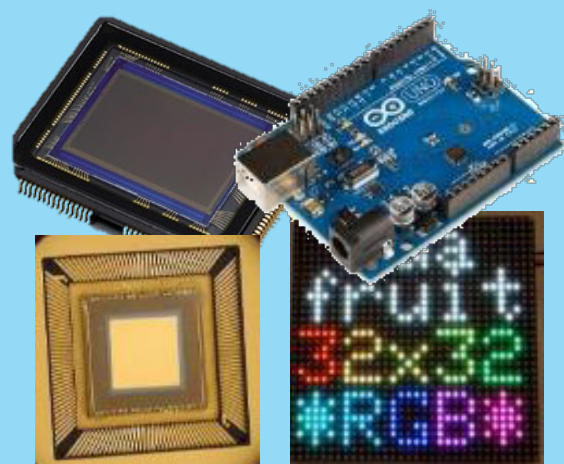


Optics



Sensors  
&  
devices



Signal  
processing  
&  
algorithms

# COMPUTATIONAL METHODS FOR IMAGING (AND VISION)

---

LECTURE 3: VECTOR SPACES  
(HILBERT SPACE)

PROF. JOHN MURRAY-BRUCE

(SUPER FAST) REVIEW

---

# VECTORS



# VECTORS AND VECTOR SPACES

- ▶ **Vector space** – is a set of objects (vectors, together with addition and scalar multiplication) that satisfy the following properties:
  - ▶ For all vectors  $\mathbf{u}, \mathbf{v}, \mathbf{w}$  and scalars  $a, b$ 
    - ▶  $\mathbf{u} + \mathbf{v} = \mathbf{v} + \mathbf{u}$
    - ▶  $\mathbf{u} + (\mathbf{v} + \mathbf{w}) = (\mathbf{u} + \mathbf{v}) + \mathbf{w}$
    - ▶ There exists a *zero vector*  $\mathbf{0}$ , such that  $\mathbf{u} + \mathbf{0} = \mathbf{0} + \mathbf{u} = \mathbf{u}$
    - ▶ For every  $\mathbf{u}$  there exists a vector  $-\mathbf{u}$ , such that  $\mathbf{u} + (-\mathbf{u}) = \mathbf{0}$
    - ▶  $1\mathbf{v} = \mathbf{v}$
    - ▶  $a(b\mathbf{u}) = (ab)\mathbf{u}$
    - ▶  $a(\mathbf{u} + \mathbf{v}) = a\mathbf{u} + a\mathbf{v}$
    - ▶  $(a + b)\mathbf{u} = a\mathbf{u} + b\mathbf{u}$

# VECTORS AND VECTOR SPACES

- ▶ **Vector space** – is a set of objects (vectors, together with addition and scalar multiplication) that satisfy the following properties:

- ▶ For all vectors  $\mathbf{u}, \mathbf{v}, \mathbf{w}$

- ▶  $\mathbf{u} + \mathbf{v} = \mathbf{v} + \mathbf{u}$

- ▶  $\mathbf{u} + (\mathbf{v} + \mathbf{w}) = (\mathbf{u} + \mathbf{v}) + \mathbf{w}$

- ▶ There exists a zero vector  $\mathbf{0}$  such that  $\mathbf{u} + \mathbf{0} = \mathbf{u}$

- ▶ For every  $\mathbf{u}$ , there exists a vector  $-\mathbf{u}$  such that  $\mathbf{u} + (-\mathbf{u}) = \mathbf{0}$

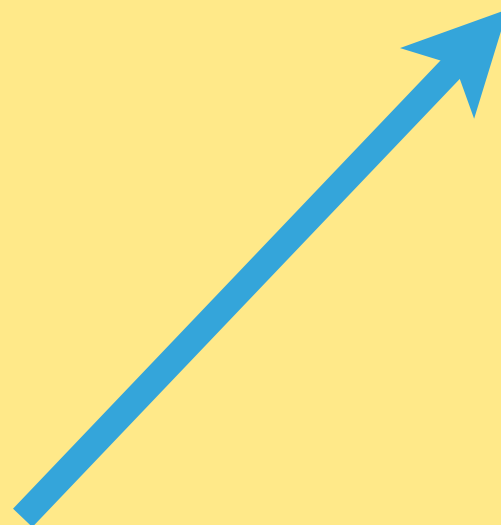
- ▶  $1\mathbf{v} = \mathbf{v}$

- ▶  $a(b\mathbf{u}) = (ab)\mathbf{u}$

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

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

**Intuition:** think of a **vector** as this little arrow.



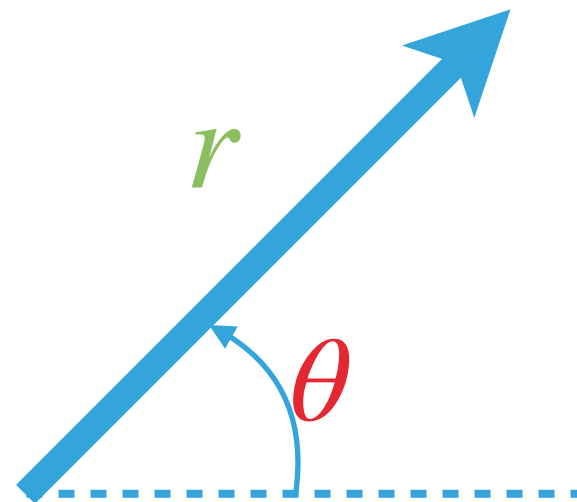
$$\mathbf{u} = \mathbf{u}$$

$$\mathbf{u} + (-\mathbf{u}) = \mathbf{0}$$

# VECTORS

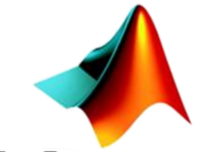
## WHAT CAN WE MEASURE/ENCODE

- ▶ Fundamentally, vectors encode **magnitude** and **direction**



- ▶ Example: a 2D vector can be encoded as length, and an angle relative to some fixed direction.

- ▶ **Norm:** measures the “length” of a vector.
- ▶ **Inner product:** measures norm along with relative orientation. The “length” of one vector along the direction of another.



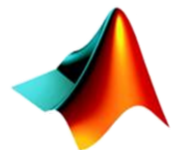
# NORM

## FORMAL DEFINITION

- ▶ A norm is any **function** that maps each vector (of a vector space) to a scalar value, and satisfies the properties:
  - ▶  $\|\mathbf{u}\| \geq 0$
  - ▶  $\|\mathbf{u}\| = 0 \iff \mathbf{u} = \mathbf{0}$
  - ▶  $\|a\mathbf{u}\| = |a|\|\mathbf{u}\|$
  - ▶  $\|\mathbf{u}\| + \|\mathbf{v}\| \geq \|\mathbf{u} + \mathbf{v}\|$  (**triangle inequality!**)

For a vector  $\mathbf{u} \in \mathbb{R}^n$ ,

$$\|\mathbf{u}\| = \sqrt{\sum_{i=1}^n u_i^2}$$





## INNER PRODUCT

### FORMAL DEFINITION

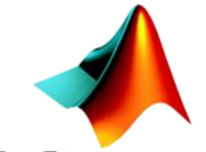
- ▶ **Inner product:** is any function that maps any two vectors to a scalar number  $\langle \mathbf{u}, \mathbf{v} \rangle$ , such that the following properties hold:
  - ▶  $\langle \mathbf{u}, \mathbf{v} \rangle = \langle \mathbf{v}, \mathbf{u} \rangle$
  - ▶  $\langle \mathbf{u}, \mathbf{u} \rangle \geq 0$
  - ▶  $\langle \mathbf{u}, \mathbf{u} \rangle = 0 \iff \mathbf{u} = \mathbf{0}$
  - ▶  $\langle a\mathbf{u}, \mathbf{v} \rangle = a\langle \mathbf{u}, \mathbf{v} \rangle$
  - ▶  $\langle \mathbf{u} + \mathbf{v}, \mathbf{w} \rangle = \langle \mathbf{u}, \mathbf{w} \rangle + \langle \mathbf{v}, \mathbf{w} \rangle$

For two vectors  $\mathbf{u}, \mathbf{v} \in \mathbb{R}^n$ , the standard inner product is

$$\langle \mathbf{u}, \mathbf{v} \rangle = \sum_{i=1}^n u_i v_i$$



**Matlab practice:** Verify each of these identities by using Matlab for some choice of vectors and scalars.



MATLAB

# INNER PRODUCT

## EXAMPLE: INNER PRODUCT IN $\mathbb{R}^2$

$$\langle \mathbf{u}, \mathbf{v} \rangle = u_0 v_0 + u_1 v_1$$

$\mathbf{v} = \begin{bmatrix} v_0 \\ v_1 \end{bmatrix}$

$\mathbf{u} = \begin{bmatrix} u_0 \\ u_1 \end{bmatrix}$

$\theta$

$$\langle \mathbf{u}, \mathbf{v} \rangle = \sqrt{(u_0^2 + u_1^2)(v_0^2 + v_1^2)} \cos(\theta)$$



**Matlab practice:** Verify the given equation, i.e. that:  $\langle \mathbf{u}, \mathbf{v} \rangle = \sqrt{(u_0^2 + u_1^2)(v_0^2 + v_1^2)} \cos(\theta)$ ,  
MATLAB for a few 2D vectors



## OUTLINE

- ▶ **Vector spaces**
  - ▶ Norm, Inner product
- ▶ **Hilbert spaces**

## LEARNING GOALS

- ▶ Understand broader meaning of vectors
- ▶ Understand basic Hilbert spaces terminology
- ▶ Understand basic manipulation of vectors using Matlab

## READING

- ▶ IIP Appendix A
- ▶ FSP 2.1 - 2.4

IMPORTANT

---

# CAUCHY-SCHWARZ INEQUALITY



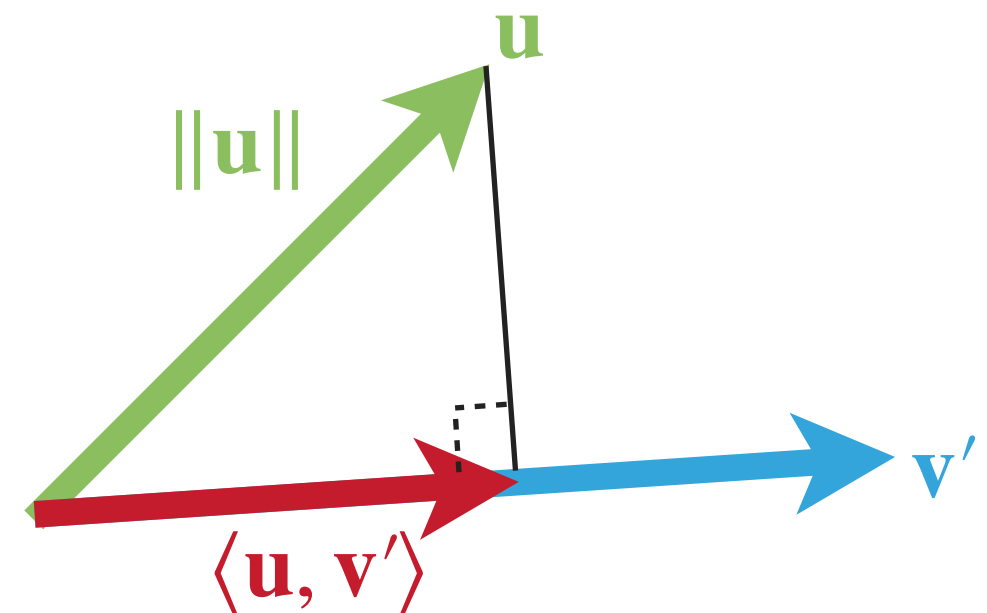
# CAUCHY-SCHWARZ INEQUALITY

- For any vectors  $\mathbf{u}$  and  $\mathbf{v}$ , belonging to some vector space then:

$$\langle \mathbf{u}, \mathbf{v} \rangle \leq \|\mathbf{u}\| \|\mathbf{v}\|$$

► **Proof (intuition):**

1. Let  $\mathbf{v}'$  be a unit vector, i.e.  $\mathbf{v}' = \frac{\mathbf{v}}{\|\mathbf{v}\|}$ , and consider  $\langle \mathbf{u}, \mathbf{v}' \rangle$ .
2. The **inner product**  $\langle \mathbf{u}, \mathbf{v}' \rangle$  is the "length" of  $\mathbf{u}$  along  $\mathbf{v}'$ .
3. Geometrical reasoning (see picture), implies that the **length of  $\mathbf{u}$  along  $\mathbf{v}'$**  must be smaller than or equal to  $\|\mathbf{u}\|$  (i.e. the length of  $\|\mathbf{u}\|$ ).
4. Thus  $\langle \mathbf{u}, \mathbf{v}' \rangle \leq \|\mathbf{u}\|$ .
5. Complete the proof, by putting  $\mathbf{v}' = \frac{\mathbf{v}}{\|\mathbf{v}\|}$  into  $\langle \mathbf{u}, \mathbf{v}' \rangle \leq \|\mathbf{u}\|$  and rearranging.



SUBSPACE

SPAN

LINEAR INDEPENDENCE

ORTHOGONALITY

---

**USEFUL DEFINITIONS**

SUBSPACE

SPAN

LINEAR INDEPENDENCE

ORTHOGONALITY

---

**USEFUL DEFINITIONS**

## USEFUL DEFINITIONS

- **Definition (Subspace):** A nonempty subset  $\mathcal{S}$  of a vector space  $\mathcal{V}$  is a subspace when it is **closed** under the operations of **vector addition** and **scalar multiplication**.

**Example:** Let us consider a 3D vector space:  $\mathcal{V} = \mathbb{R}^3$ .

$\mathcal{S}$  is a subspace of  $\mathcal{V}$ .

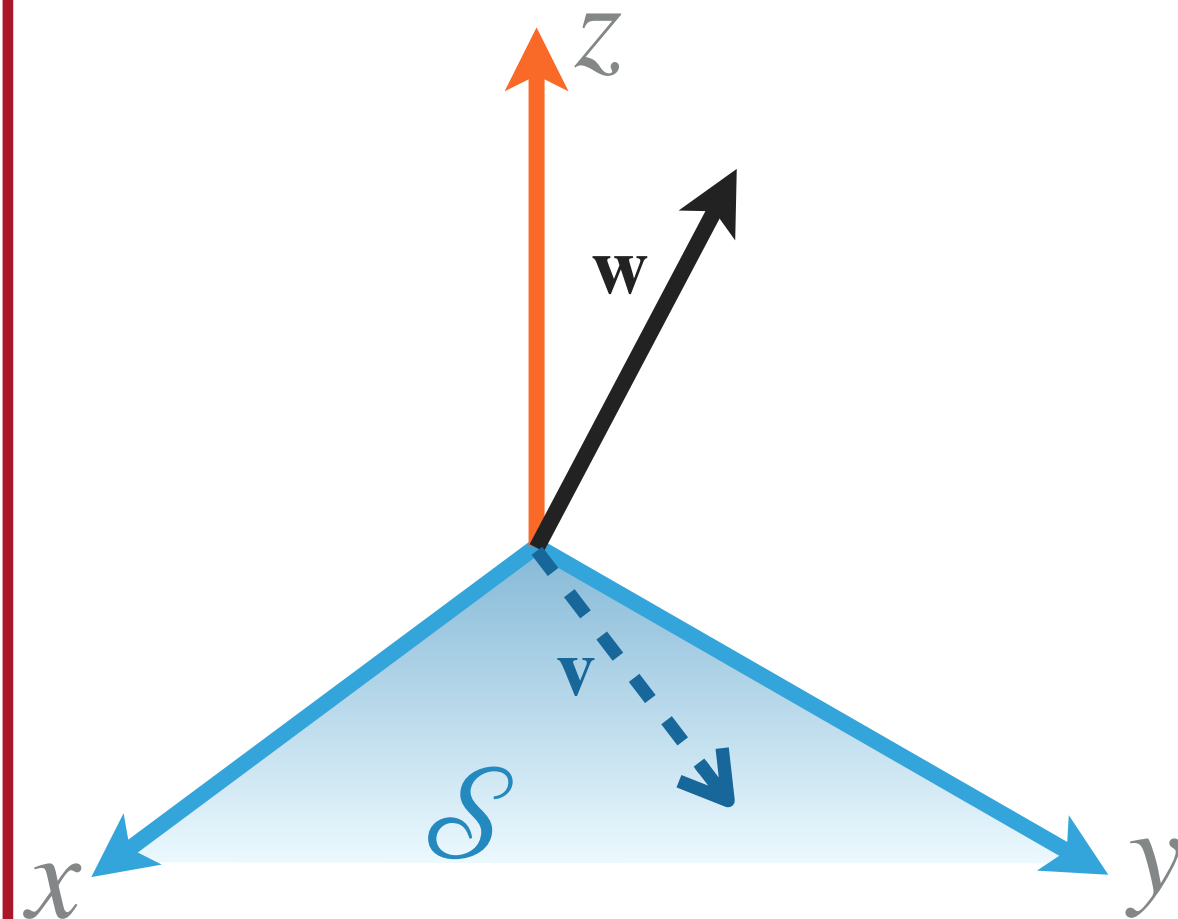
The vector  $\mathbf{w} = \begin{bmatrix} 2 \\ 3 \\ 6 \end{bmatrix} \in \mathbb{R}^3$

The vector  $\mathbf{v} = \begin{bmatrix} 2 \\ 3 \\ 0 \end{bmatrix}$  is lives in  $\mathcal{S}$

In fact, any **vector whose last entry is zero** is in  $\mathcal{S}$ .

**Closed?** - wait, but, what is that? :-/

- if we **add** any two such **vectors** that belong in  $\mathcal{S}$  the result is a vector that is also in  $\mathcal{S}$
- If we multiply such a vector by a scalar (say 0.5 or 1000), the result is a vector that also lives in  $\mathcal{S}$



**QUESTION: CAN YOU GIVE OTHER EXAMPLES OF VECTORS IN  $\mathcal{S}$ ?**

SUBSPACE

SPAN

LINEAR INDEPENDENCE

ORTHOGONALITY

---

**USEFUL DEFINITIONS**

## USEFUL DEFINITIONS

- ▶ **Definition (Span):** The span of a set of vectors  $\mathcal{S}$  is the set of all **finite linear combinations of vectors** in  $\mathcal{S}$ :

$$\text{span}(\mathcal{S}) = \left\{ \sum_{i=1}^n \alpha_i \mathbf{u}_i : \alpha_i \in \mathbb{R}, \mathbf{u}_i \in \mathcal{S}, \text{ and } n \in \mathbb{N} \right\}$$

- ▶ The  $\text{span}(\mathcal{S})$  is **always a subspace** (by definition).
- ▶ Different sets can have the same span.



## EXAMPLE: COMPUTING SPANS

► Write down the span of the following sets of vectors

1.  $\mathcal{S}_1 = \left\{ \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right\}$

✓ **Answer:**  $\text{span}(\mathcal{S}_1) = \left\{ \alpha_1 \begin{bmatrix} 1 \\ 0 \end{bmatrix} + \alpha_2 \begin{bmatrix} 0 \\ 1 \end{bmatrix} : \alpha_1, \alpha_2 \in \mathbb{R} \right\}$

2.  $\mathcal{S}_2 = \left\{ \begin{bmatrix} x \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ y \end{bmatrix} \right\}$

✓ **Answer:**  $\text{span}(\mathcal{S}_2) = \left\{ \alpha_1 \begin{bmatrix} x \\ 0 \end{bmatrix} + \alpha_2 \begin{bmatrix} 0 \\ y \end{bmatrix} : \alpha_1, \alpha_2 \in \mathbb{R} \right\}$

✓ In fact the span of  $\mathcal{S}_2$  is the same as the span of  $\mathcal{S}_1$

3.  $\mathcal{S}_3 = \left\{ \begin{bmatrix} x \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ y \\ 0 \end{bmatrix} \right\}$  and additional comments?

4.  $\mathcal{S}_4 = \left\{ \begin{bmatrix} x_1 \\ y_1 \\ z_1 \end{bmatrix}, \begin{bmatrix} x_2 \\ y_2 \\ z_2 \end{bmatrix} \right\}$

SUBSPACE

SPAN

LINEAR INDEPENDENCE

ORTHOGONALITY

---

**USEFUL DEFINITIONS**



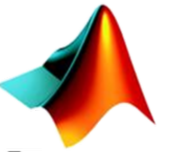
## USEFUL DEFINITIONS

- ▶ **Definition (Linear independence):** A set of vectors  $\{\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_n\}$  is **linearly independent** when  $\sum_{i=1}^n \alpha_i \mathbf{u}_i = \mathbf{0}$  if and only if  $\alpha_i = 0$  for all  $i$ .

- ▶ Otherwise the set is **linearly dependent**.

**Question:** Is the set  $\left\{ \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \right\}$  linearly independent?

- ▶ **Infinite sets** (infinite collection of vectors):
  - ▶ an **infinite set** is linearly independent, if every finite subset is linearly independent.



## EXAMPLES

- Classify each of these sets as linearly independent or linearly dependent

A.  $\left\{ \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \right\}$

B.  $\left\{ \begin{bmatrix} 1 \\ -1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} -1 \\ 0 \\ 0 \end{bmatrix} \right\}$

C.  $\left\{ \begin{bmatrix} 1 \\ -2 \\ 0 \end{bmatrix}, \begin{bmatrix} 4 \\ 0 \\ 8 \end{bmatrix}, \begin{bmatrix} 3 \\ -1 \\ 5 \end{bmatrix} \right\}$

SUBSPACE

SPAN

LINEAR INDEPENDENCE

ORTHOGONALITY

---

**USEFUL DEFINITIONS**

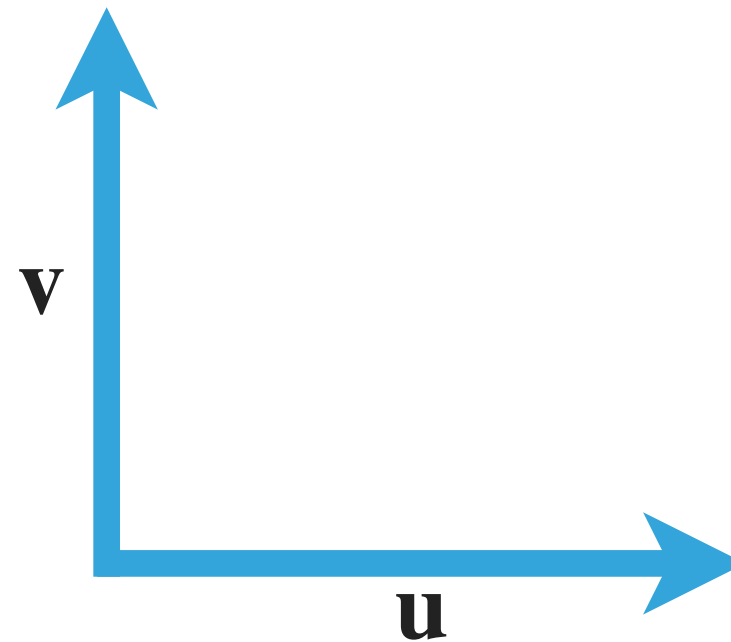


## USEFUL DEFINITIONS

### ORTHOGONALITY

- ▶ Vectors  $\mathbf{u}$  and  $\mathbf{v}$  are **orthogonal** when  $\langle \mathbf{u}, \mathbf{v} \rangle = 0$

- ▶ Again, think of the little arrows



- ▶ We will write this as  $\mathbf{u} \perp \mathbf{v}$
- ▶ **Orthogonality** can be extended to subspaces (collection of vectors) as well

## USEFUL DEFINITIONS

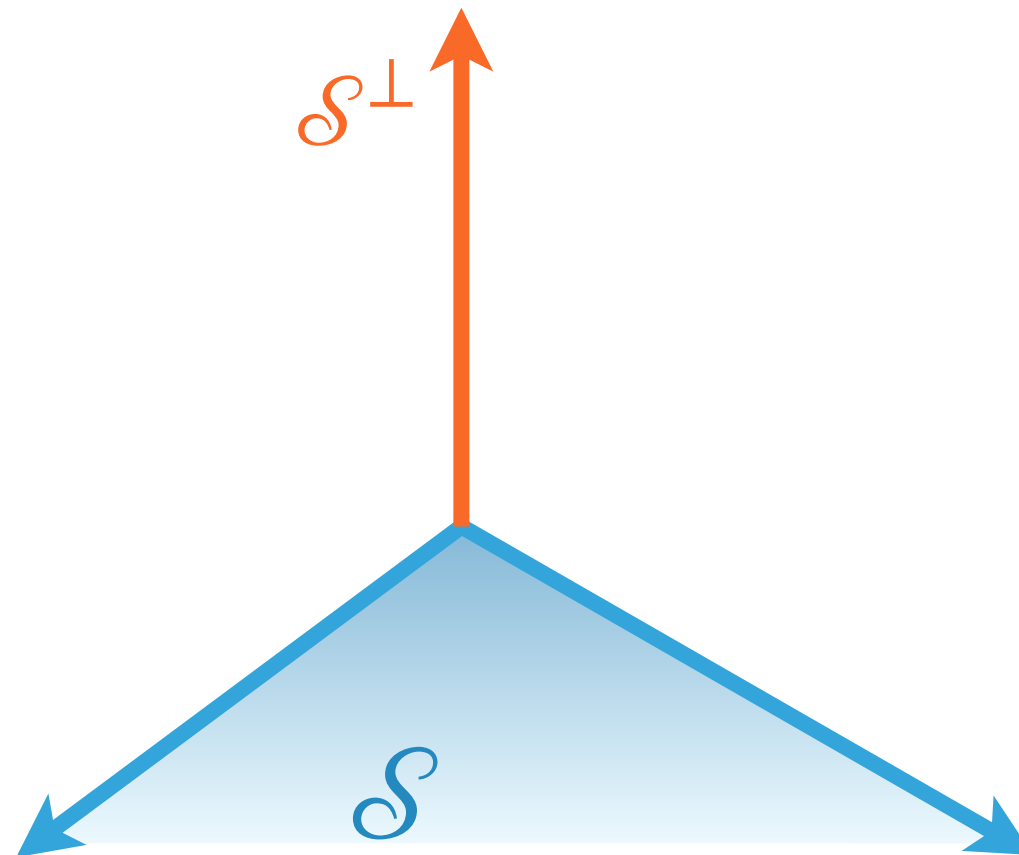
### ORTHOGONALITY

- ▶ The **set of vectors**  $\mathcal{S}$  are orthogonal if  $\langle \mathbf{u}, \mathbf{v} \rangle = 0$  for every  $\mathbf{u}, \mathbf{v} \in \mathcal{S}$ .
- ▶ **Orthonormal set**  $\mathcal{S}$ : is orthogonal, and  $\langle \mathbf{u}, \mathbf{u} \rangle = 1$  for every  $\mathbf{u} \in \mathcal{S}$ .
- ▶ A vector  $\mathbf{u}$  is orthogonal to the set of vectors  $\mathcal{S}$ , if  $\langle \mathbf{u}, \mathbf{v} \rangle = 0$  for every  $\mathbf{v} \in \mathcal{S}$ . Written as  $\mathbf{u} \perp \mathcal{S}$ .
- ▶ **Two sets of vectors**  $\mathcal{S}_0$  and  $\mathcal{S}_1$  are orthogonal when every vector in  $\mathcal{S}_0$  is orthogonal to every vector in  $\mathcal{S}_1$ .

## USEFUL DEFINITIONS

### ORTHOGONALITY

- $\mathcal{S}^\perp$  is the **orthogonal complement** of a subspace  $\mathcal{S}$ , of a vector space  $\mathcal{V}$ , i.e. the set  $\mathcal{S}^\perp = \{\mathbf{u} \in \mathcal{V} : \mathbf{u} \perp \mathcal{S}\}$ .





## USEFUL DEFINITIONS

### ORTHOGONALITY

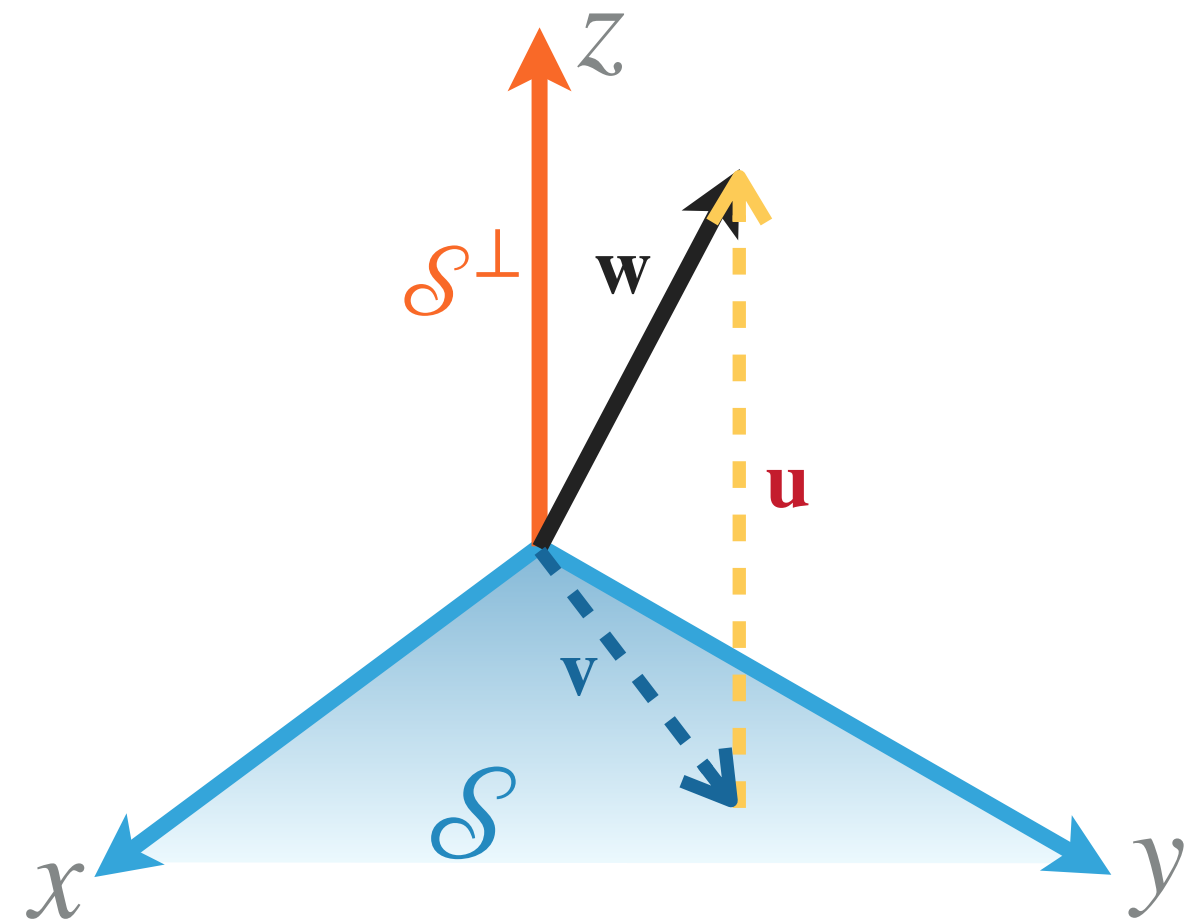
- $\mathcal{S}^\perp$  is the **orthogonal complement** of a subspace  $\mathcal{S}$ , of a vector space  $\mathcal{V}$ , i.e. the set  $\mathcal{S}^\perp = \{\mathbf{u} \in \mathcal{V} : \mathbf{u} \perp \mathcal{S}\}$ .

**Example:** Let us consider a 3D vector space:  $\mathcal{V} = \mathbb{R}^3$ .

And the vector  $\mathbf{w} = \begin{bmatrix} 2 \\ 3 \\ 6 \end{bmatrix} \in \mathbb{R}^3$

The vector  $\mathbf{v} = \begin{bmatrix} 2 \\ 3 \\ 0 \end{bmatrix}$  is lives in  $\mathcal{S}$ ,

while vector  $\mathbf{u} = \begin{bmatrix} 0 \\ 0 \\ 6 \end{bmatrix}$  lives in  $\mathcal{S}^\perp$ , i.e. orthogonal complement of  $\mathcal{S}$ .



## RECAP

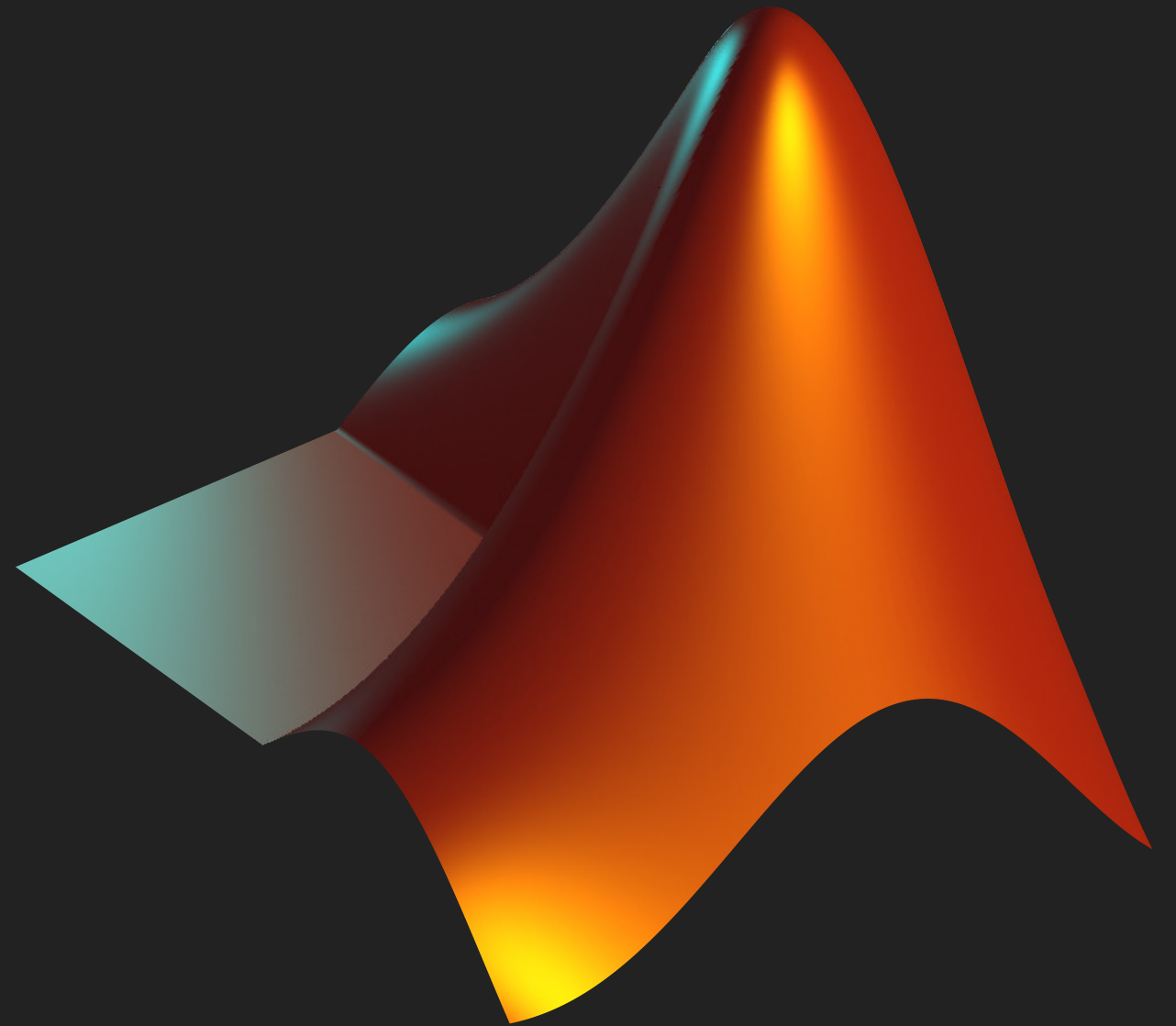
**Subspace:** is a subset of a vector space that is closed under addition and scalar multiplication

**Span:** is the set of all finite linear combinations of vectors of a vector space.

**Linear independence:** if any vector in the set can be written as a linear combination of the remaining vectors the set is said to be linearly dependent.

**Orthogonal:** two vectors are orthogonal if their inner product is zero. That is,

$$\langle \mathbf{u}, \mathbf{v} \rangle = 0$$



VECTORS

---

# MATLAB PRACTICE 1

# MATLAB CHECKLIST

- ▶ **Creating vectors**
- ▶ **Manipulating vectors**
  - ▶ Scalar multiplication
  - ▶ Vector addition
  - ▶ Indexing
  - ▶ Inner products and Norms
- ▶ **Checking linear independence**
  - ▶ Check **rank** or **determinant** of matrix representation of the set of vectors
  - ▶ Can also look at **reduced row echelon form** of matrix representation of the vectors



## WHAT WE COVERED TODAY

- ▶ Vectors and Vector spaces
  - ▶ Norms
  - ▶ Inner products
- ▶ Hilbert space
- ▶ Matlab
  - ▶ Manipulating vectors



# SEE YOU NEXT TIME!

---

HILBERT SPACE & LINEAR OPERATORS