

ECSE 343 Numerical Methods in Engineering

Roni Khazaka

Dept. of Electrical and Computer Engineering

McGill University



McGill



Vector Space

Definition: A Vector Space P is a set containing vectors $v \in P$ for which we define the two operations: **1) Scalar multiplication** and **2) Addition**.

- Scalar Multiplication: $av \rightarrow u$

$$\left. \begin{array}{l} a \in \mathbb{R} \\ v \in V \end{array} \right\} u \in V$$

- Addition: $u + v \rightarrow w$

$$\left. \begin{array}{l} v \in V \\ u \in V \end{array} \right\} w \in V$$





Axioms (Addition)

- Axiom #1: Associativity

$$\mathbf{u} + (\mathbf{v} + \mathbf{w}) = (\mathbf{u} + \mathbf{v}) + \mathbf{w} \quad \forall \mathbf{u} \in P \quad \mathbf{v} \in P \quad \mathbf{w} \in P$$

- Axiom #2: Commutativity

$$\mathbf{u} + \mathbf{v} = \mathbf{v} + \mathbf{u} \quad \forall \mathbf{u} \in P \quad \mathbf{v} \in P$$

- Axiom #3: Existence of “zero” vector $\mathbf{0} \in P$

$$\mathbf{0} + \mathbf{v} = \mathbf{v} \quad \forall \mathbf{v} \in P$$

- Axiom #4: Existence of “inverse” vector

$$\forall \mathbf{v} \in P \quad \exists \mathbf{u} = -\mathbf{v} \in P \text{ such that } \mathbf{v} + \mathbf{u} = \mathbf{v} + (-\mathbf{v}) = \mathbf{0}$$



Axioms (multiplication)

- Axiom #5:

$$1\mathbf{v} = \mathbf{v} \quad 1 \in \mathbb{R} \quad \mathbf{v} \in P$$

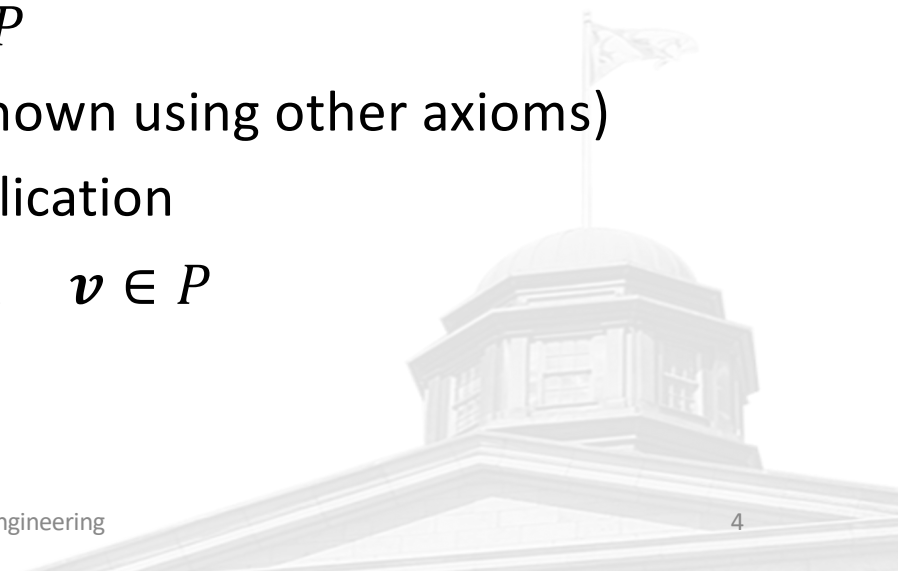
- “Axiom #6”:

$$0\mathbf{v} = \mathbf{0} \quad 0 \in \mathbb{R} \quad \mathbf{v} \in P \quad \mathbf{0} \in P$$

Technically not an axiom (can be shown using other axioms)

- Axiom #7: Associativity of Scalar Multiplication

$$a(b\mathbf{v}) = (ab)\mathbf{v} \quad a \in \mathbb{R} \quad b \in \mathbb{R} \quad \mathbf{v} \in P$$





Distributivity

Consider: $a \in \mathbb{R}$ $b \in \mathbb{R}$ and $\mathbf{u} \in P$ $\mathbf{v} \in P$

- Axiom 8

$$a(\mathbf{u} + \mathbf{v}) = a\mathbf{u} + a\mathbf{v}$$

- Axiom 9

$$(a + b)\mathbf{u} = a\mathbf{u} + b\mathbf{u}$$





Exercise

Show “Axiom 6” Using other Axioms:

$$0 \in \mathbb{R} \quad v \in P \quad \mathbf{0} \in P$$

Show that: $0v = \mathbf{0}$





Lemma 1: Uniqueness of **0** vector

If $\mathbf{a} + \mathbf{v} = \mathbf{v} \quad \forall \mathbf{v} \in P$ then $\mathbf{a} = \mathbf{0}$

$$\mathbf{a} + \mathbf{v} = \mathbf{v} \quad \forall \mathbf{v} \in P$$

$$\mathbf{a} + \mathbf{0} = \mathbf{0}$$

But: $\mathbf{a} + \mathbf{0} = \mathbf{a}$ Axiom #3

$$\mathbf{a} = \mathbf{0}$$





Lemma 2 / "Axiom 6"

Show that $0 \times v = 0$

$$\begin{aligned} v + 0 \times v &= 1 \times v + 0 \times v \\ &= (1 + 0) \times v \\ &= 1 \times v \\ &= v \end{aligned}$$

Lemma 2

Axiom #8

Axiom #5

$$0 \times v = 0$$

Lemma 1

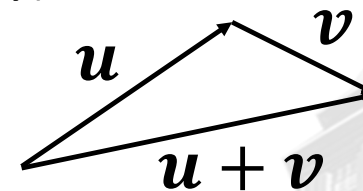




Norm (“Size”) of a Vector

Then Norm $\|\mathbf{v}\| \in \mathbb{R}$ of a vector \mathbf{v} is an indication of its size. It must be defined such that it obeys the following rules:

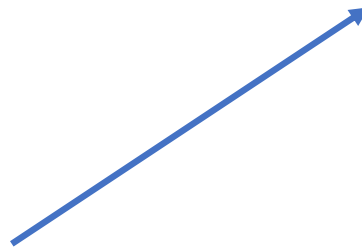
1. $\|\mathbf{v}\| > 0$
2. $\|a\mathbf{v}\| = |a|\|\mathbf{v}\|$
3. $\|\mathbf{u} + \mathbf{v}\| \leq \|\mathbf{u}\| + \|\mathbf{v}\|$ (Triangle Inequality)



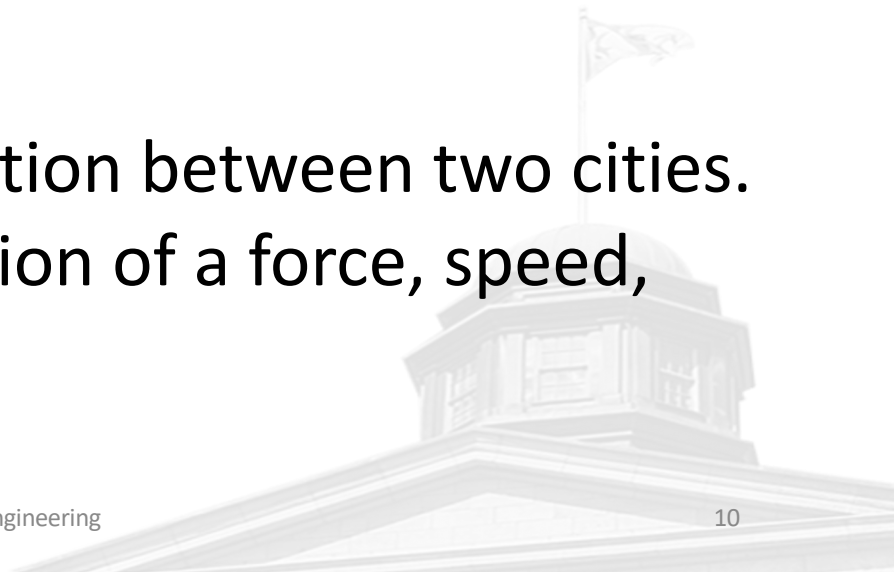


Example of a Vector Space

- Magnitude
- Direction



- Difference in location between two cities.
- Magnitude direction of a force, speed, electric field...





Cartesian vs Polar Coordinates 2D

- Polar Coordinates:

$$u = r \angle \theta = (r, \theta)$$

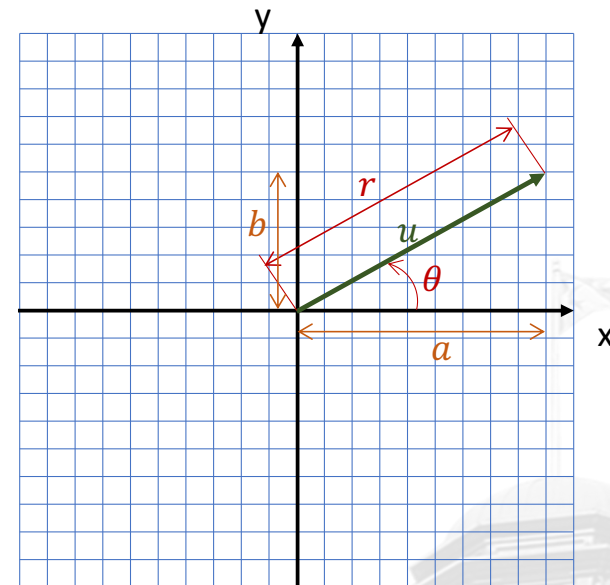
- Cartesian Coordinates:

$$u = \begin{bmatrix} a \\ b \end{bmatrix}$$

$$a = r \cos(\theta)$$

$$b = r \sin(\theta)$$

$$r^2 = a^2 + b^2$$

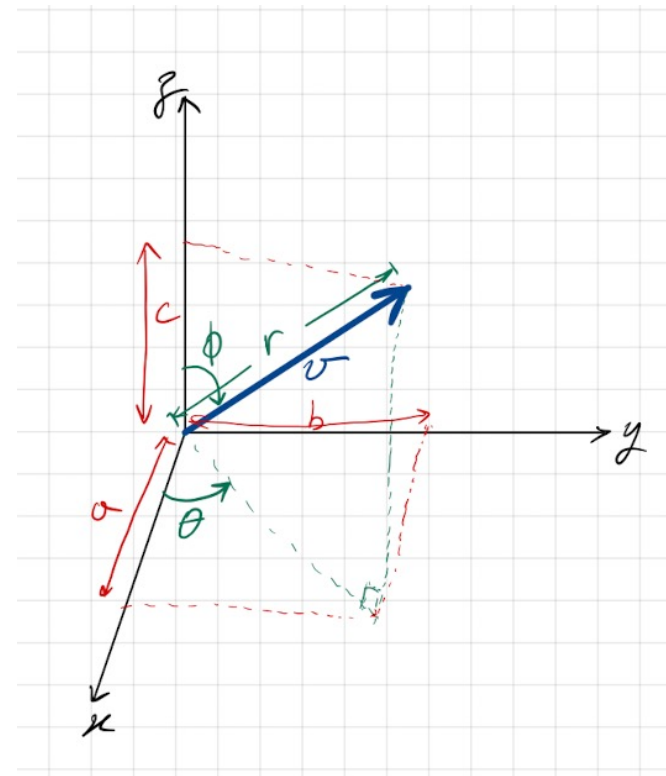




Cartesian vs Polar Coordinates 3D

- Polar Coordinates:
 $u = (r, \theta, \phi)$
- Cartesian Coordinates:

$$u = \begin{bmatrix} a \\ b \\ c \end{bmatrix}$$



n Dimensional Space: \mathbb{R}^n

- Cartesian Coordinates:

$$u = \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_n \end{bmatrix}$$





Vector Space

Definition: A Vector Space P is a set containing vectors $v \in P$ for which we define the two operations: **1) Scalar multiplication** and **2) Addition**.

- Scalar Multiplication: $av \rightarrow u$

$$\left. \begin{array}{l} a \in \mathbb{R} \\ v \in V \end{array} \right\} u \in V$$

- Addition: $u + v \rightarrow w$

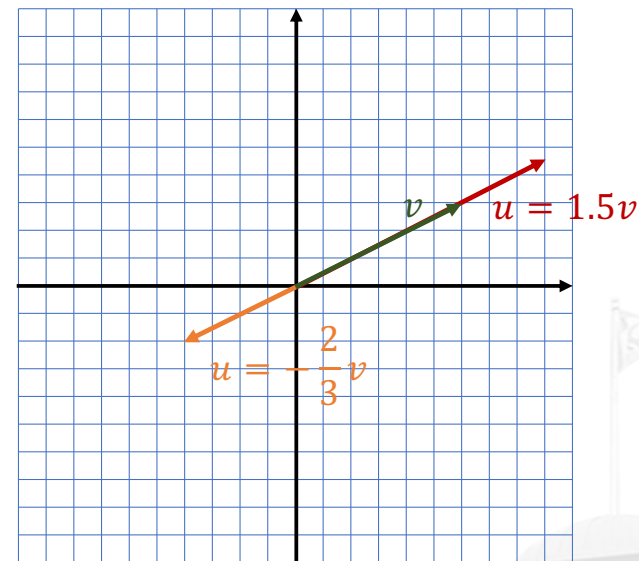
$$\left. \begin{array}{l} v \in V \\ u \in V \end{array} \right\} w \in V$$





Scalar Multiplication

- $v \in \mathbb{R}^2$; $\alpha \in \mathbb{R}$
- $v \rightarrow u = \alpha v$
- u is in the same direction as v
- Length of u is
 $|\alpha|$ times length of v
- If α is negative u and v would
 have opposite orientations.





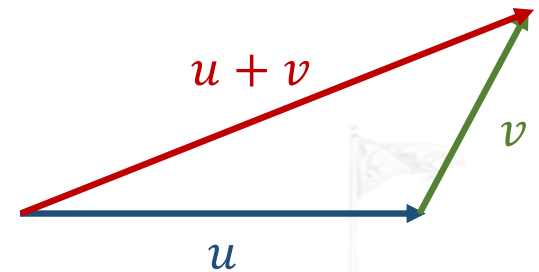
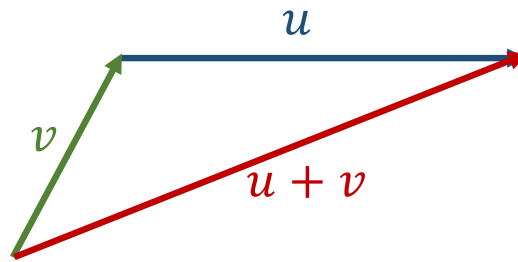
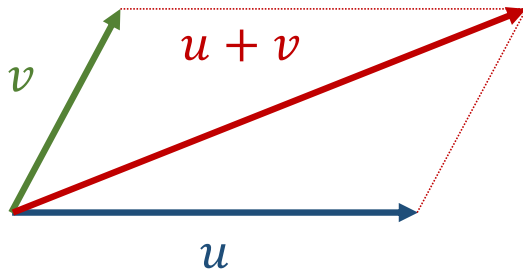
Scalar Multiplication

$$u \in \mathbb{R}^n \quad \alpha \in \mathbb{R}$$

$$u = \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_n \end{bmatrix} \quad v = \alpha u = \begin{bmatrix} \alpha u_1 \\ \alpha u_2 \\ \vdots \\ \alpha u_n \end{bmatrix}$$



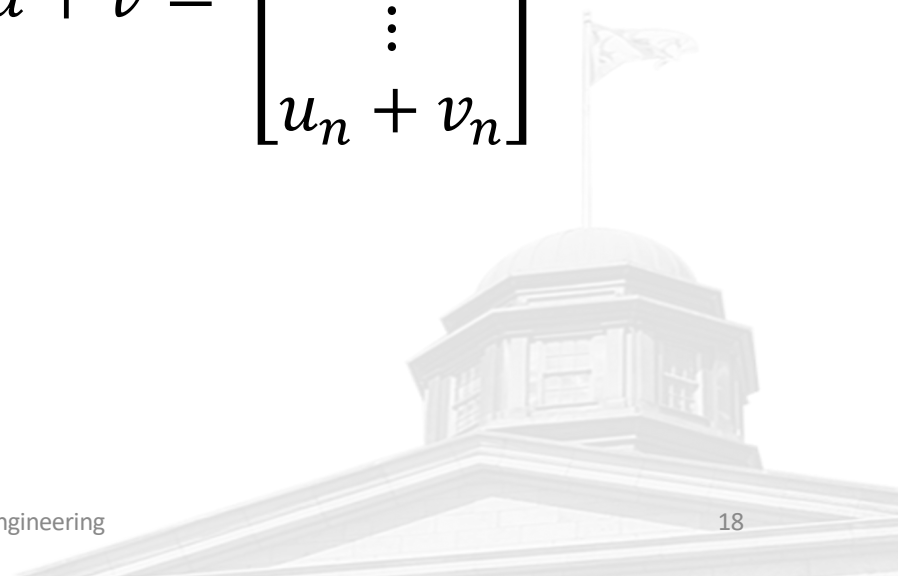
Vector Addition



Vector addition in \mathbb{R}^n



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





Axioms (Addition)

- Axiom #1: Associativity

$$\mathbf{u} + (\mathbf{v} + \mathbf{w}) = (\mathbf{u} + \mathbf{v}) + \mathbf{w} \quad \forall \mathbf{u} \in P \quad \mathbf{v} \in P \quad \mathbf{w} \in P$$

- Axiom #2: Commutativity

$$\mathbf{u} + \mathbf{v} = \mathbf{v} + \mathbf{u} \quad \forall \mathbf{u} \in P \quad \mathbf{v} \in P$$

- Axiom #3: Existence of “zero” vector $\mathbf{0} \in P$

$$\mathbf{0} + \mathbf{v} = \mathbf{v} \quad \forall \mathbf{v} \in P$$

- Axiom #4: Existence of “inverse” vector

$$\forall \mathbf{v} \in P \quad \exists \mathbf{u} = -\mathbf{v} \in P \text{ such that } \mathbf{v} + \mathbf{u} = \mathbf{v} + (-\mathbf{v}) = \mathbf{0}$$



Axioms (multiplication)

- Axiom #5:

$$1\mathbf{v} = \mathbf{v} \quad 1 \in \mathbb{R} \quad \mathbf{v} \in P$$

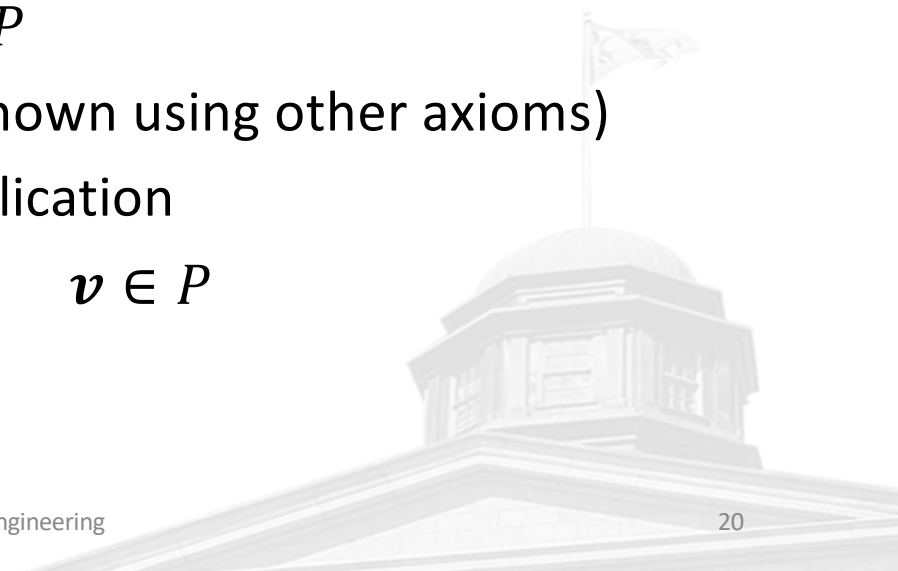
- “Axiom #6”:

$$0\mathbf{v} = \mathbf{0} \quad 0 \in \mathbb{R} \quad \mathbf{v} \in P \quad \mathbf{0} \in P$$

Technically not an axiom (can be shown using other axioms)

- Axiom #7: Associativity of Scalar Multiplication

$$a(b\mathbf{v}) = (ab)\mathbf{v} \quad a \in \mathbb{R} \quad b \in \mathbb{R} \quad \mathbf{v} \in P$$





Distributivity

Consider: $a \in \mathbb{R}$ $b \in \mathbb{R}$ and $\mathbf{u} \in P$ $\mathbf{v} \in P$

- Axiom 8

$$a(\mathbf{u} + \mathbf{v}) = a\mathbf{u} + a\mathbf{v}$$

- Axiom 9

$$(a + b)\mathbf{u} = a\mathbf{u} + b\mathbf{u}$$



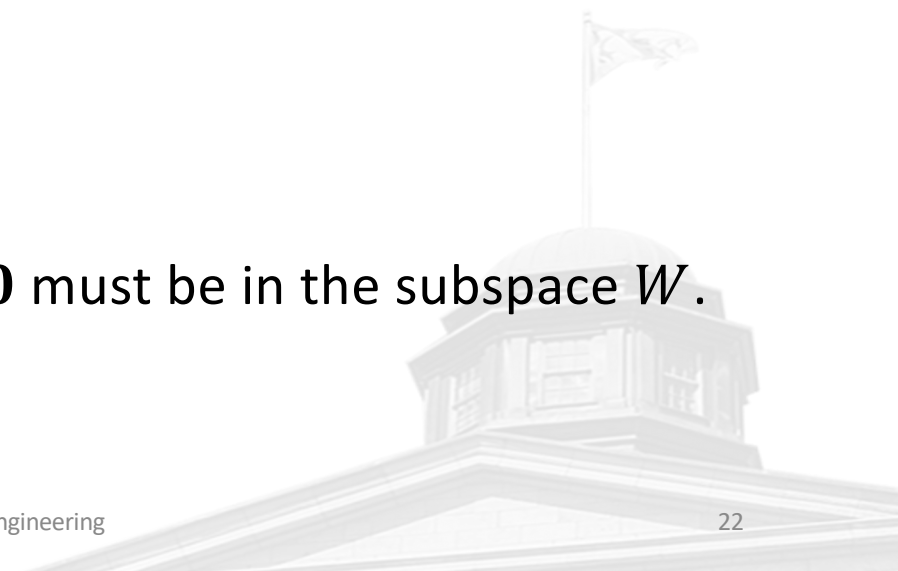


Vector Subspaces

Consider the vector space $V = \mathbb{R}^n$. W is a subspace of V ($W \subset V$) iff:

- $u \in W \Rightarrow u \in V$
- $u \in W \Rightarrow \alpha u \in W \quad (\forall \alpha \in \mathbb{R})$
- $(u \in W \ \& \ v \in W) \Rightarrow u + v \in W$

Note: The above implies that the vector **0** must be in the subspace W .

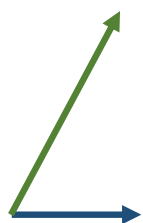




Basis of a Subspace

The vectors u_1, u_2, \dots, u_p form a basis for a vector space or a subspace P if and only if:

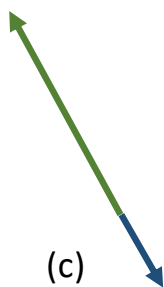
- All vectors in P can be written as a linear combination of u_1, u_2, \dots, u_p
$$v \in P \iff v = \alpha_1 u_1 + \alpha_2 u_2 + \dots + \alpha_n u_p.$$
- The Vectors u_1, u_2, \dots, u_p are linearly independent.



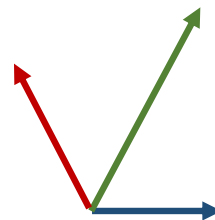
(a)



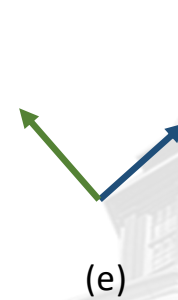
(b)



(c)



(d)



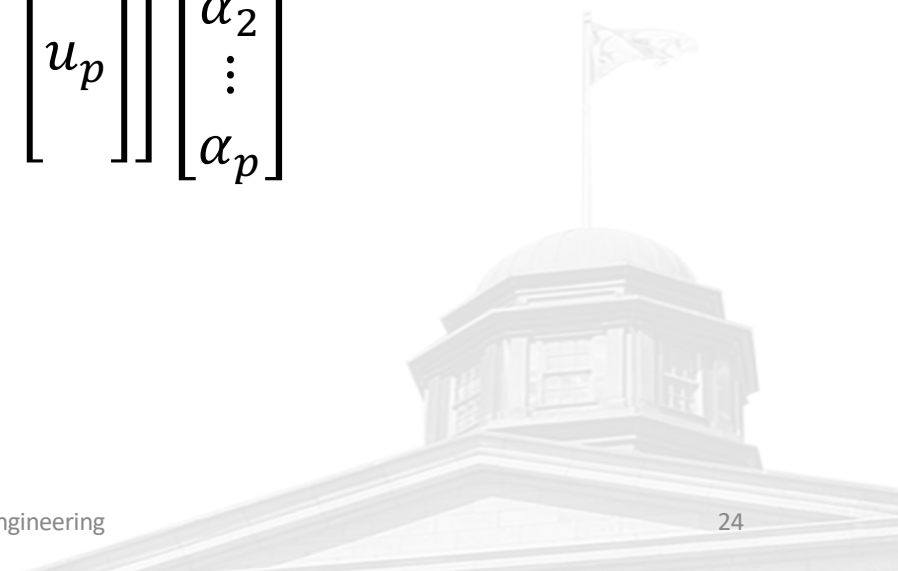
(e)



Basis of a Subspace

$$v = \alpha_1 u_1 + \alpha_2 u_2 + \cdots + \alpha_n u_p$$

$$v = \left[\begin{bmatrix} u_1 \end{bmatrix} \quad \begin{bmatrix} u_2 \end{bmatrix} \quad \cdots \quad \begin{bmatrix} u_p \end{bmatrix} \right] \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_p \end{bmatrix}$$



Example \mathbb{R}^5



$$b = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ b_4 \\ b_5 \end{bmatrix} \quad b = b_1 \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} + b_2 \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \\ 0 \end{bmatrix} + b_3 \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \\ 0 \end{bmatrix} + b_4 \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \\ 0 \end{bmatrix} + b_5 \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 1 \end{bmatrix}$$

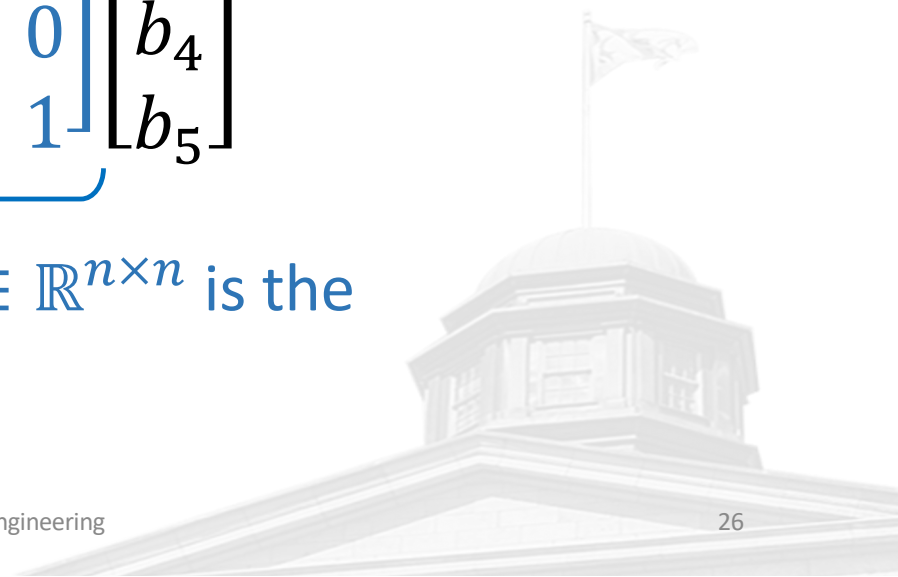
Canonical Basis for \mathbb{R}^5



Example \mathbb{R}^5

$$b = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ b_4 \\ b_5 \end{bmatrix} \quad b = \underbrace{\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}}_{U} \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ b_4 \\ b_5 \end{bmatrix}$$

The identity matrix $U \in \mathbb{R}^{n \times n}$ is the canonical basis for \mathbb{R}^n





Example \mathbb{R}^5

Consider the matrix $A \in \mathbb{R}^{5 \times 5}$, under what condition do A (or the columns of A) form a basis for \mathbb{R}^5 ?

$$b = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ b_4 \\ b_5 \end{bmatrix} \in \mathbb{R}^5 \quad \xrightarrow{\quad} \quad b = \overset{\text{Identity Matrix}}{U}b = b_1 e_1 + b_2 e_2 + \cdots + b_5 e_5$$

$x = A^{-1}b$ Columns of Identity Matrix

If A the columns of A are linearly independent (i.e. A is invertible):



Example \mathbb{R}^5

Consider the matrix $A \in \mathbb{R}^{5 \times 5}$, under what condition do A (or the columns of A) form a basis for \mathbb{R}^5 ?

If A the columns of A are linearly independent (i.e. A is invertible):

$$x = A^{-1}b \quad \longleftrightarrow \quad b = Ax$$

b is a linear combination of the columns of A .

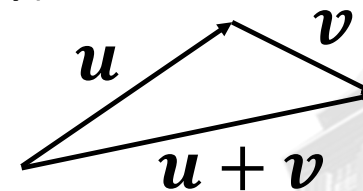




Norm (“Size”) of a Vector

Then Norm $\|\mathbf{v}\| \in \mathbb{R}$ of a vector \mathbf{v} is an indication of its size. It must be defined such that it obeys the following rules:

1. $\|\mathbf{v}\| > 0$
2. $\|a\mathbf{v}\| = |a|\|\mathbf{v}\|$
3. $\|\mathbf{u} + \mathbf{v}\| \leq \|\mathbf{u}\| + \|\mathbf{v}\|$ (Triangle Inequality)





L_p Norm

Consider $v \in \mathbb{R}^n$

The p-norm or L_p norm is defined as:

$$\|v\|_p = \left(\sum_{i=1}^n |v_i|^p \right)^{1/p}$$





Important Special Cases

The 1-norm or L_1 norm is:

$$\|v\|_1 = \sum_{i=1}^n |v_i|$$

The Euclidean (L_2) norm is:

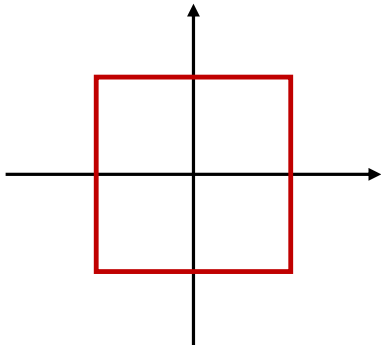
$$\|v\|_2 = \sqrt{\sum_{i=1}^n |v_i|^2}$$

Length of
the vector

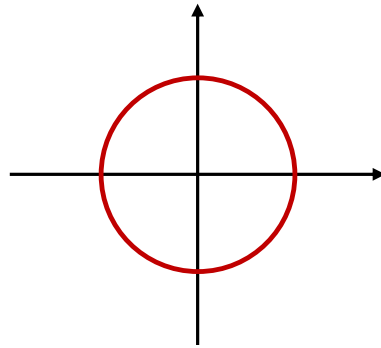
The Infinity (L_∞) norm is:

$$\|v\|_\infty = \max_{1 \leq i \leq n} |v_i|$$

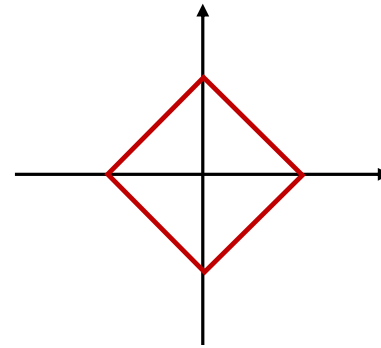
Geometric Interpretation



$$\|v\|_{\infty} = \max |v_i|$$



$$\|v\|_2 = \sqrt{\sum_{i=1}^n |v_i|^2} = 1$$



$$\|v\|_1 = \sum_{i=1}^n |v_i| = 1$$



Norm of a Matrix

Then Norm $\|A\| \in \mathbb{R}$ of a vector A is an indication of its size. It must be defined such that it obeys the following rules:

1. $\|A\| > 0$
2. $\|aA\| = |a|\|A\|$
3. $\|A + B\| \leq \|A\| + \|B\|$
4. $\|AB\| \leq \|A\|\|B\|$



Frobenius Norm



$$\|A\|_F = \sqrt{\sum_{\substack{1 \leq i \leq n \\ 1 \leq j \leq n}} a_{i,j}^2}$$





Induced Norm

Induced norm $\|A\|$ of a matrix A based on a vector norm $\|\cdot\|$

$$\|A\| = \max_{\substack{x \in \mathbb{R}^n \\ \|x\| \neq 0}} \frac{\|Ax\|}{\|x\|}$$

$$\|A\| = \max_{\substack{x \in \mathbb{R}^n \\ \|x\| = 1}} \|Ax\|$$

$$\|Ax\| \leq \|A\| \|x\| \quad \forall x \in \mathbb{R}^n$$

