Linear algebra for data science

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Outcome

<u>Module learning outcomes:</u>

1. Participants will be able to identify relationships between variables in large datasets
2. Participants will be able to identify information sufficiency in terms of both equations and variables
3. Participants will be able to understand basic linear algebra concepts that underlie the complicated data analytics algorithms

Linear Algebra

Null Space

$A_{m \times n}$

$Ax = 0$ x ? $n \times 1$

- The null space of a matrix **A** consists of all vectors ***x*** such that **A*x*** = **0**

size of column of A : $(m \times 1)$

$Ax = 0$

$m \times n$ $n \times 1$

- The set of solutions (***x***'s) in **A*x*** = **0** is itself a vector space which is called as a null space of **A**

$$N(\mathbf{A}) = \{\, x \in R^n \,/\, \mathbf{A}\boldsymbol{x} = \mathbf{0} \,\}$$

- If the column vectors are linearly independent, the null space contains only the zero vector $=$ $(x = 0)$
- The null space of an invertible matrix contains only zero vector

$A_{m \times n}$ $B_{n \times p}$

Null Space

3x4

To find null space for the matrix $A = \begin{array}{cccc} D_1 & D_2 & D_3 & D_4 \\ \end{array} \begin{bmatrix} 1 & 1 & 2 & 2 \\ 0 & 1 & 0 & 1 \\ 1 & 2 & 2 & 3 \end{bmatrix}$

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

- Null space: $N(\mathbf{A}) = \{x \in R^n \,/\, \mathbf{A}\boldsymbol{x} = \mathbf{0}\}$

3x1 3x1 3x1 3x1

$$\begin{bmatrix} 1 & 1 & 2 & 2 \\ 0 & 1 & 0 & 1 \\ 1 & 2 & 2 & 3 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \Rightarrow \left[\begin{array}{cccc|c} 1 & 1 & 2 & 2 & 0 \\ 0 & 1 & 0 & 1 & 0 \\ 1 & 2 & 2 & 3 & 0 \end{array}\right] \xrightarrow{R_3 = R_3 - R_1} \left[\begin{array}{cccc|c} 1 & 1 & 2 & 2 & 0 \\ 0 & 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 \end{array}\right]$$

$$\xrightarrow{R_3 = R_3 - R_2} \left[\begin{array}{cccc|c} 1 & 1 & 2 & 2 & 0 \\ 0 & 1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{array}\right] \xrightarrow{R_1 = R_1 - R_2} \left[\begin{array}{cccc|c} 1 & 0 & 2 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{array}\right]$$

$x = \begin{bmatrix} -2 \\ 0 \\ 1 \\ 0 \end{bmatrix}$ $\quad Ax = 0 \quad$ $x = \begin{bmatrix} -1 \\ -1 \\ 0 \\ 1 \end{bmatrix}$? $\quad Ax \overset{?}{=} 0$

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

(a)

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

3rd coln   1st column.

(b)

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

4th column   1st coln   2nd column

$$x = \begin{bmatrix} -2 \\ 0 \\ 1 \\ 0 \end{bmatrix} \qquad y = \begin{bmatrix} -1 \\ -1 \\ 0 \\ 1 \end{bmatrix}$$

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

$$-\underbrace{\begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix}}_{\text{1st col}} + -\underbrace{\begin{bmatrix} 1 \\ 1 \\ 2 \end{bmatrix}}_{\text{2nd}} + 0\underbrace{\begin{bmatrix} 2 \\ 0 \\ 2 \end{bmatrix}}_{\text{3rd}} + \underbrace{\begin{bmatrix} 2 \\ 1 \\ 3 \end{bmatrix}}_{\text{4th col}} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

$Ax = 0$ essentially combination of columns of A

Null Space

- We have the equations:

$$x_1 + 2x_3 + x_4 = 0 \Rightarrow x_1 = -2x_3 - x_4$$
$$x_2 + x_4 = 0 \Rightarrow x_2 = -x_4$$

$x_1 = 0$
$x_2 = 0$
$x_3 = 0$
$x_4 = 0$

$$\Rightarrow \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} = x_3 \begin{bmatrix} -2 \\ 0 \\ 1 \\ 0 \end{bmatrix} + x_4 \begin{bmatrix} -1 \\ -1 \\ 0 \\ 1 \end{bmatrix}$$

$C_3 = 2C_1$

$C_4 = C_1 + C_2$

- N(A) = scalar multiples of the vectors $\underbrace{\begin{bmatrix} -2 \\ 0 \\ 1 \\ 0 \end{bmatrix}}_{4\times1}$ and $\underbrace{\begin{bmatrix} -1 \\ -1 \\ 0 \\ 1 \end{bmatrix}}_{4\times1}$

& linear combination

dimension of N(A):

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

$$Ax = 0$$

$$\underbrace{\begin{bmatrix} 1 & 1 & 2 & 2 \\ 0 & 1 & 0 & 1 \\ 1 & 2 & 2 & 3 \end{bmatrix}}_{3 \times 4} \cdot \underbrace{\begin{bmatrix} -2 \\ 0 \\ 1 \\ 0 \end{bmatrix}}_{4 \times 1} = (-2)\,1^{st}\text{ col} + (0)\,2^{nd}\text{ col} + (1)\,3^{rd} + (0)\,4^{th}\text{ col} = 0$$

$+2\,(1^{st}$ column$) = 3^{rd}$ column.

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

$$= (-1)\,\text{col}^1 + (-1)\,\text{col}^2 + 0\,\text{col}^3 + (1)\,\text{col}^4 = 0$$

$$\Rightarrow \quad \text{col}^4 = \text{col}^1 + \text{col}^2 .$$

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

$$z = \underbrace{\begin{bmatrix} -3 \\ -1 \\ 1 \\ 1 \end{bmatrix}}_{= \begin{bmatrix} -2 \\ 0 \\ 1 \\ 0 \end{bmatrix} + \begin{bmatrix} -1 \\ -1 \\ 0 \\ 1 \end{bmatrix}} \qquad Az = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

Null Space

- **If the vectors are linearly independent, the null space contains only the zero vector**
- The vectors $\begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}$ and $\begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}$ are linearly independent
- What is the null space of $\begin{bmatrix} 1 & 1 \\ 1 & 0 \\ 0 & 0 \end{bmatrix}$?
- $\mathbf{A}\boldsymbol{x} = \mathbf{0} \Rightarrow \begin{bmatrix} 1 & 1 \\ 1 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$ .What are the values of x_1 and x_2?

Null Space

- We have –

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

- $x_1 = 0$ and $x_2 = 0$ is the only solution that the system of equations could take

$\Rightarrow$ If the vectors are linearly independent, the null space contains only the zero vector

Null Space

- **If the vectors are linearly independent, the null space contains only the zero vector. What about the dependent vectors?**
- Consider two dependent vectors $\begin{bmatrix} 1 \\ 2 \end{bmatrix}$ and $\begin{bmatrix} 2 \\ 4 \end{bmatrix}$
- What is the null space of $\begin{bmatrix} 1 & 2 \\ 2 & 4 \end{bmatrix}$?
- $\mathbf{A}\boldsymbol{x} = \mathbf{0} \Rightarrow \begin{bmatrix} 1 & 2 \\ 2 & 4 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$
- x_1= ? and x_2= ?

Null Space

- We have –

$$\begin{bmatrix} 1 & 2 \\ 2 & 4 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \Rightarrow \left[\begin{array}{cc|c} 1 & 2 & 0 \\ 2 & 4 & 0 \end{array}\right]$$

$$\Rightarrow \left[\begin{array}{cc|c} 1 & 2 & 0 \\ 0 & 0 & 0 \end{array}\right]$$

- We have the equations –

$$x_1 + 2x_2 = 0 \Rightarrow x_1 = -2x_2$$

$$\Rightarrow \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = x_2 \begin{bmatrix} -2 \\ 1 \end{bmatrix}$$

- We have $N(\mathrm{A})$ = scalar multiples of the vector $\begin{bmatrix} -2 \\ 1 \end{bmatrix}$
- **If the vectors are linearly dependent, the null space also contains non-zero vector(s)**

Null Space: Cause of Non-Uniqueness

- Solutions of $\mathbf{A}x = \mathbf{b}$ with **A** having n columns.

- Solution does not exist if **b** does not belong to the column space of **A**

- At least one solution exists if **b** belongs to the column space of **A**

  - Solution unique if null space of **A** has only the zero vector

  - Infinite solutions if null space of **A** has non-zero vectors

Existence and Uniqueness of a solution

$m \times n$

- $\mathbf{A}x = \mathbf{b}$ has no solution or is inconsistent iff rank($\mathbf{A}$) < rank(augmented matrix [$\mathbf{A}$ $\mathbf{b}$]) $- \; m \times (n+1)$
[$\mathbf{b}$ does not belong to column space of $\mathbf{A}$]

- $\mathbf{A}x = \mathbf{b}$ has a unique solution iff rank($\mathbf{A}$) = rank(augmented matrix [$\mathbf{A}$ $\mathbf{b}$]) = n
[$\mathbf{b}$ belongs to column space of $\mathbf{A}$ and (null space of $\mathbf{A}$ has only the zero vector])

- $\mathbf{A}x = \mathbf{b}$ has infinitely many solutions iff rank($\mathbf{A}$) = rank(augmented matrix [$\mathbf{A}$ $\mathbf{b}$]) < n
[$\mathbf{b}$ belongs to column space of $\mathbf{A}$ and (null space of $\mathbf{A}$ has non-zero vectors as well])

Existence and Uniqueness of a solution

- Consider the system,

$$\begin{bmatrix} 2 & 1 & 1 \\ 3 & 1 & 2 \\ 1 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 8 \\ 12 \\ 3 \end{bmatrix}$$

- We will include the right hand side as an extra column to **A**. That matrix is called as an 'Augmented matrix' –

$$\left[\begin{array}{ccc|c} 2 & 1 & 1 & 8 \\ 3 & 1 & 2 & 12 \\ 1 & 0 & 1 & 3 \end{array}\right]$$

- The system is inconsistent as the rank(**A**) < rank(augmented matrix)

Existence and Uniqueness of a solution

- Consider the system,

$$\begin{bmatrix} 2 & 1 & 1 \\ 3 & 2 & 1 \\ 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 8 \\ 11 \\ 6 \end{bmatrix}$$

- The system has a unique solution as the rank(**A**) = rank(augmented matrix) = n

Existence and Uniqueness of a solution

- Consider the system,

$$\begin{bmatrix} 2 & 1 & 1 \\ 3 & 1 & 2 \\ 1 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 8 \\ 11 \\ 3 \end{bmatrix}$$

- The system has infinitely many solutions as the rank(**A**) = rank(augmented matrix) < n

$$\boxed{\text{rank}(A) + \dim N(A) = 10}$$

A: 100×10 rank$(A) \le 10$

Let's say rank$(A) = 9$

9 independent col^n

How many distinct relationships = ? 1

($\dim(N(A))$ = 1

Let rank$(A) = 10$.

10 indepe col^n.

Distinct relationship = 0

$\dim(N(A)) = 0$.

Let's say ran$(A) = 8$

Independ col^n = 8

Distinct rela = 2.

$d(N(A)) = 2$

rank$(A) = 3$.

7 independ col^n.

relationships = 7.

$\dim(N(A)) = 7$.

$A \quad m \times n.$

$$\boxed{\operatorname{rank}(A) + \dim(N(A)) = n}$$

$A: \cancel{10} \, 2 \times 5$ $\qquad$ $\cancel{m \geq} 10$, $n \cancel{\geq 10}$.

$\operatorname{rank}(A) = 2$

$$\underset{r(A)}{2} + \underset{d(N(A))}{3} = 5$$

$c_1 \quad c_2 \quad c_3 \quad c_4 \quad c_5$

\# clmn $= 2$.

c_1 & c_2 are independent

$\dim N(A) = 3$

$c_3 = (\ )\, c_1 + (\ )\, c_2$

$c_4 = (\ )\, c_1 + (\ )\, c_2$

$c_5 = (\ )\, c_1 + (\ )\, c_2.$

Determinants

ONLY for SQUARE MATRIX

A: (n x n) : rank(A) $\leq$ n   rank(A) $\begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix}$ = 1

ONL

- Determinant is the value associated with the ***square matrix*** (matrix with same number of row and columns)
- Used to determine whether a nxn matrix has rank n or not
- Equivalent to finding if inverse of a square matrix exists or not
- Used for computing eigenvalues as well

Determinants

How to calculate the determinant of a square matrix ?

$\det\begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} = 4-6=-2.$

Expand using the first row

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

i+j is even assign a positive sign

$$A = \begin{bmatrix} \overset{+}{a_{11}} & \overset{-}{a_{12}} \\ a_{21} & a_{22} \end{bmatrix}_{2\times 2}$$

i+j is odd assign a negative sign

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

$$|A| = a_{11}a_{22} - a_{12}a_{21}$$

columns (rows) are dependent

A matrix is said to be singular if the determinant value is zero

Determinants

Expand using the first row

$$\begin{bmatrix} 3 & 1 & 2 \\ 0 & 2 & 1 \\ 6 & 1 & 9 \end{bmatrix}$$

3

$$\begin{array}{cccc} & + & - & + \\ A = & \left[\begin{matrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{matrix}\right]_{3\times 3} \end{array}$$

$$|A| = a_{11}\underbrace{\begin{vmatrix} a_{22} & a_{23} \\ a_{32} & a_{33} \end{vmatrix}}_{2\times 2} - a_{12}\underbrace{\begin{vmatrix} a_{21} & a_{23} \\ a_{31} & a_{33} \end{vmatrix}}_{2\times 2} + \boxed{a_{13}}\underbrace{\begin{vmatrix} a_{21} & a_{22} \\ a_{31} & a_{32} \end{vmatrix}}_{2\times 2}$$

$$A = \begin{bmatrix} 3 & 1 & 2 \\ 0 & 2 & 1 \\ 6 & 1 & 9 \end{bmatrix}$$

$$\det A = 3 \begin{vmatrix} 2 & 1 \\ 1 & 9 \end{vmatrix} - 1 \begin{vmatrix} 0 & 1 \\ 6 & 9 \end{vmatrix} + 2 \begin{vmatrix} 0 & 2 \\ 6 & 1 \end{vmatrix}$$

$$= 3(18-1) - 1(0-6) + 2(0-12)$$

$$= 3(17) + 6 - 24 \qquad = 33$$

$$\det \begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} \\ & & & \\ & & & \end{bmatrix}_{4\times 4} = a_{11}\left(\quad\right)_{3\times 3} - a_{12}(3\times 3) + a_{13}(3\times 3) - a_{14}(3\times 3)$$

4 (3x3) determinents

$$\begin{vmatrix} a_{11} & a_{12} & a_{13} & a_{14} & a_{15} \\ \vdots & \vdots & \vdots & \vdots & \vdots \end{vmatrix} = a_{11}\left(\quad\right)_{4\times 4} - a_{12}\left(\quad\right)_{4\times 4} + a_{13}\left(\quad\right)_{4\times 4} - a_{14}\left(\quad\right)_{4\times 4} + a_{15}\left(\quad\right)_{4\times 4}$$

Determinants

- If the determinant of a matrix is zero, the matrix is singular (verified by 2x2)
  - Rows or columns are dependent
  - Rank < n

If $\det(A)=0$ singular matrix.

- Singular matrices are not invertible

- If the determinant of a matrix is non-zero, the matrix is non-singular or invertible $\therefore$ A^{-1} : inverse of A.
  - Rows and columns are independent
  - Rank =n

$$\underset{n\times n}{A^{-1}}\ \underset{n\times n}{A} = \underset{n\times n}{A}\ \underset{n\times n}{A^{-1}} = \begin{bmatrix} 1 & & & & \\ & 1 & & & \\ & & 1 & & \\ & & & 1 & \\ & & & & 1 \end{bmatrix} = I_{n\times n}$$

~~A^{-1}: exists if~~

A: square $(n \times n)$.

when $\det(A) \neq 0$ $\quad A^{-1} \cdot A = A \cdot A^{-1} = I$.

Analogy.

$$\frac{1}{x} \cdot x = x \cdot \frac{1}{x} = 1$$

when $x \neq 0$.

Inverse is a generalization of reciprocal

Solving a System of Linear Equations

A: n×n.

- For solving a system of n equations with n unknowns, there are two ways
  - Gaussian elimination –We eliminate unknowns by performing operations on it until there is only one equation and one unknown, which can be solved
  - Cramer's rule – We use determinants to solve the equations
- To solve large systems of equations, we prefer Gaussian elimination over Cramer's rule. This is because it is hard to find determinant for an $n \times n$ matrix with a larger n

Gaussian Elimination

B > C > A.

- Consider a system of 3 equations

$$3x + y + 2z = 3\ ;\ 2y + z = 0\ ;\ 6x + y + 9z = -5$$

last.

This can be written in a matrix form as –

A

$$\begin{bmatrix} 3 & 1 & 2 \\ 0 & 2 & 1 \\ 6 & 1 & 9 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 3 \\ 0 \\ -5 \end{bmatrix}$$

B.

$$\begin{bmatrix} 3 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 9 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} \ \end{bmatrix}$$

- This is of the form **A*x* = b**. Now our goal is to eliminate *x* from the last two equations and *y* from the last equation

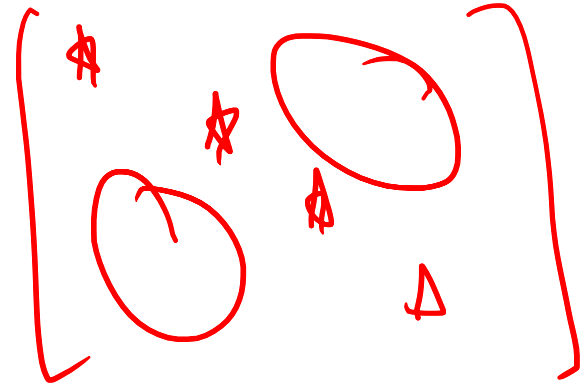
$$3x + \ y + 2z = 3$$
$$0\cancel{x} + 2y + 1z = 0$$
$$6\cancel{x} + 1\cancel{y} + 9z = -5$$

C.

$$\begin{bmatrix} 1 & 1/3 & 5 \\ 0 & 1 & 4 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix}$$

A : 

n×n.

B : 

C : 

First w, then z, then y, then x.

Back-substitution. B > C > A

Gaussian Elimination

<u>Augmented matrix</u>

- We will include the right hand side as an extra column to **A**. That matrix is called as an 'Augmented matrix' –

$$\begin{bmatrix} 3 & 1 & 2 \\ 0 & 2 & 1 \\ 6 & 1 & 9 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 3 \\ 0 \\ -5 \end{bmatrix} \Rightarrow \left[\begin{array}{ccc|c} 3 & 1 & 2 & 3 \\ 0 & 2 & 1 & 0 \\ 6 & 1 & 9 & -5 \end{array}\right]$$

- For convenience, the augmented matrix is used to solve the equations since we don't have to carry over the x, y, z and = for every step

Gaussian Elimination

Manipulating rules

- There are three manipulating rules which may be applied for transforming an augmented matrix and also leaves the value of the solution set unchanged
  - Any two rows can be exchanged
  - Any row may be multiplied (or divided) by a nonzero constant
  - A multiple of any row can be added to any other row

Gaussian Elimination

Augmented matrix and pivots

- Augmented matrix: $\left[\begin{array}{ccc|c} \boxed{3} & 1 & 2 & 3 \\ 0 & 2 & 1 & 0 \\ 6 & 1 & 9 & -5 \end{array}\right]$

- The coefficient of x in the 1^{st} equation is known as the first pivot. (First nonzero number from left in a row is called a pivot)

- **Pivots should never be zero**
- What if they happen to be zero?
  - Exchange rows or columns so that there is no zero in the pivot position

- We have 1 as pivot (at the $\mathbf{A}_{11}$ position). We need to make all the values below the pivot as zero

Gaussian Elimination

Step by step process of elimination $3x + y + 2z = 3$; $2y + z = 0$; $6x + y + 9z = -5$

Step 1

Pivot

$$\left[\begin{array}{ccc|c} \boxed{3} & 1 & 2 & 3 \\ 0 & 2 & 1 & 0 \\ 6 & 1 & 9 & -5 \end{array}\right] \Rightarrow \left[\begin{array}{ccc|c} \boxed{3} & 1 & 2 & 3 \\ 0 & \boxed{2} & 1 & 0 \\ 0 & -1 & 5 & -11 \end{array}\right] \quad [R_3 = R_3 - 2R_1]$$

3rd eqn - 2 1st eqn.

6x + y + 9z = -5.
6x + 2y + 4z = 6.

Original system:	$3x + y + 2z = 3$ $2y + z = 0$ $6x + y + 9z = -5$	On 1st step of elimination	$3x + y + 2z = 3$ 0 $2y + z = 0$ 0 $-y + 5z = -11$

- The value at the position $\mathbf{A_{21}}$ is already zero. Hence we may leave the second row unchanged

- Subtract two times the first row from the last row to get $\mathbf{A_{31}}$ as 0

Gaussian Elimination

<u>Step 2</u>

- Now, we have the second pivot to be 2 at the $\mathbf{A}_{22}$ position.
- At the second step, we need to make the -1 at $\mathbf{A}_{32}$ to be zero. So, add two times the third row with the second row

$$\left[\begin{array}{ccc|c} \boxed{3} & 1 & 2 & 3 \\ 0 & \boxed{2} & 1 & 0 \\ 0 & -1 & 5 & -11 \end{array}\right] \Rightarrow \left[\begin{array}{ccc|c} \boxed{3} & 1 & 2 & 3 \\ 0 & \boxed{2} & 1 & 0 \\ 0 & 0 & \boxed{11} & -22 \end{array}\right] \quad [R_3 = 2R_3 + R_2]$$

$$\begin{aligned} 3x + y + 2z &= 3 \\ 2y + \quad z &= 0 \\ 2(-y + 5z &= -11) \end{aligned} \quad \xrightarrow{\text{On } 2^{nd} \text{ step of elimination}} \quad \begin{aligned} 3x + y + 2z &= 3 \\ 2y + \quad z &= 0 \\ 11z &= -22 \end{aligned}$$

$x = \frac{3 - y - 22}{3}$

$y = 2/2 = 1$

$z = -2$

$x = 2$

- Now, we have the third pivot to be 11 at the $\mathbf{A}_{33}$ position

Gaussian Elimination

<u>Step by step process of elimination</u> $3x + y + 2z = 3$; $2y + z = 0$; $6x + y + 9z = -5$

$$\left[\begin{array}{ccc|c} \boxed{3} & 1 & 2 & 3 \\ 0 & 2 & 1 & 0 \\ 6 & 1 & 9 & -5 \end{array}\right] \Rightarrow \left[\begin{array}{ccc|c} \boxed{3} & 1 & 2 & 3 \\ 0 & \boxed{2} & 1 & 0 \\ 0 & -1 & 5 & -11 \end{array}\right] \quad [R_3 = R_3 - 2R_1]$$

$$\Rightarrow \left[\begin{array}{ccc|c} \boxed{3} & 1 & 2 & 3 \\ 0 & \boxed{2} & 1 & 0 \\ 0 & 0 & \boxed{11} & -22 \end{array}\right] \quad [R_3 = 2R_3 + R_2]$$

- The forward elimination of the system of equations could be seen as –

Original system:

$$\begin{aligned} 3x + y + 2z &= 3 \\ 2y + z &= 0 \\ 6x + y + 9z &= -5 \end{aligned} \quad \Rightarrow \quad \begin{aligned} 3x + y + 2z &= 3 \\ 2y + z &= 0 \\ -y + 5z &= -11 \end{aligned} \quad \Rightarrow \quad \begin{aligned} 3x + y + 2z &= 3 \\ 2y + z &= 0 \\ 11z &= -22 \end{aligned}$$

Gaussian Elimination

Forward elimination and back–substitution

- On **Forward elimination**, we have three equations,

$$3x + y + 2z = 3$$

$$2y + z = 0$$

$$11z = -22 \Rightarrow z = -2$$

- Now, we perform **Back–substitution** to obtain the solution
- Substitute $z = -2$ in the second equation

$$2y + z = 0 \Rightarrow y = 1$$

- Substitute $y = 1$ and $z = -2$ in the first equation

$$3x + y + 2z = 3 \Rightarrow x = 2$$

- Hence the solution for the given set of linear equations is $x = 2$, $y = 1$ and $z = -2$

Reduced Row Echelon Form (rref)

- We obtained the below matrix by Gaussian elimination –

$$\left[\begin{array}{ccc|c} \boxed{3} & 1 & 2 & 3 \\ 0 & \boxed{2} & 1 & 0 \\ 0 & 0 & \boxed{11} & -22 \end{array}\right]$$

- The reduced row echelon form further reduces the matrix by making the pivots 1 and making the elements even above the pivots to be zero

- It gives the solution (***x***) directly without performing forward elimination or back–substitution

Reduced Row Echelon Form (rref)

- So, the rref of the matrix $\left[\begin{array}{ccc|c} 3 & 1 & 2 & 3 \\ 0 & 2 & 1 & 0 \\ 0 & 0 & 11 & -22 \end{array}\right]$ can be calculated as follows:

$$\left[\begin{array}{ccc|c} 3 & 1 & 2 & 3 \\ 0 & 2 & 1 & 0 \\ 0 & 0 & 11 & -22 \end{array}\right] \xrightarrow[\substack{R_3 = R_3 / 11}]{\substack{R_1 = R_1 / 3 \\ R_2 = R_2 / 2}} \left[\begin{array}{ccc|c} 1 & 1/3 & 2/3 & 1 \\ 0 & 1 & 1/2 & 0 \\ 0 & 0 & 1 & -2 \end{array}\right] \xrightarrow{R_2 = R_2 - (1/2)R_3} \left[\begin{array}{ccc|c} 1 & 1/3 & 2/3 & 1 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & -2 \end{array}\right]$$

$$\xrightarrow{R_1 = R_1 - (2/3)R_3} \left[\begin{array}{ccc|c} 1 & 1/3 & 0 & 7/3 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & -2 \end{array}\right] \xrightarrow{R_1 = R_1 - (1/3)R_2} \left[\begin{array}{ccc|c} 1 & 0 & 0 & 2 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & -2 \end{array}\right]$$

- Thus the solution for the given set of linear equations is $x = 2$, $y = 1$ and $z = -2$

Gaussian Elimination

<u>When could the process break down?</u>

- ***Zero in the pivot position***
- Pivots should not be zero. Note that a zero can appear in a pivot position, even if the original coefficient in that place was not zero
- This could be cured by row exchanges

Example: Non singular case:

$$\begin{aligned} 3x + y + 2z &= \_ \\ 6x + 2y + 9z &= \_ \\ 2y + z &= \_ \end{aligned} \xrightarrow{(R_2 = R_2 - 2R_1)} \begin{aligned} 3x + y + 2z &= \_ \\ 5z &= \_ \\ 2y + z &= \_ \end{aligned} \xrightarrow{\text{(On exchanging rows 2 and 3)}} \begin{aligned} 3x + y + 2z &= \_ \\ 2y + z &= \_ \\ 5z &= \_ \end{aligned}$$

- Now the system could be solved by **back–substitution**

Gaussian Elimination

Rank $\begin{bmatrix} 3 & 1 & 2 \\ 6 & 2 & 9 \\ 3 & 1 & 1 \end{bmatrix}$

Example: Singular case:

$$\begin{aligned} 3x + y + 2z &= \_ \\ 6x + 2y + 9z &= \_ \\ 3x + y + z &= \_ \end{aligned} \quad \xrightarrow{(R_2 = R_2 - 2R_1 \text{ and } R_3 = R_3 - R_1)} \quad \begin{aligned} 3x + y + 2z &= \_ \\ 5z &= \_ \\ -z &= \_ \end{aligned}$$

- No exchange of equations could be done here to avoid zero in the pivot position
- If we have the last two equations to be $5z = 10$ and $-z = 3$, there is no solution
- If we have $5z = 10$ and $-z = -2$, then we have infinity number of solutions. (Since we have $z = 2$ but the first equation cannot decide both x and y)

Infinite Solutions: Null space use

- Suppose we solve:

$$\begin{bmatrix} 1 & 2 \\ 2 & 4 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 4 \\ 8 \end{bmatrix}$$

- How many solutions?
- Infinite solutions : Rank(A) = Rank(A|b) < 2
- How do we characterize these infinite solutions?

Infinite Solutions: Null space use (2)

- Gaussian elimination leads to:

$$\begin{bmatrix} 1 & 2 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 4 \\ 0 \end{bmatrix}$$

- Infinite solutions characterized as:

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 4 \\ 0 \end{bmatrix} + \alpha \begin{bmatrix} -2 \\ 1 \end{bmatrix}$$

Inverses – Gauss–Jordan Method

<u>To find inverse of A</u>

- Consider a matrix $A = \begin{bmatrix} 2 & 1 & 0 \\ 1 & 2 & 1 \\ 0 & 1 & 2 \end{bmatrix} = \left[\begin{array}{ccc|ccc} 2 & 1 & 0 & 1 & 0 & 0 \\ 1 & 2 & 1 & 0 & 1 & 0 \\ 0 & 1 & 2 & 0 & 0 & 1 \end{array}\right]$

$$\Rightarrow \left[\begin{array}{ccc|ccc} \boxed{1} & 2 & 1 & 0 & 1 & 0 \\ 2 & 1 & 0 & 1 & 0 & 0 \\ 0 & 1 & 2 & 0 & 0 & 1 \end{array}\right] (R_2 \leftrightarrow R_1)$$

$$\Rightarrow \left[\begin{array}{ccc|ccc} \boxed{1} & 2 & 1 & 0 & 1 & 0 \\ 0 & -3 & -2 & 1 & -2 & 0 \\ 0 & 1 & 2 & 0 & 0 & 1 \end{array}\right] (R_2 = R_2 - 2R_1)$$

$$\Rightarrow \left[\begin{array}{ccc|ccc} \boxed{1} & 2 & 1 & 0 & 1 & 0 \\ 0 & \boxed{1} & 2 & 0 & 0 & 1 \\ 0 & -3 & -2 & 1 & -2 & 0 \end{array}\right] (R_2 \leftrightarrow R_3)$$

Inverses – Gauss–Jordan Method

$$\Rightarrow \left[\begin{array}{ccc|ccc} \boxed{1} & 0 & -3 & 0 & 1 & -2 \\ 0 & \boxed{1} & 2 & 0 & 0 & 1 \\ 0 & 0 & 4 & 1 & -2 & 3 \end{array}\right] \quad (R_1 = R_1 - 2R_2\ ; \; R_3 = R_3 + 3R_2)$$

$$\Rightarrow \left[\begin{array}{ccc|ccc} \boxed{1} & 0 & -3 & 0 & 1 & -2 \\ 0 & \boxed{1} & 2 & 0 & 0 & 1 \\ 0 & 0 & \boxed{1} & 1/4 & -1/2 & 3/4 \end{array}\right] \quad (R_3 = R_3/4)$$

$$\Rightarrow \left[\begin{array}{ccc|ccc} \boxed{1} & 0 & 0 & 3/4 & -1/2 & 1/4 \\ 0 & \boxed{1} & 0 & -1/2 & 1 & -1/2 \\ 0 & 0 & \boxed{1} & 1/4 & -1/2 & 3/4 \end{array}\right] \quad (R_2 = R_2 - 2R_3\ ; \; R_1 = R_1 + 3R_3)$$

Inverse of $A = \begin{bmatrix} 2 & 1 & 0 \\ 1 & 2 & 1 \\ 0 & 1 & 2 \end{bmatrix}$ is $\begin{bmatrix} 3/4 & -1/2 & 1/4 \\ -1/2 & 1 & -1/2 \\ 1/4 & -1/2 & 3/4 \end{bmatrix}$

Inverses – Gauss–Jordan Method

- Inverse of **A** is denoted as $\mathbf{A}^{-1}$ and when **A** is multiplied with its inverse, it produces an identity matrix : $\mathbf{A}\mathbf{A}^{-1} = \mathbf{I}$

- We have $\mathbf{A}\boldsymbol{x} = \mathbf{b}$,

  multiply by $\mathbf{A}^{-1} \Rightarrow \boldsymbol{x} = \mathbf{A}^{-1}\mathbf{b}$

  $\Rightarrow$ we may get the solution $\boldsymbol{x}$ directly by multiplying **b** with $\mathbf{A}^{-1}$

- Not all matrices can have inverses

  - Singular matrices cannot have an inverse i.e. if its determinant is zero, the matrix cannot have an inverse
  - If $\mathbf{A}\boldsymbol{x} = 0$ and $\boldsymbol{x} \neq 0$, **A** cannot have an inverse

Orthogonality

- A basis is a linearly independent spanning set. Geometrically, it is a set of coordinate axes

- We need a basis to convert geometric constructions into algebraic calculations and we need an orthonormal basis to make those calculations simple

- To achieve that, we need to know–
  - length of a vector
  - test for orthogonality
  - how to create perpendicular vectors from linearly independent vectors

Orthogonality (Perpendicular)

u, $n\times 1$ $\quad$ v: $n\times 1$ $\quad$ $\underset{1\times n}{u^T}\ \underset{n\times 1}{v} = (\text{scalar})$.

- Two vectors are orthogonal if their inner product u^Tv is zero. It means that the angle between the two vectors is 90°

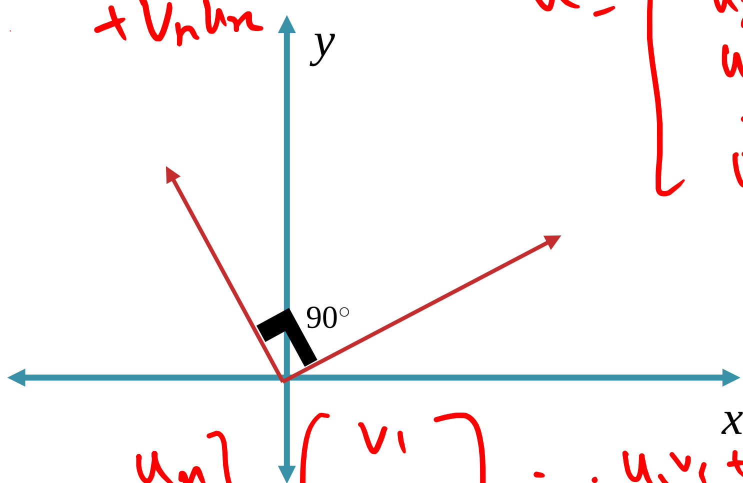
$u^Tv = v^Tu$

- If $u^Tv > 0$, their angle is less than 90° and if $u^Tv < 0$, their angle is greater than 90°

$v^Tu = v_1u_1 + v_2u_2 + \dots + v_nu_n$

$= u^Tv$.

$u = \begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ \vdots \\ u_n \end{bmatrix}$ $\quad$ $v = \begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_n \end{bmatrix}$



$u^Tv = \begin{bmatrix} u_1 & u_2 & \dots & u_n \end{bmatrix} \begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_n \end{bmatrix} = u_1v_1 + u_2v_2 + \dots + u_nv_n$.

$\boxed{u^Tv = v^Tu}$ $\quad$ u, v are vectors

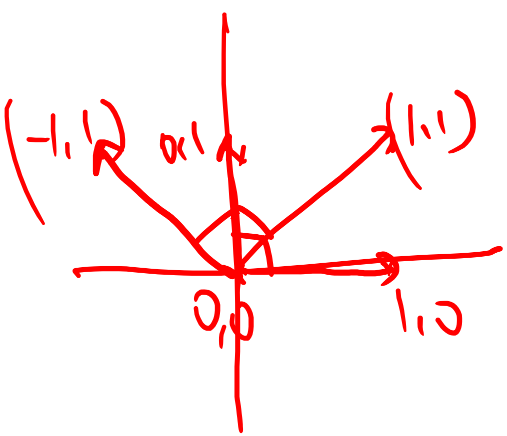
Orthogonality (Perpendicularity)

ONLY for vectors

- Consider two vectors $u = [u_1, u_2, \ldots, u_n]$ and $v = [v_1, v_2, \ldots, v_n]$

$$v^T u = \quad u^T v = u_1 v_1 + u_2 v_2 + \ldots + u_n v_n = \sum_{i=1}^{n} u_i v_i$$

If $u^T v = 0$, then the two vectors are said to be orthogonal to each other



$u = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$ $\quad u^T v = v^T u = 0$

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

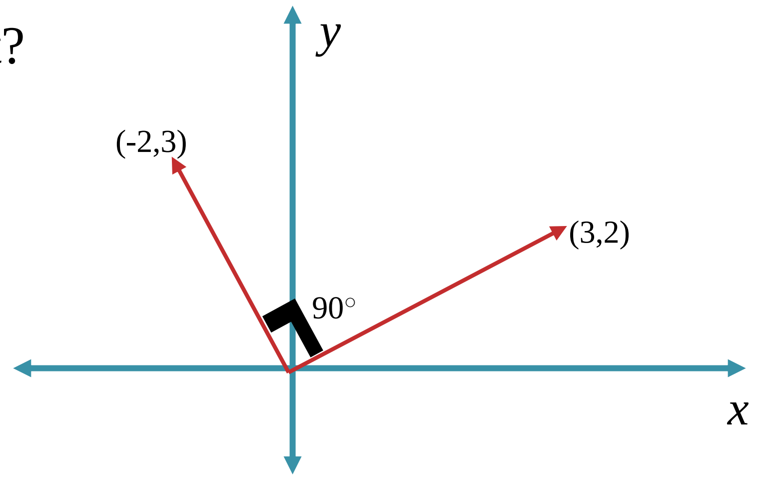
$u = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$ $\quad v = \begin{bmatrix} -1 \\ 1 \end{bmatrix}$

$u^T v = 0$

Orthogonality

Example:

The vectors $\begin{bmatrix} 3 \\ 2 \end{bmatrix}$ and $\begin{bmatrix} -2 \\ 3 \end{bmatrix}$ are orthogonal or not?



- Test for orthogonality:

$u^T v = 0$

$v^T u = 0$

$$u^T v = \begin{bmatrix} 3 & 2 \end{bmatrix} \begin{bmatrix} -2 \\ 3 \end{bmatrix}$$

$$= -6 + 6 = 0$$

and hence the vectors are orthogonal to each other

Are they orthonormal ? No $\|u\| = \sqrt{13}$ $\|v\| = \sqrt{13}$

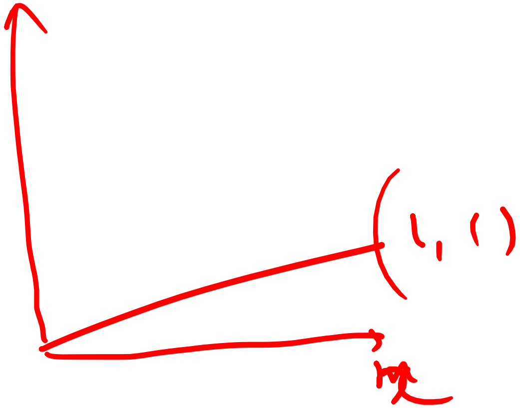
Are they independent ? Yes.

Orthogonality

- Length of a vector: $\|x\| = \sqrt{x_1^2 + x_2^2 + \cdots + x_n^2}$ $= \sqrt{x^T x}$
- Length of a vector (1,2) is $\sqrt{(1^2 + 2^2)} = \sqrt{5}$
- Two vectors which are orthogonal and of length 1 are said to be **orthonormal**
- $\boxed{\text{Orthogonality always implies linear independence but not vice–versa}}$
- Zero vector is orthogonal to all vectors

$$x^T x = [x_1 \quad x_2 \quad \cdots \quad x_n] \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} = \underbrace{x_1^2 + x_2^2 + \cdots + x_n^2}_{\geq 0 \quad \geq 0 \quad \geq 0}$$

$$x^T x \geq 0$$



$x_1 = 1$

$x_2 = 1$

length of vector: (m).

$\underbrace{x_1}^2 + x_2^2$

$m^2 + m^2$

$(\quad)m^2$

$x^T x$

$\sqrt{x^T x}$ has units m.

$\therefore \|x\| = \sqrt{x^T x}$

Orthogonality

- **Orthogonality always implies linear independence but not vice–versa**

- Orthogonality implies linear independence?

- The vectors $\begin{bmatrix} 3 \\ 2 \end{bmatrix}$ and $\begin{bmatrix} -2 \\ 3 \end{bmatrix}$ are orthogonal. Are they linearly independent?

$$c_1 \begin{bmatrix} 3 \\ 2 \end{bmatrix} + c_2 \begin{bmatrix} -2 \\ 3 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

- The only values that c_1 and c_2 could take is 0 and hence they are linearly independent

Orthogonality

- Linear independence implies orthogonality always?
- The vectors $\begin{bmatrix}1\\1\\0\end{bmatrix}$ and $\begin{bmatrix}1\\0\\0\end{bmatrix}$ are linearly independent. Are they orthogonal?
- Test for orthogonality: $x^T y = 0$

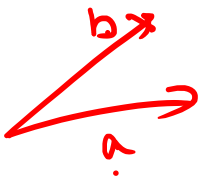
$$\begin{bmatrix}1 & 1 & 0\end{bmatrix}\begin{bmatrix}1\\0\\0\end{bmatrix} = 1 \neq 0$$

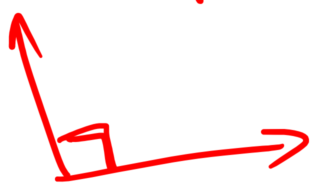
- The vectors are linearly independent but not orthogonal

$\Rightarrow$ Orthogonality always implies linear independence but not vice–versa

Why orthogonality.

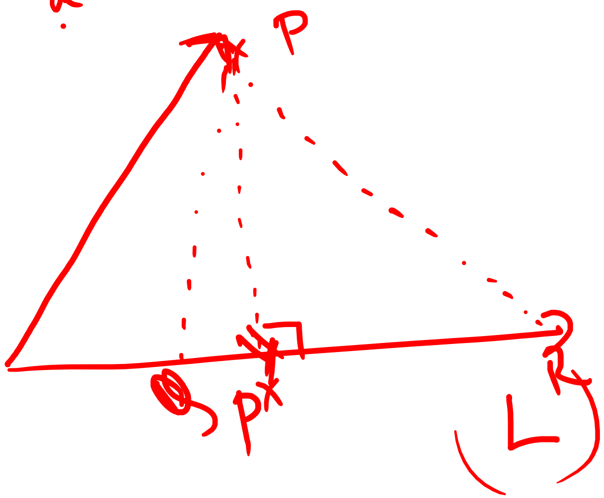
If $a \perp b$.





no relation between a & b.

shortest distance of P from L is the $\perp$ar distance of P from L.



"L is my model"

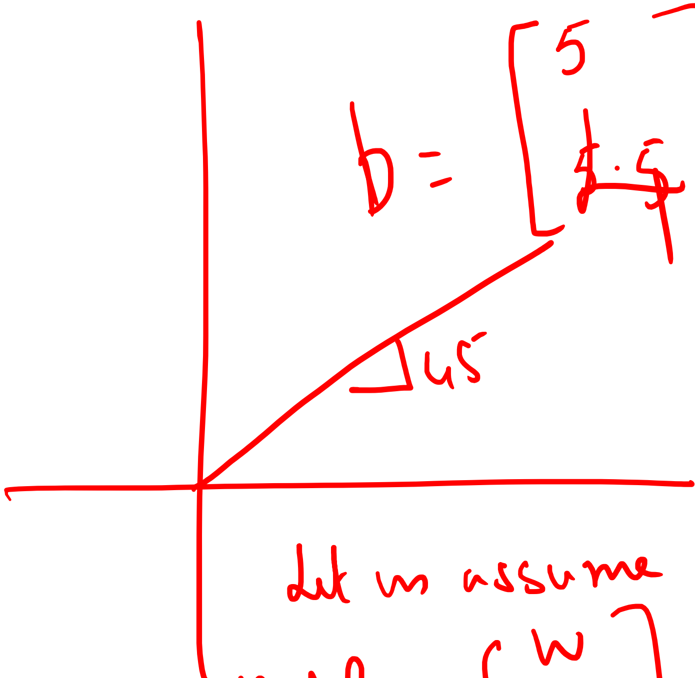
"P is my data."

Find p^* p^* lies on the model.

(PP^* $\perp$ar to L)!

$W = \begin{bmatrix} 62 \\ 62.1 \end{bmatrix}$ 2 readings of my weight

What is a reasonable guess for my weight - $\frac{62 + 62.1}{2} = 62.05$



$b = \begin{bmatrix} 5 \\ 4.5 \end{bmatrix}$

$b = \begin{bmatrix} 5 \\ 5.5 \end{bmatrix}$

$b = \begin{bmatrix} 5 \\ 4 \end{bmatrix}$

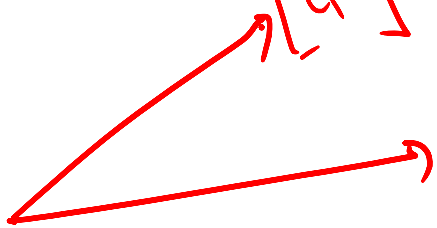
Let us assume true weight is w.

Model: $\begin{bmatrix} w \\ w \end{bmatrix} = w \begin{bmatrix} 1 \\ 1 \end{bmatrix}$

$b = \begin{bmatrix}5\\4\end{bmatrix}$ Model $= \begin{bmatrix}1\\1\end{bmatrix} = a$

Data $\begin{bmatrix}5\\4\end{bmatrix}$

Project b on a.



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

Model

$$p = \frac{a^T b}{a^T a} \cdot a.$$

$$\hat{x} = \frac{a^T b}{a^T a} = \frac{5+4}{2} = \frac{9}{2} = 4.5$$

$\begin{bmatrix}5\\4\\6\end{bmatrix}$ $\hat{w} = 5$

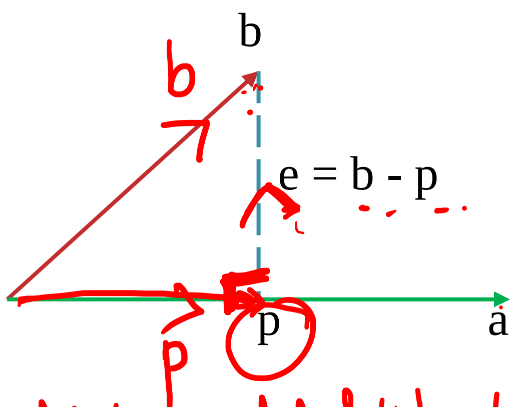
$b = \begin{bmatrix}5\\4\\6\end{bmatrix}$ $a = \begin{bmatrix}1\\1\\1\end{bmatrix}$ $\hat{x} = \frac{a^T b}{a^T a} = \frac{15}{3} = 5$

Projection

- Consider 2 vectors *a* and *b*. Project *b* on *a* and *p* is the point on *a* which is closest to *b*. The point *p* is called as the projection of *b* onto line through *a*

p is unknown! $p = \hat{x} a$ (?)

- Geometrical fact: The line from b to the closest point $p = \hat{x}a$ is perpendicular to the vector *a*



$$p = \hat{x}a \;\; ; \;\; \hat{x} = ? \; ; \; e = b - \hat{x}a$$

$$(b - \hat{x}a) \perp a$$

$b - p \perp a$ r a.

$$\hat{x} = \frac{a^T b}{a^T a} = \frac{b^T a}{a^T a} \Rightarrow a^T(b - \hat{x}a) = 0$$

$$\hat{x} = \frac{a^T b}{a^T a}$$

What should be added to p to form b?

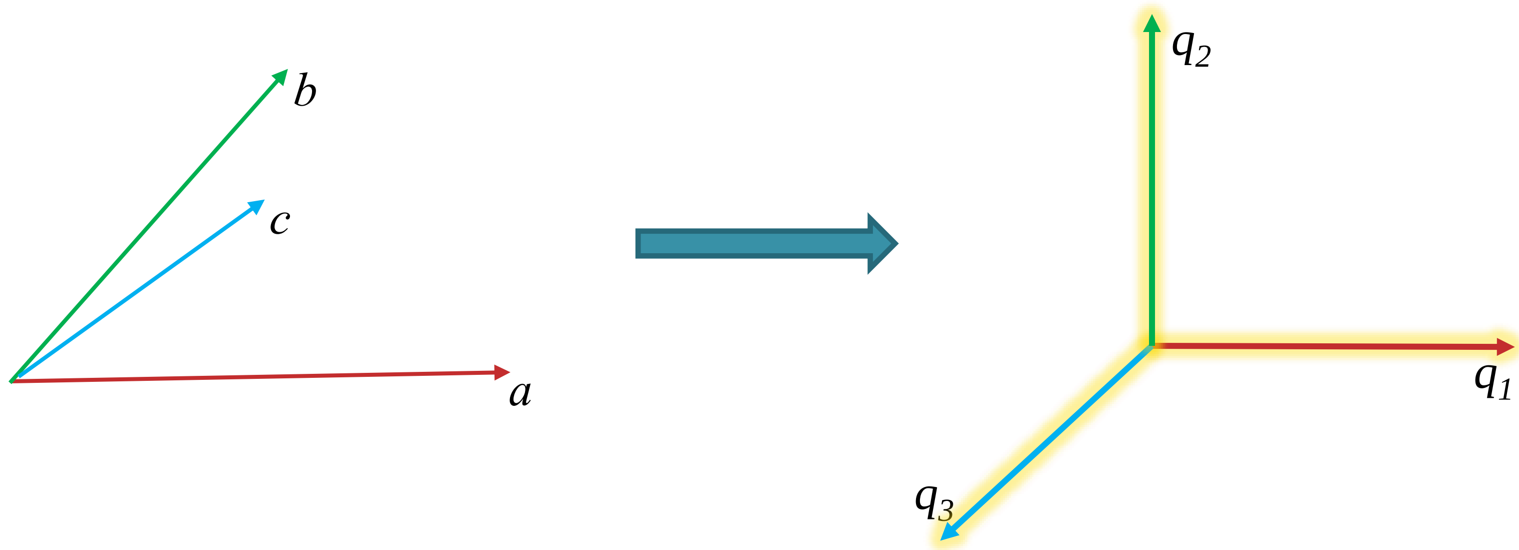
$(b - p) + p = b$.

$$p = \hat{x}a = \boxed{\frac{a^T b}{a^T a} a}$$

$(b - \hat{x}a)^T a = 0 \quad b^T a = \hat{x} a^T a$

Gram–Schmidt Orthogonalization

Goal: To make the vectors a, b, c into new glowing vectors q_1, q_2, q_3



Gram–Schmidt Orthogonalization

- In an orthogonal basis, every vector is perpendicular to every other vector. The coordinate axes are mutually orthogonal

- The vectors $q_1, \ldots, q_n$ are orthonormal if:

$$q_i^T q_j = \begin{cases} 0 \text{ whenever } i \neq j \text{, giving the orthogonality;} \\ 1 \text{ whenever } i = j \text{, giving the normalization} \end{cases}$$

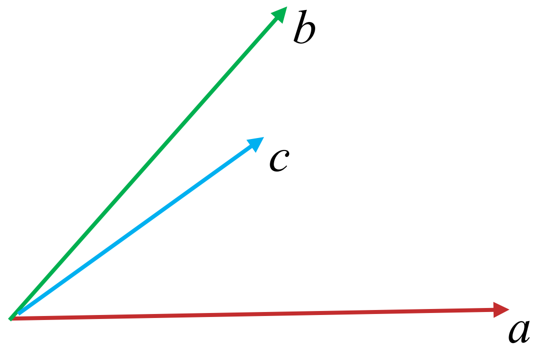
- To change an orthogonal basis into orthonormal basis, we may simply divide each vector by its length which will make it a unit vector

Gram–Schmidt Orthogonalization

The Gram–Schmidt process:

- Consider 3 independent vectors a, b, c and we seek orthonormal vectors q_1, q_2, q_3

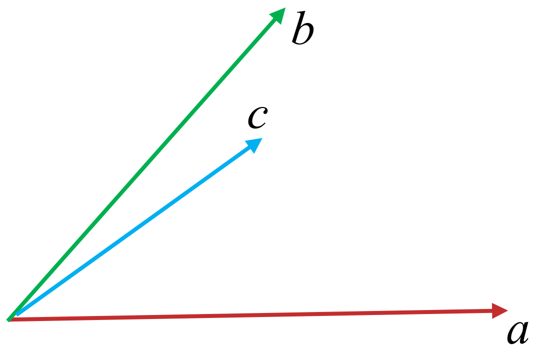
  i.e. to make the vectors a, b, c perpendicular to each other and also their length has to be 1



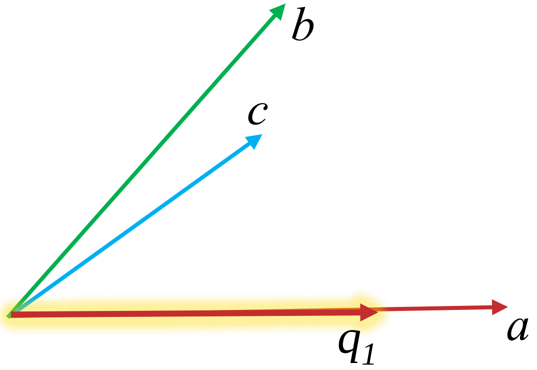
The vector c is in a different plane

Gram–Schmidt Orthogonalization

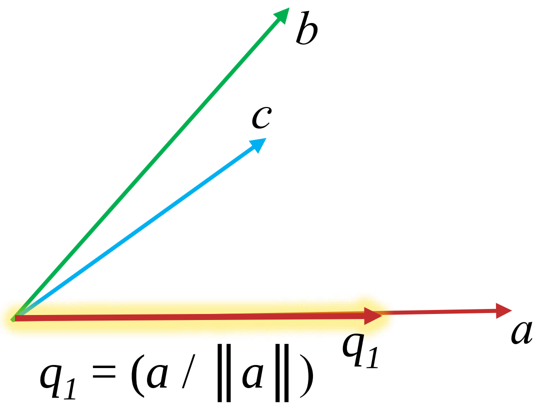
Gram–Schmidt Orthogonalization



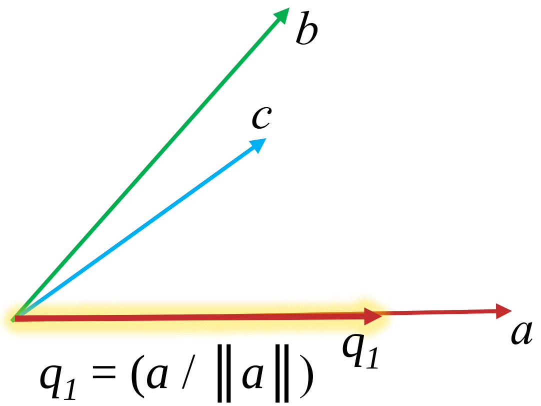
Gram–Schmidt Orthogonalization

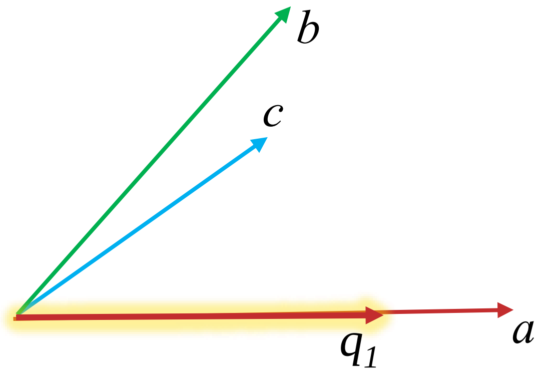


Gram–Schmidt Orthogonalization

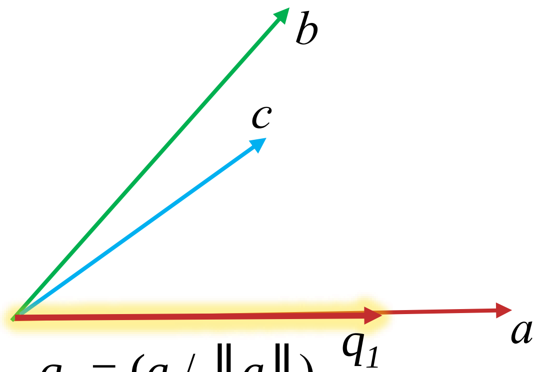


Gram–Schmidt Orthogonalization

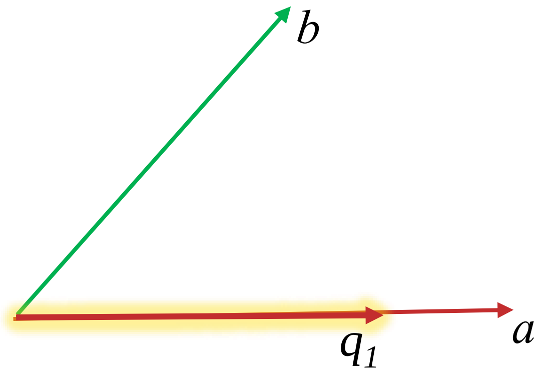




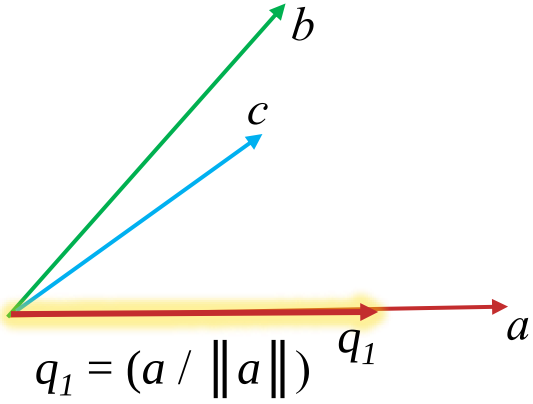
Gram–Schmidt Orthogonalization

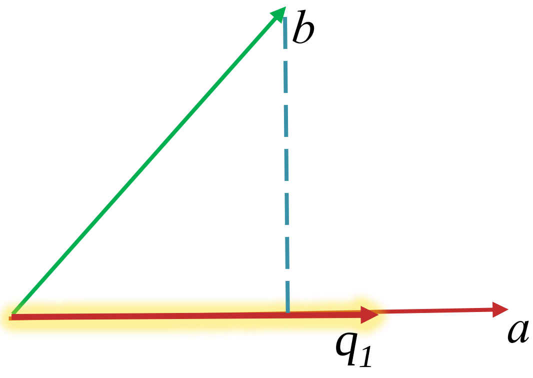


$q_1 = (a \,/\, \|a\|)$

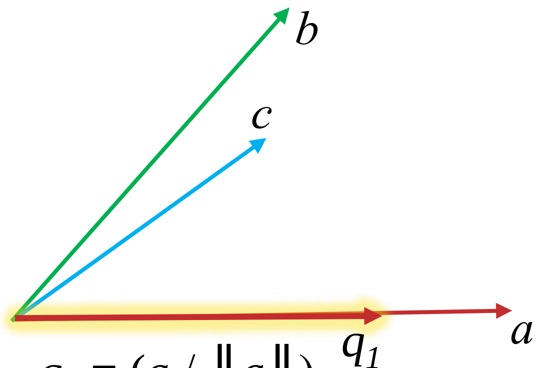


Gram–Schmidt Orthogonalization





Gram–Schmidt Orthogonalization



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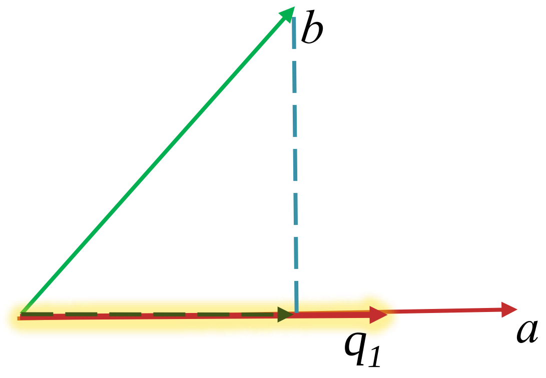

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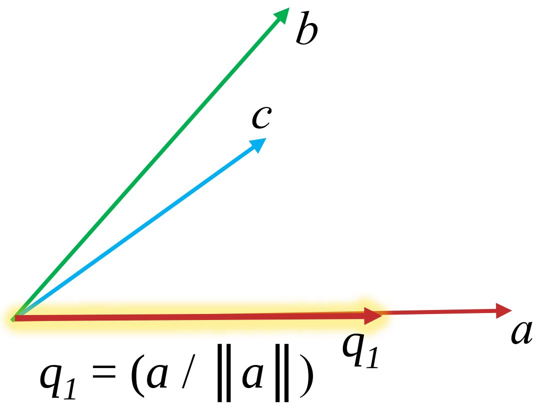

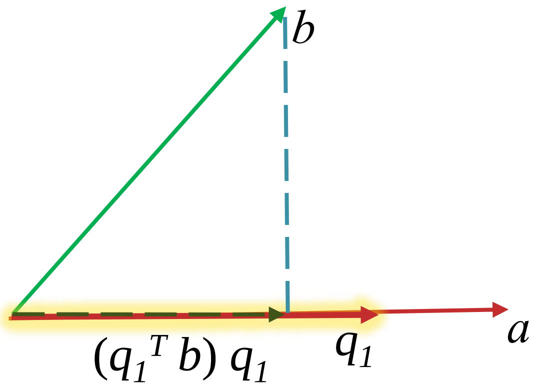

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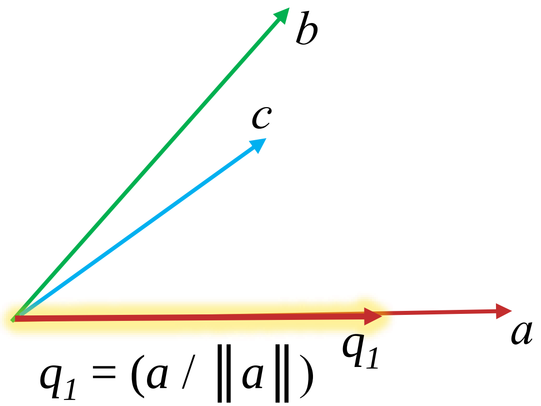
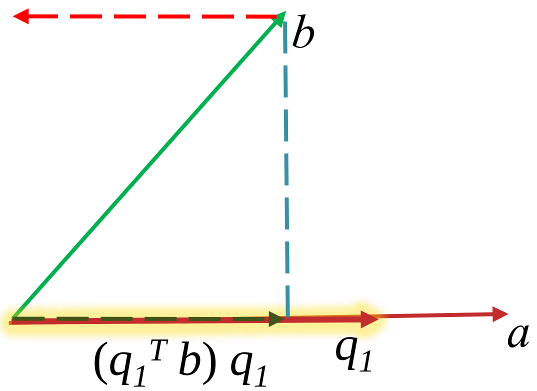
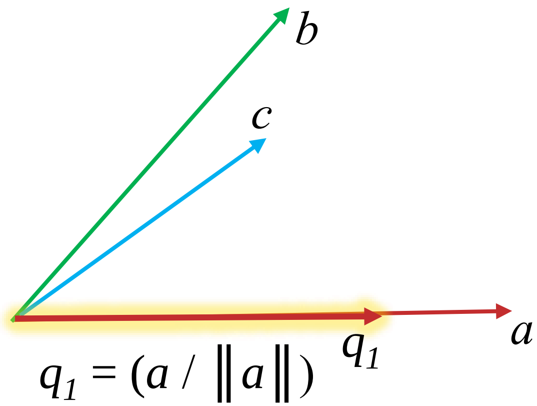
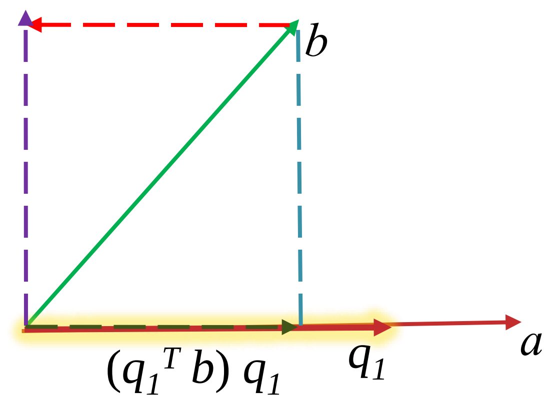


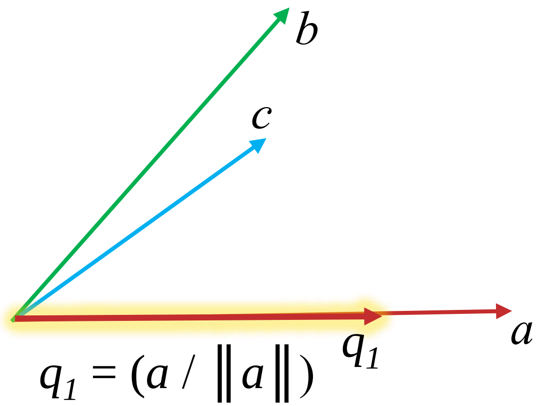


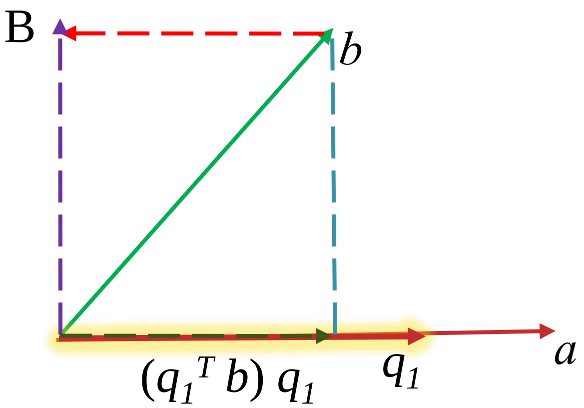
Gram–Schmidt Orthogonalization



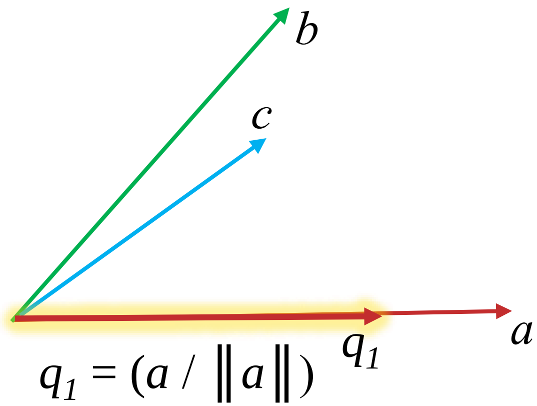


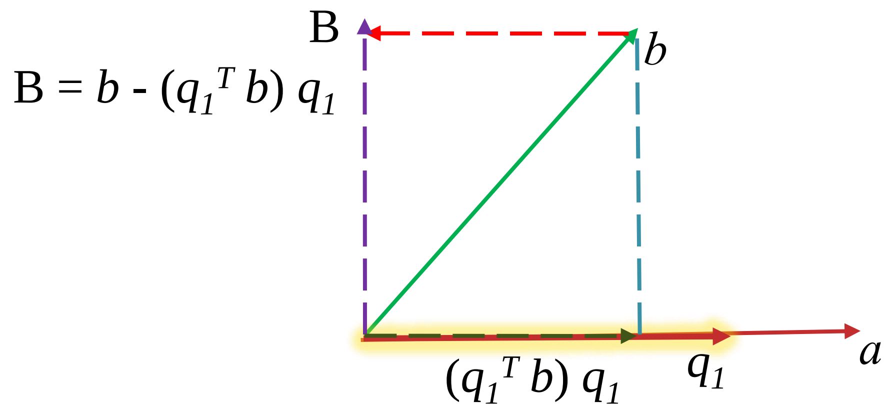
Gram–Schmidt Orthogonalization



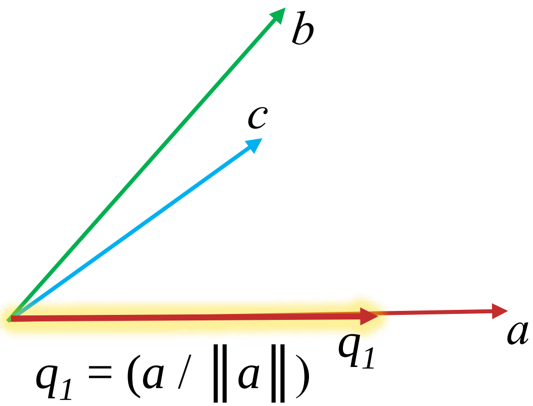


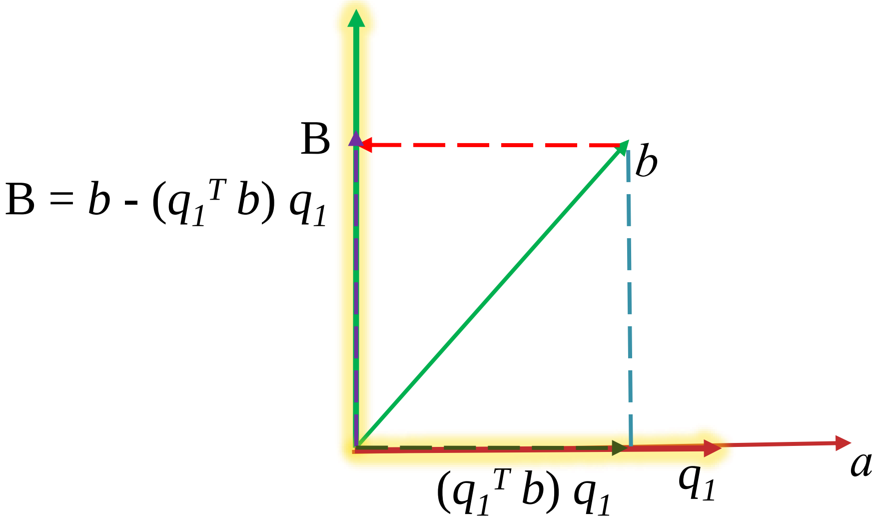
Gram–Schmidt Orthogonalization



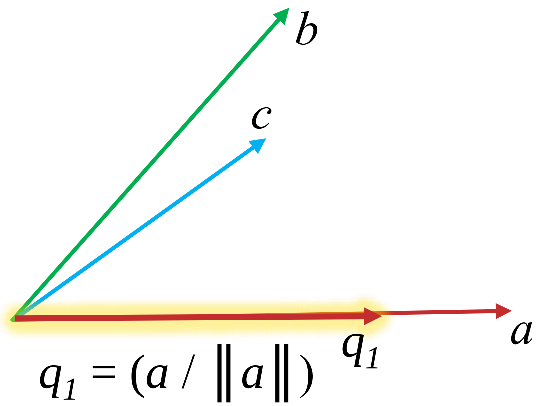


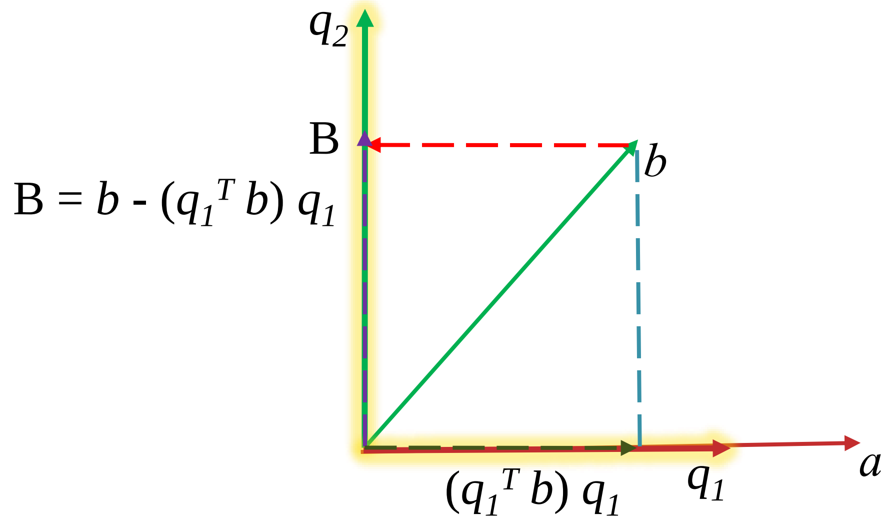
Gram–Schmidt Orthogonalization





Gram–Schmidt Orthogonalization





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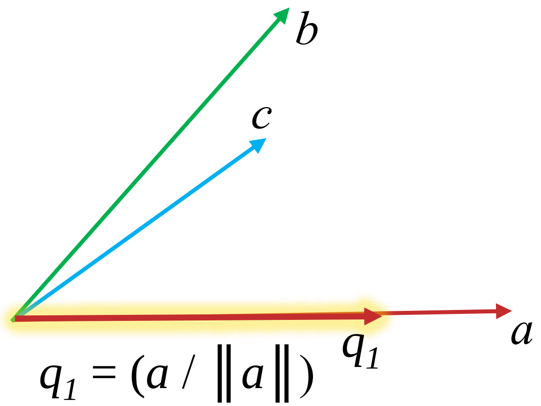

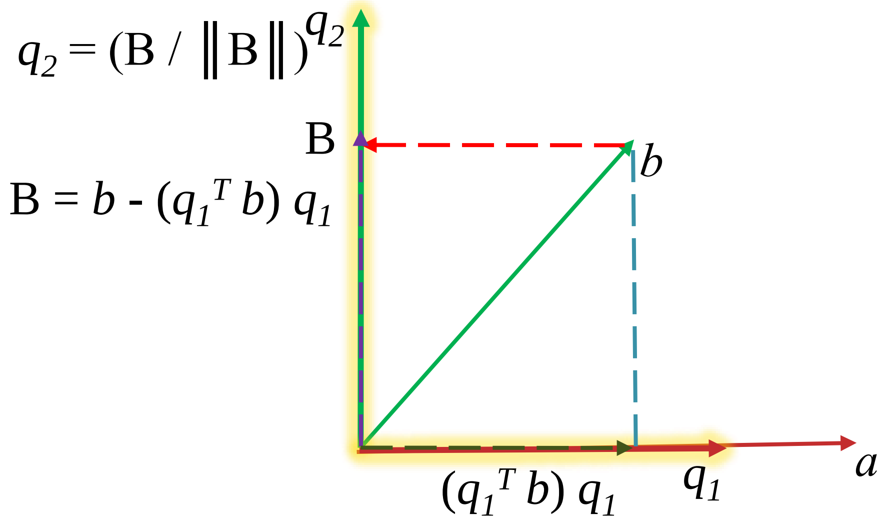

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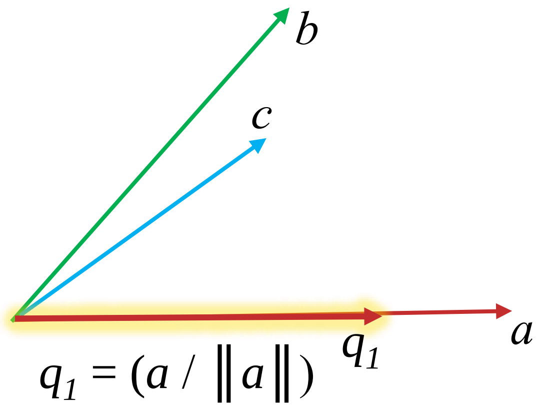

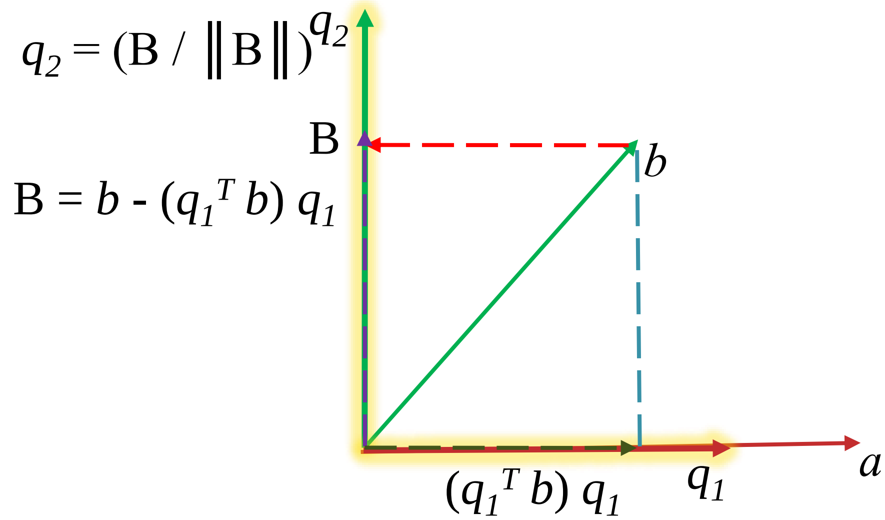

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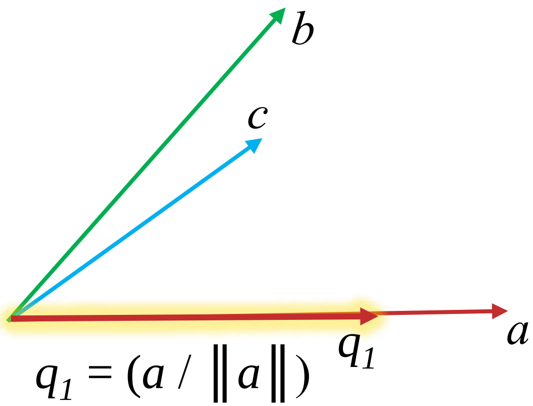

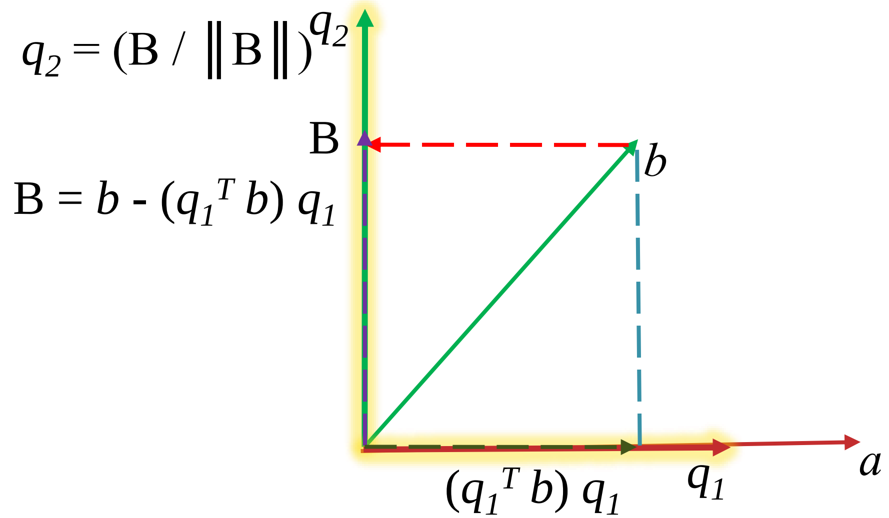

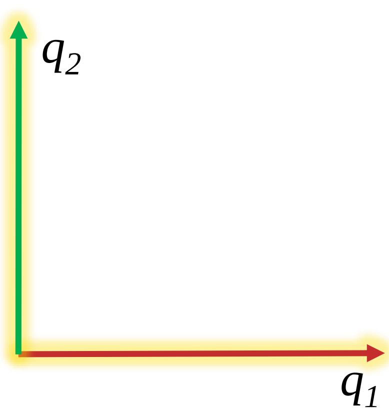

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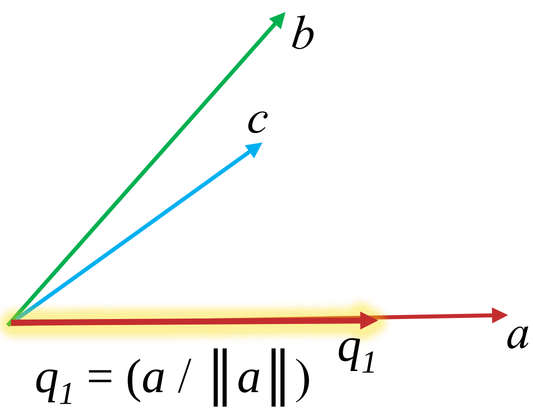

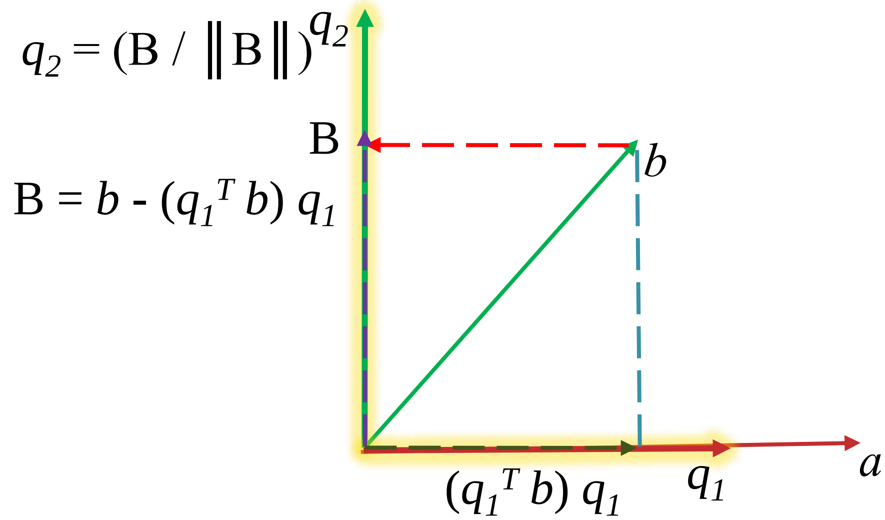

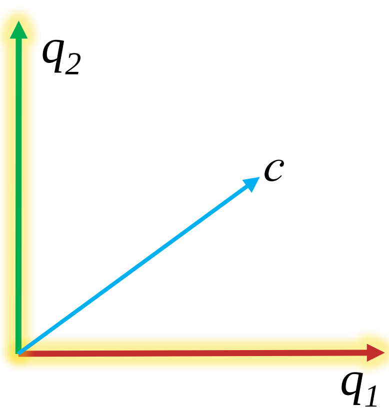

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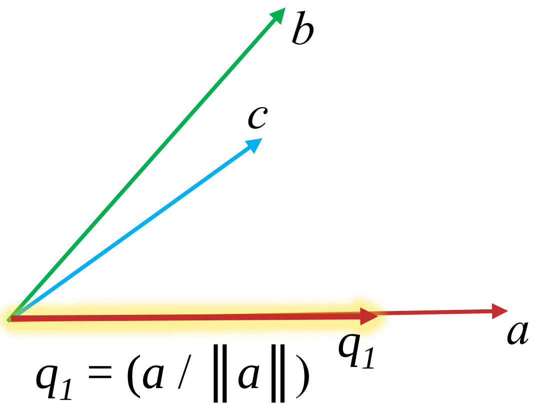

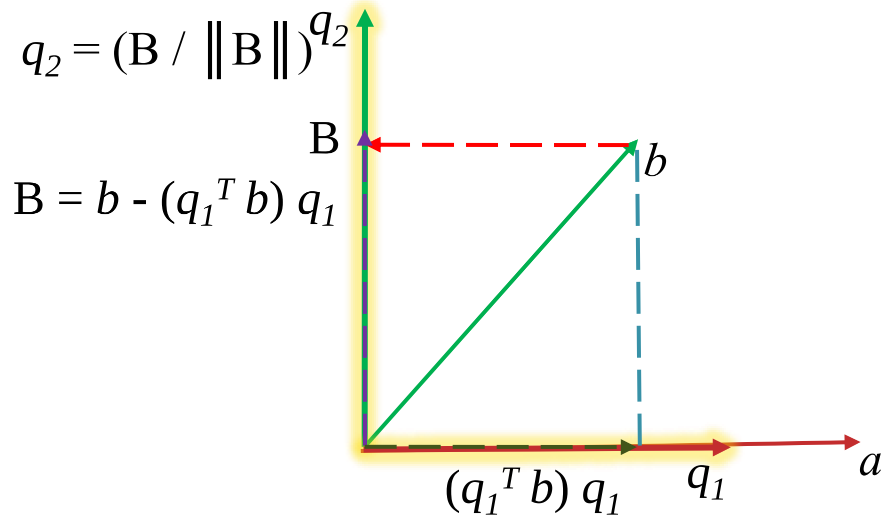

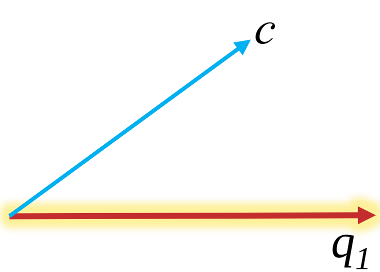

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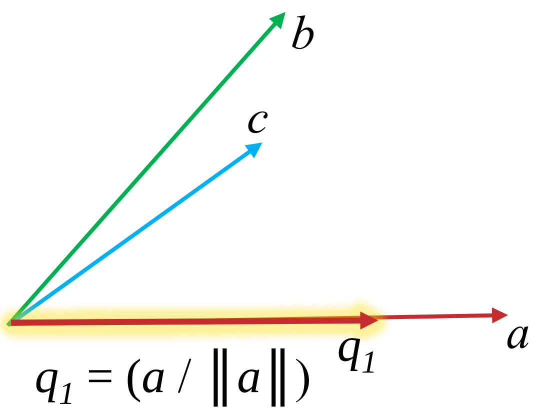

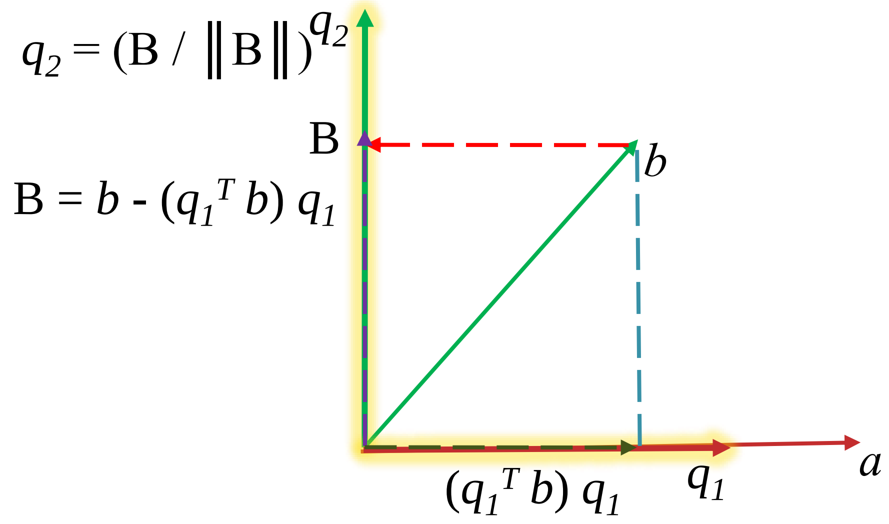

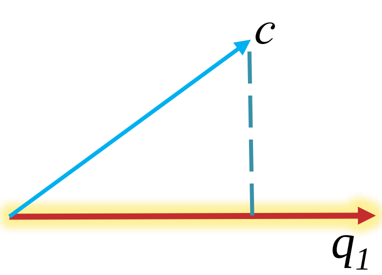

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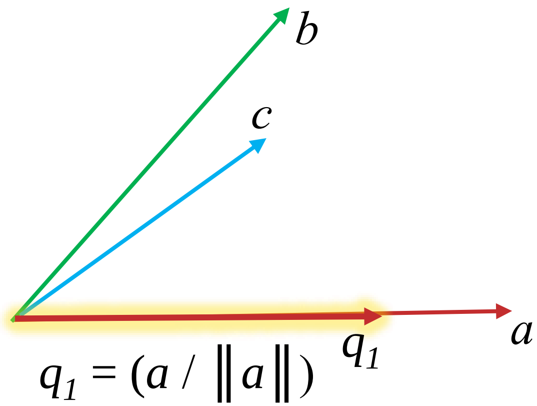

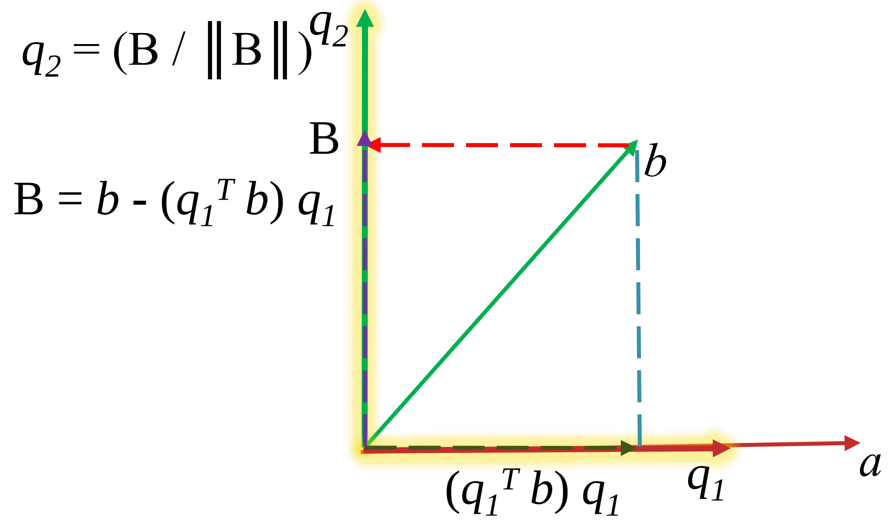

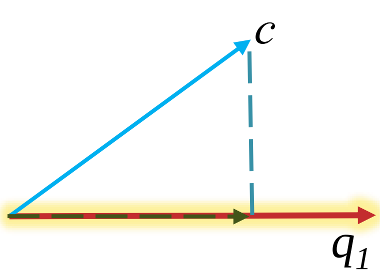

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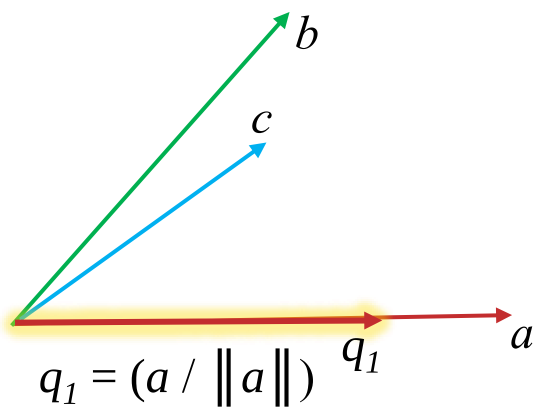

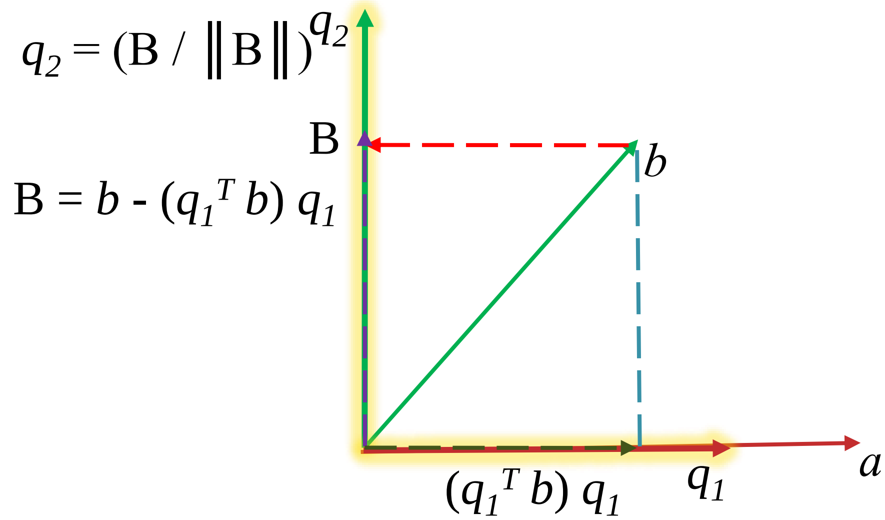

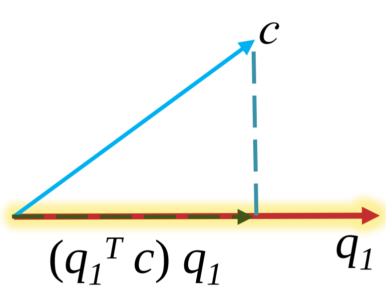

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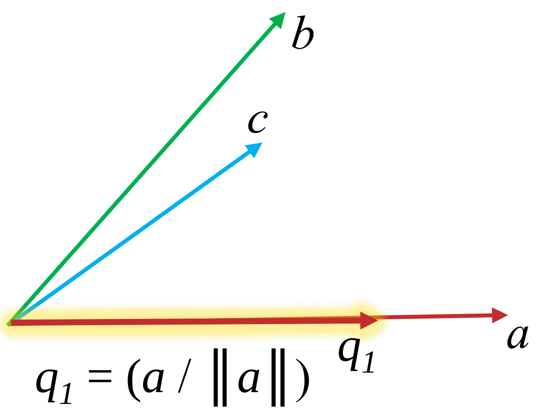

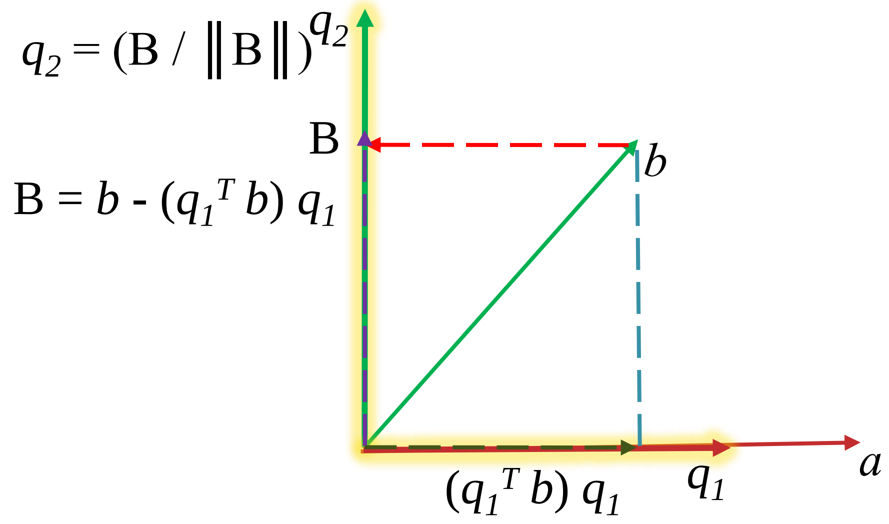

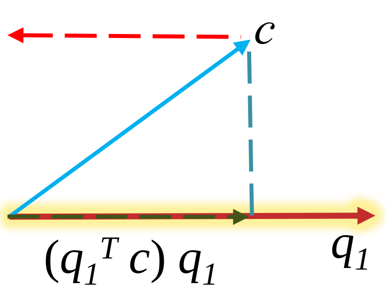

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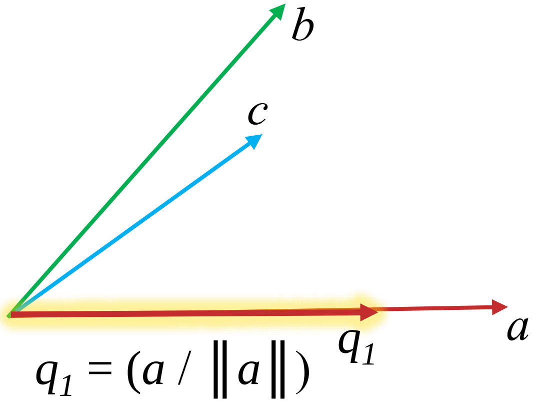

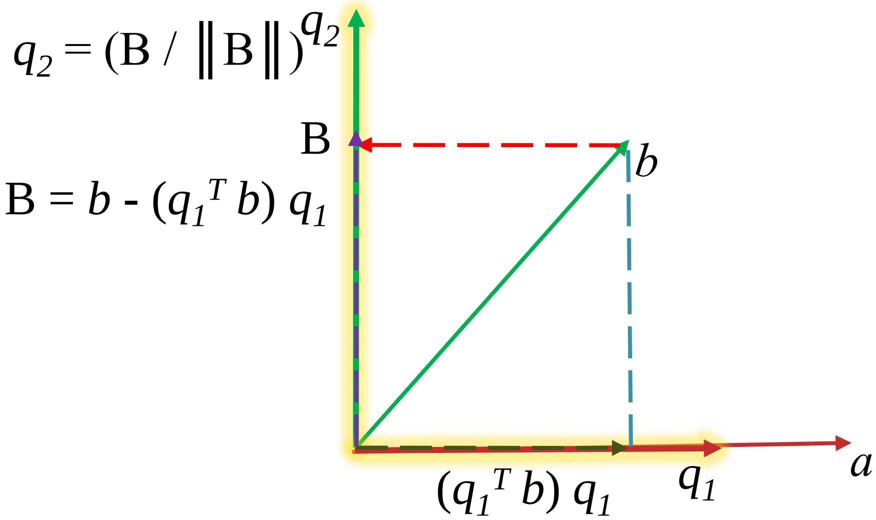

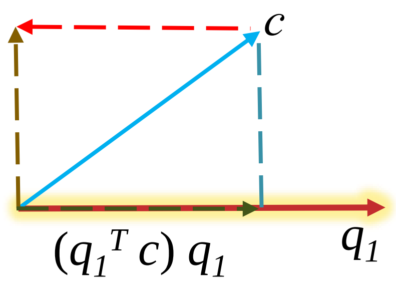

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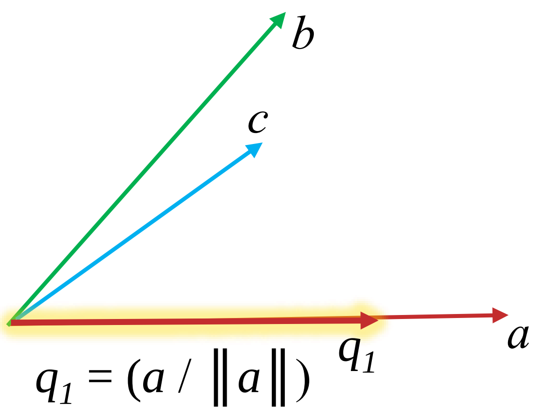

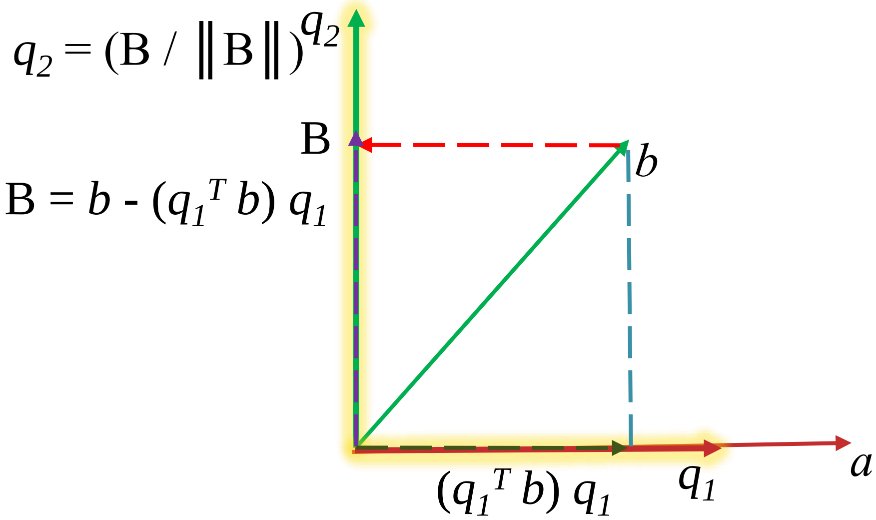

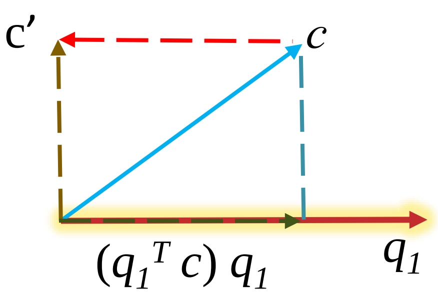

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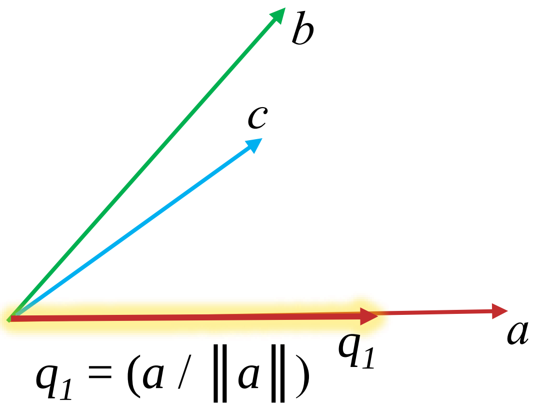

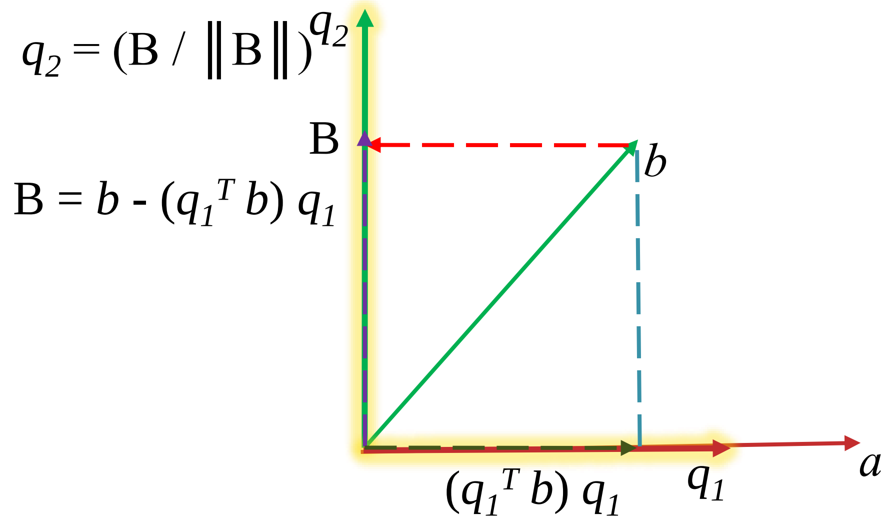

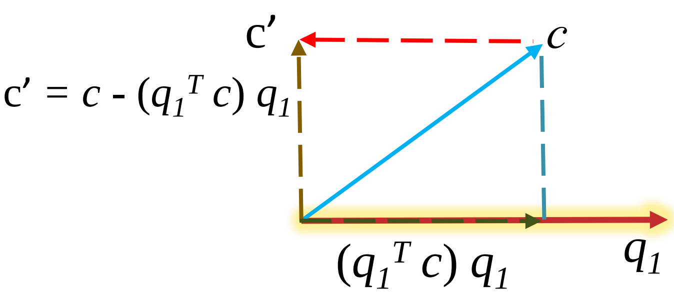

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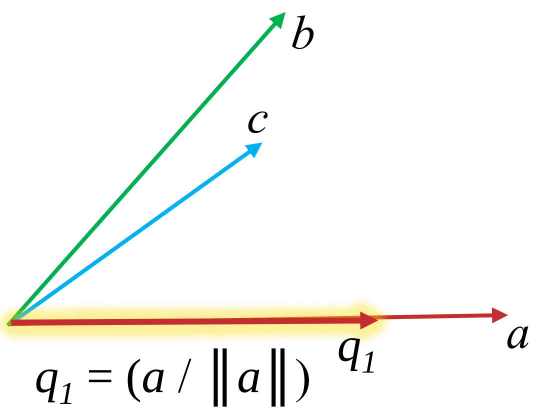

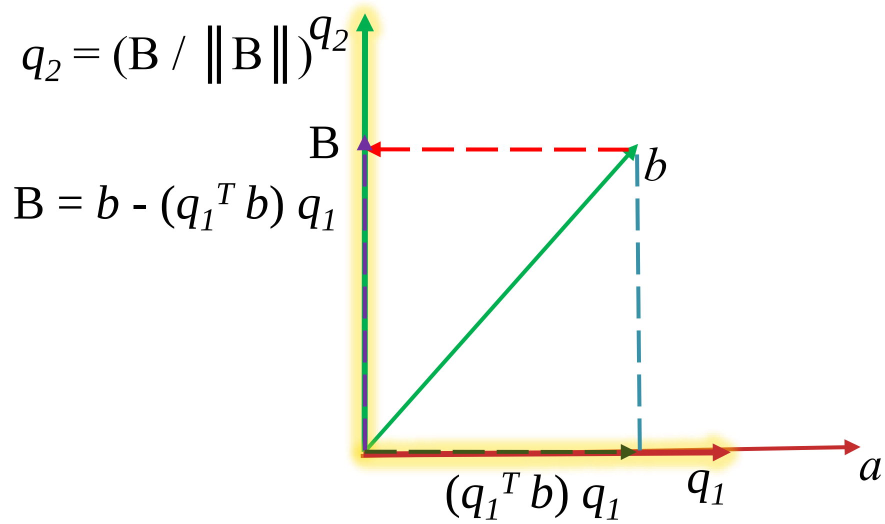

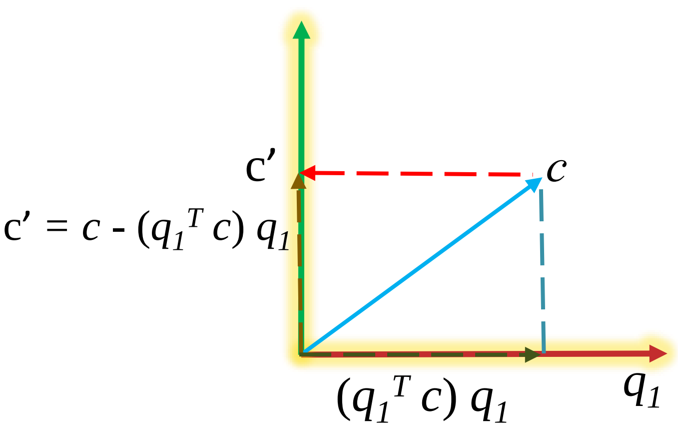

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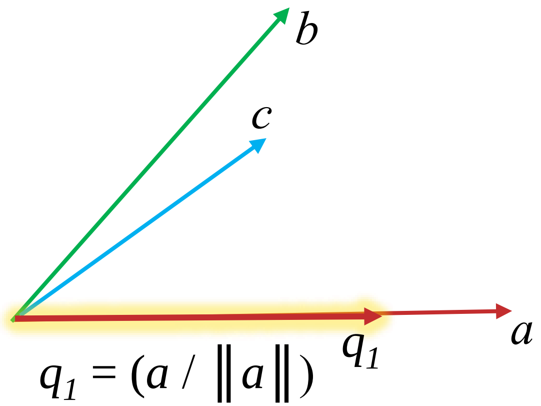

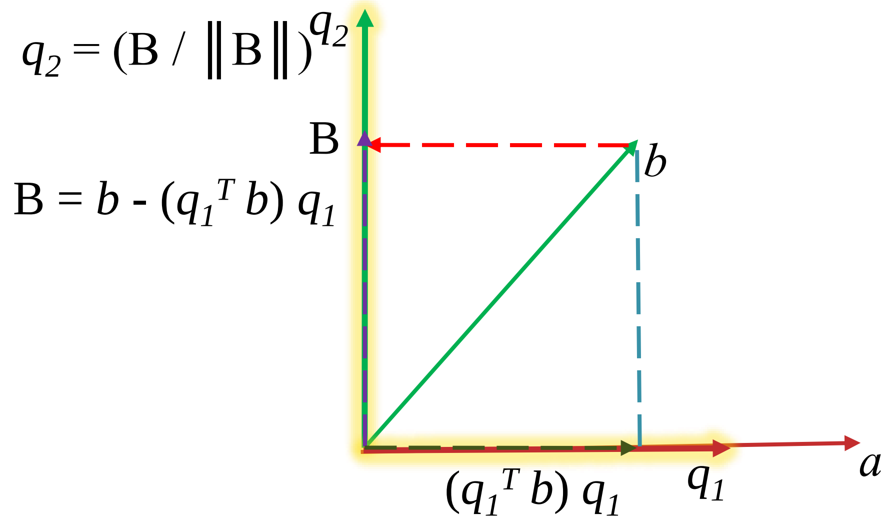

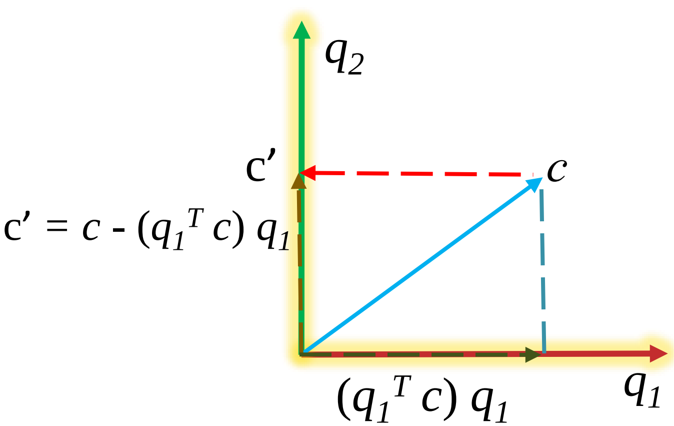

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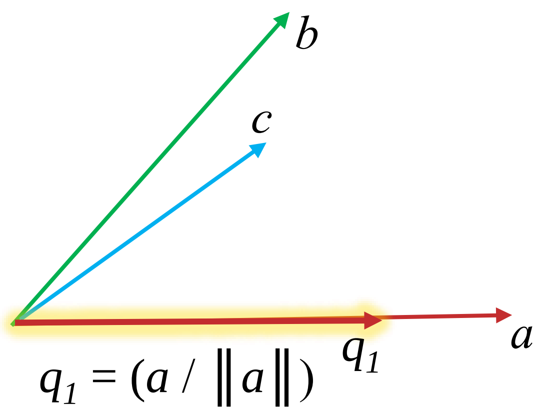

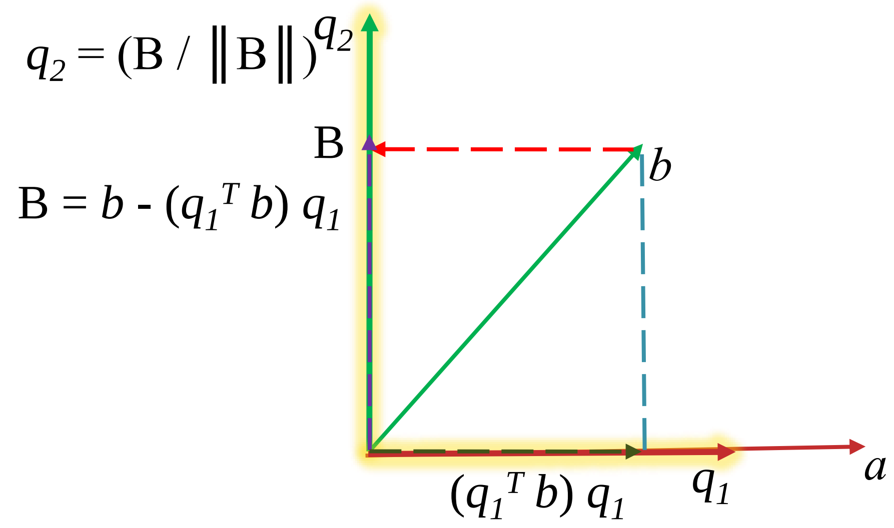

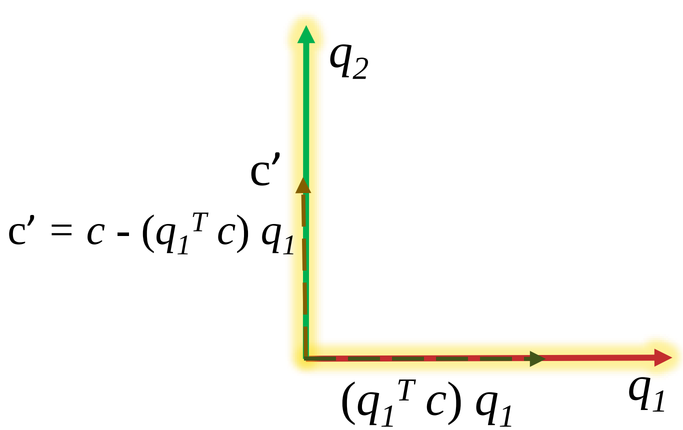

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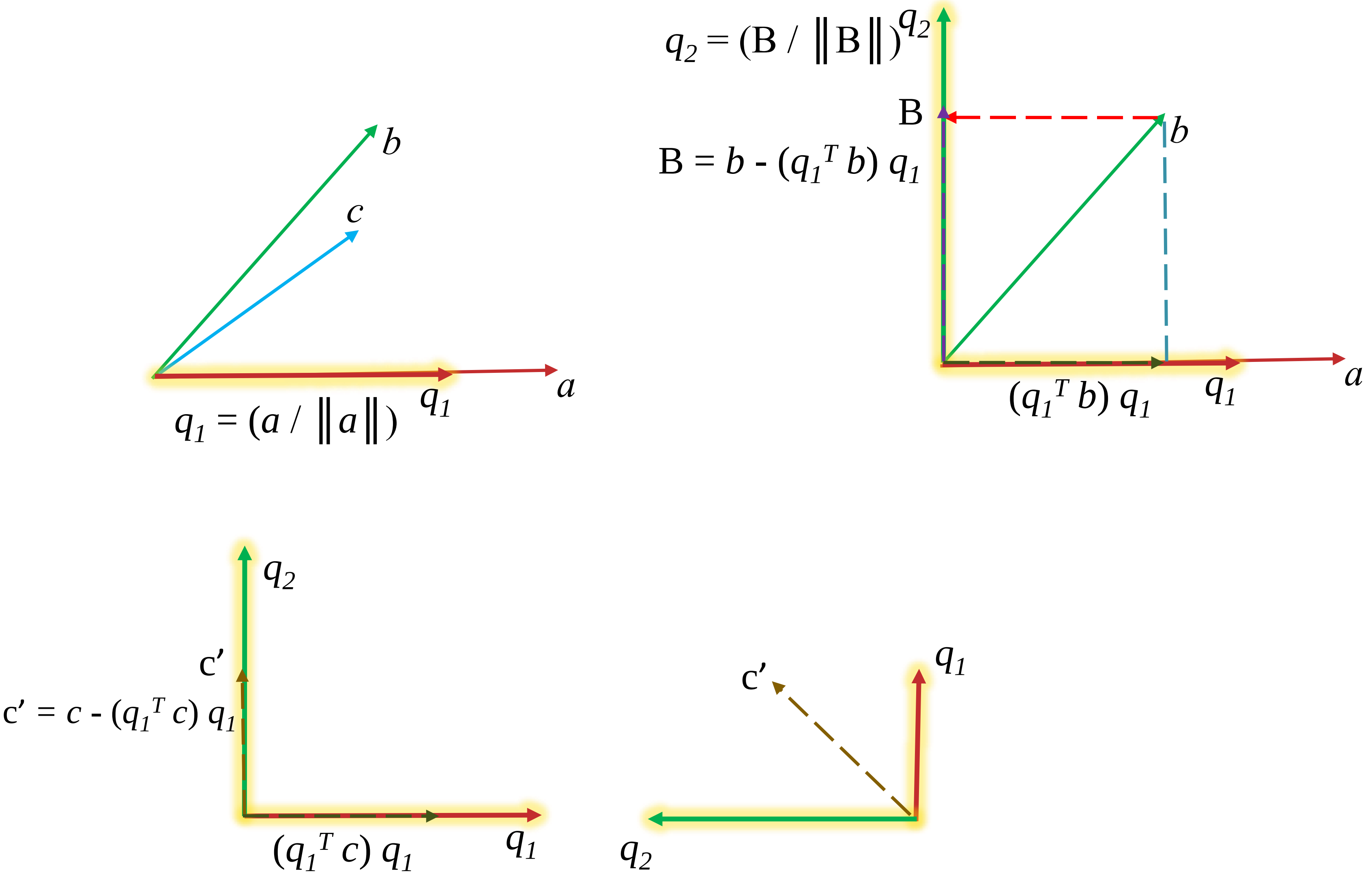

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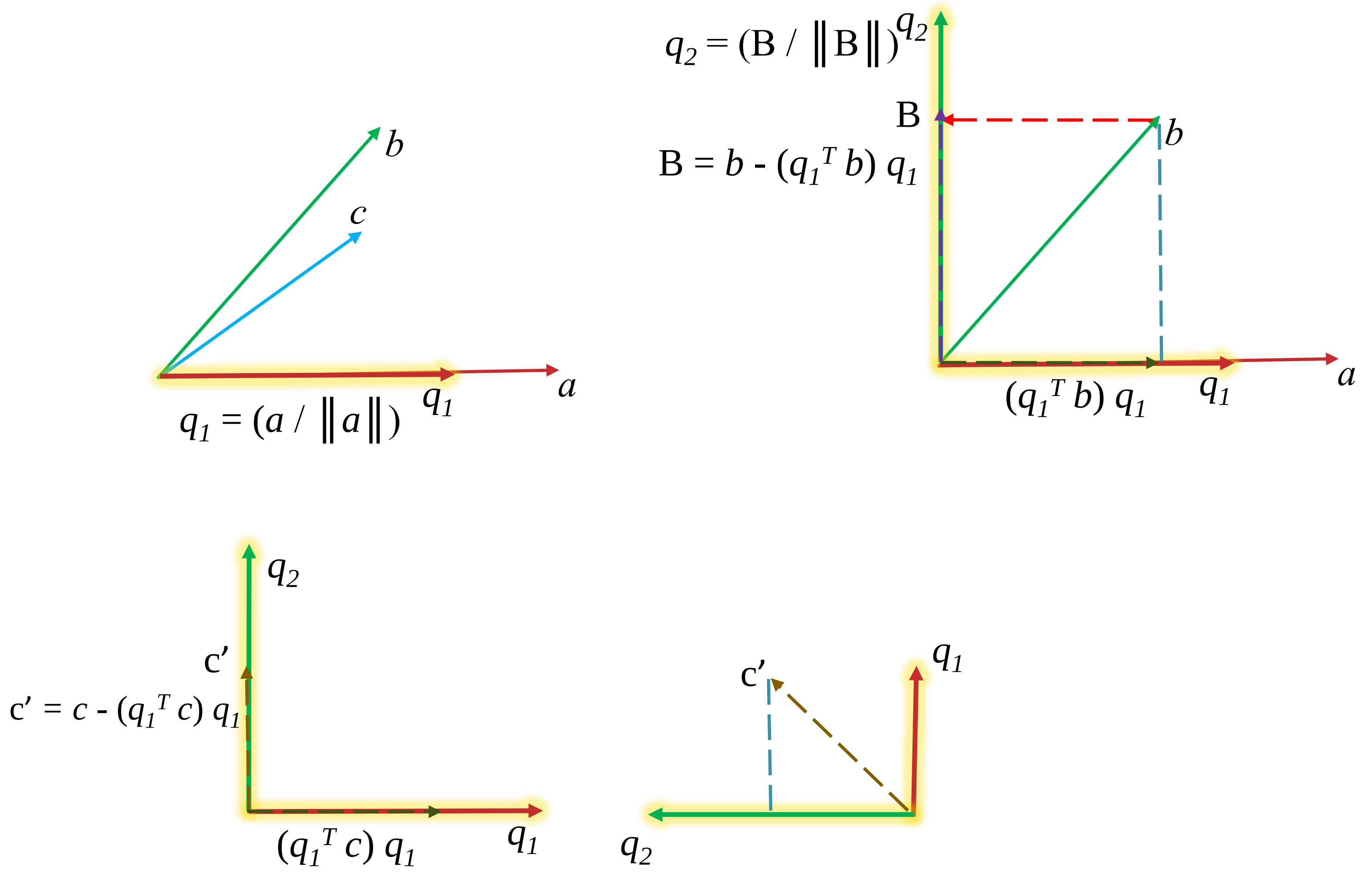

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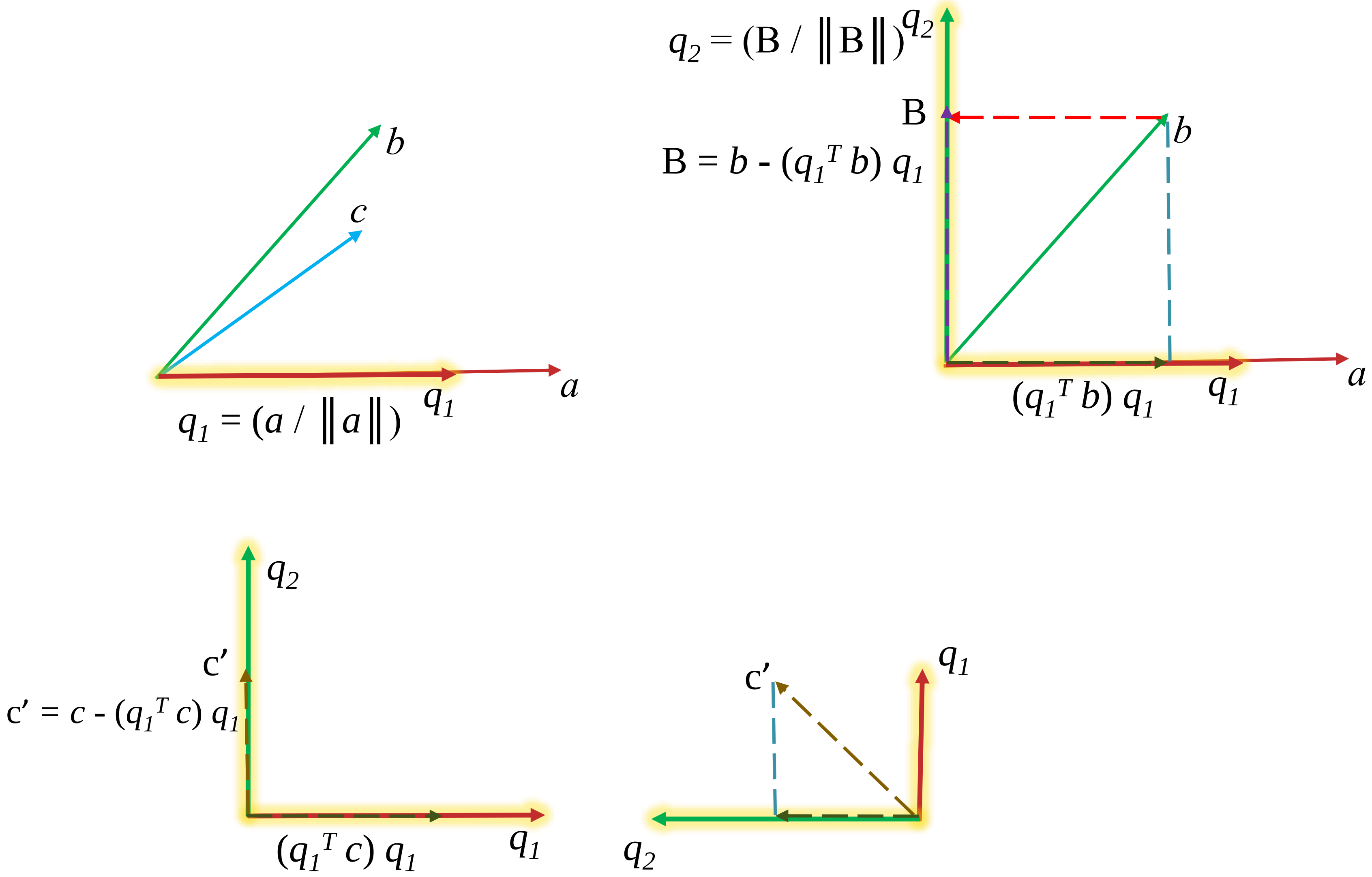

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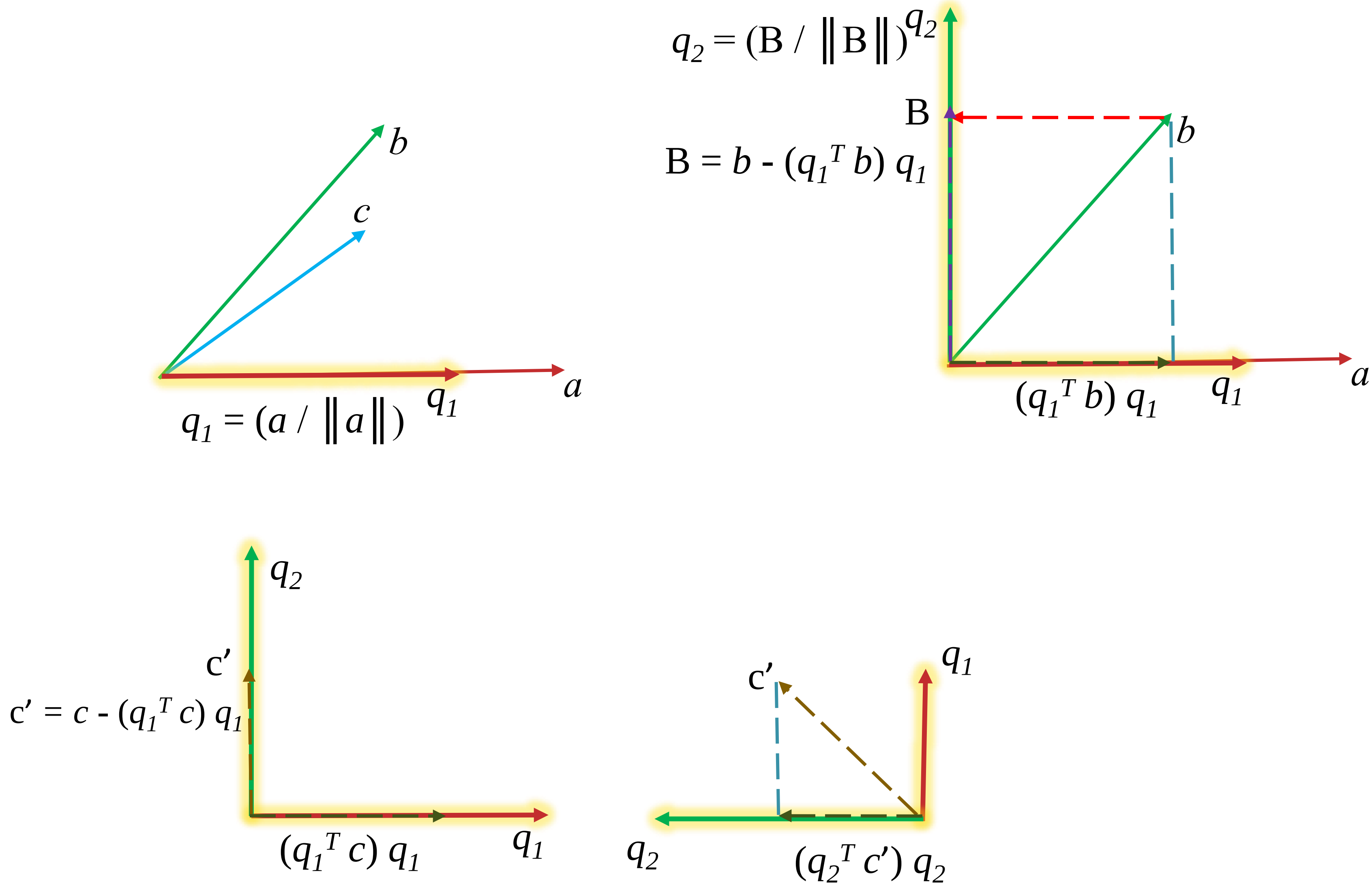

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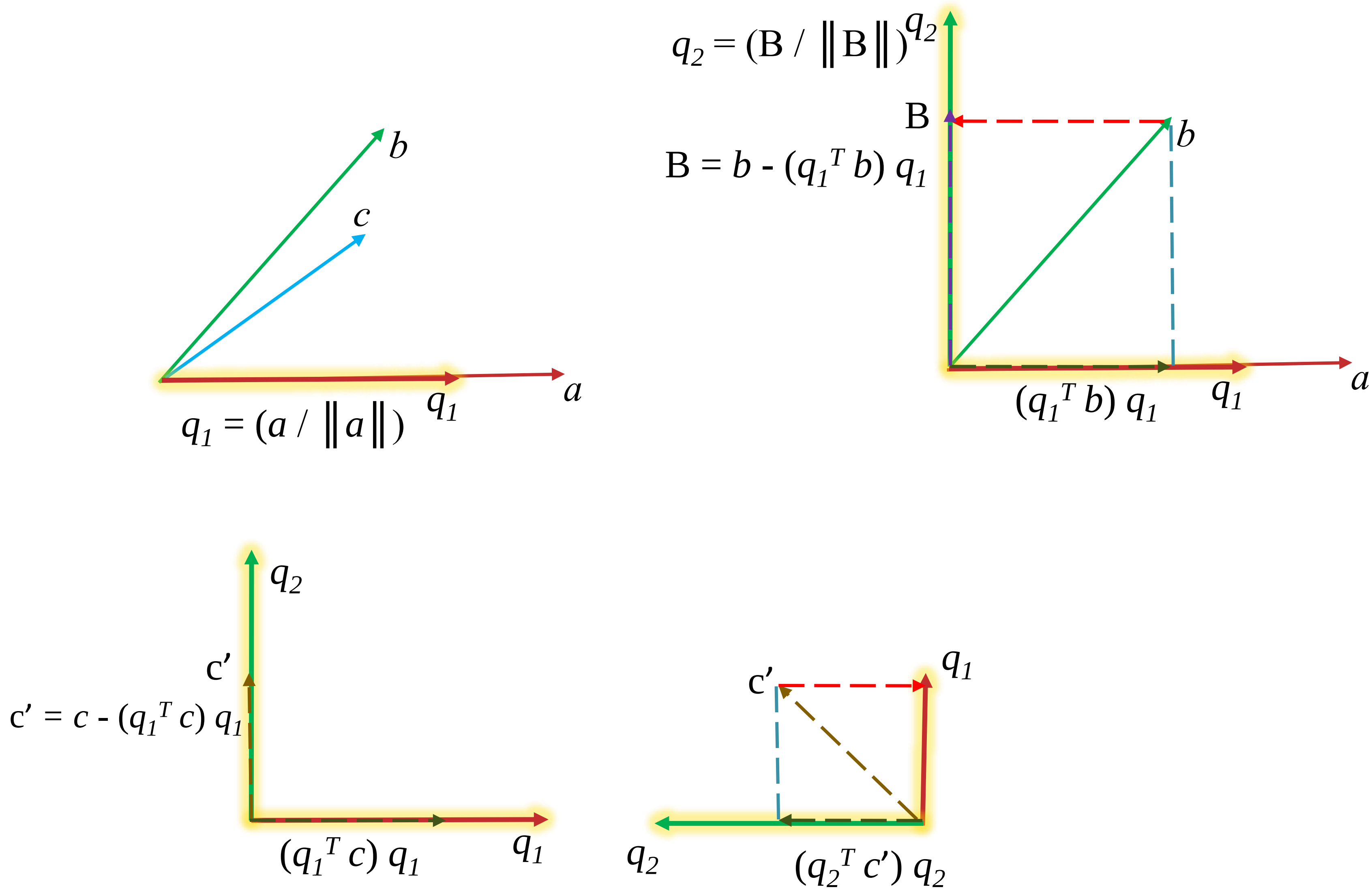

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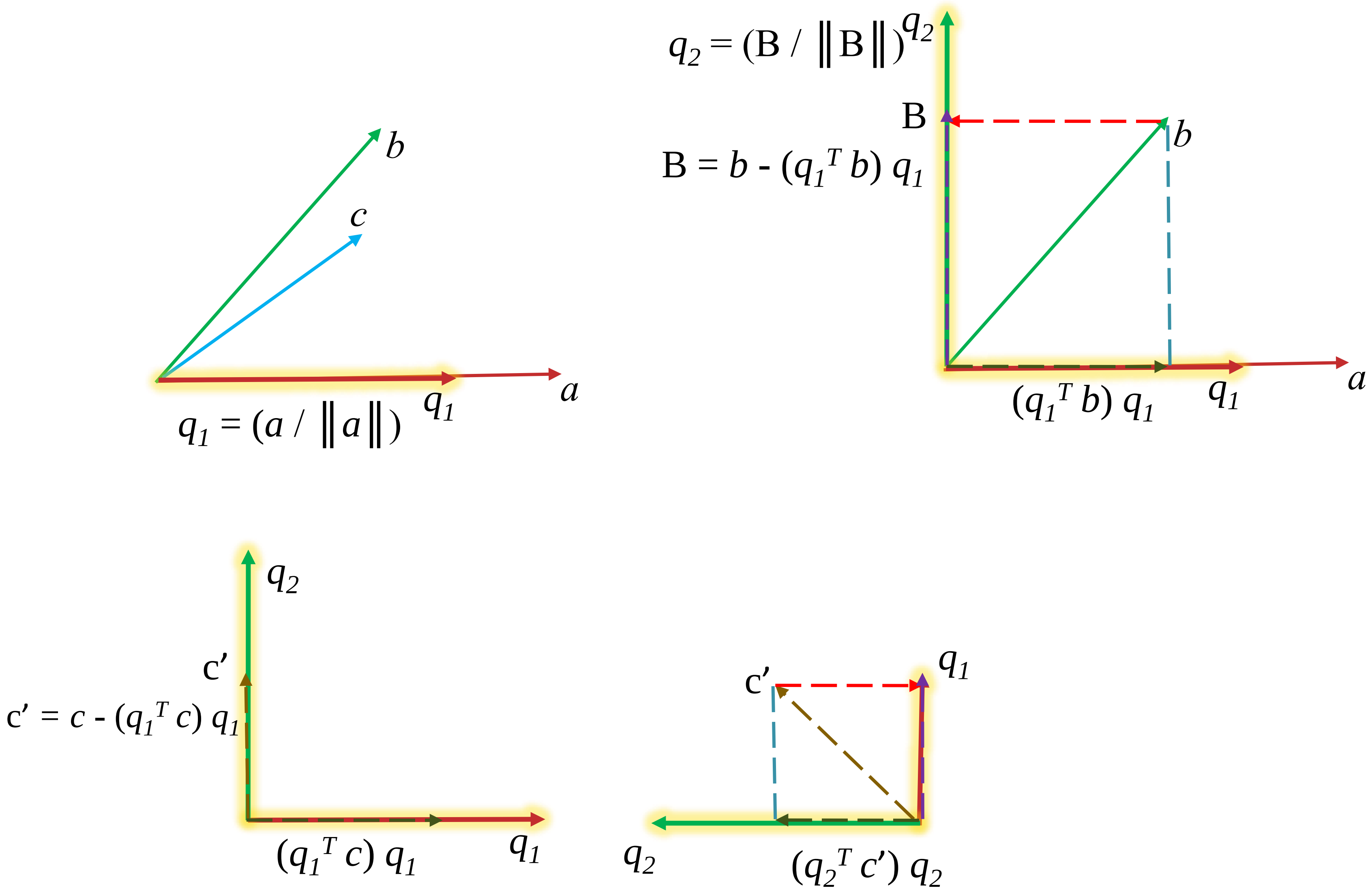

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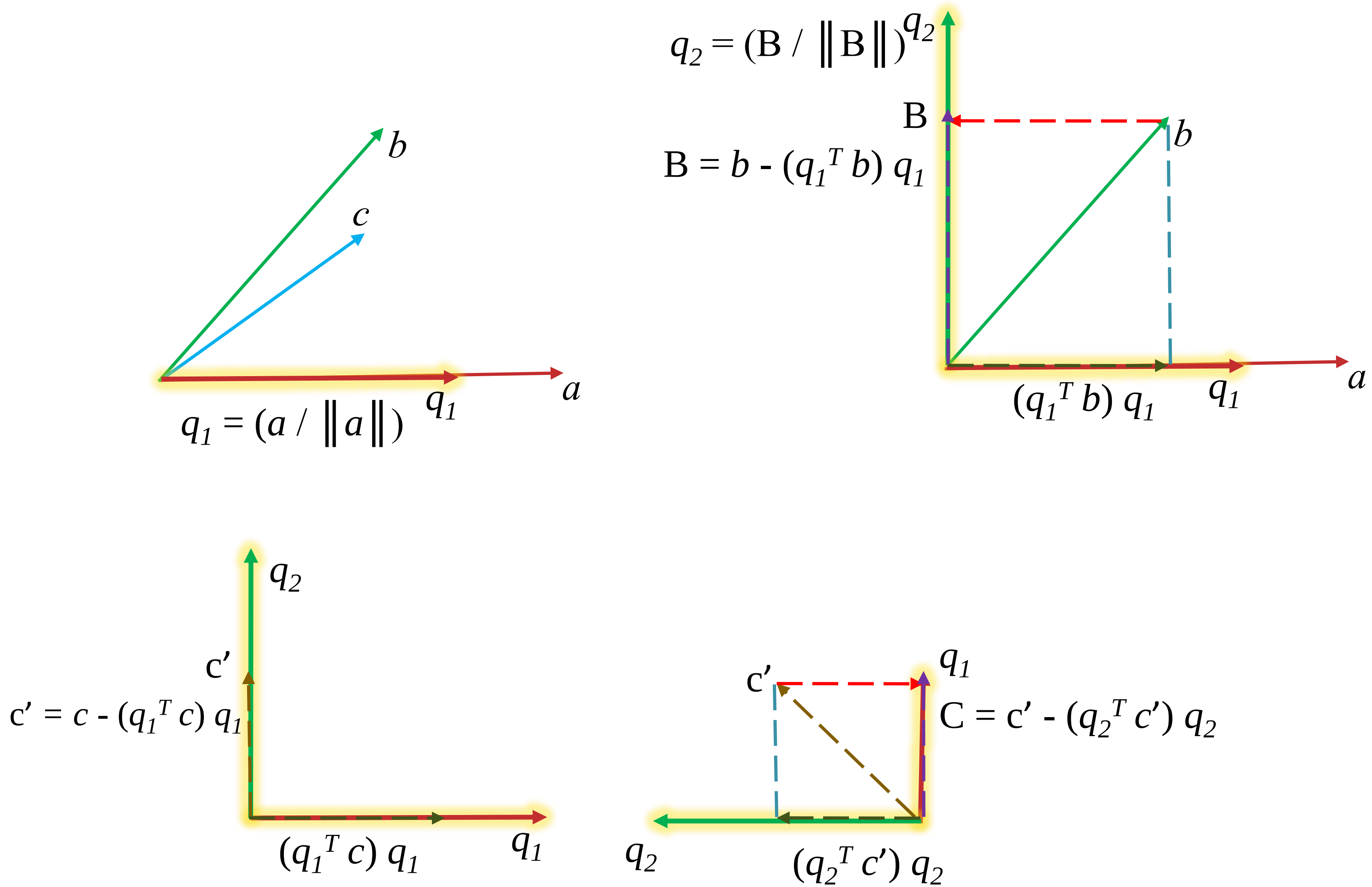

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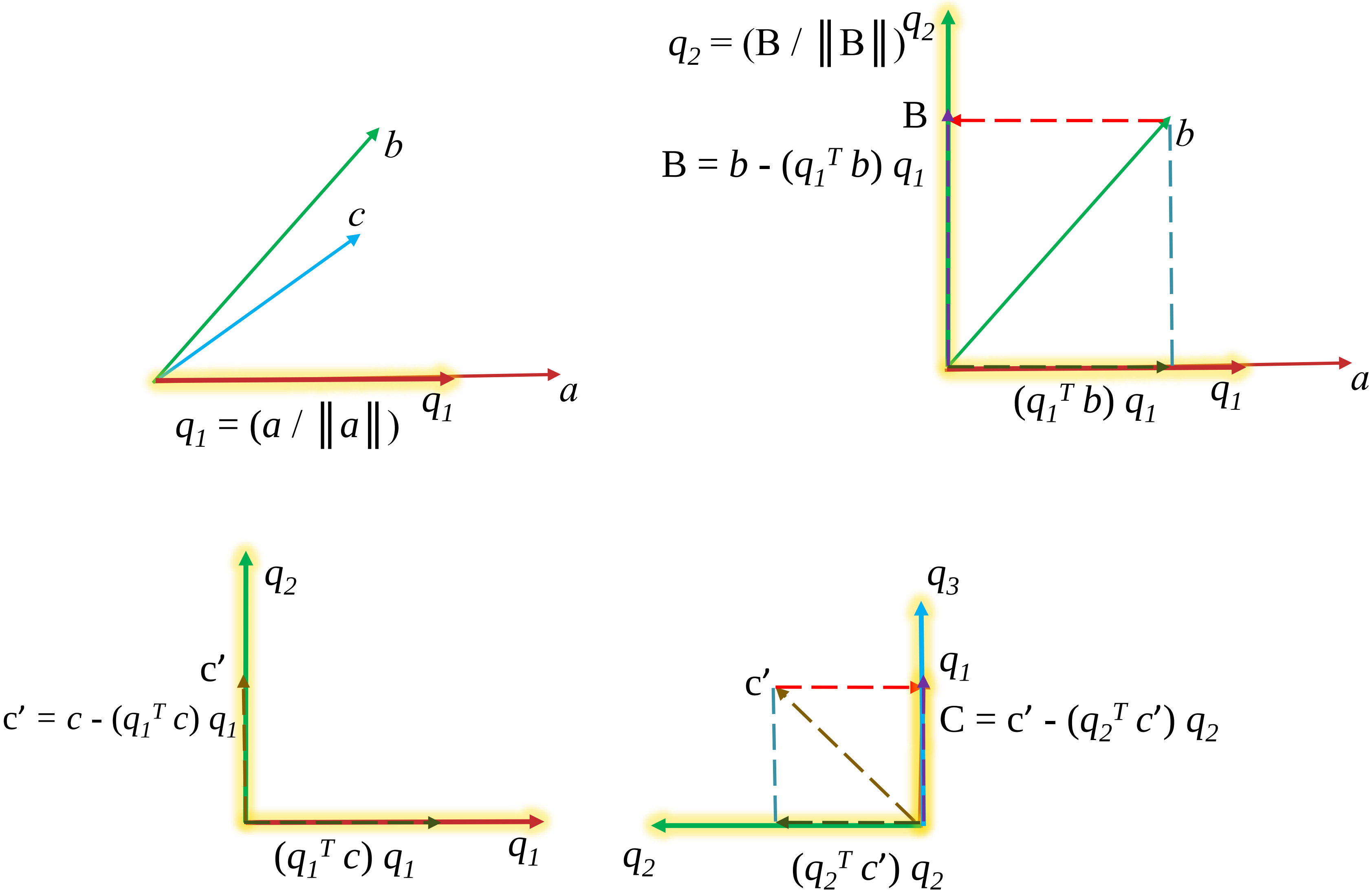

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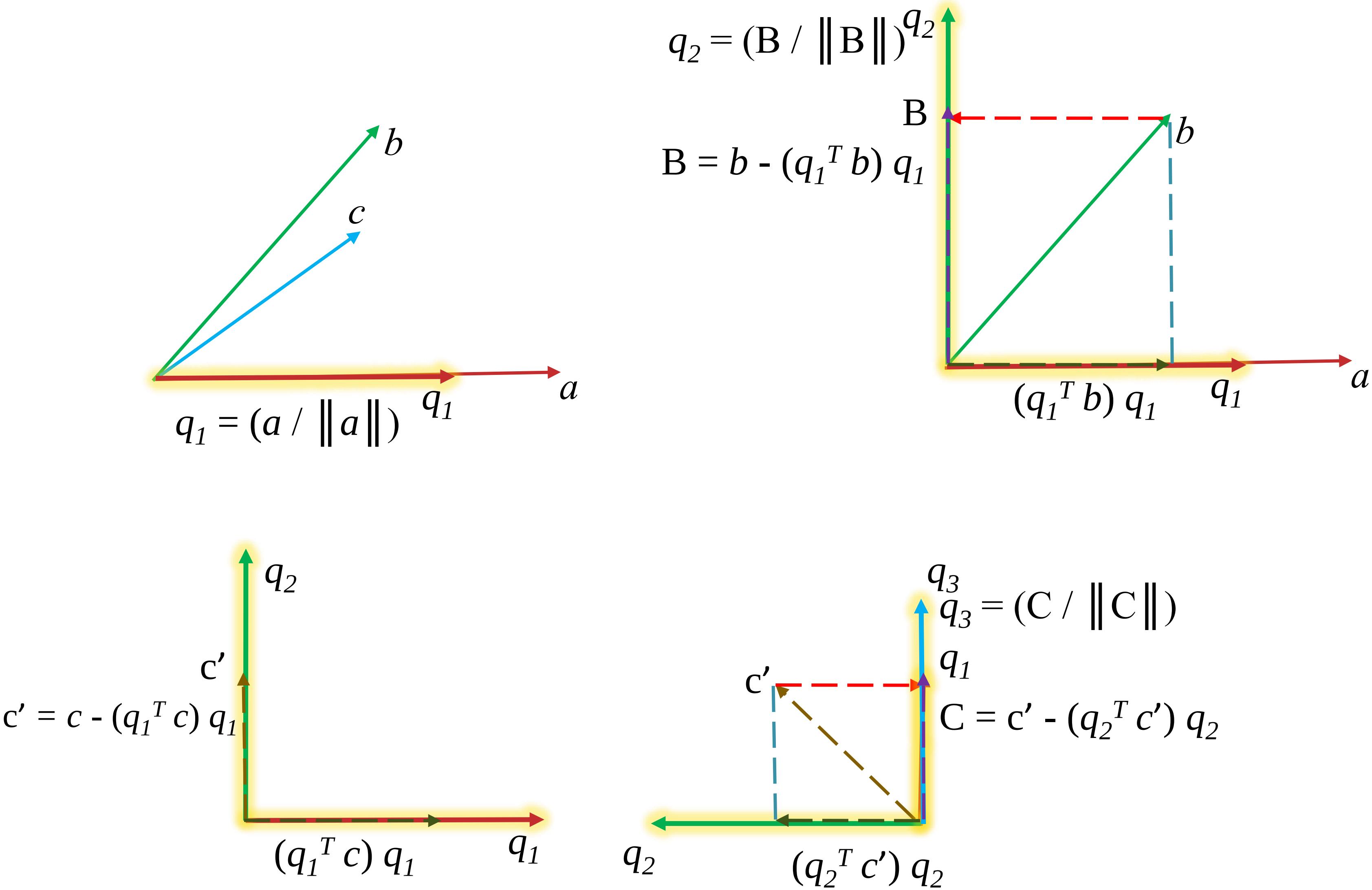

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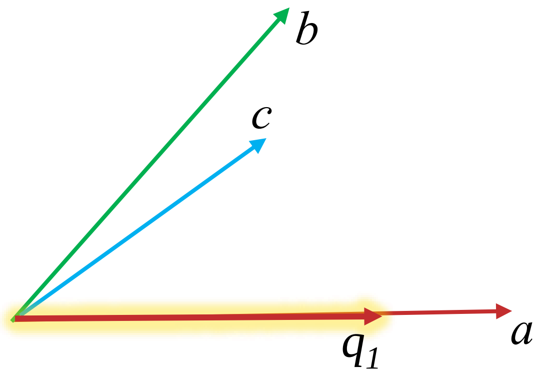
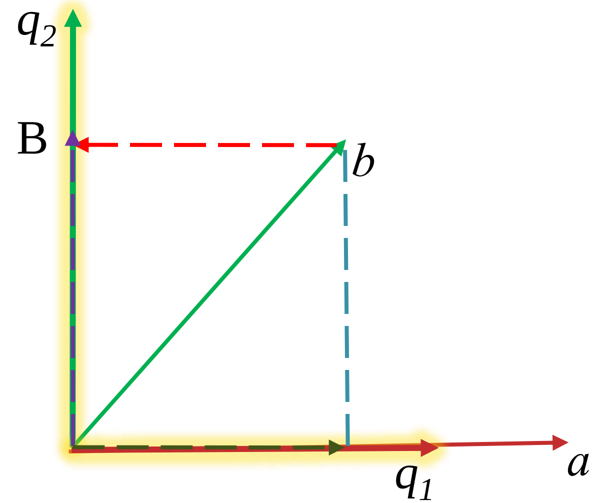
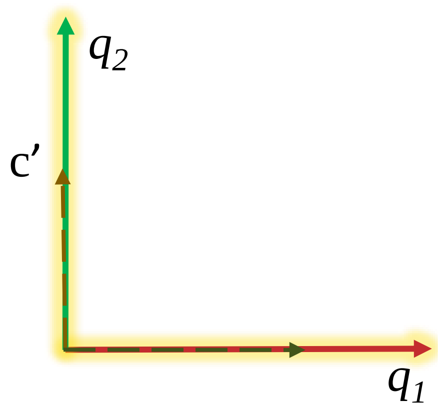
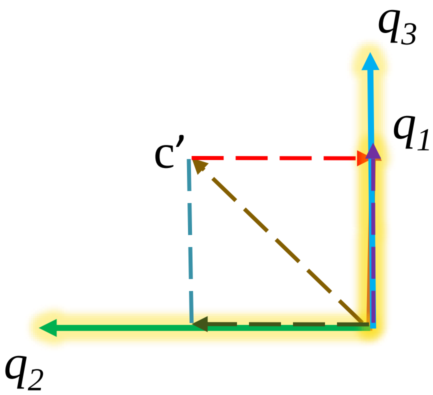
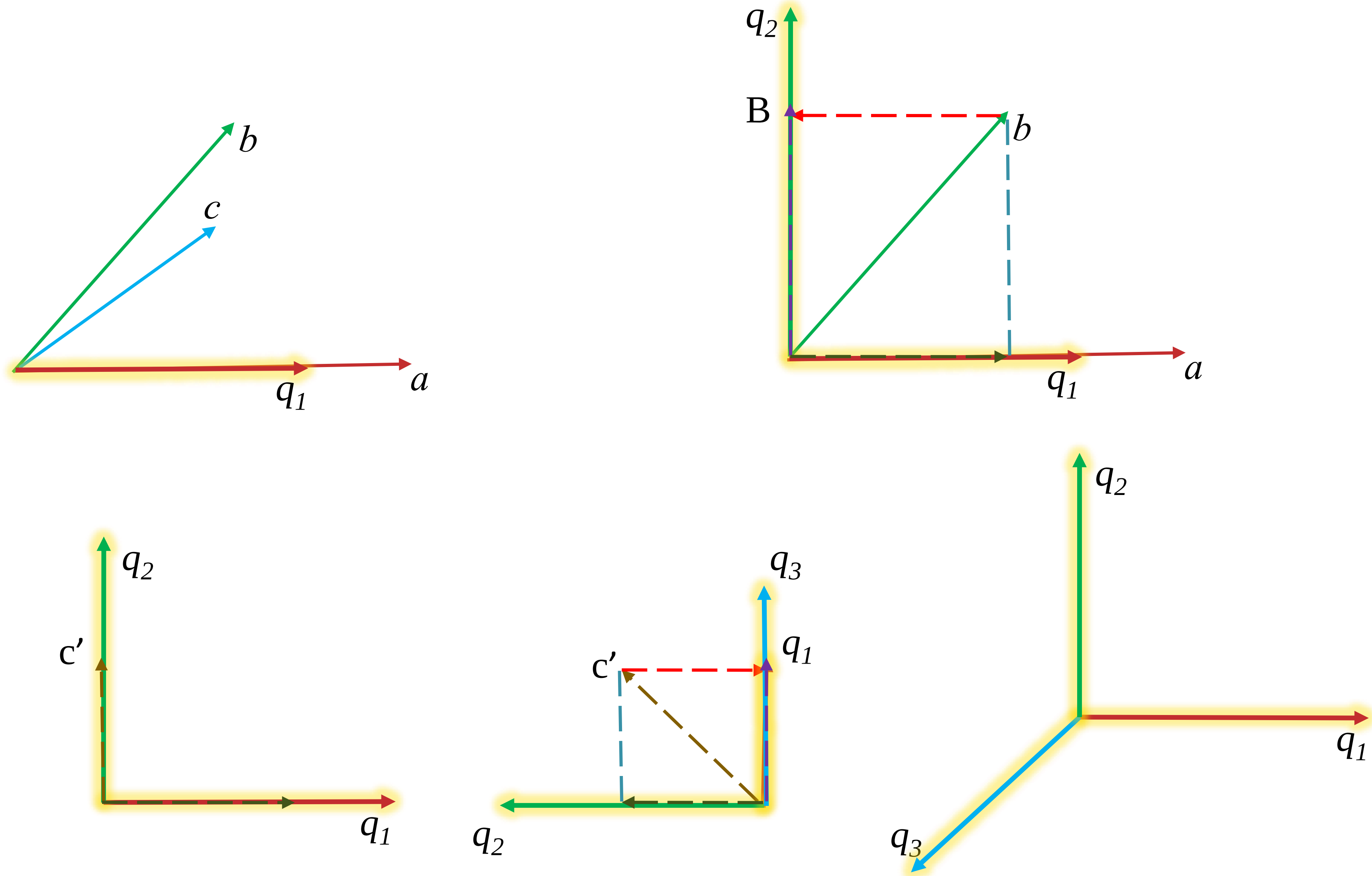








Gram–Schmidt Orthogonalization



Gram–Schmidt Orthogonalization

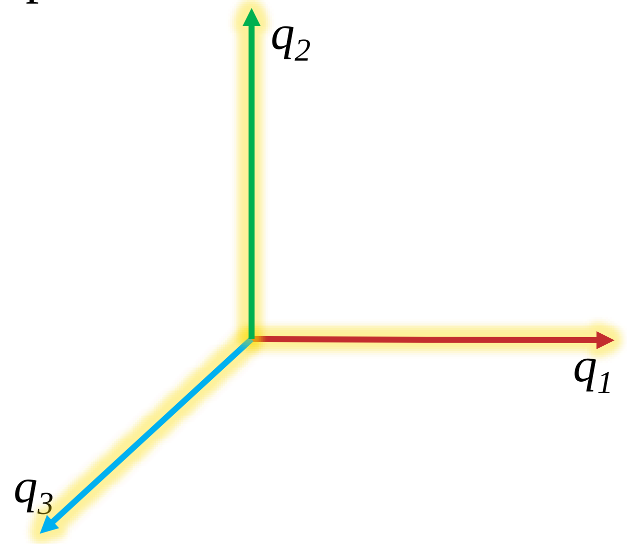
- Thus the three independent vectors *a*, *b*, *c* have been converted into three orthonormal vectors q_1, q_2, q_3 by Gram–Schmidt process

  $q_1 = (a \,/\, \|a\|)$

  $q_2 = (B \,/\, \|B\|)$ where $B = b - (q_1^T b)\, q_1$

  $q_3 = (C \,/\, \|C\|)$ where $C = c - (q_1^T c)\, q_1 - (q_2^T c)\, q_2$

- The whole idea of the Gram–Schmidt process is to subtract from every new vector its components in the directions that are already settled



Gram–Schmidt Orthogonalization

Example: Suppose the independent vectors are *a*, *b*, *c*:

$$a = \begin{bmatrix} 1 \\ 2 \\ 0 \end{bmatrix}, \; b = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}, \; c = \begin{bmatrix} 0 \\ 1 \\ 4 \end{bmatrix}$$

- To find q_1 divide the first vector a by its length:

$$q_1 = (a \,/\, \|a\|) \quad ; \qquad \|a\| = \sqrt{5}$$

$$\Rightarrow q_1 = \begin{bmatrix} 1/\sqrt{5} \\ 2/\sqrt{5} \\ 0 \end{bmatrix}$$

Gram–Schmidt Orthogonalization

- To find q_2, subtract from the second vector its component in the first direction: B = b - $(q_1^T b)q_1$

$$B = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} - \left(\begin{bmatrix} 1/\sqrt{5} & 2/\sqrt{5} & 0 \end{bmatrix} \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} \right) \begin{bmatrix} 1/\sqrt{5} \\ 2/\sqrt{5} \\ 0 \end{bmatrix}$$

$$= \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} - \left(2/\sqrt{5}\right) \begin{bmatrix} 1/\sqrt{5} \\ 2/\sqrt{5} \\ 0 \end{bmatrix} \Rightarrow \begin{bmatrix} -2/5 \\ 1/5 \\ 0 \end{bmatrix}$$

$$\|B\| = 1/\sqrt{5} \;\Rightarrow\; q_2 = \begin{bmatrix} -2/\sqrt{5} \\ 1/\sqrt{5} \\ 0 \end{bmatrix}$$

Gram–Schmidt Orthogonalization

- To find q_3 , subtract from c its components along q_1 and q_2 :

  $C = c - (q_1^T c)\, q_1 - (q_2^T c)\, q_2$

$$C = \begin{bmatrix} 0 \\ 1 \\ 4 \end{bmatrix} - \left(\begin{bmatrix} 1/\sqrt{5} & 2/\sqrt{5} & 0 \end{bmatrix} \begin{bmatrix} 0 \\ 1 \\ 4 \end{bmatrix} \right) \begin{bmatrix} 1/\sqrt{5} \\ 2/\sqrt{5} \\ 0 \end{bmatrix} - \left(\begin{bmatrix} -2/\sqrt{5} & 1/\sqrt{5} & 0 \end{bmatrix} \begin{bmatrix} 0 \\ 1 \\ 4 \end{bmatrix} \right) \begin{bmatrix} -2/\sqrt{5} \\ 1/\sqrt{5} \\ 0 \end{bmatrix}$$

$$= \begin{bmatrix} 0 \\ 1 \\ 4 \end{bmatrix} - \left(2/\sqrt{5}\right) \begin{bmatrix} 1/\sqrt{5} \\ 2/\sqrt{5} \\ 0 \end{bmatrix} - \left(1/\sqrt{5}\right) \begin{bmatrix} -2/\sqrt{5} \\ 1/\sqrt{5} \\ 0 \end{bmatrix} \Rightarrow \begin{bmatrix} 0 \\ 0 \\ 4 \end{bmatrix}$$

$$\|C\| = 4 \;\Rightarrow\; q_3 = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$$

Gram–Schmidt Orthogonalization

- Orthonormal basis:

$$Q = \begin{bmatrix} q_1 & q_2 & q_3 \end{bmatrix} = \begin{bmatrix} 1/\sqrt{5} & -2/\sqrt{5} & 0 \\ 2/\sqrt{5} & 1/\sqrt{5} & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

- So, we have constructed an orthonormal basis Q from a set of linearly independent vectors $\begin{bmatrix} 1 \\ 2 \\ 0 \end{bmatrix}$, $\begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}$ and $\begin{bmatrix} 0 \\ 1 \\ 4 \end{bmatrix}$

Matrix Multiplication

- How to multiply two matrices?
- Consider $A = \begin{bmatrix} 1 & -2 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$ and $B = \begin{bmatrix} 2 & 4 & -2 \\ 1 & -6 & 7 \\ 1 & 0 & 2 \end{bmatrix}$
- AB = ?
- $AB = \begin{bmatrix} 1 & -2 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 2 & 4 & -2 \\ 1 & -6 & 7 \\ 1 & 0 & 2 \end{bmatrix}$ (High–school method)

$$= \begin{bmatrix} 0 & 16 & -16 \\ 1 & -6 & 7 \\ 1 & 0 & 2 \end{bmatrix}$$

Matrix Multiplication

- We may also view the matrix multiplication by rows and columns

<u>Multiplication by columns</u>

$$AB = \begin{bmatrix} 1 & -2 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 2 & 4 & -2 \\ 1 & -6 & 7 \\ 1 & 0 & 2 \end{bmatrix}$$

$$= \left[\begin{pmatrix} 1 & -2 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} 2 \\ 1 \\ 1 \end{pmatrix} \quad \begin{pmatrix} 1 & -2 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} 4 \\ -6 \\ 0 \end{pmatrix} \quad \begin{pmatrix} 1 & -2 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} -2 \\ 7 \\ 2 \end{pmatrix} \right]$$

$$= \begin{bmatrix} 0 & 16 & -16 \\ 1 & -6 & 7 \\ 1 & 0 & 2 \end{bmatrix}$$

Matrix Multiplication

Multiplication by rows

$$AB=\begin{bmatrix}1 & -2 & 0\\0 & 1 & 0\\0 & 0 & 1\end{bmatrix}\begin{bmatrix}2 & 4 & -2\\1 & -6 & 7\\1 & 0 & 2\end{bmatrix}$$

$$=\begin{bmatrix}(1\ \ -2\ \ 0)\begin{pmatrix}2\\1\\1\end{pmatrix} & (1\ \ -2\ \ 0)\begin{pmatrix}4\\-6\\0\end{pmatrix} & (1\ \ -2\ \ 0)\begin{pmatrix}-2\\7\\2\end{pmatrix}\\ (0\ \ 1\ \ 0)\begin{pmatrix}2\\1\\1\end{pmatrix} & (0\ \ 1\ \ 0)\begin{pmatrix}4\\-6\\0\end{pmatrix} & (0\ \ 1\ \ 0)\begin{pmatrix}-2\\7\\2\end{pmatrix}\\ (0\ \ 0\ \ 1)\begin{pmatrix}2\\1\\1\end{pmatrix} & (0\ \ 0\ \ 1)\begin{pmatrix}4\\-6\\0\end{pmatrix} & (0\ \ 0\ \ 1)\begin{pmatrix}-2\\7\\2\end{pmatrix}\end{bmatrix}=\begin{bmatrix}0 & 16 & -16\\1 & -6 & 7\\1 & 0 & 2\end{bmatrix}$$

Eigenvalues and Eigenvectors

A : n×n · size $\underbrace{A x}_{n\times n}$ n×1

- Defined only for square matrices.
- A system of equations can be expressed as $\mathbf{A}x = \mathbf{b}$

  When a vector x is multiplied by **A**, it gives a new vector **b**

$$x \longrightarrow \boxed{\mathbf{A}} \longrightarrow \mathbf{A}x = \mathbf{b}$$

Ax, x · are (n×1) vector

- This new vector **b**, could be in any direction and it depends upon the vector x

- Which x will give a **b** that will be in the same direction as x ?

$$x \longrightarrow \boxed{\mathbf{A}} \longrightarrow \mathbf{A}x = \mathbf{b} = \lambda x$$

$$A: \begin{bmatrix} 1 & -2 \\ 1 & 4 \end{bmatrix} \qquad Ax$$

$$x = \begin{bmatrix} -2 \\ 1 \end{bmatrix} \qquad Ax = \begin{bmatrix} 1(-2)-2(1) \\ 1(-2)+4 \end{bmatrix} \qquad Ax = \begin{bmatrix} -4 \\ 2 \end{bmatrix}$$

$$\begin{bmatrix} 1 \\ 2 \end{bmatrix} \qquad \begin{bmatrix} 1-4 \\ 1+8 \end{bmatrix}^{3} \qquad \begin{bmatrix} -3 \\ 9 \end{bmatrix}$$

$$\begin{bmatrix} 1 \\ 1 \end{bmatrix} \qquad \begin{bmatrix} 1-2 \\ 1+4 \end{bmatrix} \qquad \begin{bmatrix} -1 \\ 5 \end{bmatrix}$$

$$\begin{bmatrix} -1 \\ 1 \end{bmatrix} \qquad \begin{bmatrix} -1-2=-3 \\ -1+4=3 \end{bmatrix} \qquad \begin{bmatrix} -3 \\ 3 \end{bmatrix}$$

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

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

$$A \begin{bmatrix} -2 \\ 1 \end{bmatrix} = \begin{bmatrix} -4 \\ 2 \end{bmatrix} = 2 \begin{bmatrix} -2 \\ 1 \end{bmatrix} \quad \underline{\lambda = 2}$$

$$A \begin{bmatrix} -1 \\ 1 \end{bmatrix} = \begin{bmatrix} -3 \\ 3 \end{bmatrix} = 3 \begin{bmatrix} -1 \\ 1 \end{bmatrix} \quad \underline{\lambda = 3}$$

Ax, x are multiples of each other.

These "x" are special & called eigenvector

$$Ax = \lambda x.$$

Eigenvalues and Eigenvectors

- Certain exceptional vectors ***x*** are in the same direction as **A*x*** and those are called as the ‘eigenvectors’

  i.e. it may be written as $\mathbf{A}\boldsymbol{x} = \lambda \boldsymbol{x}$. The number λ is an eigenvalue of **A**

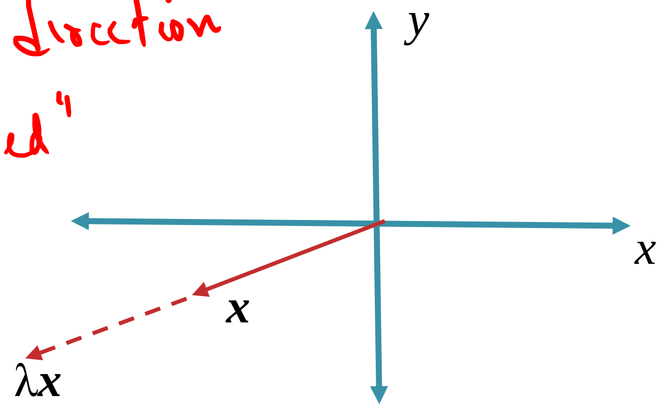
$|\lambda| > 1$ $|\lambda| < 1$

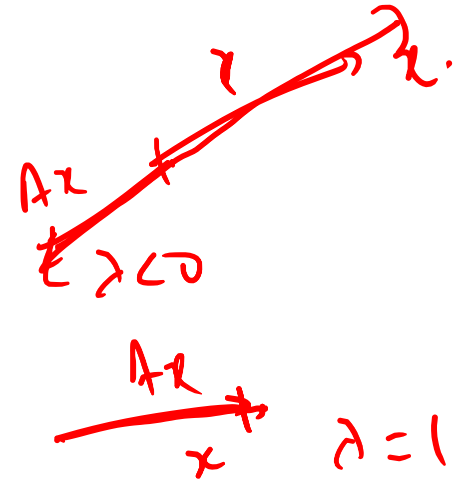
- The eigenvalue λ tells whether the special vector ***x*** is stretched or shrunk or reversed or left unchanged when it is multiplied by **A**

$\lambda = 1$

λ : (+) same direction

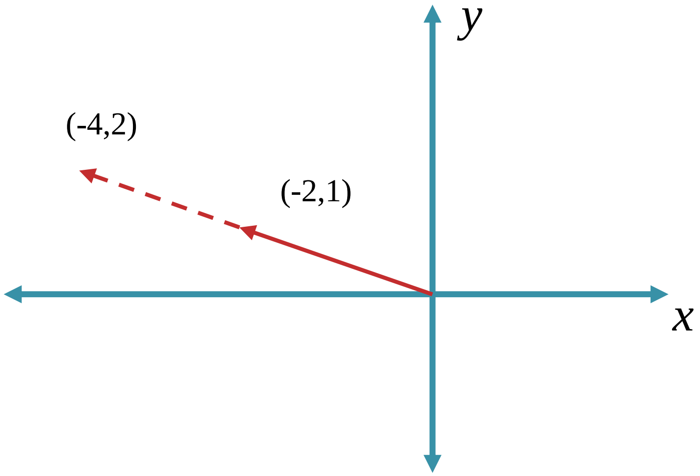
λ : - "flipped"





Eigenvalues and Eigenvectors

- $\mathbf{A}\boldsymbol{x} = \lambda\boldsymbol{x}$ where $\mathbf{A} = \begin{bmatrix} 1 & -2 \\ 1 & 4 \end{bmatrix}$ and $\boldsymbol{x}$ is a multiple of $\begin{bmatrix} -2 \\ 1 \end{bmatrix}$
- Take $\boldsymbol{x} = \begin{bmatrix} -2 \\ 1 \end{bmatrix}$; when **A** is multiplied with ***x***, we get $\mathbf{A}\boldsymbol{x} = \begin{bmatrix} -4 \\ 2 \end{bmatrix}$

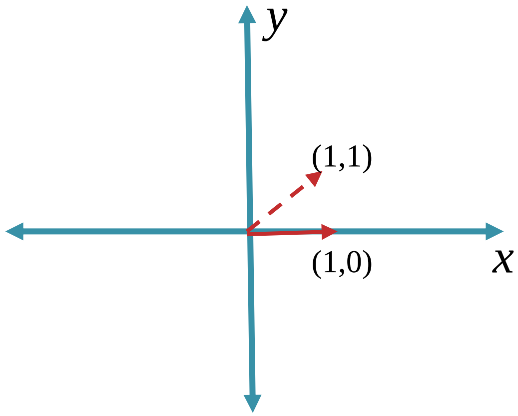


- The direction of the vector ***x*** hasn't changed even on multiplication with the matrix **A**. Such a vector ***x*** is called as the eigenvector of the matrix **A**

Eigenvalues and Eigenvectors

- Consider some vector $\begin{bmatrix} 1 \\ 0 \end{bmatrix}$. Let us see what happens when this vector is multiplied by **A**

$$\begin{bmatrix} 1 & -2 \\ 1 & 4 \end{bmatrix} \begin{bmatrix} 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \end{bmatrix} ; \boldsymbol{x} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \mathbf{A}\boldsymbol{x} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$



- Clearly, the vectors ***x*** and **A*x*** are not in the same direction. Hence, it is not an eigenvector

Eigenvalues and Eigenvectors

- The eigenvalue λ could be zero. Then $\mathbf{A}\boldsymbol{x} = 0\boldsymbol{x}$ means that this eigenvector $\boldsymbol{x}$ is in the null space

- If **A** is the identity matrix,

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

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \lambda \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \Rightarrow \lambda = 1$$

all vectors are eigenvectors of I and all eigenvalues are $\lambda = 1$

Eigenvalues and Eigenvectors

rank(A) = 2

Example–1:

- Consider a matrix A = $\begin{bmatrix} 1 & -2 \\ 1 & 4 \end{bmatrix}$

$\underset{n\times n}{A}\,\underset{n\times 1}{x} = \lambda \underset{n\times 1}{x}$.

∴ Rule out $x = 0$ (Not interesting)

$Ax - \lambda I x = 0$

$\underbrace{\underset{n\times n}{(A - \lambda \underset{n\times n}{I})}}_{n\times n} \cdot \underset{n\times 1}{x} = \underset{n\times 1}{0}$

- To find eigenvalue: det(A- λI) = 0

$$\text{det}(A- \lambda I) = \begin{vmatrix} 1-\lambda & -2 \\ 1 & 4-\lambda \end{vmatrix} = 0$$

$$(1- \lambda)(4- \lambda) + 2 = 0$$

size $(A - \lambda I)$: 2×2.

$\underset{n\times n.}{I}\, x = x$.

On solving, we get,

$\lambda = 3, 2$

I want $x \neq 0$

x is in nullspace of $(A - \lambda I)$

rank$(\underbrace{A - \lambda I}) < 2$.

columns of $(A - \lambda I)$ should be L.D ⇒ det$(A - \lambda I) = 0$

Null Space

$A_{m\times n}$

$Ax=0$ $x=?$ $n\times 1$

- The null space of a matrix **A** consists of all vectors ***x*** such that **A*x*** = **0**

size of columns of A: $(m\times 1)$

$Ax=0$
$m\times n$ $n\times 1$

- The set of solutions (***x***'s) in **A*x*** = **0** is itself a vector space which is called as a null space of **A**

$$N(\mathbf{A}) = \{\, x \in R^n \,/\, \mathbf{A}\boldsymbol{x} = \mathbf{0} \,\}$$

- If the column vectors are linearly independent, the null space contains only the zero vector $=$ $(x=0)$
- The null space of an invertible matrix contains only zero vector

A B
$m\times n$ $n\times p$

$(A-\lambda I)$

Eigenvalues and Eigenvectors

- Eigenvalues: $\lambda = 3, 2$

- When $\lambda = 3$,

$$A\text{-}3I = \begin{bmatrix} -2 & -2 \\ 1 & 1 \end{bmatrix} \xrightarrow[R_2 = R_2 + 2R_1]{R_1 \leftrightarrow R_2} \begin{bmatrix} 1 & 1 \\ 0 & 0 \end{bmatrix}$$

- So, we have the equation –

$$x_1 + x_2 = 0 \Rightarrow x_1 = -x_2$$

- Eigenvector x is any multiple of $\begin{bmatrix} -1 \\ 1 \end{bmatrix}$

$$\begin{bmatrix} 1 & -2 \\ 1 & 4 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 3x_1 \\ 3x_2 \end{bmatrix}$$

$$x_1 - 2x_2 = 3x_1$$

$$\boxed{x_1 = -x_2}$$

Eigenvalues and Eigenvectors

- when λ=2,

$$A-2I = \begin{bmatrix} -1 & -2 \\ 1 & 2 \end{bmatrix} \xrightarrow[R_2 = R_2 + R_1]{R_1 \leftrightarrow R_2} \begin{bmatrix} 1 & 2 \\ 0 & 0 \end{bmatrix}$$

$$Ax = 2x$$

$$\begin{bmatrix} 1 & -2 \\ 1 & 4 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 2x_1 \\ 2x_2 \end{bmatrix}$$

So, we have the equation –

$$x_1 - 2x_2 = 2x_1$$

$$x_1 + 2x_2 = 0 \Rightarrow x_1 = -2x_2$$

$$x_1 + 4x_2 = 2x_2$$

$$x_1 + 2x_2 = 0$$

- Eigenvector x is any multiple of $\begin{bmatrix} -2 \\ 1 \end{bmatrix} \alpha$

- So the eigenvalues are 3, 2 and corresponding eigenvectors are

$$a\begin{bmatrix} -1 \\ 1 \end{bmatrix} \text{ and } b\begin{bmatrix} -2 \\ 1 \end{bmatrix}, \; a,b \neq 0$$

Eigenvalues and Eigenvectors

Example–2:

- To find the eigenvalues and eigenvectors of the matrix

$$A = \begin{bmatrix} 1 & -3 & 3 \\ 3 & -5 & 3 \\ 6 & -6 & 4 \end{bmatrix}$$

- We first find the eigenvalue λ which satisfies the characteristic equation of the matrix A,

$$\det(A - \lambda I) = 0$$

$$A - \lambda I = \begin{bmatrix} 1 & -3 & 3 \\ 3 & -5 & 3 \\ 6 & -6 & 4 \end{bmatrix} - \begin{bmatrix} \lambda & 0 & 0 \\ 0 & \lambda & 0 \\ 0 & 0 & \lambda \end{bmatrix} = \begin{bmatrix} 1-\lambda & -3 & 3 \\ 3 & -5-\lambda & 3 \\ 6 & -6 & 4-\lambda \end{bmatrix}$$

Eigenvalues and Eigenvectors

- Let us calculate det (A- λI) now

$$\det(A-\lambda I) = (1-\lambda)\begin{vmatrix} -5-\lambda & 3 \\ -6 & 4-\lambda \end{vmatrix} - (-3)\begin{vmatrix} 3 & 3 \\ 6 & 4-\lambda \end{vmatrix} + 3\begin{vmatrix} 3 & -5-\lambda \\ 6 & -6 \end{vmatrix}$$

$$\det(A-\lambda I) = [\,(1-\lambda)(-2+\lambda+\lambda^2)\,] + [\,3(-6-3\lambda)] + [\,3(12+6\lambda)\,]$$

$$= 16 + 12\lambda - \lambda^3$$

- Therefore, det (A- λI) = $-\lambda^3+12\lambda+16 = 0$

Eigenvalues and Eigenvectors

- To solve: $-\lambda^3+12\lambda+16 = 0$

  $-\lambda^3 + 12\lambda + 16 = (\lambda - 4)(\lambda^2 + 4\lambda + 4)$

- On solving $\lambda^2 + 4\lambda + 4$, we get $\lambda = -2$ (repeated root)
- Hence, the eigenvalues of A are $\boxed{\lambda = 4 , -2 , -2}$
- Once the eigenvalues of a matrix have been found, we can find the eigenvectors by Gaussian Elimination

Eigenvalues and Eigenvectors

- For each eigenvalue λ, we have

$$(A - \lambda I)\, x = 0$$

  where x is the eigenvector associated with eigenvalue λ

- Case1: when λ=4,

$$A - \lambda I = \begin{bmatrix} 1-\lambda & -3 & 3 \\ 3 & -5-\lambda & 3 \\ 6 & -6 & 4-\lambda \end{bmatrix}$$

$$A - 4I = \begin{bmatrix} -3 & -3 & 3 \\ 3 & -9 & 3 \\ 6 & -6 & 0 \end{bmatrix}$$

- Augmented matrix: $\left[\begin{array}{ccc|c} -3 & -3 & 3 & 0 \\ 3 & -9 & 3 & 0 \\ 6 & -6 & 0 & 0 \end{array}\right]$

Eigenvalues and Eigenvectors

$$\begin{bmatrix} -3 & -3 & 3 & 0 \\ 3 & -9 & 3 & 0 \\ 6 & -6 & 0 & 0 \end{bmatrix} \xrightarrow[R_1 = R_1 \times (-1/3)]{} \left[\begin{array}{ccc|c} 1 & 1 & -1 & 0 \\ 3 & -9 & 3 & 0 \\ 6 & -6 & 0 & 0 \end{array}\right]$$

$$\xrightarrow[\substack{R_2 = R_2 - (3R_1) \\ R_3 = R_3 - (6R_1)}]{} \left[\begin{array}{ccc|c} 1 & 1 & -1 & 0 \\ 0 & -12 & 6 & 0 \\ 0 & -12 & 6 & 0 \end{array}\right]$$

$$\xrightarrow[R_2 = R_2\,(-1/12)]{} \left[\begin{array}{ccc|c} 1 & 1 & -1 & 0 \\ 0 & 1 & -1/2 & 0 \\ 0 & -12 & 6 & 0 \end{array}\right]$$

$$\xrightarrow[R_3 = R_3 + 12R_2]{} \left[\begin{array}{ccc|c} 1 & 1 & -1 & 0 \\ 0 & 1 & -1/2 & 0 \\ 0 & 0 & 0 & 0 \end{array}\right]$$

$$\xrightarrow[R_1 = R_1 - R_2]{} \left[\begin{array}{ccc|c} 1 & 0 & -1/2 & 0 \\ 0 & 1 & -1/2 & 0 \\ 0 & 0 & 0 & 0 \end{array}\right]$$

Eigenvalues and Eigenvectors

- So, we get the equations –

$$x_1 - ½\, x_3 = 0$$

$$x_2 - ½\, x_3 = 0$$

- So the eigenvector *x* is given by:

$$x = \begin{bmatrix} x_1 = x_3/2 \\ x_2 = x_3/2 \\ x_3 \end{bmatrix} = x_3 \begin{bmatrix} 1/2 \\ 1/2 \\ 1 \end{bmatrix}$$

Eigenvalues and Eigenvectors

- Case2: when $\lambda = -2$

$$A - \lambda I = \begin{bmatrix} 1-\lambda & -3 & 3 \\ 3 & -5-\lambda & 3 \\ 6 & -6 & 4-\lambda \end{bmatrix}$$

$$A + 2I = \begin{bmatrix} 3 & -3 & 3 \\ 3 & -3 & 3 \\ 6 & -6 & 6 \end{bmatrix}$$

- Augmented matrix:

$$\left[\begin{array}{ccc|c} 3 & -3 & 3 & 0 \\ 3 & -3 & 3 & 0 \\ 6 & -6 & 6 & 0 \end{array}\right]$$

Eigenvalues and Eigenvectors

$$\left[\begin{array}{ccc|c} 3 & -3 & 3 & 0 \\ 3 & -3 & 3 & 0 \\ 6 & -6 & 6 & 0 \end{array}\right] \xrightarrow{R_1 = R_1 / 3} \left[\begin{array}{ccc|c} 1 & -1 & 1 & 0 \\ 3 & -3 & 3 & 0 \\ 6 & -6 & 6 & 0 \end{array}\right]$$

$$\xrightarrow{\substack{R_2 = R_2 - 3R_1 \\ R_3 = R_3 - 6R_1}} \left[\begin{array}{ccc|c} 1 & -1 & 1 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{array}\right]$$

So, we get the equations –

$$x_1 - x_2 + x_3 = 0$$

So the eigenvectors x associated with the eigenvalue $\lambda = -2$ are given by:

$$x = \begin{bmatrix} x_2 - x_3 \\ x_2 \\ x_3 \end{bmatrix} = x_3 \begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix} + x_2 \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}$$

Eigenvalues and Eigenvectors

- So the eigenvalues are λ = 4, -2, -2 and the eigenvectors are any multiple of

$$\begin{bmatrix} 1/2 \\ 1/2 \\ 1 \end{bmatrix}, \begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix} \text{ and } \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}$$

Eigenvalue Decomposition

- Let **A** be an $n \times n$ matrix with n linearly independent eigenvectors then **A** can be factored into

$$\boxed{\mathbf{A} = \mathbf{S}\boldsymbol{\Lambda}\mathbf{S}^{-1}}$$

- The columns of **S** are eigenvectors of **A**
- The diagonal matrix **Λ** has eigenvalues of **A**

- With **A**, **S** and $\mathbf{S}^{-1}$ available, we may find **Λ**

  $\boldsymbol{\Lambda} = \mathbf{S}^{-1}\mathbf{A}\,\mathbf{S}$

Eigenvalue Decomposition

Example:

Consider a matrix $A = \begin{bmatrix} 1 & -1 \\ -2 & 0 \end{bmatrix}$

- To find eigenvalue: $\det(A - \lambda I) = 0$

$$\begin{vmatrix} 1-\lambda & -1 \\ -2 & -\lambda \end{vmatrix} = 0 \quad \Rightarrow \lambda^2 - \lambda - 2$$

$$\Rightarrow \lambda = 2, -1$$

- Eigenvalues: $\lambda = 2, -1$

Eigenvalue Decomposition

- To find eigenvector: (A - λI) x = 0

- when λ = 2,

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

$$(A - \lambda I)x = 0 \Rightarrow \begin{bmatrix} -1 & -1 \\ -2 & -2 \end{bmatrix} x = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$x = \begin{bmatrix} -1 \\ 1 \end{bmatrix}$$

- when λ = -1,

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

$$(A - \lambda I)x = 0 \Rightarrow \begin{bmatrix} 2 & -1 \\ -2 & 1 \end{bmatrix} x = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$x = \begin{bmatrix} 1 \\ 2 \end{bmatrix}$$

- Eigenvectors: $\begin{bmatrix} -1 \\ 1 \end{bmatrix}$ and $\begin{bmatrix} 1 \\ 2 \end{bmatrix}$

Eigenvalue Decomposition

- λ = 2, -1 and corresponding eigenvectors are $\begin{bmatrix} -1 \\ 1 \end{bmatrix}$ and $\begin{bmatrix} 1 \\ 2 \end{bmatrix}$

- The matrix S contains eigenvectors of A in its columns –

$$S = \begin{bmatrix} -1 & 1 \\ 1 & 2 \end{bmatrix} \text{ and } S^{-1} = \begin{bmatrix} -2/3 & 1/3 \\ 1/3 & 1/3 \end{bmatrix}$$

- The diagonal matrix Λ contains eigenvalues of A –

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

- $$A = \underbrace{\begin{bmatrix} -1 & 1 \\ 1 & 2 \end{bmatrix}}_{\mathbf{S}} \underbrace{\begin{bmatrix} 2 & 0 \\ 0 & -1 \end{bmatrix}}_{\mathbf{\Lambda}} \underbrace{\begin{bmatrix} -2/3 & 1/3 \\ 1/3 & 1/3 \end{bmatrix}}_{\mathbf{S^{-1}}} = \begin{bmatrix} 1 & -1 \\ -2 & 0 \end{bmatrix}$$

Symmetric matrix

- Symmetric matrix is a square matrix which is equal to its transpose

Example:

$$A = \begin{bmatrix} 4 & 8 & 3 \\ 8 & 5 & 7 \\ 3 & 7 & 1 \end{bmatrix} \qquad A^T = \begin{bmatrix} 4 & 8 & 3 \\ 8 & 5 & 7 \\ 3 & 7 & 1 \end{bmatrix}$$

- Symmetric matrices need not be invertible. A matrix with zero entries is symmetric but not invertible

Eigenvalue Decomposition

- A real symmetric matrix can be factored into

$$\boxed{\mathbf{A} = \mathbf{Q}\mathbf{\Lambda}\mathbf{Q}^{\mathbf{T}} = \text{(orthogonal) (diagonal) (orthogonal)}}$$

- A symmetric matrix has real eigenvalues

- The eigenvectors of a real symmetric matrix can be chosen to be orthogonal to one another

Eigenvalue Decomposition

Example:

For a matrix A = $\begin{bmatrix} 3 & 2 \\ 2 & 3 \end{bmatrix}$ To factorize A as $\mathbf{A} = \mathbf{Q\Lambda Q^T}$

- A is symmetric

- To find eigenvalue: det(A - λI) = 0

$$\begin{vmatrix} 3-\lambda & 2 \\ 2 & 3-\lambda \end{vmatrix} = 0 \quad \Rightarrow \lambda^2 - 6\lambda + 5 = 0 \quad \Rightarrow \lambda = 5, 1$$

- Eigenvalues: λ = 5, 1

Eigenvalue Decomposition

- To find eigenvector: (A - λI) x = 0

- when λ = 5,

$$A-\lambda I=\begin{bmatrix}-2 & 2\\ 2 & -2\end{bmatrix}$$

$$(A-\lambda I)x=0 \Rightarrow \begin{bmatrix}-2 & 2\\ 2 & -2\end{bmatrix}x=\begin{bmatrix}0\\ 0\end{bmatrix}$$

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

- when λ = 1,

$$A-\lambda I=\begin{bmatrix}2 & 2\\ 2 & 2\end{bmatrix}$$

$$(A-\lambda I)x=0 \Rightarrow \begin{bmatrix}2 & 2\\ 2 & 2\end{bmatrix}x=\begin{bmatrix}0\\ 0\end{bmatrix}$$

$$x=\begin{bmatrix}1\\ -1\end{bmatrix}$$

e.v are orthogonal

- Eigenvectors: $\begin{bmatrix}1\\ 1\end{bmatrix}$ and $\begin{bmatrix}1\\ -1\end{bmatrix}$

Eigenvalue Decomposition

- For the matrix A = $\begin{bmatrix} 3 & 2 \\ 2 & 3 \end{bmatrix}$, we have eigenvalues ($\lambda$) = 5, 1 and eigenvectors $\begin{bmatrix} 1 \\ 1 \end{bmatrix}$ and $\begin{bmatrix} 1 \\ -1 \end{bmatrix}$

- We may factorize the matrix A into $\mathbf{Q\Lambda Q^T}$ as –

$$A = \begin{bmatrix} 3 & 2 \\ 2 & 3 \end{bmatrix} = \underbrace{\begin{bmatrix} 1/\sqrt{2} & 1/\sqrt{2} \\ 1/\sqrt{2} & -1/\sqrt{2} \end{bmatrix}}_{\mathbf{Q}} \underbrace{\begin{bmatrix} 5 & 0 \\ 0 & 1 \end{bmatrix}}_{\mathbf{\Lambda}} \underbrace{\begin{bmatrix} 1/\sqrt{2} & 1/\sqrt{2} \\ 1/\sqrt{2} & -1/\sqrt{2} \end{bmatrix}}_{\mathbf{Q^T}}$$

- **Q** has orthonormal vectors in its columns and **Λ** has eigenvalues in its columns

A: 3x3 symmetric matrix

$$\left[\begin{array}{ccc} A & A & A \\ & A & A \\ & & A \end{array}\right] \quad (6) \text{ unique \#s}$$

$\lambda = 2, 0, 0.$

$v_1 \quad v_2 \quad v_3$ (orthonormal) $v_1^T v_2 = 0 = v_1^T v_3 = v_2^T v_3$

$v_1^T v_1 = 1 = v_2^T v_2 = v_3^T v_3.$

$$\underset{3\times3}{A} = \overbrace{\begin{bmatrix} \underset{3\times1}{v_1} & \underset{3\times1}{v_2} & \underset{3\times1}{v_3} \end{bmatrix}}^{3\times3} \underbrace{\begin{bmatrix} 2 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}}_{3\times3} \underbrace{\begin{bmatrix} v_1^T \\ v_2^T \\ v_3^T \end{bmatrix}}_{3\times3} \begin{array}{l} 1\times3 \\ 1\times3 \\ 1\times3 \end{array}$$

$$\begin{bmatrix} v_1 & v_2 & v_3 \end{bmatrix} \begin{bmatrix} 2v_1^T + 0 + 0 \\ 0 + 0 + 0 \\ 0 + 0 + 0 \end{bmatrix} =$$

$A = [v_1 \quad v_2 \quad v_3]$ $\begin{bmatrix} 2v_1^T \\ 0 \\ 0 \end{bmatrix}$

3×3

$v_1^T v_1 = 1$

A: 6 #s

$\pm\ 2 v_1^T v_1$ (number)

$= 2 v_1 v_1^T + \cancel{0 v_2 + 0 v_3}$

$= 2 v_1 v_1^T$.

How many numbers to store?

$3 + 1$

$v_1 \quad \lambda = 2$

A: 100 × 100 How many numbers? $\sim \frac{10000}{2}$.

~ 5000.

However if only $\lambda_1 \neq 0$ $\lambda_2 \neq 0$.

$A = \lambda_1 v_1 v_1^T + \lambda_2 v_2 v_2^T + (0) + \ldots$

storage required: v_1 100 λ_1

v_2 100 λ_2.

202 numbers only required as opposed to ~5000

However if $\lambda_1 \lambda_2 \ldots \lambda_{10}$ are non-zero.

storage = (100 × 10) evectors + 10 evalues. } = 1010

Singular Value Decomposition

- SVD – factorization of 1 matrix (any matrix) into 3 matrices

- Any $m \times n$ matrix **A** can be factored into

$$\boxed{\mathbf{A} = \mathbf{U\Sigma V^T} = \text{(orthogonal) (diagonal) (orthogonal)}}$$

- The columns of **U** ($m \times m$) are eigenvectors of $\mathbf{AA^T}$
- The columns of **V** ($n \times n$) are eigenvectors of $\mathbf{A^TA}$

- The diagonal matrix $\mathbf{\Sigma}$ has square roots of eigenvalues from $\mathbf{A^TA}$ and not from **A**
- Those positive entries will be $\sigma_1, \ldots, \sigma_r$. They are the **singular values** of **A** and they fill the first r places in the main diagonal of $\mathbf{\Sigma}$ – when **A** has rank r. The rest of $\mathbf{\Sigma}$ is zero

Singular Value Decomposition

Example:

For a matrix $A = \begin{bmatrix} 1 & 0 & 1 \\ 0 & 2 & 0 \end{bmatrix}$ To factorize A as $\mathbf{A} = \mathbf{U}\boldsymbol{\Sigma}\mathbf{V}^{\mathbf{T}}$

- To find **U**:

$$AA^T = \begin{bmatrix} 1 & 0 & 1 \\ 0 & 2 & 0 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 2 \\ 1 & 0 \end{bmatrix} = \begin{bmatrix} 2 & 0 \\ 0 & 4 \end{bmatrix} \quad ; \text{ eigenvalues} = 4, 2$$

Eigenvectors of $AA^T = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$ for the eigenvalue 4 and $\begin{bmatrix} 1 \\ 0 \end{bmatrix}$ for the eigenvalue 2

- To make the vectors orthonormal, divide them by its length, which will

give $\begin{bmatrix} 0 \\ 1 \end{bmatrix}$ and $\begin{bmatrix} 1 \\ 0 \end{bmatrix}$; $\mathbf{U} = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$

Singular Value Decomposition

- To find **V**:

$$A^TA = \begin{bmatrix} 1 & 0 \\ 0 & 2 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} 1 & 0 & 1 \\ 0 & 2 & 0 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 1 \\ 0 & 4 & 0 \\ 1 & 0 & 1 \end{bmatrix} \quad ; \text{ eigenvalues} = 4, 2, 0$$

Eigenvectors of $A^TA = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}$ for the eigenvalue 4 , $\begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix}$ for the eigenvalue 2

and $\begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix}$ for the eigenvalue 0

- To make the vectors orthonormal, divide them by its length, which will

give $\begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}$, $\begin{bmatrix} 1/\sqrt{2} \\ 0 \\ 1/\sqrt{2} \end{bmatrix}$ and $\begin{bmatrix} -1/\sqrt{2} \\ 0 \\ 1/\sqrt{2} \end{bmatrix}$; $\mathbf{V} = \begin{bmatrix} 0 & 1/\sqrt{2} & -1/\sqrt{2} \\ 1 & 0 & 0 \\ 0 & 1/\sqrt{2} & 1/\sqrt{2} \end{bmatrix}$

Singular Value Decomposition

- The diagonal matrix **Σ** takes the square root of the nonzero eigenvalues

$$\boldsymbol{\Sigma} = \begin{bmatrix} \sqrt{4} & 0 & 0 \\ 0 & \sqrt{2} & 0 \end{bmatrix}$$

- So, we have,

$$A = \underbrace{\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}}_{\mathbf{U}} \underbrace{\begin{bmatrix} \sqrt{4} & 0 & 0 \\ 0 & \sqrt{2} & 0 \end{bmatrix}}_{\boldsymbol{\Sigma}} \underbrace{\begin{bmatrix} 0 & 1 & 0 \\ 1/\sqrt{2} & 0 & 1/\sqrt{2} \\ -1/\sqrt{2} & 0 & 1/\sqrt{2} \end{bmatrix}}_{\mathbf{V}^{\mathbf{T}}} = \begin{bmatrix} 1 & 0 & 1 \\ 0 & 2 & 0 \end{bmatrix}$$

Singular Value Decomposition

Example:

For a matrix $A = \begin{bmatrix} 1 & 1 \\ 0 & 1 \\ 1 & 0 \end{bmatrix}$ To factorize A as $\mathbf{A} = \mathbf{U\Sigma V^T}$

- To find **U**:

$$AA^T = \begin{bmatrix} 1 & 1 \\ 0 & 1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} 1 & 0 & 1 \\ 1 & 1 & 0 \end{bmatrix} = \begin{bmatrix} 2 & 1 & 1 \\ 1 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix}; \text{ eigenvalues} = 3, 1, 0$$

Eigenvectors of $AA^T = \begin{bmatrix} 2 \\ 1 \\ 1 \end{bmatrix}$ for the eigenvalue 3 , $\begin{bmatrix} 0 \\ 1 \\ -1 \end{bmatrix}$ for the eigenvalue 1

and $\begin{bmatrix} -1 \\ 1 \\ 1 \end{bmatrix}$ for the eigenvalue 0

Singular Value Decomposition

- To make the vectors orthonormal, divide them by its length, which will give $\begin{bmatrix} \sqrt{2/3} \\ 1/\sqrt{6} \\ 1/\sqrt{6} \end{bmatrix}$, $\begin{bmatrix} 0 \\ 1/\sqrt{2} \\ -1/\sqrt{2} \end{bmatrix}$ and $\begin{bmatrix} -1/\sqrt{3} \\ 1/\sqrt{3} \\ 1/\sqrt{3} \end{bmatrix}$

$$\Rightarrow \mathbf{U} = \begin{bmatrix} \sqrt{2/3} & 0 & -1/\sqrt{3} \\ 1/\sqrt{6} & 1/\sqrt{2} & 1/\sqrt{3} \\ 1/\sqrt{6} & -1/\sqrt{2} & 1/\sqrt{3} \end{bmatrix}$$

Singular Value Decomposition

- To find **V**:

$$A^TA = \begin{bmatrix} 1 & 0 & 1 \\ 1 & 1 & 0 \end{bmatrix} \begin{bmatrix} 1 & 1 \\ 0 & 1 \\ 1 & 0 \end{bmatrix} = \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix} \quad ; \text{ eigenvalues} = 3, 1$$

Eigenvectors of A^TA = $\begin{bmatrix} 1 \\ 1 \end{bmatrix}$ for the eigenvalue 3 and $\begin{bmatrix} -1 \\ 1 \end{bmatrix}$ for the eigenvalue 1

- To make the vectors orthonormal, divide them by its length, which will give $\begin{bmatrix} 1/\sqrt{2} \\ 1/\sqrt{2} \end{bmatrix}$ and $\begin{bmatrix} -1/\sqrt{2} \\ 1/\sqrt{2} \end{bmatrix}$; $\mathbf{V} = \begin{bmatrix} 1/\sqrt{2} & -1/\sqrt{2} \\ 1/\sqrt{2} & 1/\sqrt{2} \end{bmatrix}$

Singular Value Decomposition

- The diagonal matrix $\mathbf{\Sigma}$ takes the square root of the nonzero eigenvalues

$$\mathbf{\Sigma} = \begin{bmatrix} \sqrt{3} & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix}$$

- So, we have,

$$A = \underbrace{\begin{bmatrix} \sqrt{2/3} & 0 & -1/\sqrt{3} \\ 1/\sqrt{6} & 1/\sqrt{2} & 1/\sqrt{3} \\ 1/\sqrt{6} & -1/\sqrt{2} & 1/\sqrt{3} \end{bmatrix}}_{\mathbf{U}} \underbrace{\begin{bmatrix} \sqrt{3} & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix}}_{\mathbf{\Sigma}} \underbrace{\begin{bmatrix} 1/\sqrt{2} & 1/\sqrt{2} \\ -1/\sqrt{2} & 1/\sqrt{2} \end{bmatrix}}_{\mathbf{V}^{\mathbf{T}}} = \begin{bmatrix} 1 & 1 \\ 0 & 1 \\ 1 & 0 \end{bmatrix}$$

Complex Numbers?

- Till now we have dealt only with real numbers. What about the complex numbers?

- In real life problems, we mostly deal only with real values and hence we have ignored the complex numbers

Thank you