

SC1004 Part 2

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(teaching materials by Prof Chng Eng Siong)

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Quiz 2 and Exam:

1. Quiz 2

- **Coverage** : Ch 6 ,7, 8
- **Time/Date**: Week 13, last lecture time (10:30-11.20am, 17th April 2024)

2. Final Exam

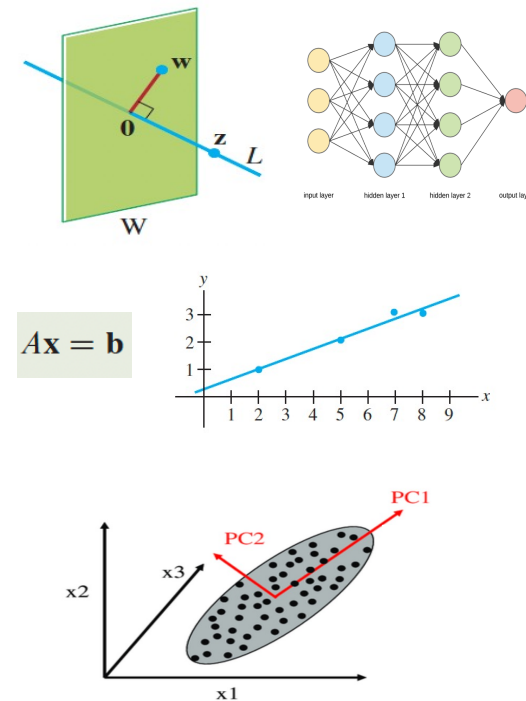
- **Coverage** : Ch 6, 7, 8 (Q3 & Q4)
- **Date/Time**: 2 May 2024 (Thursday), 1.00-3.00pm

(Ch 9 will not be tested)

Syllabus for Part 2

Chapter	Topics	Week (Lecture)	Week (Tut)
6	Orthogonality	8-9	9-10
7	Least Squares	9-10	10-11
8	EigenValue and Eigenvectors	11-12	12-13
9	Singular Value Decomposition (SVD)	13	

Table 1: schedule



Online Video learning Schedule

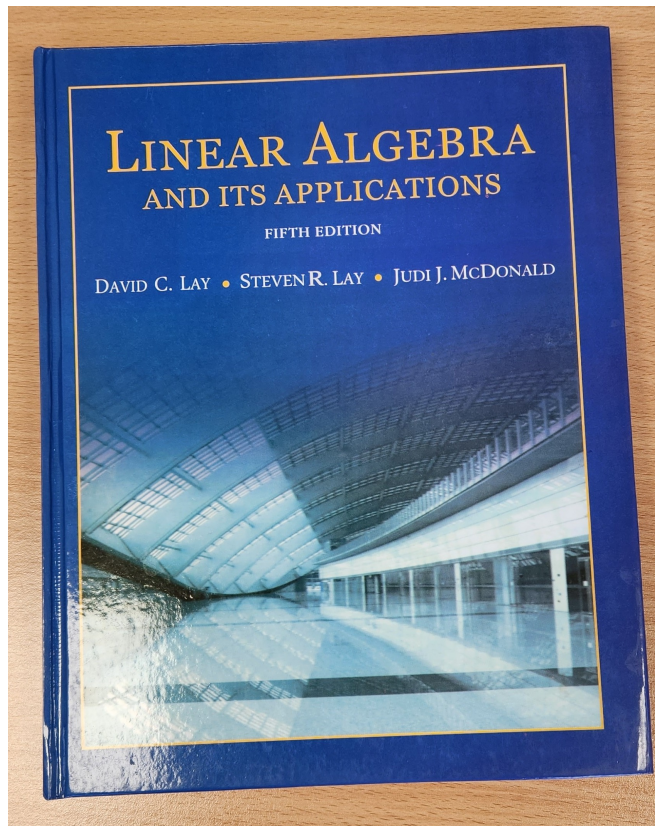
<https://www.youtube.com/channel/UCBzG5jg3huxiPkCt-Serrjw>

Week	Part	Topic	Notes
8	6.1.1-6.2.3	Orthogonality, Normalization, Dot-Product, Inequalities,	Lecture 1: 6.1.1 - 6.1.3 Lecture 2: 6.1.4 - 6.2.3
9	6.2.4-6.3.2	Orthogonal/Orthonormal Sets, Basis, Gram Schmidt and QR Decomposition	Lecture 3: 6.2.4 Lecture 4: 6.2.5 – 6.3.2
10	7.1.1-7.2.1	Least Squares and Normal Eqn, Projection Matrix, Applications	Lecture 5: 7.1.1 – 7.1.3 Lecture 6: 7.1.4 – 7.2.1
11	8.1.1-8.1.2	Eigenvectors, Eigen-values, Characteristics Eqn	Lecture 7: 8.1.1 Lecture 8: 8.1.2
12	8.1.3-8.1.5	Diagonalisation, Power of A, Change of basis	Lecture 9: 8.1.3 Lecture 10: 8.1.4 – 8.1.5
13	9.1.1-9.2	Introduction to SVD and PCA (Not examined in quiz/exam)	Lecture 11: 9.1.1 – 9.2 Lecture 12: Quiz 2

How will we conduct the course?

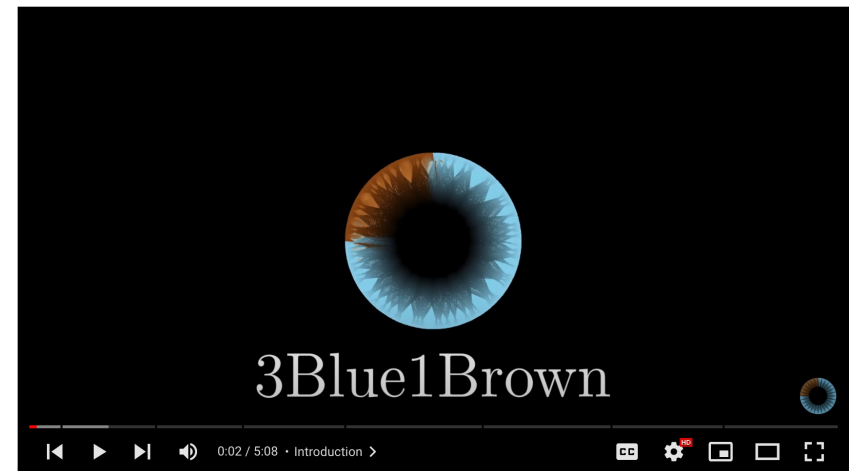
- 1) Before the lectures, watch the videos according to the schedule in Table 1
 - You can watch past years zoom video recordings at https://www.youtube.com/@linearalgebra1884/playlists?view=50&sort=dd&shelf_id=2
- 2) During lecture hours –
 - We will summarize the lectures and highlight the key points
 - Q&A.

References



Linear Algebra and Its Applications
by David Lay, Steven Lay, Judi McDonald

3Blue1Brown on YouTube



Essence of linear algebra preview

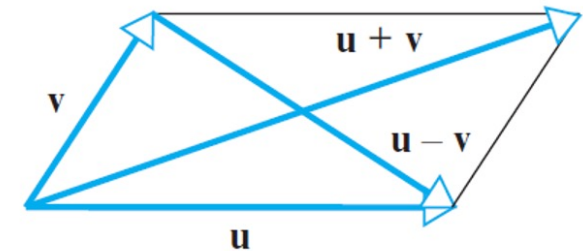
https://www.youtube.com/playlist?list=PLZHQObOWTQDPD3MizzM2xVFitgF8hE_ab

Lecture (Week 8)

(Chapter 6.1.1- 6.2.3)

Key points – 6.1.1 Geometric Vectors

- Vector $\mathbf{v} = \begin{bmatrix} v_1 \\ \vdots \\ v_n \end{bmatrix}$
- Vector direction & length
 - $\|\mathbf{v}\| = \sqrt{v_1^2 + v_2^2 + \cdots + v_n^2}$
- Vector addition & subtraction
 - $\mathbf{u} = \mathbf{v}_1 + \mathbf{v}_2$
 - $\mathbf{u} = \mathbf{v}_1 - \mathbf{v}_2$
- Euclidean space: R^n – n dimensional real numbers



Key points – 6.1.2 Norm (Euclidean Norm)

- Norm: $\|\mathbf{v}\| = \sqrt{v_1^2 + v_2^2 + \dots + v_n^2}$
 - $\|\mathbf{v}\| \geq 0$
 - $\|\mathbf{v}\| = 0$ *iff* $\mathbf{v} = 0$
 - $\|k\mathbf{v}\| = |k|\|\mathbf{v}\|$
- Normalizing a vector (unit length vector)
 - $\mathbf{u} = \frac{\mathbf{v}}{\|\mathbf{v}\|}$
- Vector distance
 - $\mathbf{dist}(\mathbf{u}, \mathbf{v}) = \|\mathbf{u} - \mathbf{v}\| = \sqrt{(u_1 - v_1)^2 + \dots + (u_n - v_n)^2}$

Key points – 6.1.3 Dot Product/Inner Product

- Definition

- $\mathbf{v} = \begin{bmatrix} v_1 \\ \vdots \\ v_n \end{bmatrix}, \mathbf{u} = \begin{bmatrix} u_1 \\ \vdots \\ u_n \end{bmatrix}$

- Geometric formula: $\mathbf{u} \cdot \mathbf{v} = \|\mathbf{u}\| \|\mathbf{v}\| \cos\theta$

- $\cos\theta = \frac{\mathbf{u} \cdot \mathbf{v}}{\|\mathbf{u}\| \|\mathbf{v}\|}$

- if $\|\mathbf{u}\| = 1, \|\mathbf{v}\| = 1, \cos\theta = \mathbf{u} \cdot \mathbf{v}$

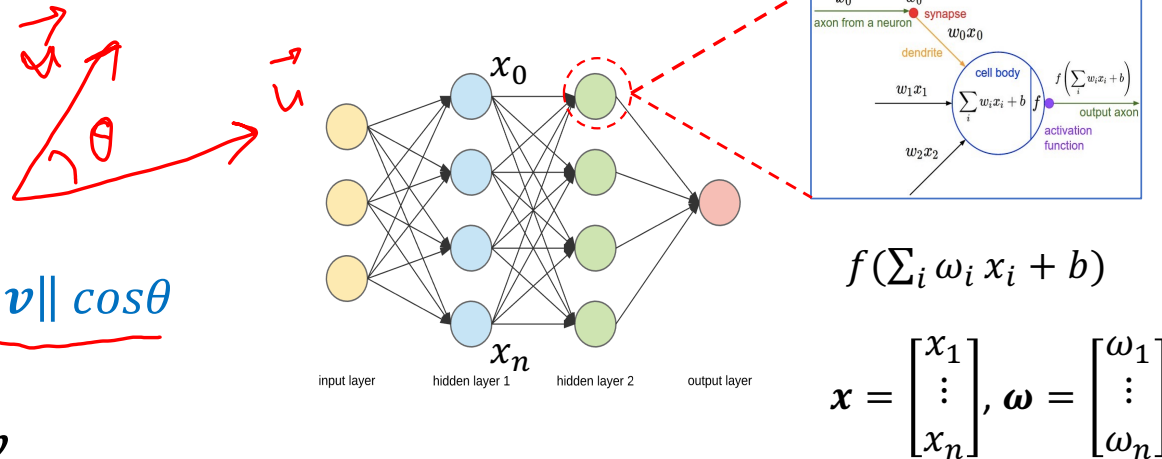
- $\|\mathbf{u}\|^2 = \mathbf{u} \cdot \mathbf{u}$, or $\|\mathbf{u}\| = \sqrt{\mathbf{u} \cdot \mathbf{u}}$

- Component formula: $\mathbf{u} \cdot \mathbf{v} = u_1 v_1 + \dots + u_n v_n$

- Explanation of dot product using the geometric formula

- Projection: $\mathbf{u} \cdot \mathbf{v} = \|\mathbf{u}\| (\|\mathbf{v}\| \cos\theta) = \|\mathbf{v}\| (\|\mathbf{u}\| \cos\theta)$

- Perpendicular: $\mathbf{u} \cdot \mathbf{v} = 0$



Key points – 6.1.3 Dot Product/Inner Product (2).

• Properties of dot product

Dot products have many of the same algebraic properties as products of real numbers.

THEOREM 3.2.2 If \mathbf{u} , \mathbf{v} , and \mathbf{w} are vectors in \mathbb{R}^n , and if k is a scalar, then:

- (a) $\mathbf{u} \cdot \mathbf{v} = \mathbf{v} \cdot \mathbf{u}$ [Symmetry property]
- (b) $\mathbf{u} \cdot (\mathbf{v} + \mathbf{w}) = \mathbf{u} \cdot \mathbf{v} + \mathbf{u} \cdot \mathbf{w}$ [Distributive property]
- (c) $k(\mathbf{u} \cdot \mathbf{v}) = (k\mathbf{u}) \cdot \mathbf{v}$ [Homogeneity property]
- (d) $\mathbf{v} \cdot \mathbf{v} \geq 0$ and $\mathbf{v} \cdot \mathbf{v} = 0$ if and only if $\mathbf{v} = \mathbf{0}$ [Positivity property]

• Transformation on dot product

$$\begin{cases} \circ \mathbf{A}\mathbf{u} \cdot \mathbf{v} = \mathbf{u} \cdot \mathbf{A}^T \mathbf{v} \\ \circ \mathbf{u} \cdot \mathbf{A}\mathbf{v} = \mathbf{A}^T \mathbf{u} \cdot \mathbf{v} \end{cases}$$

➤ Using $\mathbf{u} \cdot \mathbf{v} = \mathbf{u}^T \mathbf{v}$, and $(\mathbf{AB})^T = \mathbf{B}^T \mathbf{A}^T$ to derive

$$\begin{aligned} \vec{u} \cdot \vec{v} &= \sum u_i v_i \\ &= \underbrace{\vec{u}^T}_{1 \times n} \underbrace{\vec{v}}_{n \times 1} \\ &= \underbrace{\vec{u}^T \vec{v}}_{1 \times 1} \end{aligned}$$

$$\mathbf{A} \vec{u} \cdot \vec{v} = (\mathbf{A} \vec{u})^T \vec{v}$$

$$\vec{u}^T (\mathbf{A}^T \vec{v}) = \vec{u} \cdot (\mathbf{A}^T \vec{v})$$

$n \times 1$

Key points – 6.1.4 Inequalities

- Inequalities

- $|\mathbf{u} \cdot \mathbf{v}| \leq \|\mathbf{u}\| \|\mathbf{v}\|$

- Triangular inequality: $\|\mathbf{u} + \mathbf{v}\| \leq \|\mathbf{u}\| + \|\mathbf{v}\|$

THEOREM 3.2.4 Cauchy–Schwarz Inequality

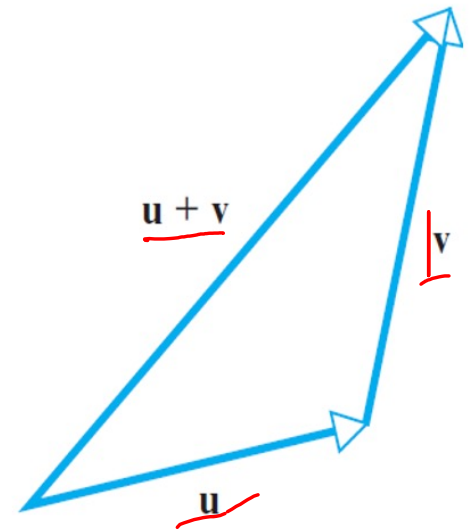
If $\mathbf{u} = (u_1, u_2, \dots, u_n)$ and $\mathbf{v} = (v_1, v_2, \dots, v_n)$ are vectors in R^n , then

$$|\mathbf{u} \cdot \mathbf{v}| \leq \|\mathbf{u}\| \|\mathbf{v}\| \quad (22)$$

or in terms of components

$$|u_1 v_1 + u_2 v_2 + \dots + u_n v_n| \leq (u_1^2 + u_2^2 + \dots + u_n^2)^{1/2} (v_1^2 + v_2^2 + \dots + v_n^2)^{1/2} \quad (23)$$

- Prove



Explain

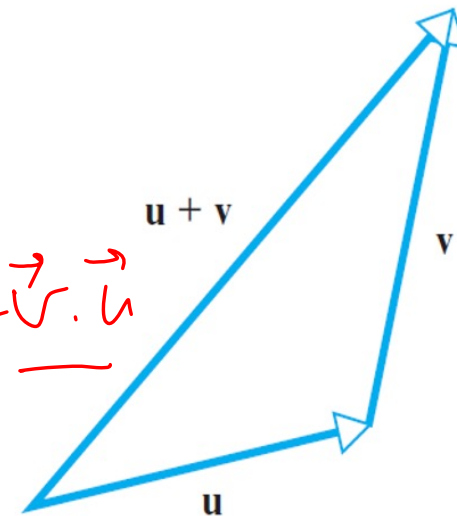
○ $|\mathbf{u} \cdot \mathbf{v}| \leq \|\mathbf{u}\| \|\mathbf{v}\|$

○ $\|\mathbf{u} + \mathbf{v}\| \leq \|\mathbf{u}\| + \|\mathbf{v}\|$

$$|\vec{u} \cdot \vec{u}|^2 = u_1^2 + \dots + u_n^2 = \|\vec{u}\|^2$$

$$|\cos \theta| \leq 1$$

$$\vec{u} \cdot \vec{v} = \vec{v} \cdot \vec{u}$$



$$|\vec{u} \cdot \vec{v}| = \|\vec{u}\| \|\vec{v}\| |\cos \theta|$$

$$|\vec{u} \cdot \vec{v}| \leq \|\vec{u}\| \|\vec{v}\|$$

$$\|\vec{u} + \vec{v}\|^2 = (\vec{u} + \vec{v}) \cdot (\vec{u} + \vec{v}) = \vec{u} \cdot \vec{u} + \vec{v} \cdot \vec{v} + 2 \vec{u} \cdot \vec{v}$$

$$\leq \|\vec{u}\|^2 + \|\vec{v}\|^2 + 2 \|\vec{u}\| \|\vec{v}\| = (\|\vec{u}\| + \|\vec{v}\|)^2$$

Key points – 6.2.1 Orthogonality

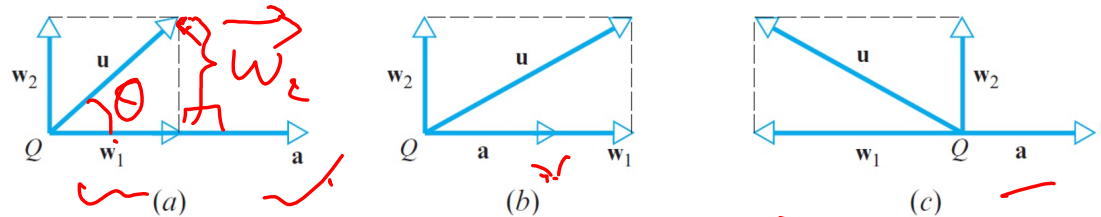
- Definition (vectors orthogonal to each other)
 - $\underline{u} \cdot \underline{v} = 0$ = $\|\vec{u}\| \|\vec{v}\| \cos \theta$
 - $\underline{\cos \theta} = 0 \rightarrow \theta = \underline{90^\circ}$, or $\theta = \underline{\pi/2}$
- Orthonormal
 - u and v are orthogonal with unit length ($\|u\|=1$, $\|v\|=1$)

Key points – 6.2.2 Orthogonal Projection

- Decomposition of a vector

- Standard basis in \mathbb{R}^n

$$\vec{u} \cdot \vec{v} = \|\vec{u}\| \|\vec{v}\| \cos \theta$$



- Projection theorem

- $\vec{w}_1 = \text{Proj}_a \vec{u} = \frac{\vec{u} \cdot \vec{a}}{\vec{a} \cdot \vec{a}} \vec{a}$ (projection) – prove & example

- $\vec{w}_2 = \vec{u} - \text{Proj}_a \vec{u} = \vec{u} - \frac{\vec{u} \cdot \vec{a}}{\vec{a} \cdot \vec{a}} \vec{a}$ (residual)

- $\vec{u} = \vec{w}_1 + \vec{w}_2$

- Distance from \vec{u} to \vec{a} : $\|\vec{u} - \vec{w}_1\| = \|\vec{w}_2\|$

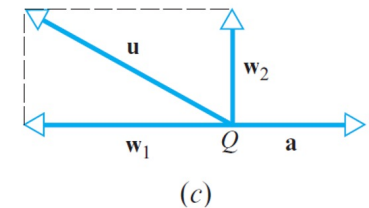
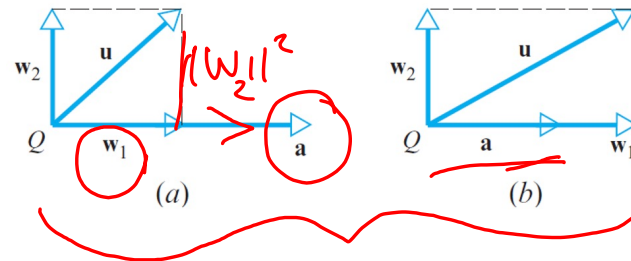
$$\begin{aligned} \vec{w}_1 &= k \vec{a} = \frac{\|\vec{w}_1\|}{\|\vec{a}\|} \vec{a} \\ &= \|\vec{u}\| \cos \theta \cdot \frac{\vec{a}}{\|\vec{a}\|} \\ &= \frac{\vec{u} \cdot \vec{a}}{\|\vec{a}\|} \cdot \frac{\vec{a}}{\|\vec{a}\|} \\ &= \frac{\vec{u} \cdot \vec{a}}{\vec{a} \cdot \vec{a}} \vec{a} \end{aligned}$$

Explain

$$\bullet \mathbf{w}_1 = \text{Proj}_{\mathbf{a}} \mathbf{u} = \frac{\mathbf{u} \cdot \mathbf{a}}{\mathbf{a} \cdot \mathbf{a}} \mathbf{a}$$

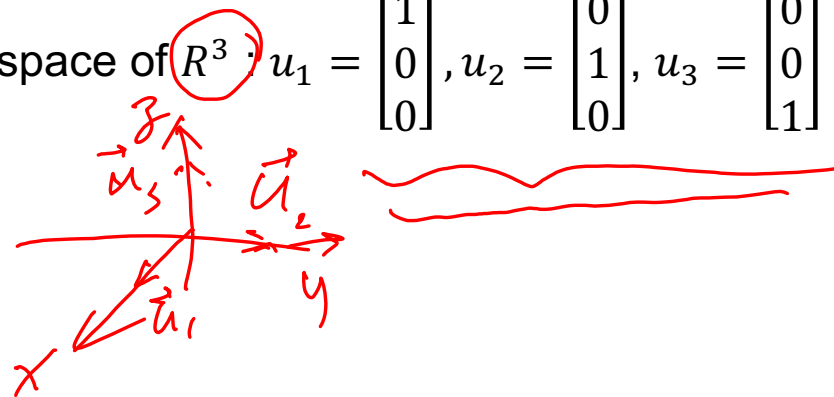
$$\vec{w}_1 = \frac{\vec{u} \cdot (\vec{a})}{(\vec{a}) \cdot (\vec{a})} (\vec{a}) \quad \left\{ \begin{array}{l} \vec{w}_1 = \text{Proj}_{\vec{a}} \vec{u} \\ \vec{w}_1 ? \end{array} \right.$$

$\frac{\vec{u} \cdot \vec{a}}{\vec{a} \cdot \vec{a}}$



Key points – 6.2.3 Orthogonal Sets and Basis

- A set of vectors $\{\mathbf{u}_1, \mathbf{u}_2 \cdots \mathbf{u}_p\}$ in R^n is said to be an orthogonal set if each pair of distinct vectors from the set is orthogonal, that is, if $\mathbf{u}_i \cdot \mathbf{u}_j = 0$, whenever $i \neq j$.
 - If $p = n$, $\{\mathbf{u}_1, \mathbf{u}_2 \cdots \mathbf{u}_n\}$ spans R^n
 - If $p < n$, $\{\mathbf{u}_1, \mathbf{u}_2 \cdots \mathbf{u}_p\}$ spans a subspace W in R^n
 - $\{\mathbf{u}_1, \mathbf{u}_2 \cdots \mathbf{u}_p\}$ are the basis of the subspace
 - Standard basis for Euclidian space of R^3 : $u_1 = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}, u_2 = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}, u_3 = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$



Key points – 6.2.3 Orthogonal Decomposition

- Project a vector \mathbf{y} on to subspace spanned by $\{\mathbf{u}_1, \mathbf{u}_2 \cdots \mathbf{u}_p\}$ in R^n
 - Let W be a subspace of R^n . Then each \mathbf{y} in R^n can be written **uniquely** in the form:

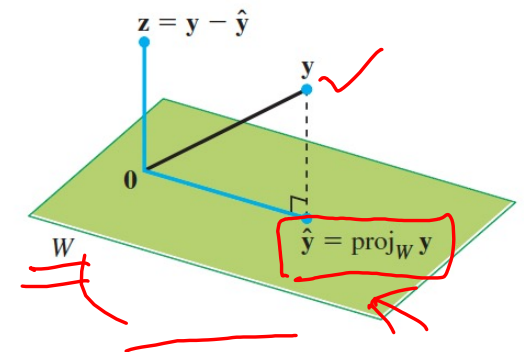
$$\mathbf{y} = \hat{\mathbf{y}} + \mathbf{z}$$

Where $\hat{\mathbf{y}}$ is in W and \mathbf{z} is in W^\perp .

If $\{\mathbf{u}_1, \mathbf{u}_2 \cdots \mathbf{u}_p\}$ is any orthogonal basis of W , then

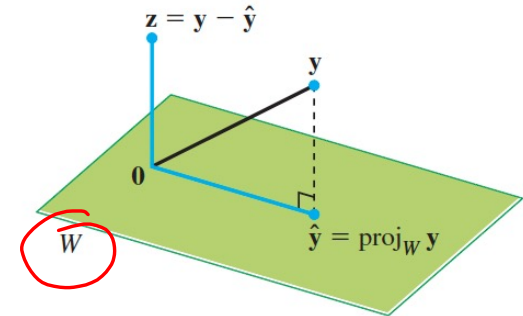
$$\hat{\mathbf{y}} = \text{Proj}_W \mathbf{y} = \frac{\mathbf{y} \cdot \mathbf{u}_1}{\mathbf{u}_1 \cdot \mathbf{u}_1} \mathbf{u}_1 + \cdots + \frac{\mathbf{y} \cdot \mathbf{u}_p}{\mathbf{u}_p \cdot \mathbf{u}_p} \mathbf{u}_p$$

- Explain using: $\hat{\mathbf{y}} = \mathbf{y} - \mathbf{z} = c_1 \mathbf{u}_1 + c_2 \mathbf{u}_2 + \cdots + c_p \mathbf{u}_p$



Explain

$$\bullet \hat{\mathbf{y}} = \text{Proj}_W \mathbf{y} = \frac{\mathbf{y} \cdot \mathbf{u}_1}{\mathbf{u}_1 \cdot \mathbf{u}_1} \mathbf{u}_1 + \dots + \frac{\mathbf{y} \cdot \mathbf{u}_p}{\mathbf{u}_p \cdot \mathbf{u}_p} \mathbf{u}_p$$



$$\hat{\mathbf{y}} = c_1 \vec{u}_1 + c_2 \vec{u}_2 + \dots + c_p \vec{u}_p$$

$$\vec{u}_1 \cdot \hat{\mathbf{y}} = c_1 \underbrace{\vec{u}_1 \cdot \vec{u}_1}_{1} + \underbrace{c_2 \vec{u}_2 \cdot \vec{u}_1 + \dots + c_p \vec{u}_p \cdot \vec{u}_1}_0$$

$$c_1 = \frac{\vec{u}_1 \cdot \hat{\mathbf{y}}}{\vec{u}_1 \cdot \vec{u}_1} = \frac{\hat{\mathbf{y}} \cdot \vec{u}_1}{\vec{u}_1 \cdot \vec{u}_1}$$

Key points – for tutorial questions

• Orthogonal matrix A

- If A is square with orthonormal columns (in fact, the row of an orthogonal matrix is also orthonormal)

$$A^T A = I$$

$$A A^T = I$$

$$A = \begin{bmatrix} \vec{a}_1 & \vec{a}_2 & \cdots & \vec{a}_n \end{bmatrix}$$

$n \times n$

$$A^T = A^{-1}$$

✓ • Vector orthogonal to a subspace

- If a vector \underline{u} is orthogonal to every vector in a subspace W of R^n , then \underline{u} is said to be orthogonal to W – all \underline{u} called the orthogonal complement of W (W^\perp)

$$A \underline{x} = \underline{0}$$

Subspace. $\left\{ \begin{array}{l} \vec{u} = \underline{0} \\ c\vec{u} \\ \vec{u}_1 + \vec{u}_2 \end{array} \right. : \begin{bmatrix} W^\perp \\ W^\perp \\ W^\perp \end{bmatrix}$

End