

④ Set all the values below the pivot to $\underline{0}$: using row operations

$$\begin{array}{l}
 \text{updated} \\
 R_3 \leftarrow R_3 - 3R_2 \quad \Rightarrow \quad R_3 [0 \ 3 \ -2 \ 2] \\
 - 3R_2 [0 \ 3 \ 3 \ -3] \\
 \hline
 \text{new } R_3 [0 \ 0 \ -5 \ 5] \quad \text{updated row} \\
 \hline
 3
 \end{array}$$

⑤ Step 3 for the pivot of third row.

$$R_3 \leftarrow \frac{1}{5} R_3$$

Updated Matrix :

R_1	1	$-\frac{1}{2}$	$\frac{1}{2}$	$\frac{1}{2}$
R_2	0	1	1	-1
R_3	0	0	1	-1
	}			

⑦ Back Substitution: Use the information in the last column to solve the system of equations. How? We will start from the bottom row and work our way to the top. We will use the pivot from each row to cancel the values in the cells above it. This process actually looks very similar to creating the pivots in the first place.

⑥ Back substitution :

R_1	1	$-\frac{1}{2}$	$\frac{1}{2}$	$\frac{1}{2}$
R_2	0	1	1	-1
R_3	0	0	1	-1

$$1) R_2 \leftarrow R_2 - R_3 \Rightarrow$$

$$\begin{array}{r} -R_2 [0 \ 1 \ 1 \ -1] \\ -R_3 [0 \ 0 \ 1 \ -1] \\ \hline \text{new } R_2 [0 \ 1 \ 0 \ 0] \end{array}$$

$$2) R_1 \leftarrow R_1 - \frac{1}{2} R_3 \Rightarrow$$

$$\begin{array}{r} -R_1 [1 \ -\frac{1}{2} \ \frac{1}{2} \ \frac{1}{2}] \\ \frac{1}{2} R_3 [0 \ 0 \ \frac{1}{2} \ -\frac{1}{2}] \\ \hline \text{new } R_1 [1 \ -\frac{1}{2} \ 0 \ 1] \end{array}$$

3) for second column :

$$R_1 \leftarrow R_1 + \frac{1}{2} R_2 \Rightarrow$$

$$\begin{array}{r} R_1 [1 \ -\frac{1}{2} \ 0 \ 1] \\ + \frac{1}{2} R_2 [0 \ \frac{1}{2} \ 0 \ 0] \\ \hline \text{new } R_1 [1 \ 0 \ 0 \ 1] \end{array}$$

R_1	1	0	0	1
R_2	0	1	0	0
R_3	0	0	1	-1

The result :

$$a = 1$$

$$b = 0$$

$$c = -1$$

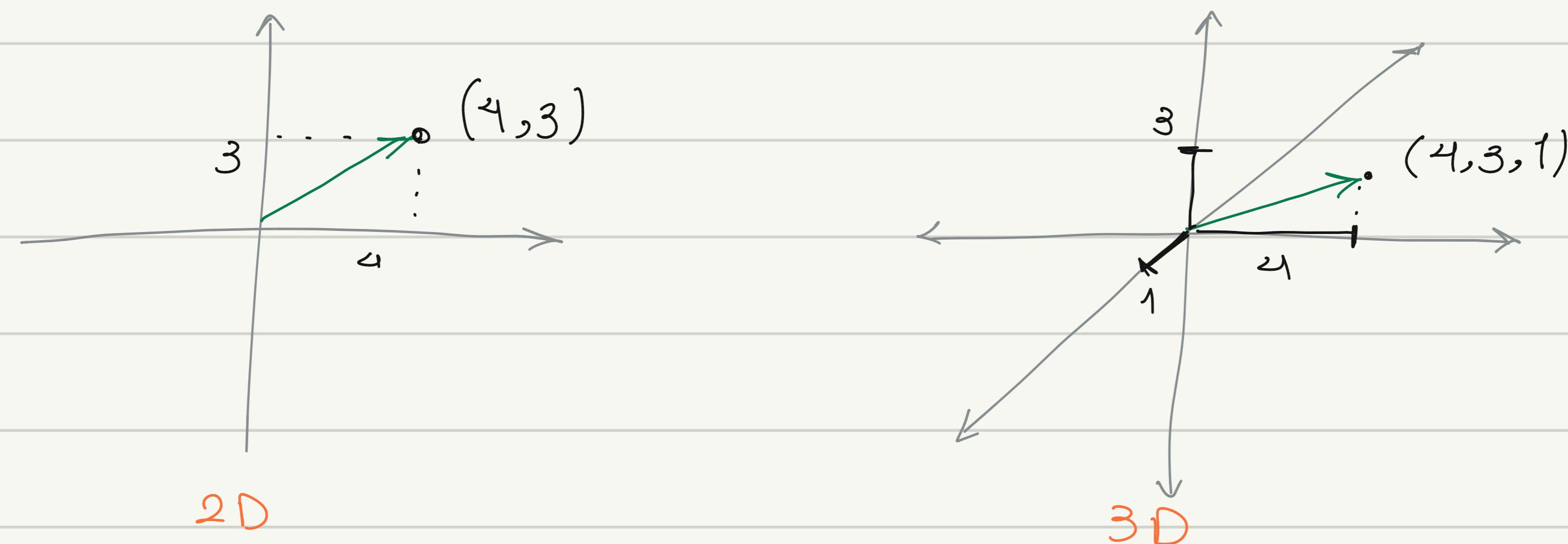
solution to
the system

reduced row
echelon form

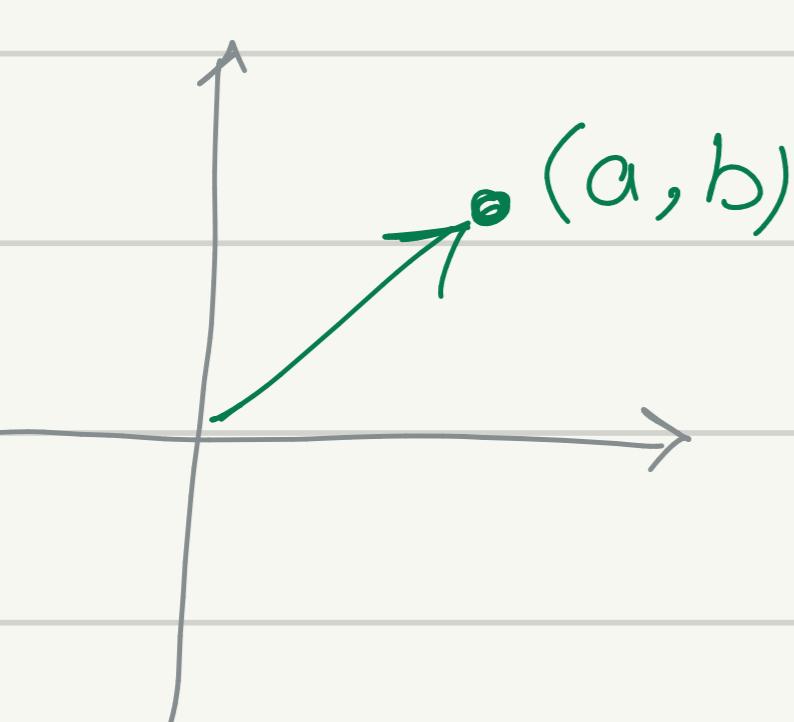
Identity Matrix : is the square matrix that has only 1s in the diagonal.

Week 3 - Vectors and Linear Transformations

Vectors



Norms



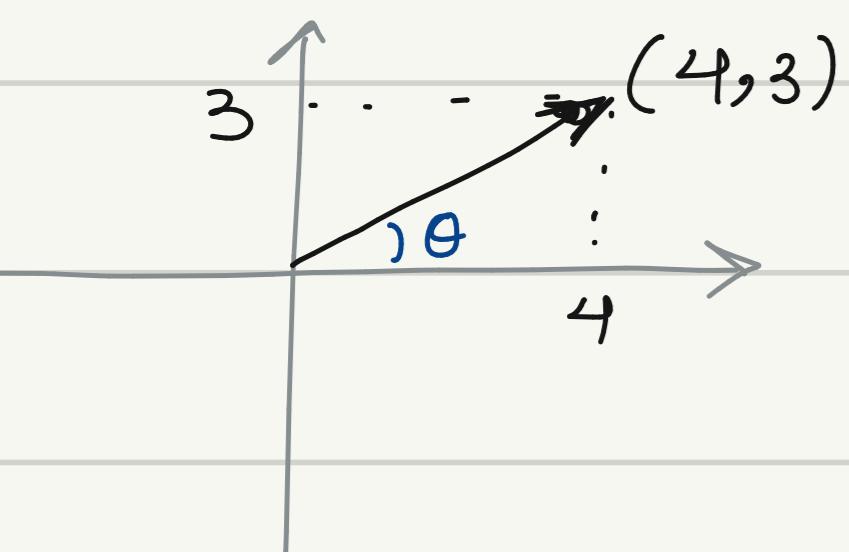
$$L_1\text{-norm} = \|(a, b)\|_1 = |a| + |b|$$

$$L_2\text{-norm} = \|(a, b)\|_2 = \sqrt{a^2 + b^2}$$

Example :

• Norm of a vector

• Direction of a vector



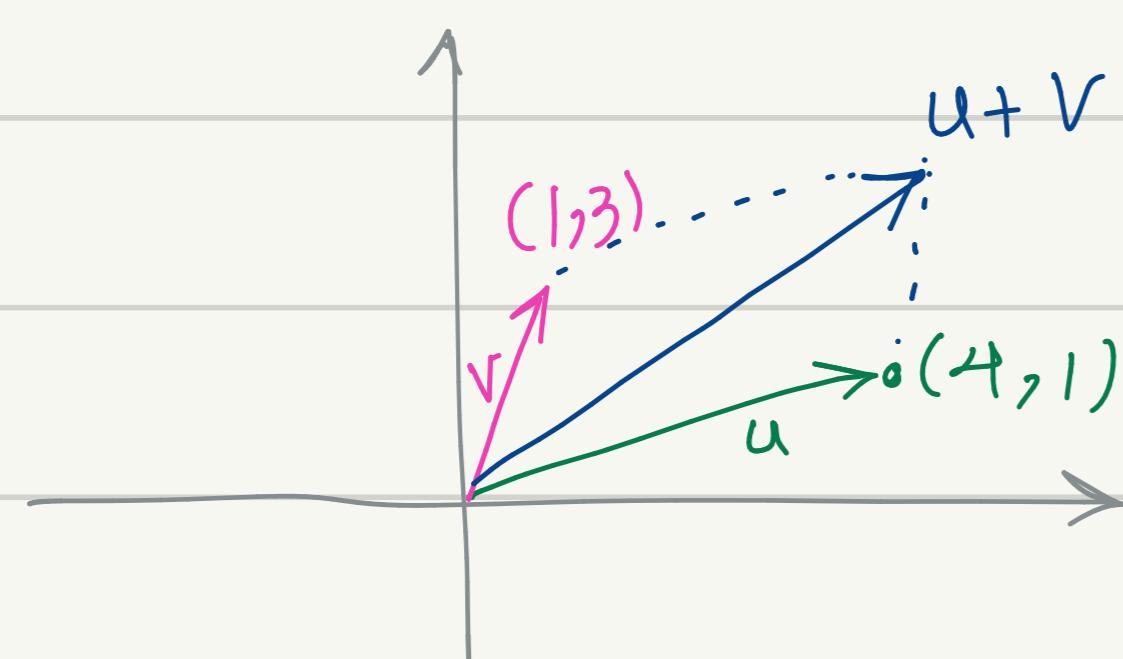
$$\sqrt{4^2 + 3^2} = \sqrt{25} = 5$$

$$\tan(\theta) = \frac{3}{4}$$

$$\theta = \arctan\left(\frac{3}{4}\right) = 0.64 = 36.87^\circ$$

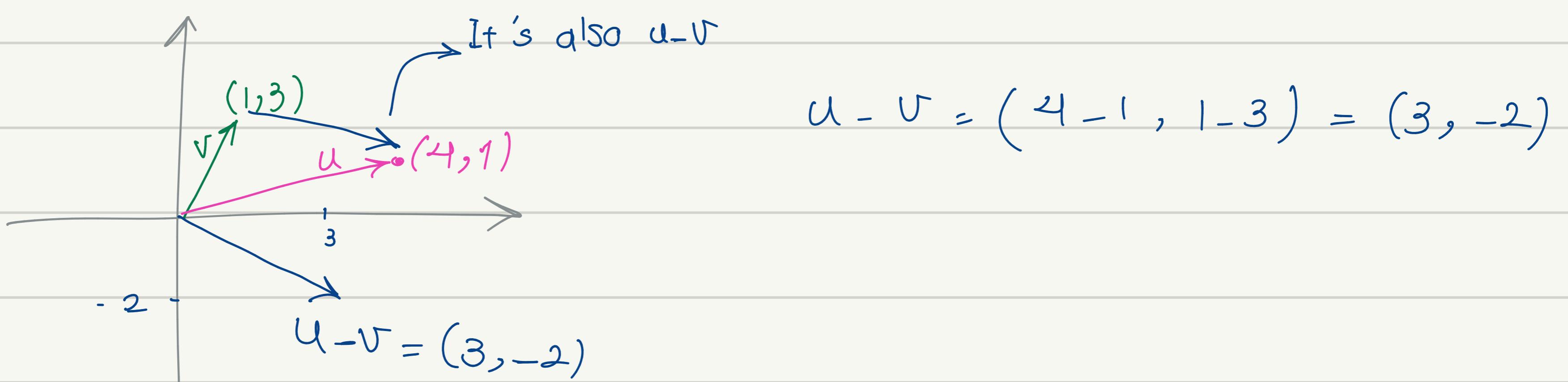
Vector Operations

1) Sum of vectors :



$$u+v = (4+1, 1+3) = (5, 4)$$

2) Difference of Vectors :



General Definition

$$x = (x_1, x_2, \dots, x_n)$$

Sum

$$y = (y_1, y_2, \dots, y_n)$$

Difference

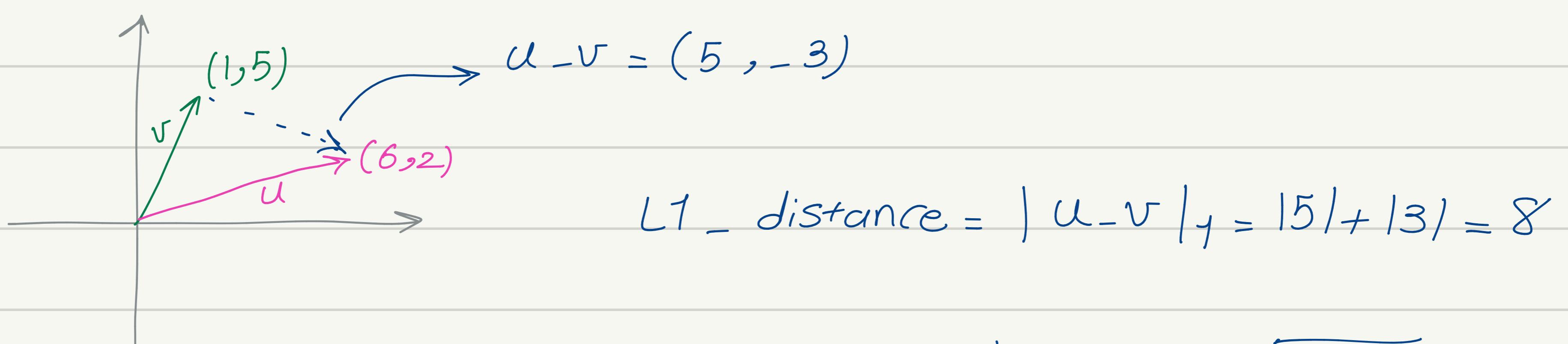
Sum component by component

subtract component by component

$$x+y = (x_1+y_1, x_2+y_2, \dots, x_n+y_n)$$

$$x-y = (x_1-y_1, x_2-y_2, \dots, x_n-y_n)$$

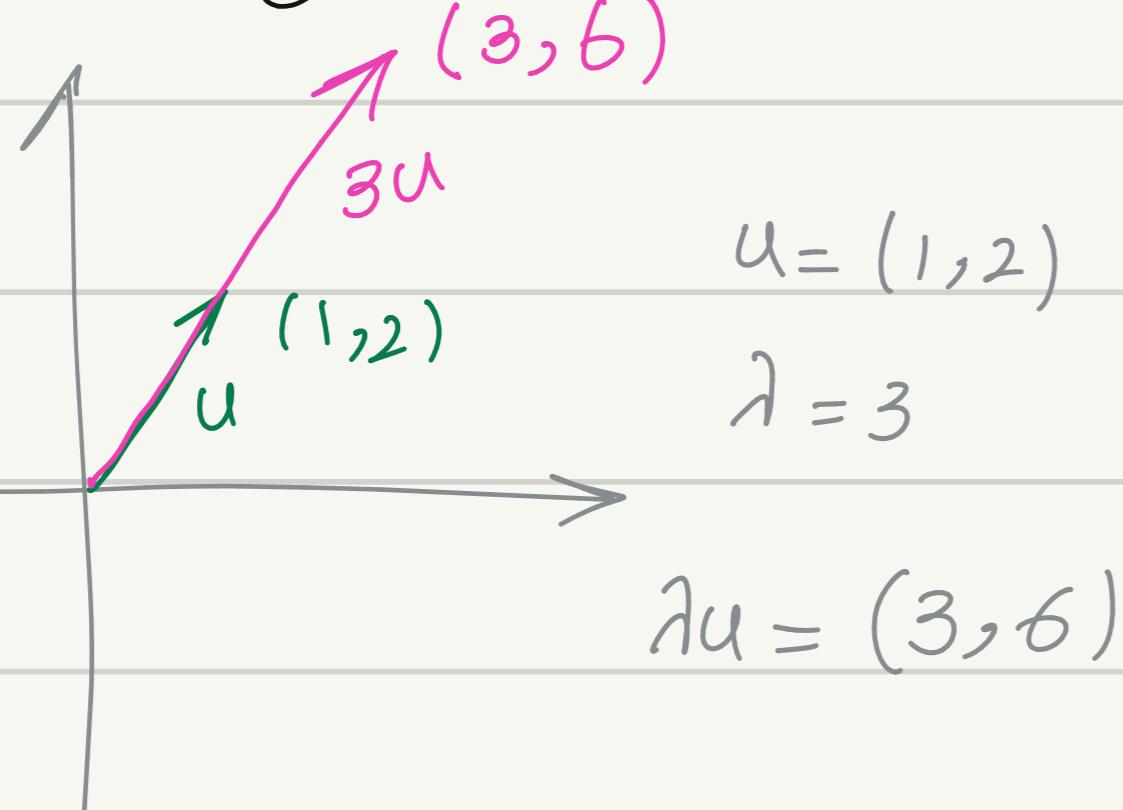
Distance : The difference between two vectors is helpful to tell how far apart two vectors are from each other.



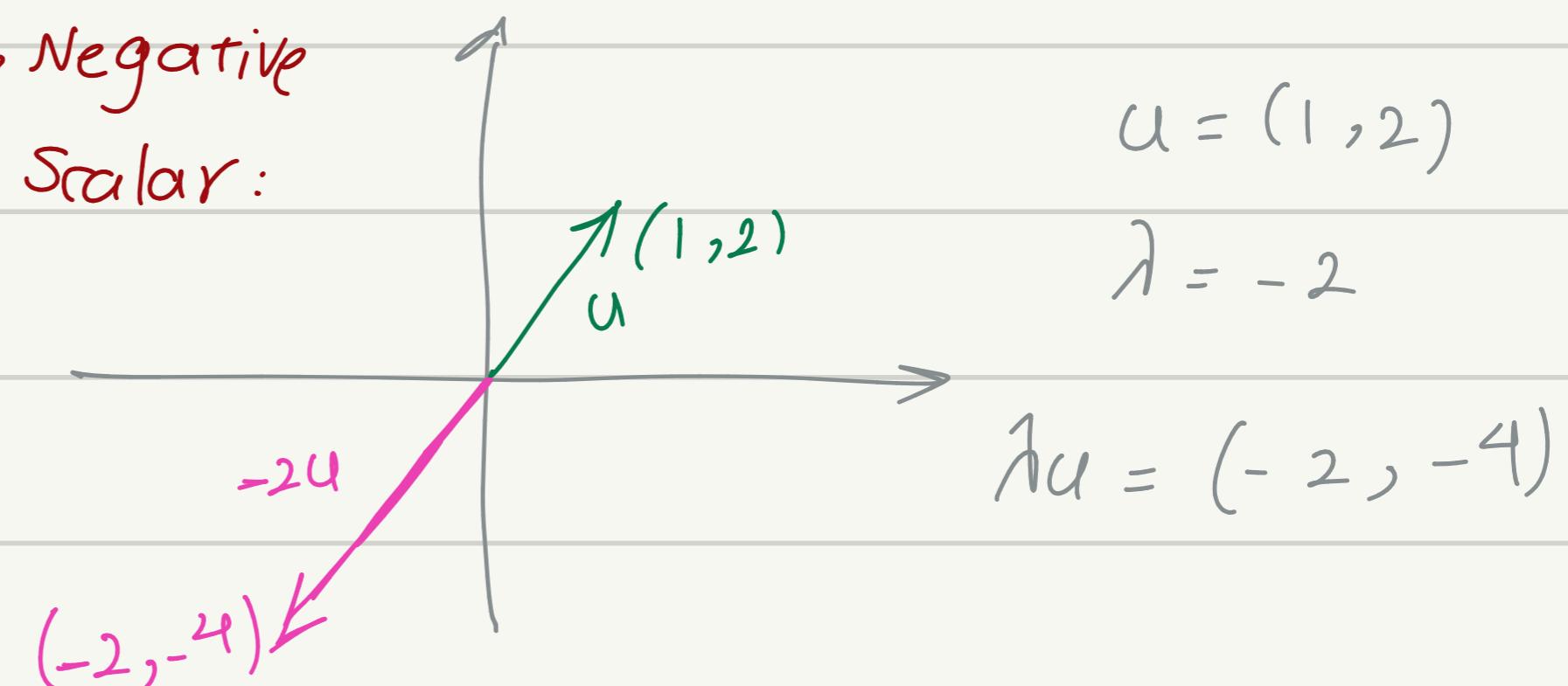
$$L2\text{-distance} = |u - v|_2 = \sqrt{5^2 + 3^2} = 5.83$$

3) Multiplying a vector by a scalar:

• Positive scalar:

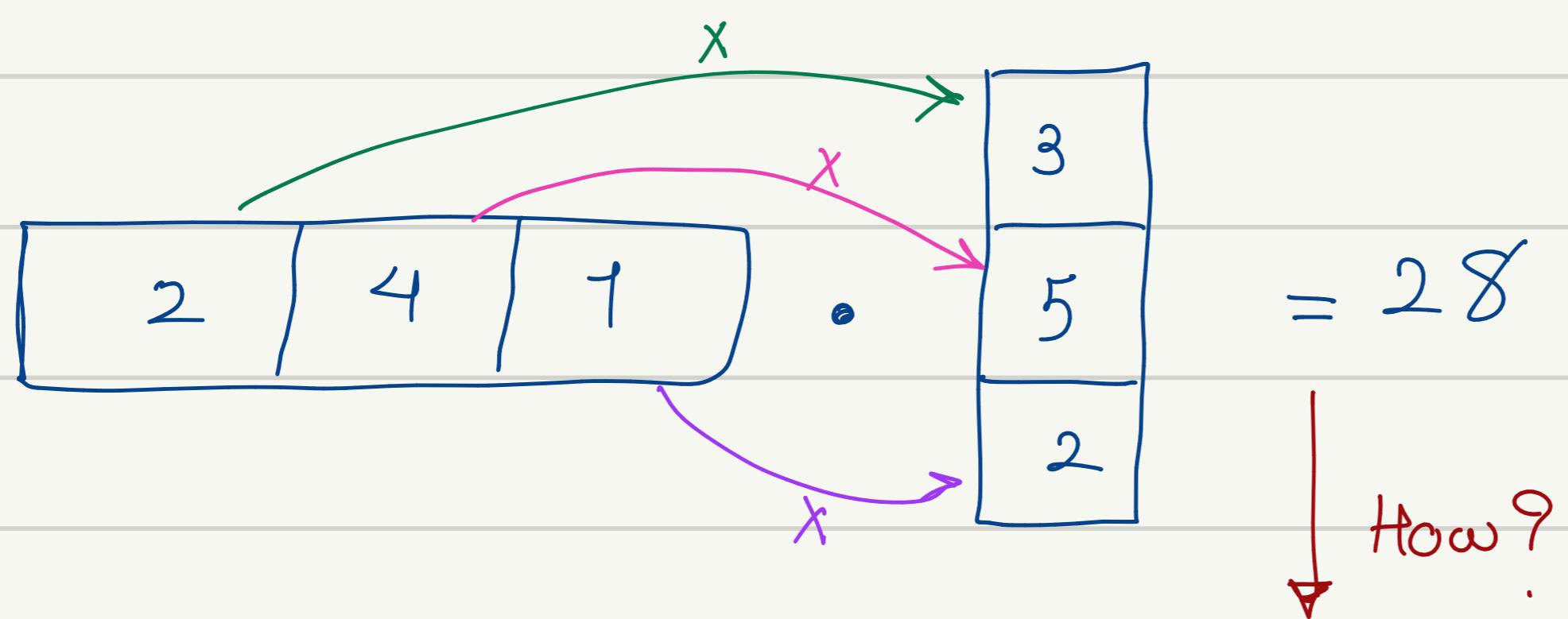


• Negative scalar:



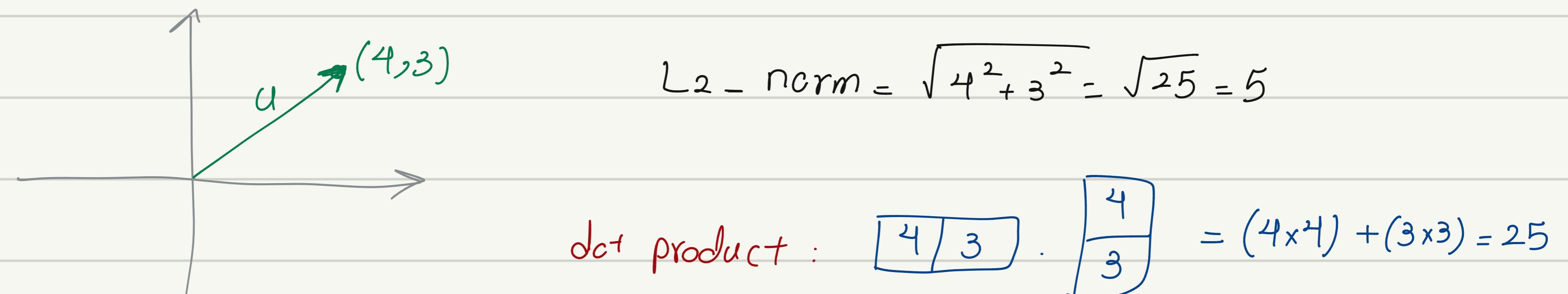
• General Def : $x = (x_1, x_2, \dots, x_n) \rightarrow \lambda x = (\lambda x_1, \lambda x_2, \dots, \lambda x_n)$

The Dot Product : Sum of each corresponding pair of entries.



$$2 \cdot 3 + 4 \cdot 5 + 1 \cdot 2 = 28$$

Norm of a Vector using dot product :



So: $L_2\text{-norm} = \sqrt{\text{dot product}(u, u)} = \|u\|_2 = \sqrt{\langle u, u \rangle}$ another notation for
dot product

Vector Transpose ■ Transpose: Convert columns to rows

$$\begin{bmatrix} 2 \\ 4 \\ 1 \end{bmatrix}^T = \begin{bmatrix} 2 & 4 & 1 \end{bmatrix} \quad \text{and vice versa} \quad \begin{bmatrix} 2 & 4 & 1 \end{bmatrix}^T = \begin{bmatrix} 2 \\ 4 \\ 1 \end{bmatrix}$$

Matrix Transpose ■

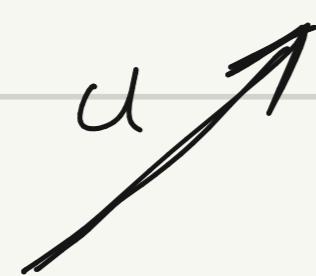
$$\begin{bmatrix} 2 & 5 \\ 4 & 7 \\ 1 & 3 \end{bmatrix}^T = \begin{bmatrix} 2 & 4 & 1 \\ 5 & 7 & 3 \end{bmatrix} \quad \text{Columns} \rightarrow \text{Rows}$$

General Def: $x = (x_1, x_2, \dots, x_n), y = (y_1, y_2, \dots, y_n)$

$$x \cdot y = \langle x, y \rangle = (x_1 y_1) + (x_2 y_2) + \dots + (x_n y_n)$$

* The dot Product *

1)



$$\langle u, u \rangle = \|u\|^2 = \|u\| \cdot \|u\|$$

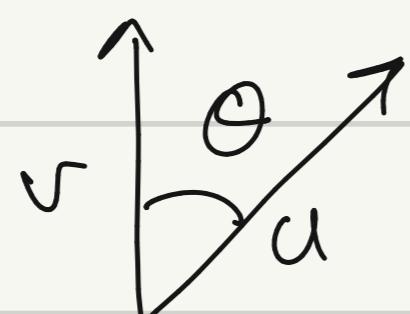
2)



$$\langle u, v \rangle = 0$$

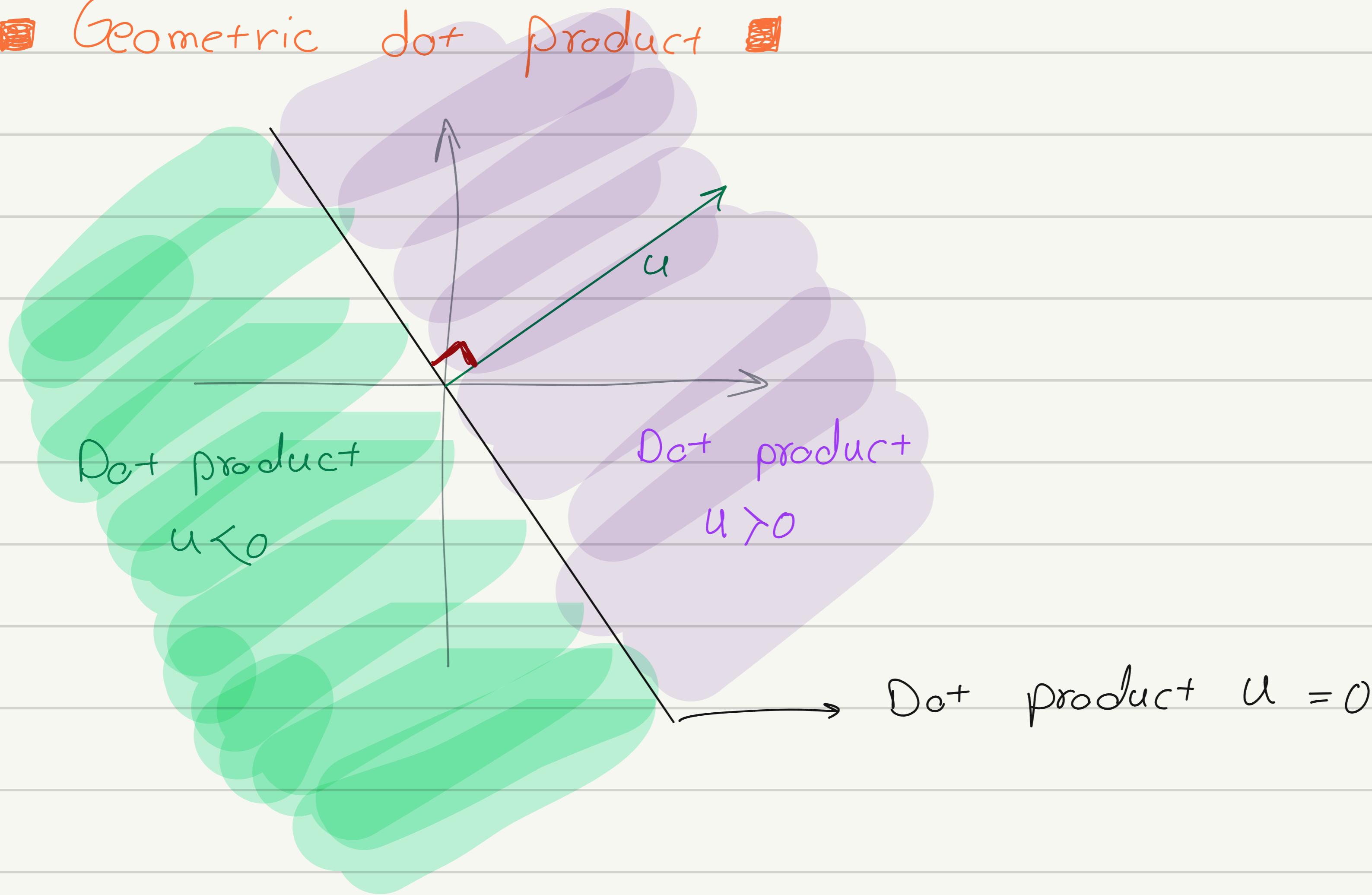
* orthogonal vectors have dot product 0 *

3)



$$\langle u, v \rangle = \|u\| \cdot \|v\| \cdot \cos(\theta)$$

■ Geometric dot product ■



■ Equations as dot+ product ■

$$a + b + c = 10$$

$$a + 2b + c = 15$$

$$a + b + 2c = 12$$

$$\begin{bmatrix} 1 & 1 & 1 \end{bmatrix} \cdot \begin{bmatrix} a \\ b \\ c \end{bmatrix} = 10$$

$$\begin{bmatrix} 1 & 2 & 1 \end{bmatrix} \cdot \begin{bmatrix} a \\ b \\ c \end{bmatrix} = 15$$

$$\begin{bmatrix} 1 & 1 & 2 \end{bmatrix} \cdot \begin{bmatrix} a \\ b \\ c \end{bmatrix} = 12$$

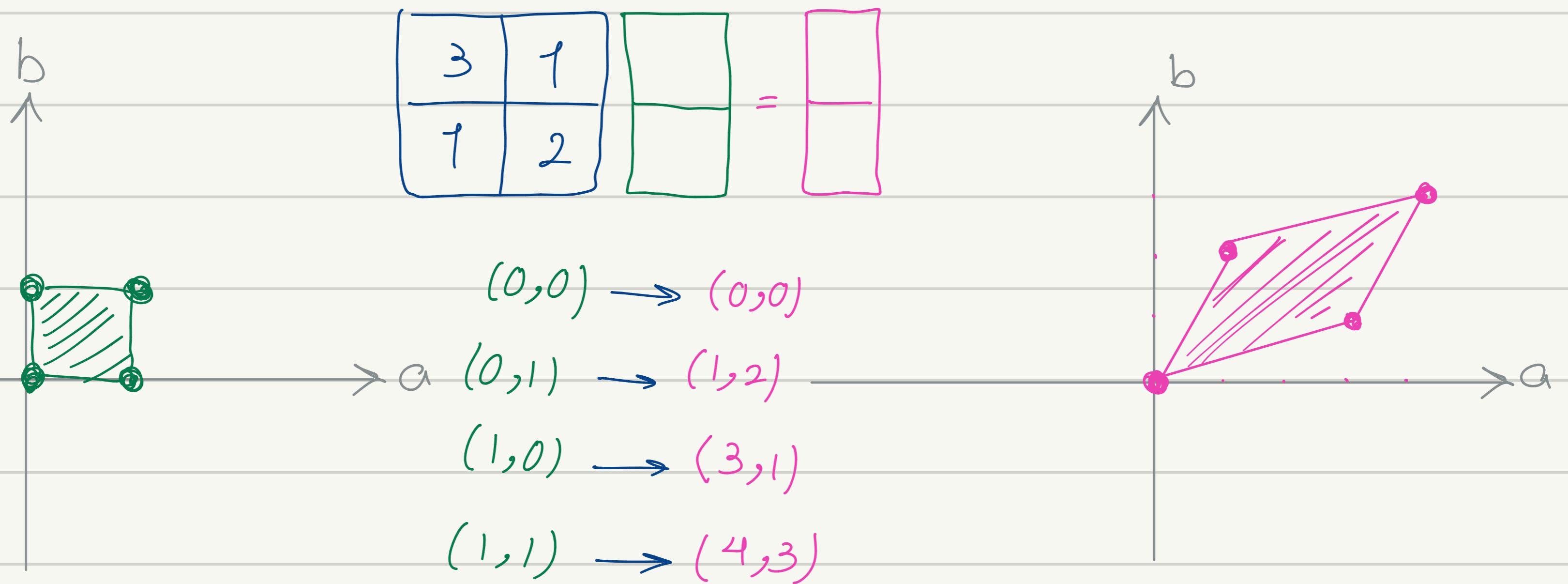
matrix product

→ Merging:

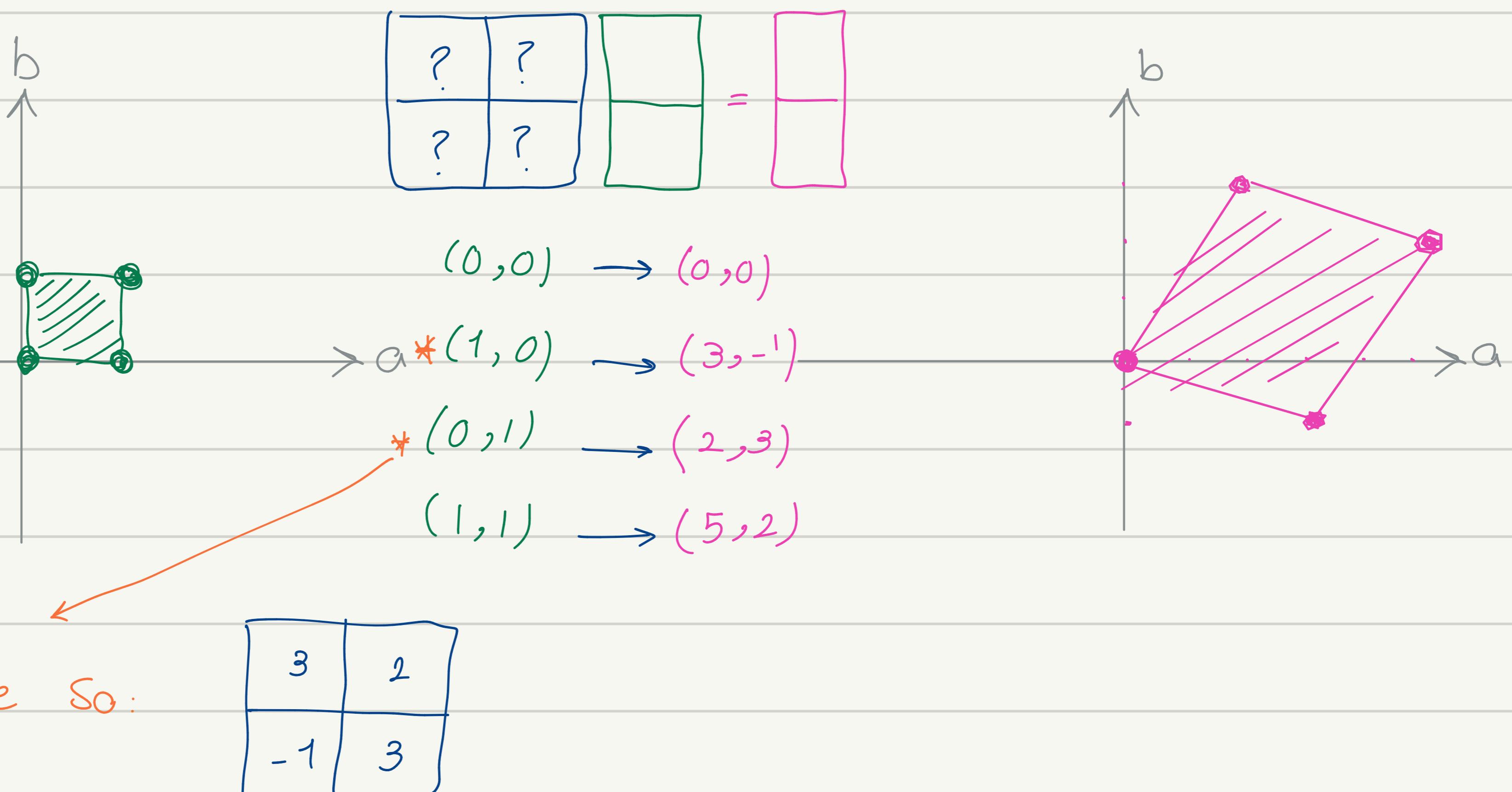
$$\begin{bmatrix} 1 & 1 & 1 \\ 1 & 2 & 1 \\ 1 & 1 & 2 \end{bmatrix} \cdot \begin{bmatrix} a \\ b \\ c \end{bmatrix} = \begin{bmatrix} 10 \\ 15 \\ 12 \end{bmatrix}$$

* A columns = length of vector *

Matrices as Linear Transformations



Linear Transformations as Matrices



Multiplying Matrices → we can show multiplication of matrices with combining linear transformations.

$$\begin{bmatrix} 2 & -1 \\ 0 & 2 \end{bmatrix} \cdot \begin{bmatrix} 3 & 1 \\ 1 & 2 \end{bmatrix} = \begin{bmatrix} 5 & [2 -1] \begin{bmatrix} 3 \\ 1 \end{bmatrix} & [2 -1] \begin{bmatrix} 1 \\ 2 \end{bmatrix} & 0 \\ 2 & [0 2] \begin{bmatrix} 3 \\ 1 \end{bmatrix} & [0 2] \begin{bmatrix} 1 \\ 2 \end{bmatrix} & 4 \end{bmatrix}$$

Dimension of Matrices

3	1	4
2	-1	2

3	0	1	-2
1	5	2	0
-2	1	4	0

2	9	21	-6
1	-3	8	-4

2×3

$= 3 \times 4$

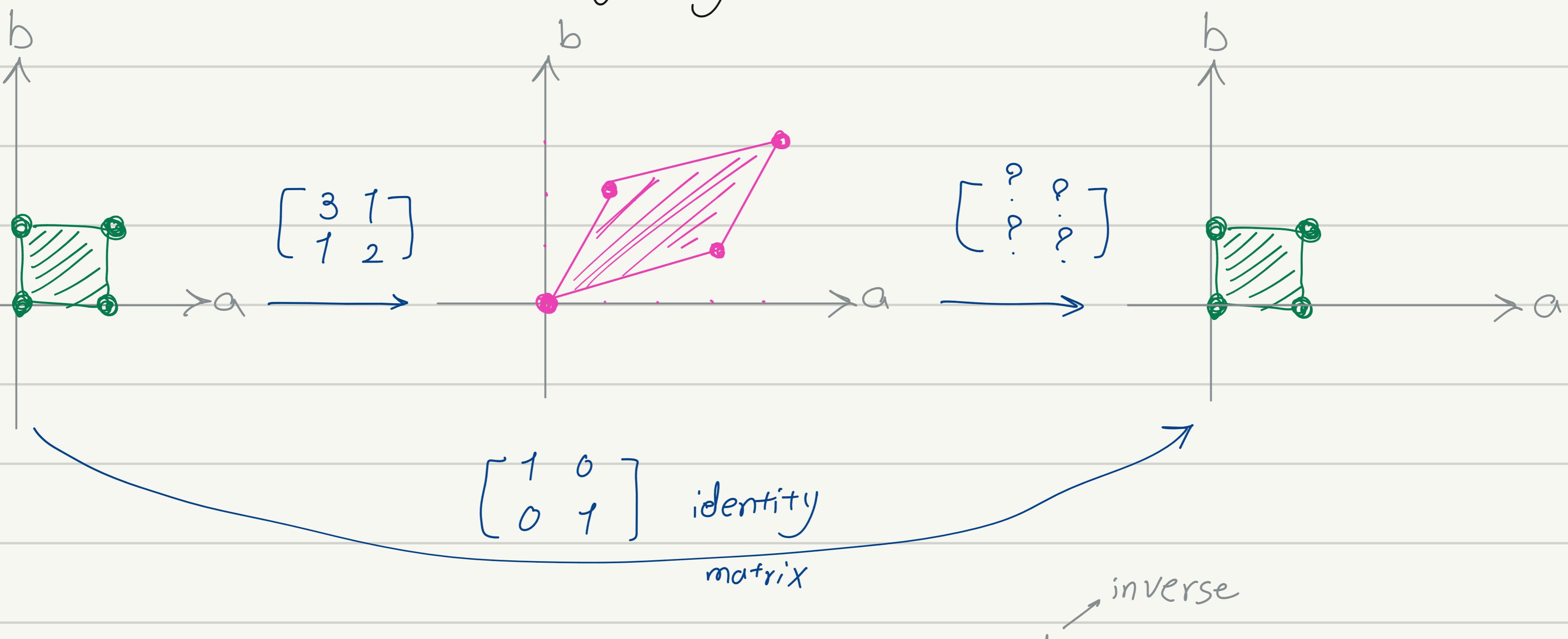
output will be 2×4

must be equal

- ① **Identity Matrix**: is the matrix that when multiplied by any other matrix, it gives the same matrix. ($1s$ in the diagonal, $0s$ every where else.)

- ② **Matrix Inverses**: is the matrix which the product of the matrices is the identity matrix.

- ③ In Linear Transformations, the inverse matrix is the one that undoes the job of the original matrix, namely the one that returns the plane to where it was at the beginning.



$$\begin{bmatrix} 3 & 1 \\ 1 & 2 \end{bmatrix} \cdot \begin{bmatrix} a & c \\ b & d \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \Rightarrow \begin{bmatrix} 3 & 1 \\ 1 & 2 \end{bmatrix}^{-1} = \begin{bmatrix} 2/5 & -1/5 \\ -1/5 & 3/5 \end{bmatrix}$$

solving 4 linear equations

QUESTION

Which matrices have inverse?

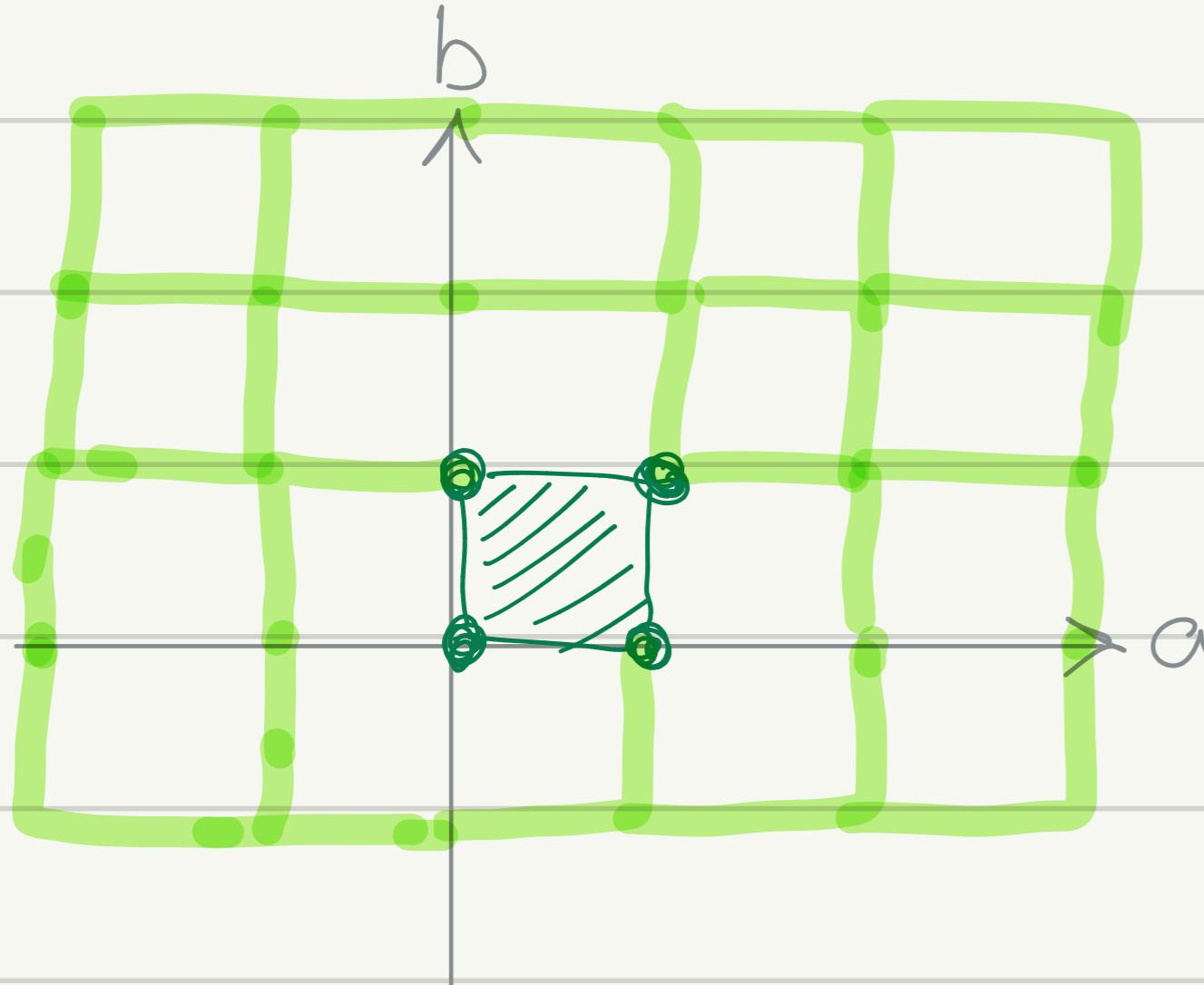
Non-Singular matrices always have inverse, So we call them Invertible matrices. ($\text{Det} \neq 0$)

Singular matrices never have inverse, So we call them Non-Invertible. ($\text{Det} = 0$)

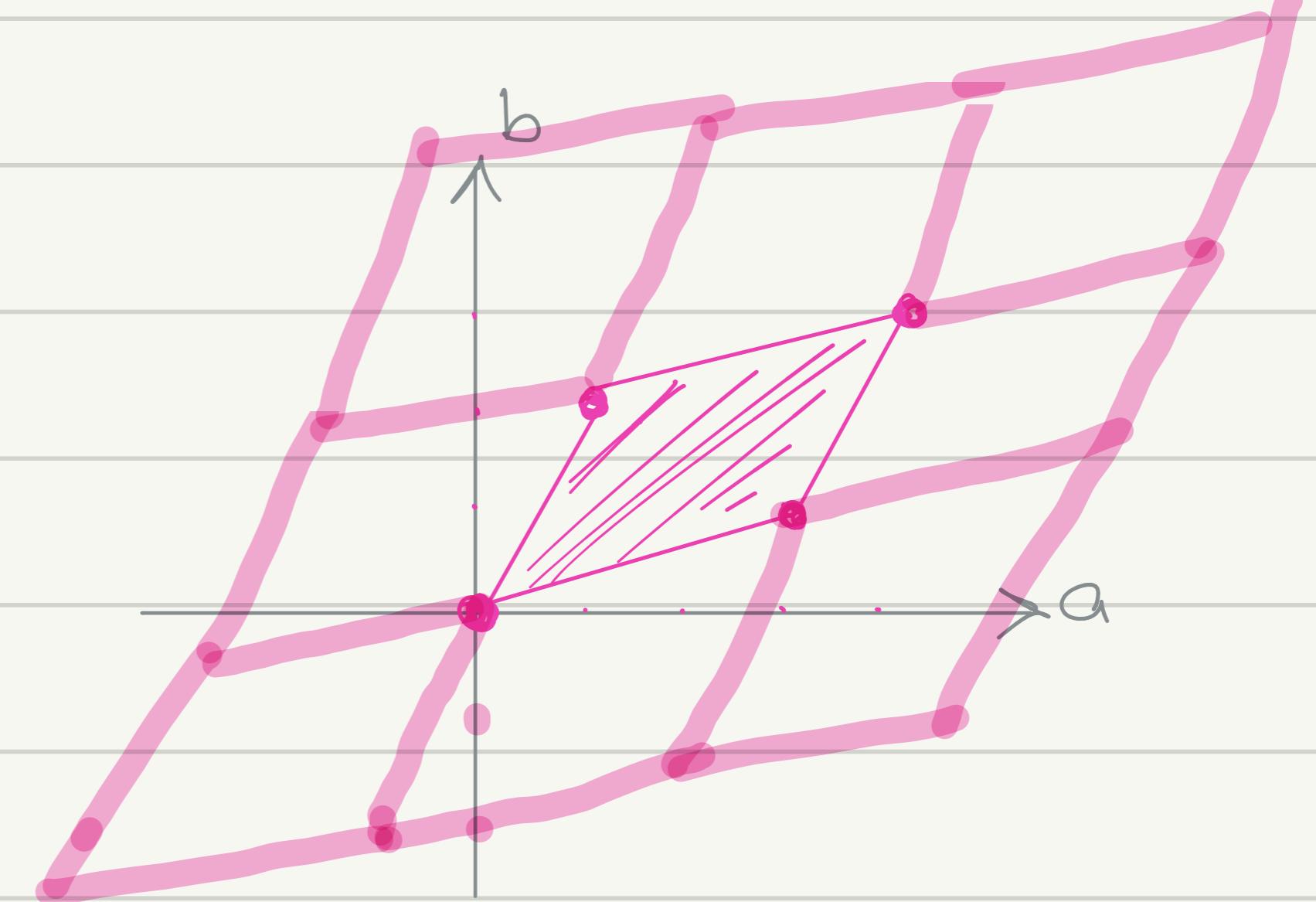
② Week 4 - Determinants and Eigenvectors ②

■ Singularity and rank of linear transformations ■

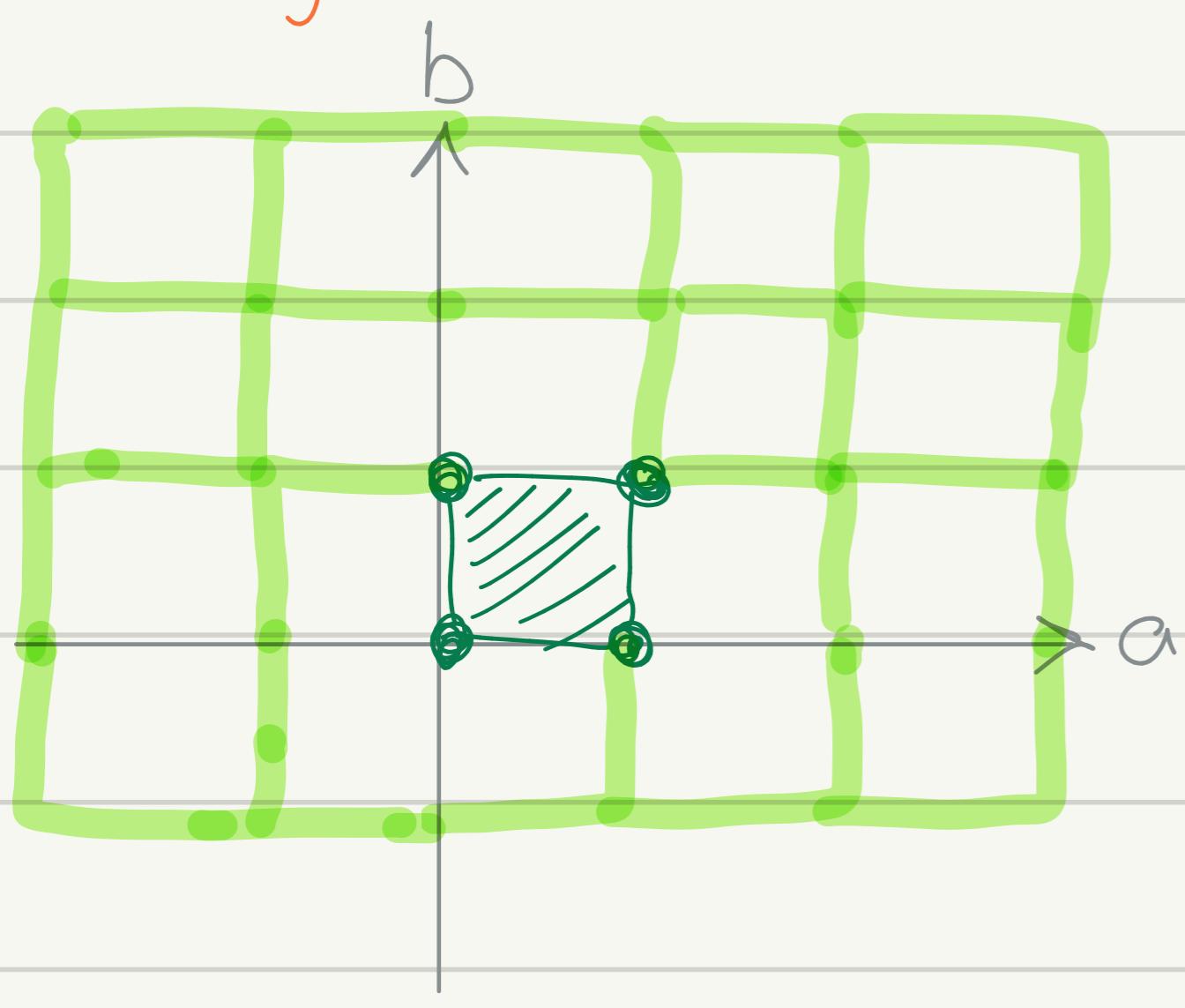
→ Non-singular transformation:



$$\begin{array}{|c|c|} \hline 3 & 1 \\ \hline 1 & 2 \\ \hline \end{array}$$



→ Singular transformation:



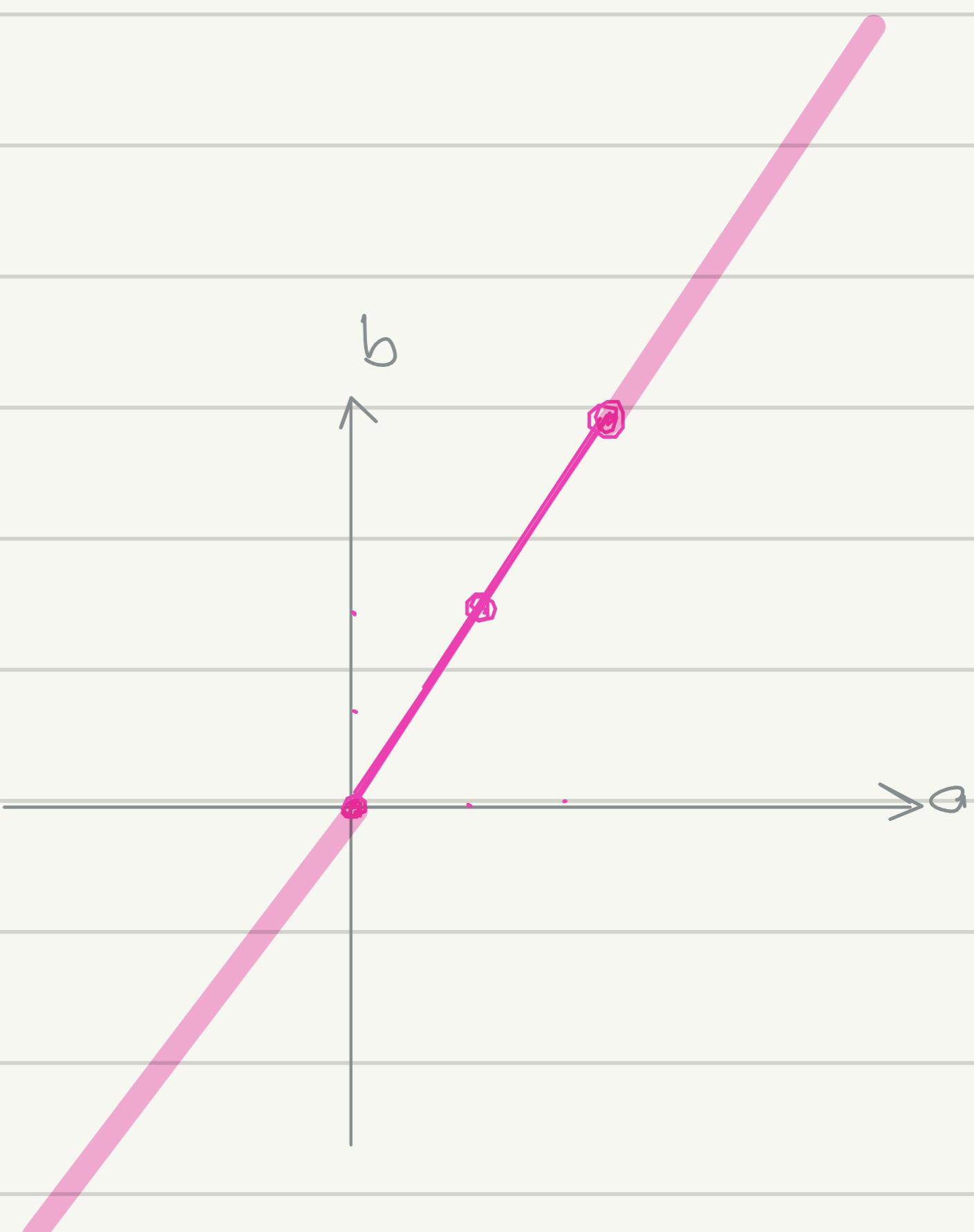
$$\begin{array}{|c|c|} \hline 1 & 1 \\ \hline 2 & 2 \\ \hline \end{array} \quad \begin{array}{|c|} \hline \text{---} \\ \hline \end{array} = \begin{array}{|c|} \hline \text{---} \\ \hline \end{array}$$

$$(0,0) \rightarrow (0,0)$$

$$(1,0) \rightarrow (1,2)$$

$$(0,1) \rightarrow (1,2)$$

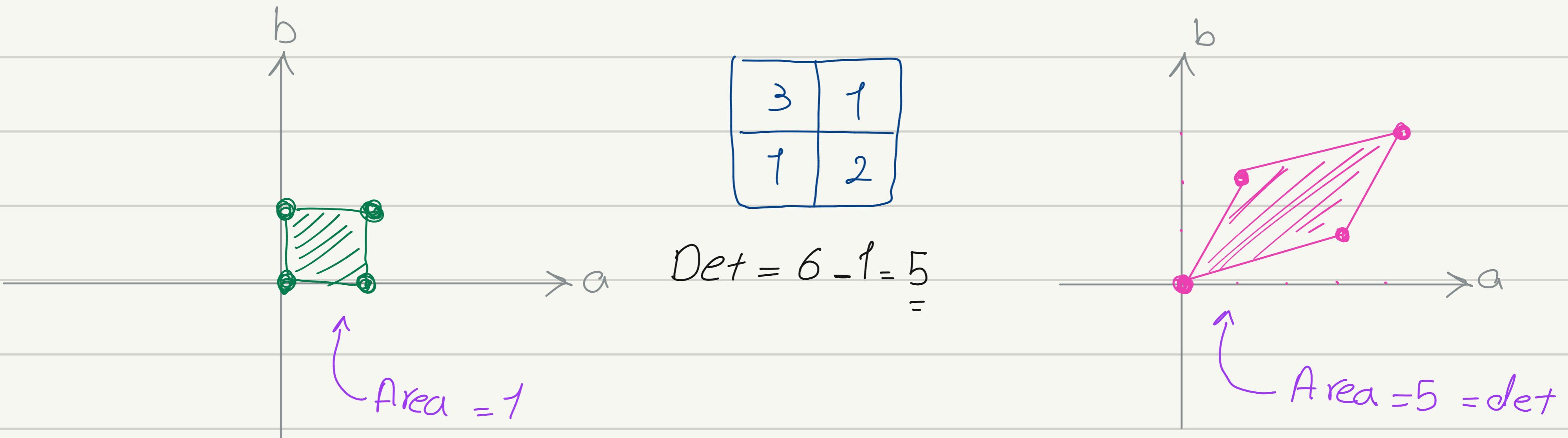
$$(1,1) \rightarrow (2,4)$$



⇒ When a matrix is singular, the transformation plane is not covered entirely.

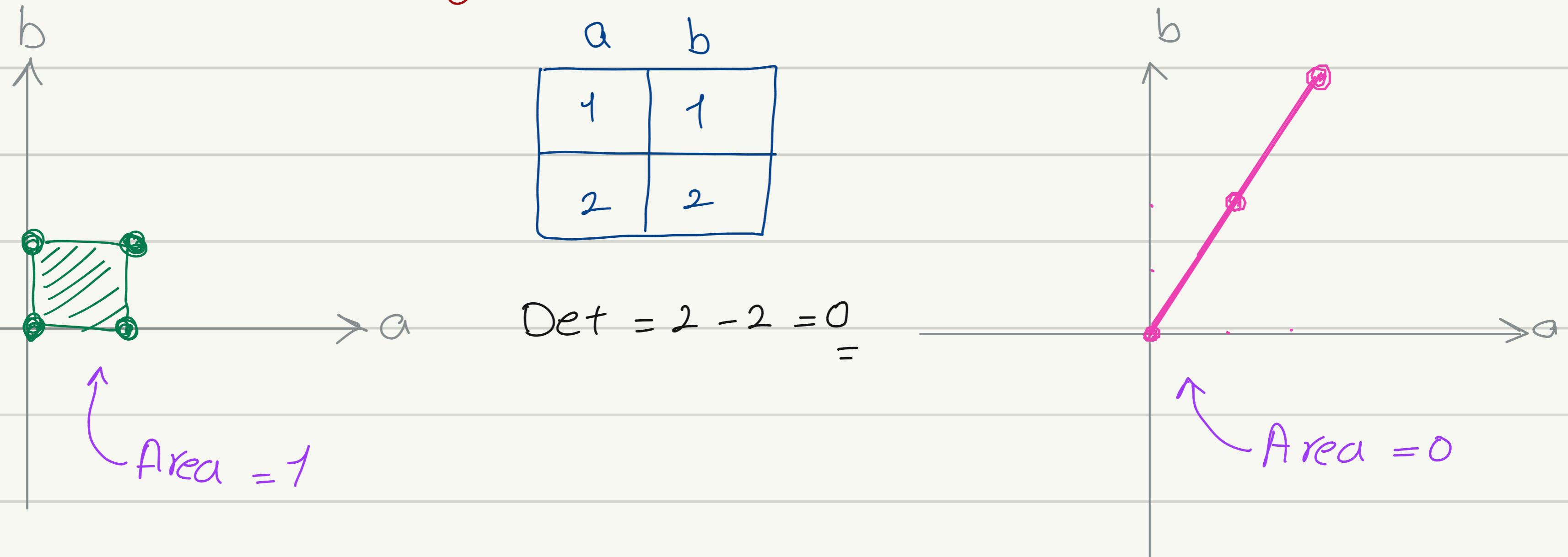
* Rank of linear transformation: the dimension of the image of the linear transformation.

Determinant as an area

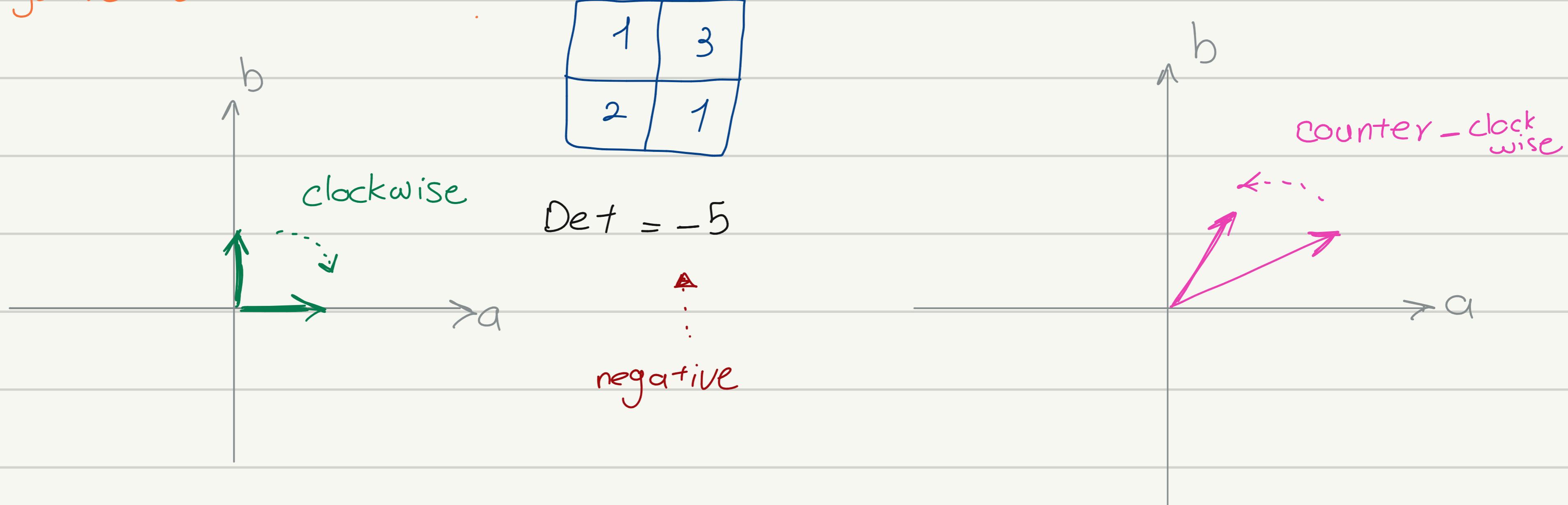


* The determinant of a matrix is the area of the image of the fundamental basis formed by the unit square on the left.

What if the matrix is singular?



Negative determinants?



Determinant of a product

$$\begin{vmatrix} 3 & 1 \\ 1 & 2 \end{vmatrix} \cdot \begin{vmatrix} 1 & 1 \\ -2 & 1 \end{vmatrix} = \begin{vmatrix} 1 & 4 \\ -3 & 3 \end{vmatrix}$$

$$\det = 5$$

$$\det = 3$$

$$\det = 15$$

$$* \det(AB) = \det(A) \cdot \det(B) *$$

Determinant of inverse

$$\begin{vmatrix} 3 & 1 \\ 1 & 2 \end{vmatrix}^{-1} = \begin{vmatrix} 0.4 & -0.2 \\ -0.2 & 0.6 \end{vmatrix}$$

$$\det = 5$$

$$\det = 0.2$$

$$5^{-1} = 0.2$$

$$* \det(A^{-1}) = \frac{1}{\det(A)} *$$

A is a invertible matrix ↪

Determinant of the identity Matrix

$$* \det(I) = 1 *$$

■ Bases (plural of 'Basis') ■

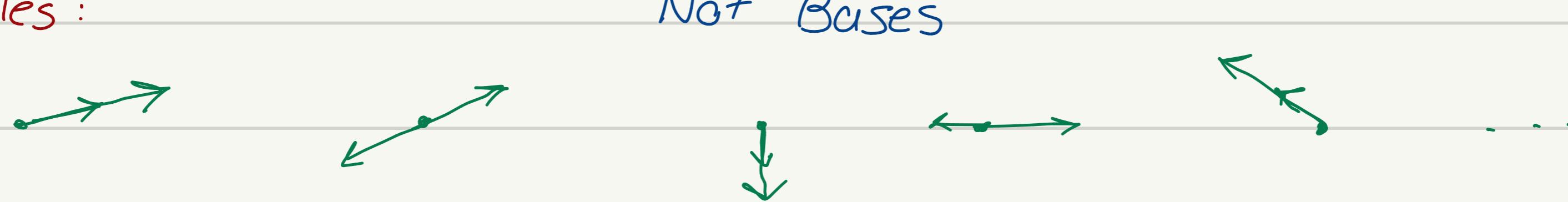
• **Basis** : The main property of a basis is that every point in the space can be expressed as a linear combination of elements in the basis.

Examples:



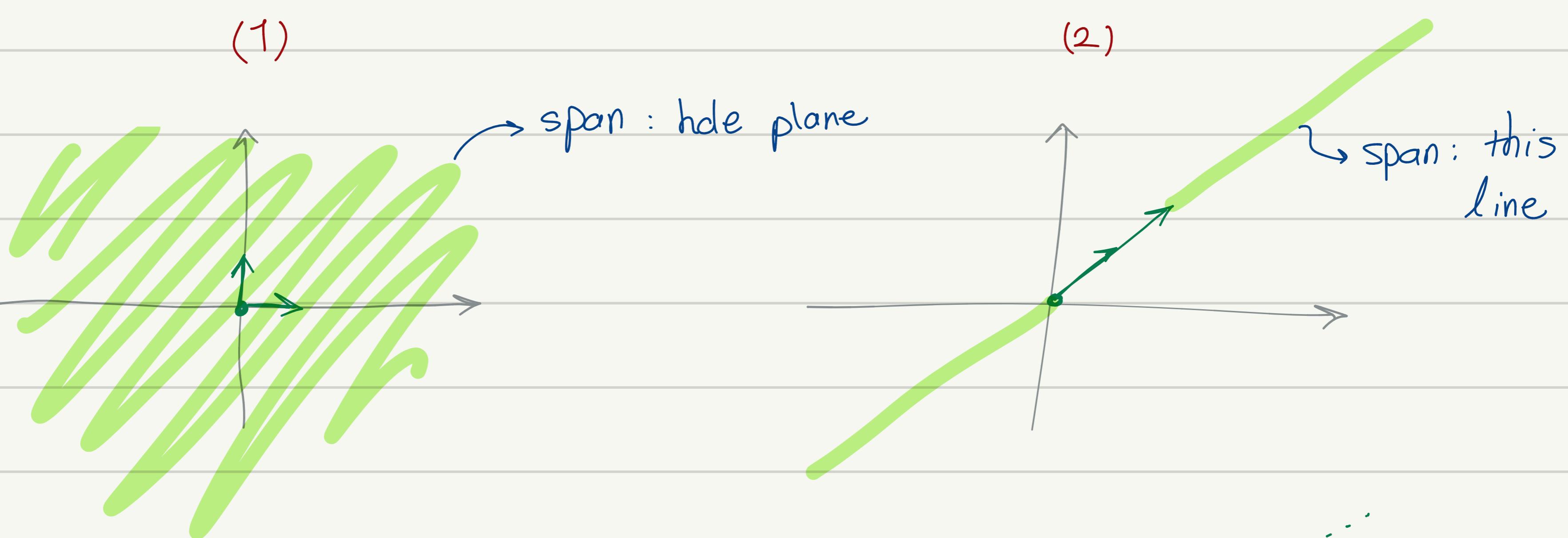
• **Non-Basis** : Anything that comprises two vectors that go in the same direction and they could be opposite. (As long as they belong to the same line, the two vectors don't form a basis.)

Examples:



■ **Span**: The span of a set of vectors is simply the set of points that can be reached by walking in the direction of these vectors in any combination.

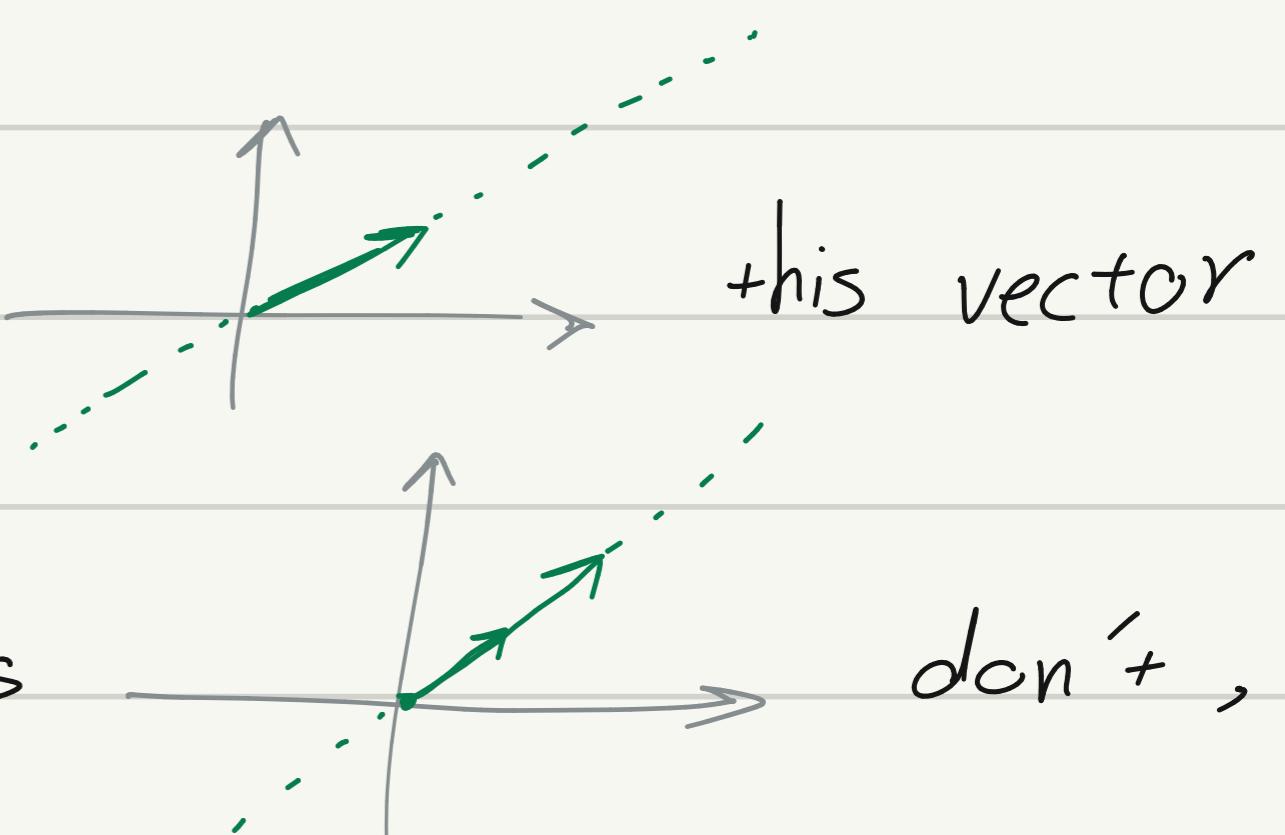
Example:



* A basis is a minimal spanning set. So

forms a basis of the line. But these 2 vectors

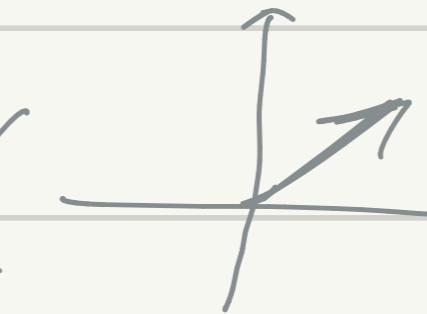
because they are too many.



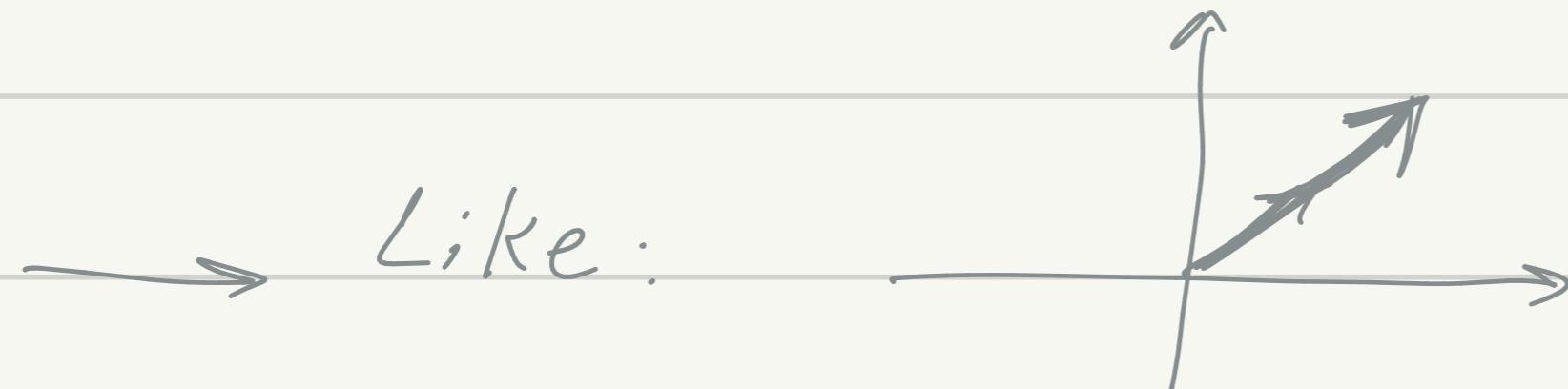
* Number of elements in the basis is the dimension.

■ Linearly Independent and Linearly Dependent vectors ■

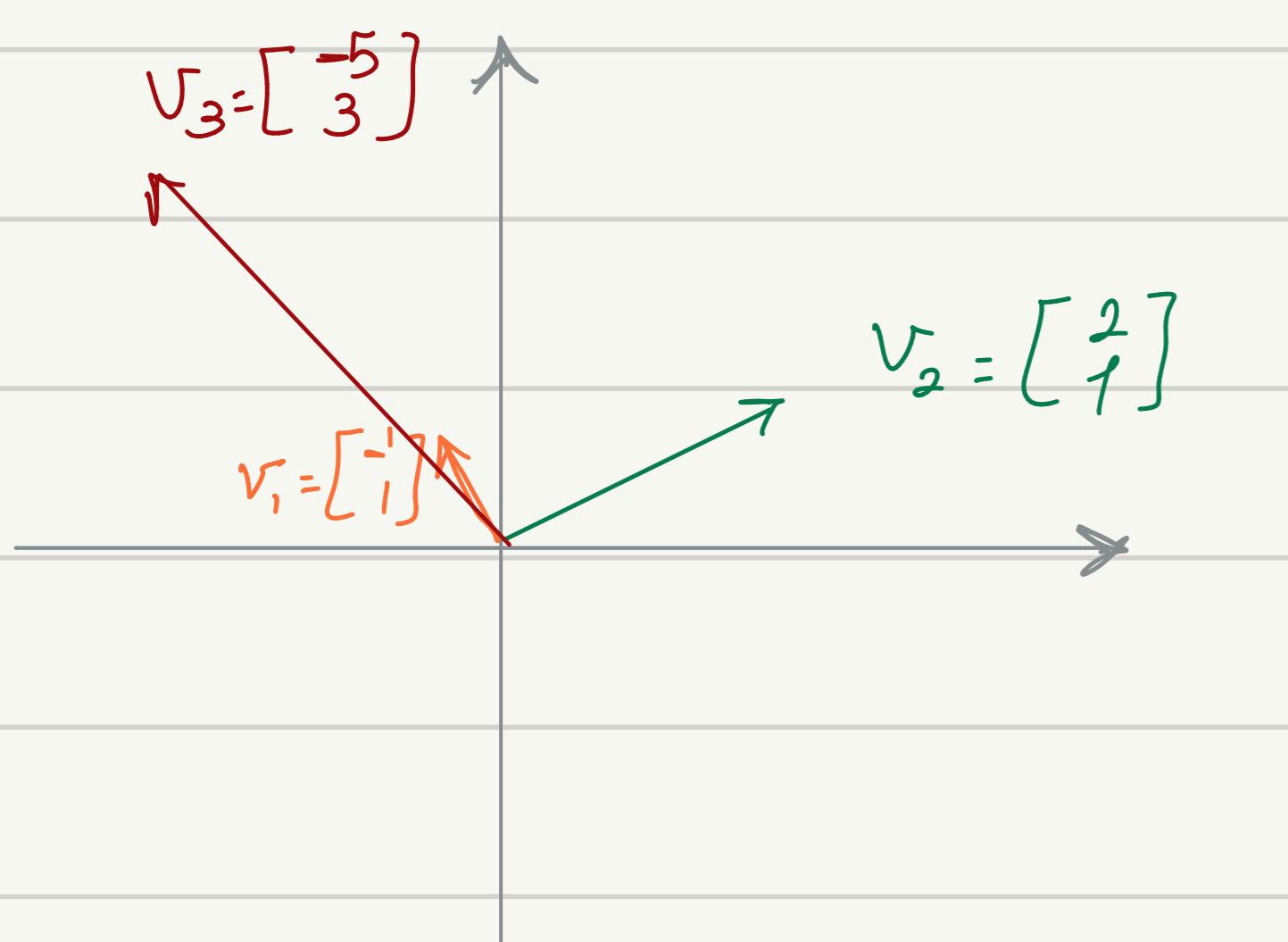
• **linearly independent**: A group of vectors is said to be linearly independent if none of the vectors in the group can be obtained as a linear combination of the others.

→ Just one vector in the plane (), it is always going to be linearly independent.

• **linearly dependent**: Since one vector can be obtained as a linear combination of the others, this set of vectors is called linearly dependent.



→ Let's see how to check for linear dependence:



$$\alpha v_1 + \beta v_2 = v_3$$

$$\alpha \begin{bmatrix} -1 \\ 1 \end{bmatrix} + \beta \begin{bmatrix} 2 \\ 1 \end{bmatrix} = \begin{bmatrix} -5 \\ 3 \end{bmatrix}$$

↓

$$-\alpha + 2\beta = -5$$

$$\alpha + \beta = 3$$

$$\left| \begin{array}{l} \alpha = \frac{11}{3} \\ \beta = \frac{-2}{3} \end{array} \right.$$

* v_3 is a linear combination of v_1 and v_2 , So this set is **linearly dependent**.

If the system has no solution, the set is **linearly independent**.

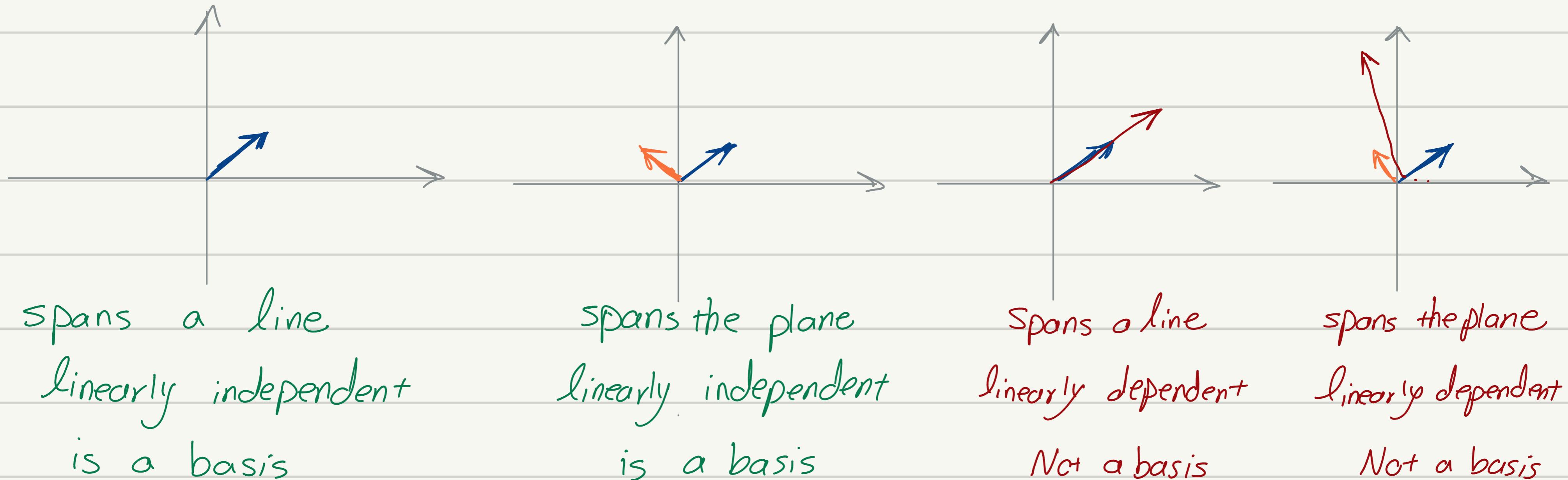
■ Basis : a formal definition

A Basis is a set of vectors that :

- Spans a vector space.

- Is linearly independent.

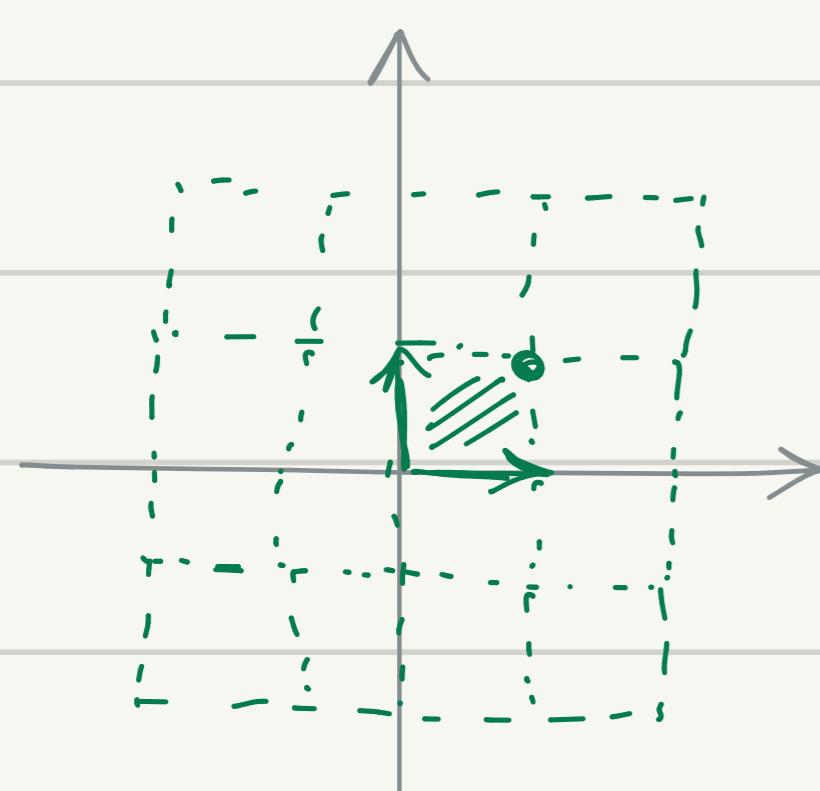
Ex :



** Not all sets of N vectors are a basis for N-dimensional space.

■ Eigenbasis : If a set of eigenvectors of T forms a basis of the domain of T, then this basis is called an eigenbasis.

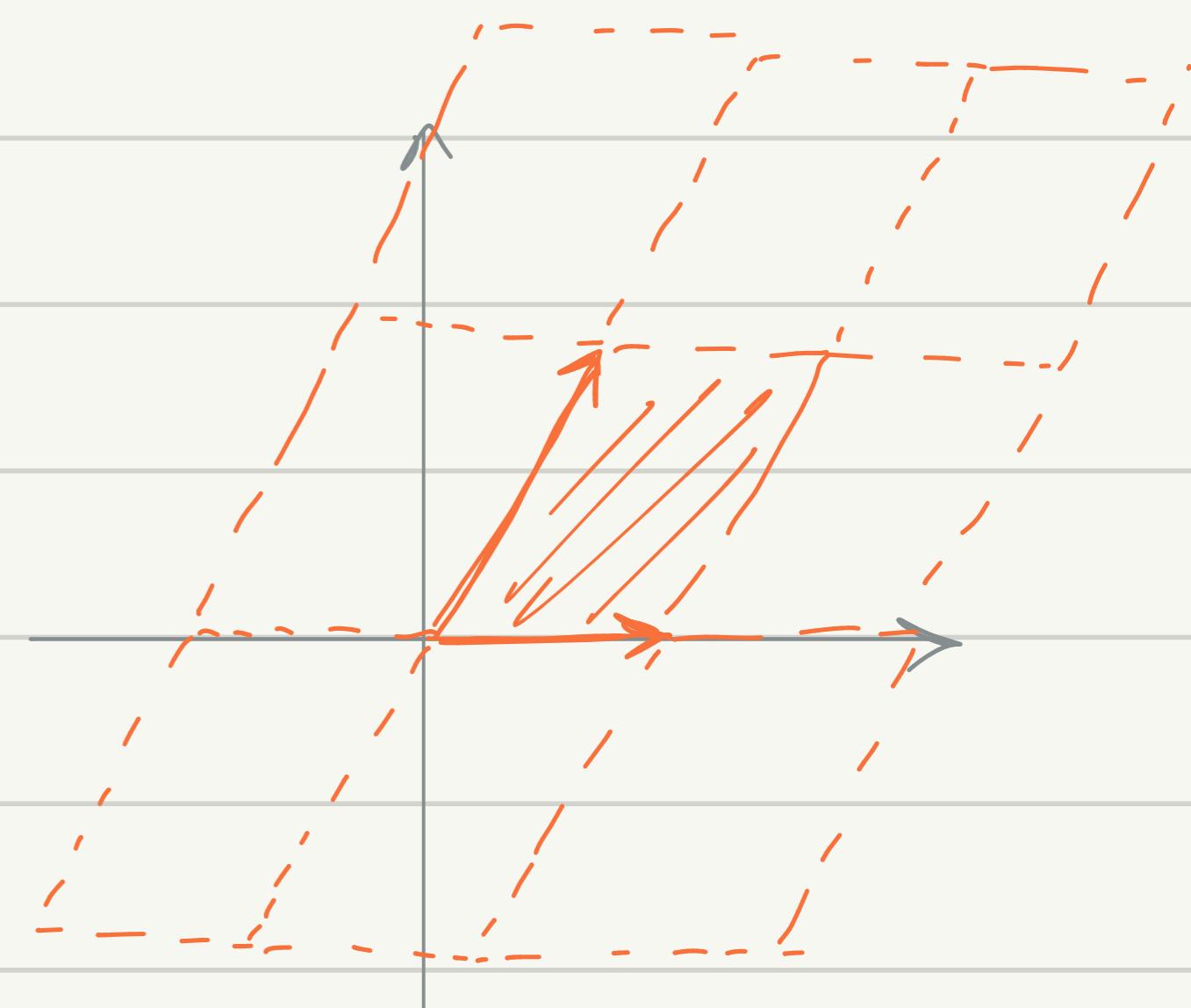
• Basis



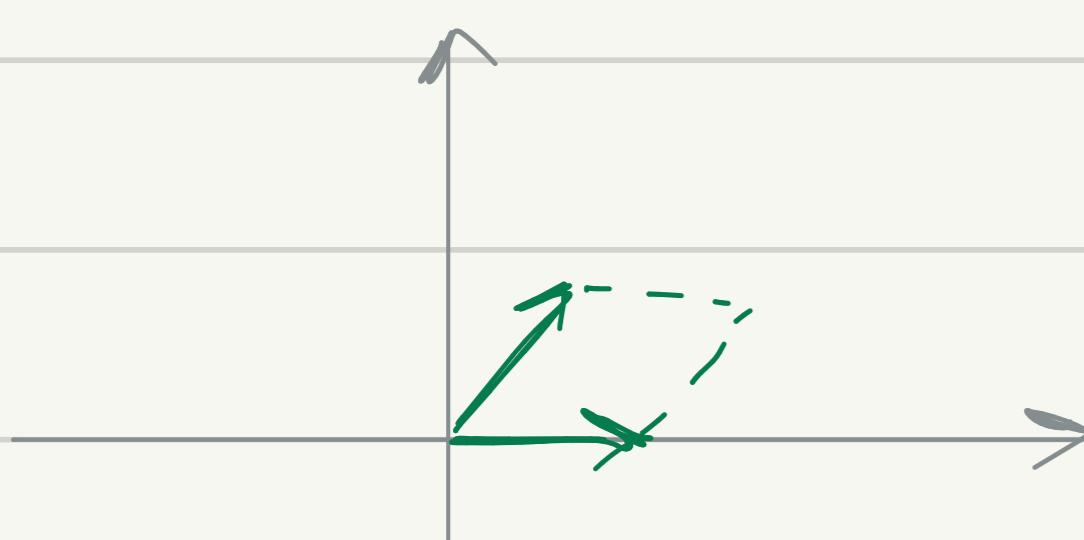
$$\begin{bmatrix} 2 & 1 \\ 0 & 3 \end{bmatrix} \begin{bmatrix} 0 \\ 1 \end{bmatrix} = \begin{bmatrix} 1 \\ 3 \end{bmatrix}$$

$$(1,0) \rightarrow (2,0)$$

$$(0,1) \rightarrow (1,3)$$



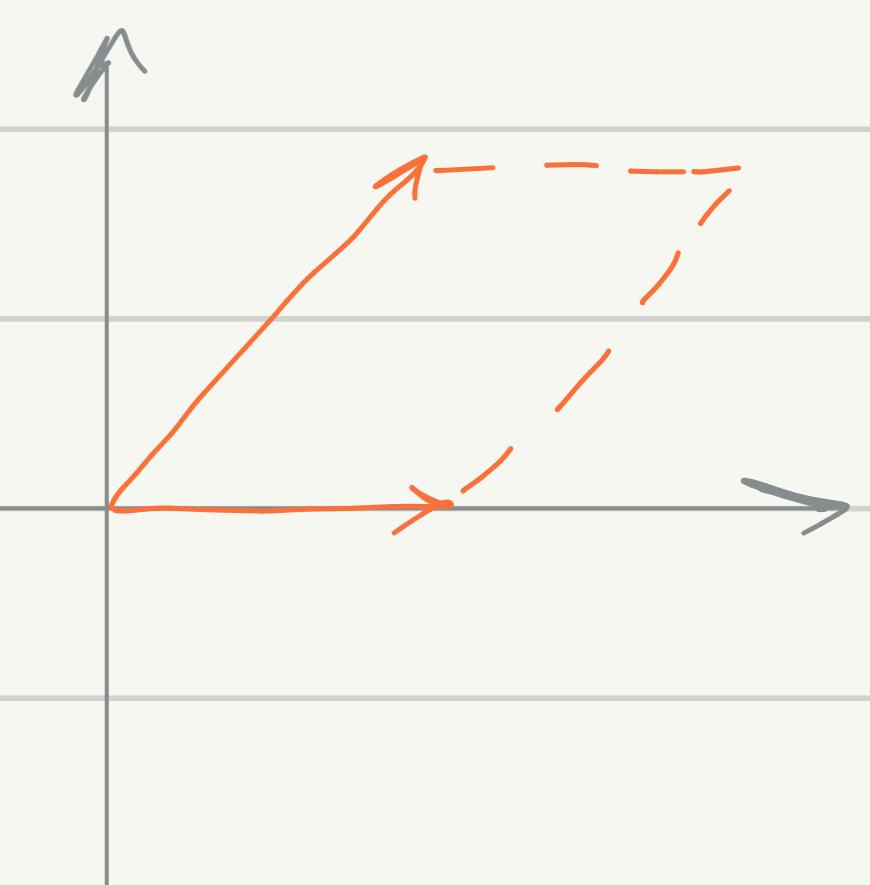
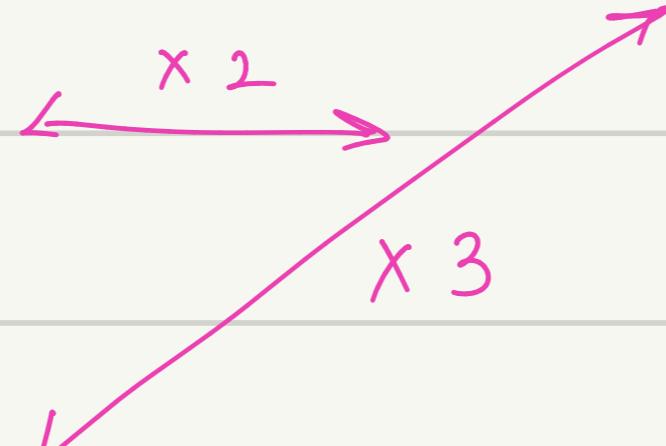
• Eigenbasis



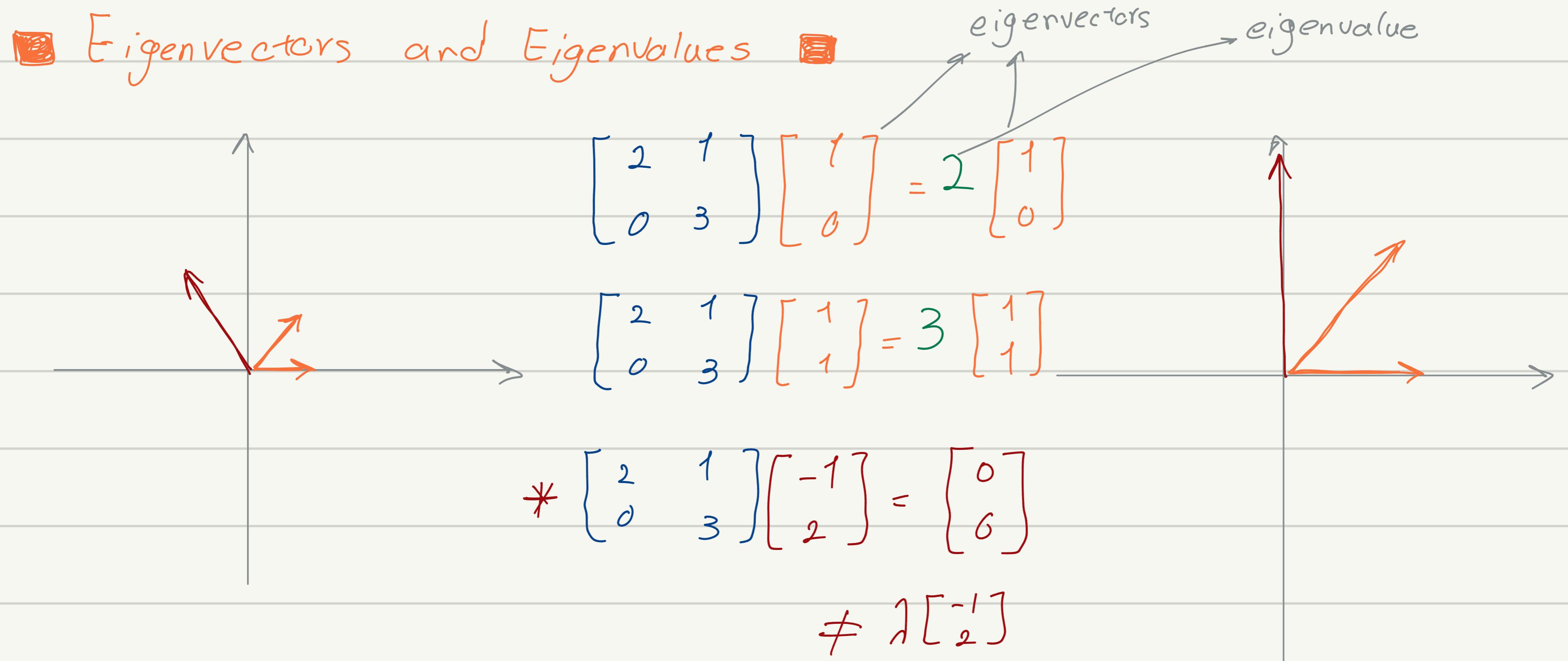
$$\begin{bmatrix} 2 & 1 \\ 0 & 3 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 3 \\ 3 \end{bmatrix}$$

$$(1,0) \rightarrow (2,0)$$

$$(1,1) \rightarrow (3,3)$$



Eigenvectors and Eigenvalues



So:

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

8 multiplications
2 muls

Matrix Mul

More work

Scalar Mul

less work

$$A \mathbf{v}_1 = \lambda_1 \mathbf{v}_1$$

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

Eigenvectors
Eigenvalues

$$A \mathbf{v}_2 = \lambda_2 \mathbf{v}_2$$

* Change $\begin{bmatrix} 2 & 1 \\ 0 & 3 \end{bmatrix} \begin{bmatrix} -1 \\ 2 \end{bmatrix} = \begin{bmatrix} 0 \\ 6 \end{bmatrix}$ to Eigenvectors and Eigenvalues:

$$\begin{bmatrix} 2 & 1 \\ 0 & 3 \end{bmatrix} \begin{bmatrix} -1 \\ 2 \end{bmatrix} = \begin{bmatrix} 2 & 1 \\ 0 & 3 \end{bmatrix} \left(-3 \begin{bmatrix} 1 \\ 0 \end{bmatrix} + 2 \begin{bmatrix} 1 \\ 1 \end{bmatrix} \right) = -6 \begin{bmatrix} 1 \\ 0 \end{bmatrix} + 6 \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 0 \\ 6 \end{bmatrix}$$

In summary: • $A\mathbf{v} = \lambda\mathbf{v}$ for each eigenvector / eigenvalue

• Eigenvectors: Direction of stretch • Eigenvalues: how much stretch

• Eigenbasis: the set of a matrix's eigenvectors, can be arranged as a matrix with one eigenvector in each column

• Save work and characterize a transformation.

* Finding Eigenvalues : 2×2 matrix *

if λ is an eigenvalue :
$$\begin{bmatrix} 2 & 1 \\ 0 & 3 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} \lambda & 0 \\ 0 & \lambda \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

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

For infinitely many (x, y)

$$\left(\begin{bmatrix} 2 & 1 \\ 0 & 3 \end{bmatrix} - \begin{bmatrix} \lambda & 0 \\ 0 & \lambda \end{bmatrix} \right) \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \rightarrow \text{Has infinitely many solutions}$$

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

characteristic polynomial $(2-\lambda)(3-\lambda) - 1 = 0$ $\lambda=2$
 $\lambda=3$

* Finding Eigenvectors : 2×2 matrix *

Eigenvalues: $\lambda=2$
 $\lambda=3$

Solve the equations:

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

$$\begin{aligned} 2x + y &= 2x \\ 0x + 3y &= 2y \end{aligned}$$

$$\begin{aligned} x &= 1 \\ y &= 0 \end{aligned}$$

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

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

$$\begin{aligned} 2x + y &= 3x \\ 0x + 3y &= 3y \end{aligned}$$

$$\begin{aligned} x &= 1 \\ y &= 1 \end{aligned}$$

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

* Finding Eigenvalues : 3×3 matrix *

$$A = \begin{bmatrix} 2 & 1 & -1 \\ 1 & 0 & -3 \\ -1 & -3 & 0 \end{bmatrix} \quad A - \lambda I = \begin{bmatrix} 2-\lambda & 1 & -1 \\ 1 & 0 & -3 \\ -1 & -3 & 0 \end{bmatrix}$$

characteristic polynomial: $\det(A - \lambda I) = 0$

$$\det \begin{bmatrix} 2-\lambda & 1 & -1 \\ 1 & 0 & -3 \\ -1 & -3 & 0 \end{bmatrix} = 0 \rightarrow (2-\lambda)\lambda^2 + 3 + 3 - 9(2-\lambda) + \lambda + \lambda = \lambda^3 + 2\lambda^2 + 11\lambda - 12 = 0$$

$$-(\lambda+3)(\lambda-1)(\lambda-4) = 0 \quad \left. \begin{array}{l} \lambda = -3 \\ \lambda = 1 \\ \lambda = 4 \end{array} \right.$$

* Finding Eigen vectors : 3×3 matrix *

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

$$\text{Eigenvalues: } \begin{array}{l} \lambda = -3 \\ \lambda = 1 \\ \lambda = 4 \end{array}$$

For $\lambda = 4$: $AV = \lambda V$

$$\begin{bmatrix} 2 & 1 & -1 \\ 1 & 0 & -3 \\ -1 & -3 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = 4 \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \Rightarrow \begin{array}{l} 2x_1 + x_2 - x_3 = 4x_1 \\ x_1 - 3x_2 = 4x_2 \\ -x_1 - 3x_2 = 4x_3 \end{array}$$

$$\text{Eigenvector} = \begin{bmatrix} 1 \\ 1 \\ -1 \end{bmatrix} \quad \text{Solving}$$

$$\lambda_1 = 4 \quad \lambda_2 = 1 \quad \lambda_3 = -3$$

Do the same thing for $-3, 1$:

$$\text{Eigenvectors: } \begin{bmatrix} 1 \\ 1 \\ -1 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 2 \\ -1 \\ 1 \end{bmatrix}$$

* * Note : Eigenvalues \rightarrow determinant \rightarrow just square matrix

Number of Eigenvectors

2×2 matrix

Eigenvalues

λ_1, λ_2

if $\lambda_1 \neq \lambda_2 \rightarrow$ 2 eigenvectors
(2 different directions)

if $\lambda_1 = \lambda_2$
 Repeated Eigenvalues

- 1 eigenvector (1 direction)
- 2 eigenvectors (2 different dir)

3×3 matrix

$\lambda_1, \lambda_2, \lambda_3$

if $\lambda_1 \neq \lambda_2 \neq \lambda_3 \rightarrow$ 3 eigenvectors
(3 different dir)

if $\lambda_1 = \lambda_2 \neq \lambda_3$

- 2 eigenvectors (2 different dir)
- 3 eigenvectors (3 different dir)

if $\lambda_1 = \lambda_2 = \lambda_3$

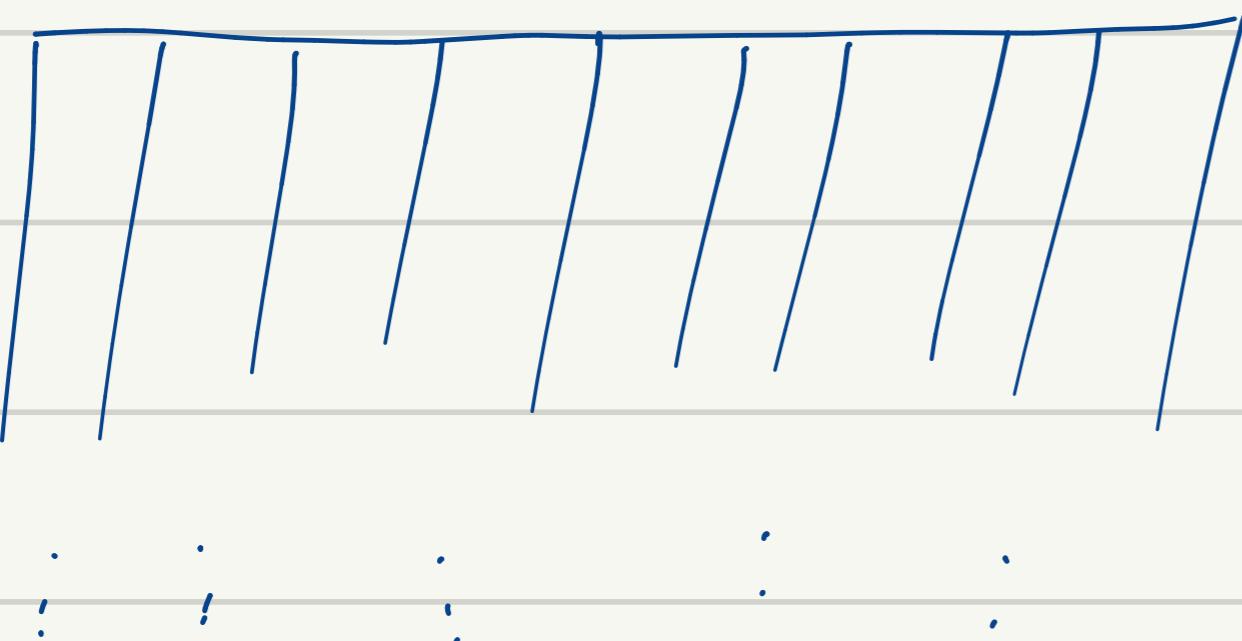
- 1 eigenvector (1 direction)
- 2 eigenvectors (2 different dir)
- 3 eigenvectors (3 different dir)

Dimensionality Reduction

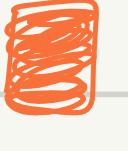
* Advantages *

- Reduce dimensions (# of columns) of dataset
 - preserve as much information as possible
- ↳ Leads to smaller dataset
- ↳ Easier to visualize

Large table
Many Features



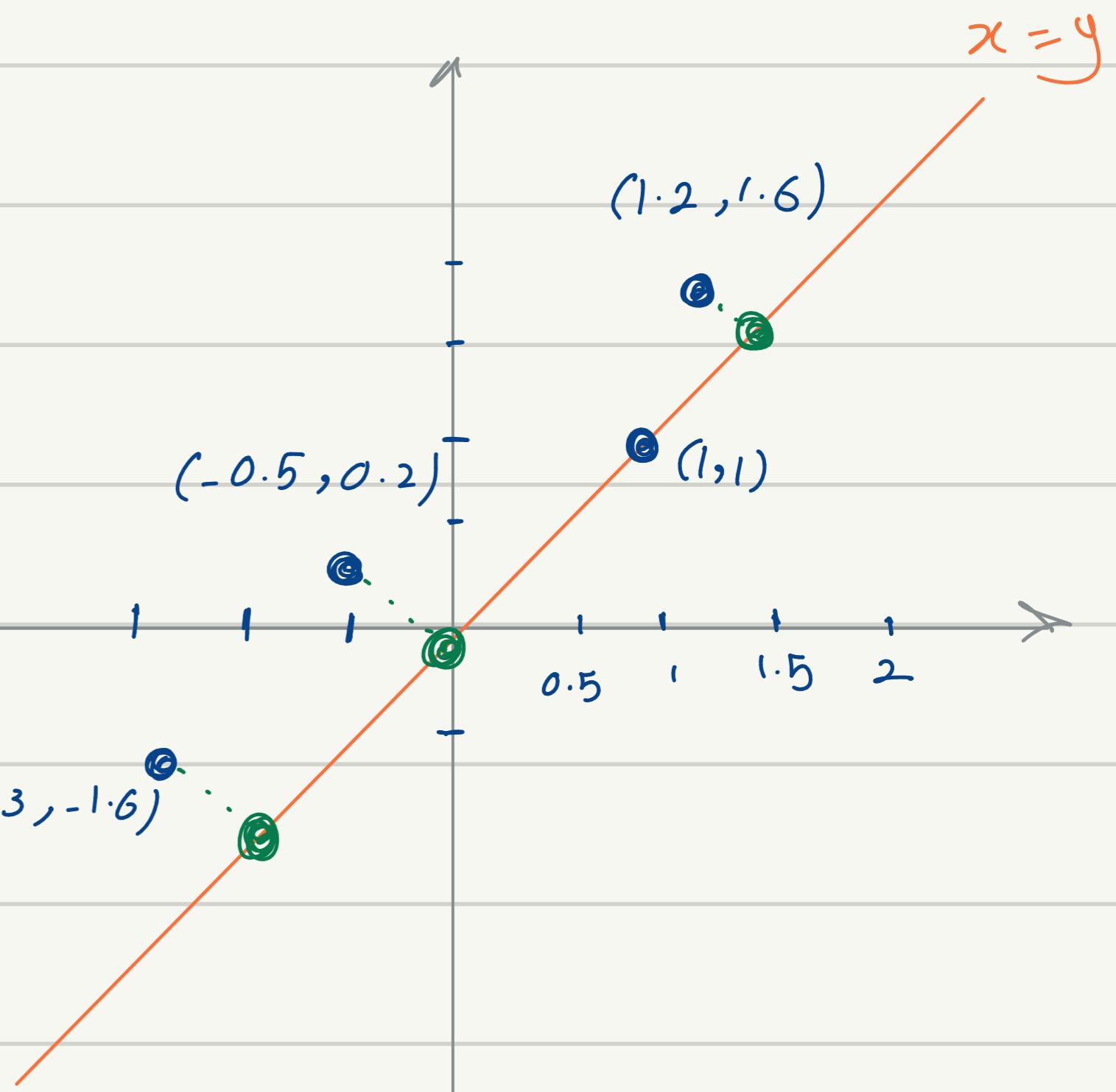
Smaller table
Fewer Features

 **Projections:** The idea behind dimensionality reduction is to move your data points into a vector space with fewer dimensions. This is

call a projection.

Ex:

$$\begin{array}{c|c}
 x & y \\
 \hline
 1.0 & 1.0 \\
 1.2 & 1.6 \\
 -0.5 & 0.2 \\
 -1.3 & -0.6
 \end{array} \cdot \begin{bmatrix} 1 \\ 1 \end{bmatrix} \cdot \frac{1}{\sqrt{2}} = \frac{(1+1)}{\sqrt{2}} = \frac{(1.2+1.6)}{\sqrt{2}} = \frac{(-0.5+0.2)}{\sqrt{2}} = \frac{(-1.3-1.6)}{\sqrt{2}}$$



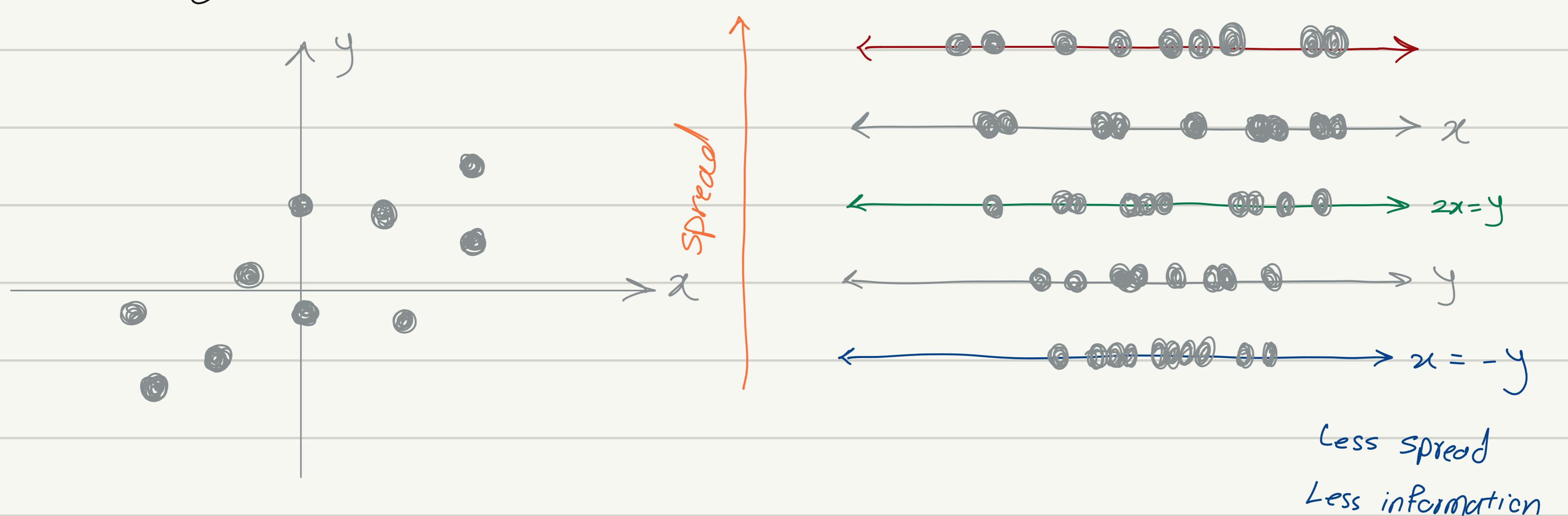
* To project a matrix A onto a vector v

$$\begin{aligned}
 \xrightarrow{1)} \quad Ap &= A \cdot \frac{v}{\|v\|_2} \xrightarrow{\text{norm}} & Ap &= A v \\
 r \times 1 & \quad r \times c & r \times 2 & \quad r \times c & \quad c \times 1 & \quad c \times 2 \\
 & & \Rightarrow & & & \\
 \xrightarrow{2)} \quad Ap &= A \cdot \left[\frac{v_1}{\|v\|_2} \quad \frac{v_2}{\|v\|_2} \right] & & & &
 \end{aligned}$$

Principal Component Analysis (PCA)

Goal: The goal of PCA will be to find the projection that preserve

the max possible spread in your data, even as you reduce the dimensionality of your dataset.



* Benefits of Dimensionality Reduction *

- Easier data set to manage
- PCA reduces dimensions while minimizing information loss
- Simpler visualization

▲ Mean : The average of the data

$$\text{Mean}(\mathbf{x}) = \frac{1}{n} \sum_{i=1}^n \mathbf{x}_i$$

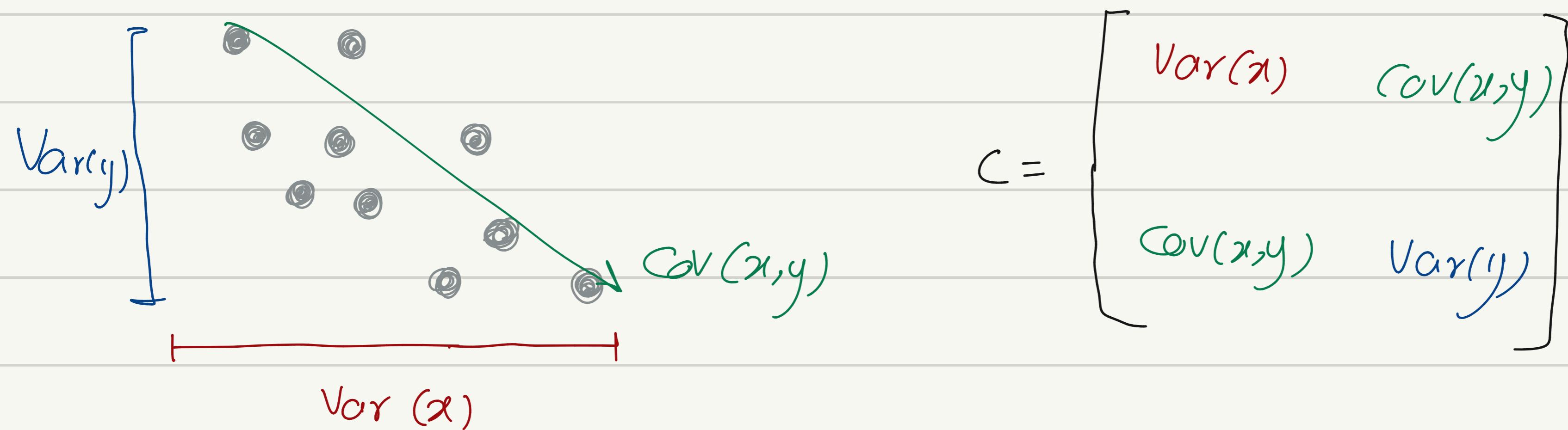
▲ Variance : The average squared distance from the mean (how spread out our data is)

$$\text{Var}(\mathbf{x}) = \frac{1}{n-1} \sum_{i=1}^n (\mathbf{x}_i - \mu_x)^2$$

▲ Covariance : The direction of the relationship between two variables

$$\text{Cov}(\mathbf{x}, \mathbf{y}) = \frac{1}{n-1} \sum_{i=1}^n (\mathbf{x}_i - \mu_x)(\mathbf{y}_i - \mu_y)$$

■ **Covariance Matrix** : is a square matrix giving the covariance between each pair of elements of a given random vector.



$$* \quad \text{Cov}(x, x) = \text{Var}(x)$$

→ Calculating Covariance Matrix:

$$A = \begin{bmatrix} x_1 & y_1 \\ x_2 & y_2 \\ \vdots & \vdots \\ x_n & y_n \end{bmatrix} \quad \begin{matrix} \text{Some} \\ \text{shape} \end{matrix} \quad \mu = \begin{bmatrix} \mu_x & \mu_y \\ \mu_x & \mu_y \\ \vdots & \vdots \end{bmatrix}$$

\downarrow $\quad \quad \quad \downarrow$

mean
matrix

observation's

$$C = \frac{1}{n-1} (A - \mu)^T (A - \mu) \quad \text{transport}$$

$$C = \frac{1}{n-1} \begin{bmatrix} x_1 - \mu_x & x_2 - \mu_x & \dots \\ y_1 - \mu_y & y_2 - \mu_y & \dots \end{bmatrix} \begin{bmatrix} x_1 - \mu_x & y_1 - \mu_y \\ x_2 - \mu_x & y_2 - \mu_y \\ \vdots & \vdots \\ x_n - \mu_x & y_n - \mu_y \end{bmatrix}$$

covariance matrix

2×2 $2 \times n$ $n \times 2$

After multiplying: $C = \begin{bmatrix} \text{Var}(x) & \text{Cov}(x,y) \\ \text{Cov}(x,y) & \text{Var}(y) \end{bmatrix}$

Matrix Formula

$$A = \begin{bmatrix} x_1 & y_1 & z_1 \\ \vdots & \vdots & \vdots \\ x_n & y_n & z_n \end{bmatrix} \quad C = \frac{1}{n-1} (A - \mu)^T (A - \mu)$$

1. Arrange data with a difference feature in each column
2. Calculate column averages
3. Subtract each average from their respective column to generate $A - \mu$
4. $\frac{1}{n-1} (A - \mu)^T (A - \mu)$ gives the covariance matrix C

PCA

Projections

Eigenvalues / Eigenvectors

PCA

Covariance matrix

1. First we should calculate covariance matrix
2. Then we should find the eigenvalues and eigenvectors and Sort them according to eigenvalue, from the biggest to smallest (because for projection, we need the eigenvector with the biggest eigenvalue)
3. Imagine that you want to reduce your data to 2 variables, So you should select 2 biggest eigenvalue and their associated eigenvectors.
4. Project data:

Large table (9 features)

n observations

$$\left[\frac{v_1}{\|v_1\|_2}, \frac{v_2}{\|v_2\|_2} \right]$$

Small Table

2 (features)

n observations

* PCA Mathematical Formulation *

We have n observations of 5 variables $(x_1, x_2, x_3, x_4, x_5)$

Goal: Reduce to 2 variables

1) Create Matrix:

$$X = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{15} \\ x_{21} & x_{22} & \dots & x_{25} \\ \vdots & \vdots & & \\ x_{n1} & x_{n2} & \dots & x_{n5} \end{bmatrix}$$

↑ n observations

2) Center the data:

$$X - \mu = \begin{bmatrix} x_{11} - \mu_1 & x_{12} - \mu_2 & \dots & x_{15} - \mu_5 \\ x_{21} - \mu_1 & x_{22} - \mu_2 & \dots & x_{25} - \mu_5 \\ \vdots & \vdots & & \vdots \\ x_{n1} - \mu_1 & x_{n2} - \mu_2 & & x_{n5} - \mu_5 \end{bmatrix}$$

3) Calculate Covariance Matrix:

$$C = \frac{1}{n-1} (X - \mu)^T (X - \mu)$$

4) Calculate Eigenvectors
and Eigenvalues:

5) Create Projection
Matrix:

6) Project Centered
data:

big	λ_1	v_1
	λ_2	v_2
	λ_3	v_3
	λ_4	v_4
Small	λ_5	v_5

$$V = \begin{bmatrix} v_1 & v_2 \\ \frac{v_1}{\|v_1\|_2} & \frac{v_2}{\|v_2\|_2} \end{bmatrix}$$

$$X_{PCA} = (X - \mu) \cdot V$$