SC1004 Part 2

Lectured by Prof Guan Cuntai
(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

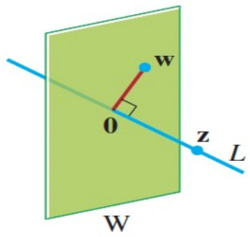
- **Coverage** : Ch 6, 7, 8 (Q3 & Q4)
- **Date/Time**: 2 May 2024 (Thursday), 1.00-3.00pm

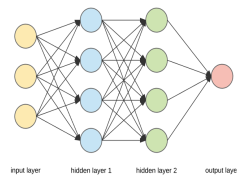
(Ch 9 will not be tested)

Syllabus for Part 2

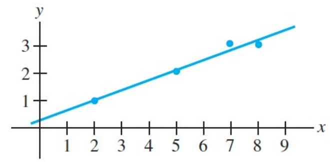
Chapter	Topics	Week (Lecture)	Week (Tut)
6	Orthogonality	8-9	9-10
7	Least Squares	9-10	10-11
8	EigenValue and Eigenvectors	11-12	12-13
9	Singular Value Decomposition (SVD)	13	

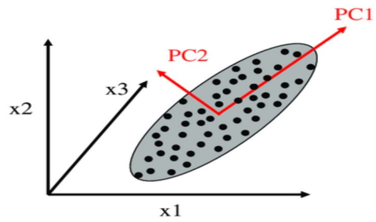
Table 1: schedule





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





Online Video learning Schedule

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

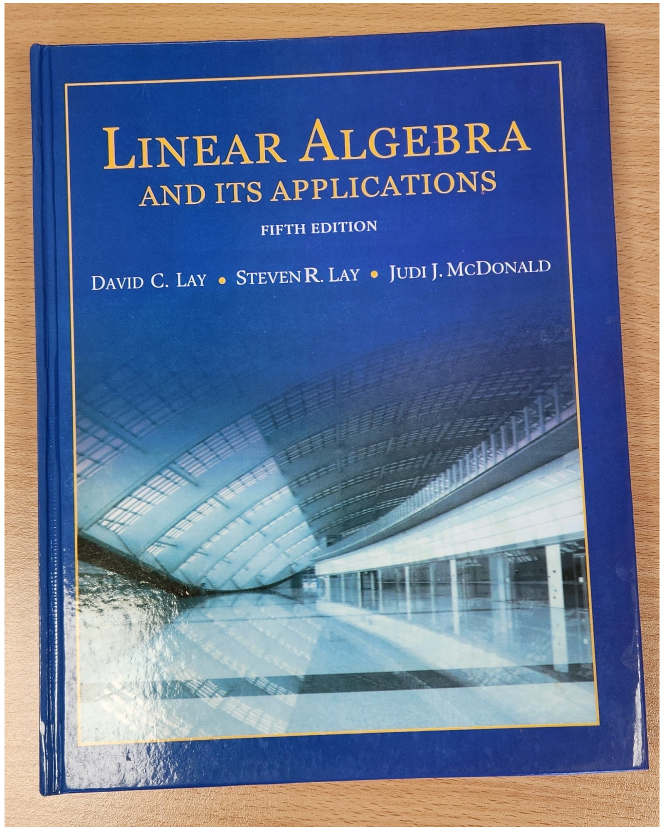
Week	Part	Topic	Notes
8	6.1.1-6.2.3	Orthogonality, Normalization, Dot-Product, Inequalities,	Lecture 1: **6.1.1 - 6.1.3** Lecture 2: **6.1.4 - 6.2.3**
9	6.2.4-6.3.2	Orthogonal/Orthonormal Sets, Basis, Gram Schmidt and QR Decomposition	Lecture 3: **6.2.4** Lecture 4: **6.2.5 – 6.3.2**
10	7.1.1-7.2.1	Least 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

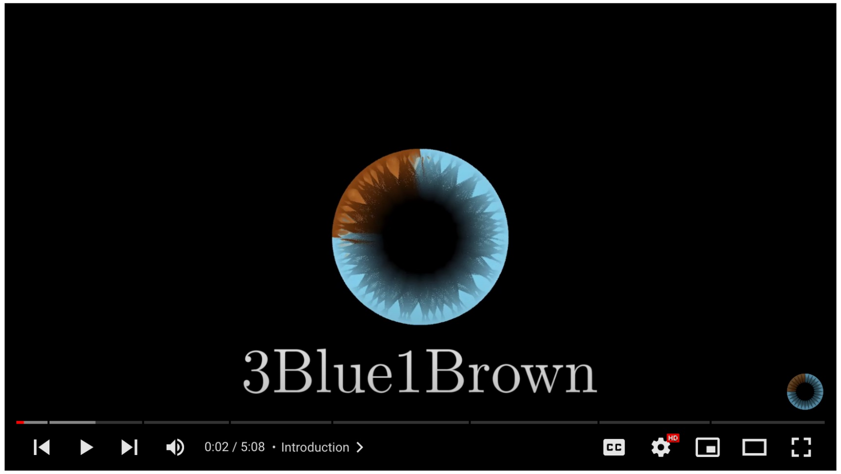
2) During lecture hours –
    - We will summarize the lectures and highlight the key points
    - Q&A.

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 9)

(Chapter 6.2.3- 6.3.3)

Revision

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* 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
  - $A\boldsymbol{u}\cdot\boldsymbol{v}=\boldsymbol{u}\cdot A^T\boldsymbol{v}$
  - $\boldsymbol{u}\cdot A\boldsymbol{v}=A^T\boldsymbol{u}\cdot\boldsymbol{v}$

  (Using $\boldsymbol{u}\cdot\boldsymbol{v}=\boldsymbol{u}^T\boldsymbol{v}$, and $(AB)^T=B^TA^T$ to derive)

Explanation to transformation on dot product:

- Let's write the dot product in matrix form:
  $$A\boldsymbol{u}\cdot\boldsymbol{v}=(A\boldsymbol{u})^T\boldsymbol{v}$$
- Using $(AB)^T=B^TA^T$
  $$(A\boldsymbol{u})^T\boldsymbol{v}=(\boldsymbol{u}^TA^T)\boldsymbol{v}$$
- Using the distributive property of matrix
  $$(\boldsymbol{u}^TA^T)\boldsymbol{v}=\boldsymbol{u}^T(A^T\boldsymbol{v})$$
- Write back to dot product format
  $$\boldsymbol{u}^T(A^T\boldsymbol{v})=\boldsymbol{u}\cdot A^T\boldsymbol{v}$$

So we get: $A\boldsymbol{u}\cdot\boldsymbol{v}=\boldsymbol{u}\cdot A^T\boldsymbol{v}$

Revision

Key points – 6.2.2 Orthogonal Projection

- Projection theorem (~~projection from one vector to another~~)
  - Project vector $\boldsymbol{y}$ on to $\boldsymbol{u}$: $\hat{\boldsymbol{y}} = Proj_u\, \boldsymbol{y} = \frac{\boldsymbol{y}\cdot\boldsymbol{u}}{\boldsymbol{u}\cdot\boldsymbol{u}}\boldsymbol{u}$
  - Residual: $\boldsymbol{z} = \boldsymbol{y} - \hat{\boldsymbol{y}} = \boldsymbol{y} - \frac{\boldsymbol{y}\cdot\boldsymbol{u}}{\boldsymbol{u}\cdot\boldsymbol{u}}\boldsymbol{u}$

$Proj_L\, \vec{y}$

- Explain
  1) Geometric approach:

     $\hat{\boldsymbol{y}}$ is on the line of $\boldsymbol{u}$ with the length of $\|\hat{\boldsymbol{y}}\|$

     $$\hat{\boldsymbol{y}} = \|\hat{\boldsymbol{y}}\|\frac{\boldsymbol{u}}{\|\boldsymbol{u}\|}$$

     From triangle (see figure on the right): $\|\hat{\boldsymbol{y}}\| = \|\boldsymbol{y}\|cos\theta$

     From $\boldsymbol{y}\cdot\boldsymbol{u} = \|\boldsymbol{y}\|\|\boldsymbol{u}\|cos\theta$, we get: $\|\boldsymbol{y}\|cos\theta = \frac{\boldsymbol{y}\cdot\boldsymbol{u}}{\|\boldsymbol{u}\|}$

     So, we get $\hat{\boldsymbol{y}} = \|\hat{\boldsymbol{y}}\|\frac{\boldsymbol{u}}{\|\boldsymbol{u}\|} = \|\boldsymbol{y}\|cos\theta\frac{\boldsymbol{u}}{\|\boldsymbol{u}\|} = \frac{\boldsymbol{y}\cdot\boldsymbol{u}}{\|\boldsymbol{u}\|}\frac{\boldsymbol{u}}{\|\boldsymbol{u}\|} = \frac{\boldsymbol{y}\cdot\boldsymbol{u}}{\|\boldsymbol{u}\|^2}\boldsymbol{u} = \frac{\boldsymbol{y}\cdot\boldsymbol{u}}{\boldsymbol{u}\cdot\boldsymbol{u}}\boldsymbol{u}$

  2) Orthogonal approach:

     As $\hat{\boldsymbol{y}}$ is on the line of $\boldsymbol{u}$, so $\hat{\boldsymbol{y}} = c\boldsymbol{u}$ (c is a scalar to be found)

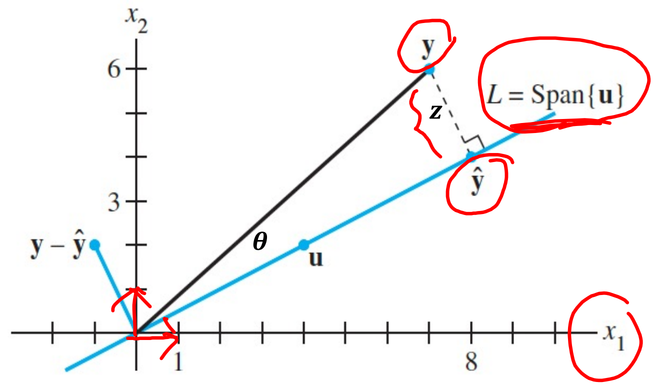
     $$\hat{\boldsymbol{y}} = \boldsymbol{y} - \boldsymbol{z} = c\boldsymbol{u}$$

     Take the dot product with $\boldsymbol{u}$ on both sides: $(\boldsymbol{y} - \boldsymbol{z})\cdot\boldsymbol{u} = c\boldsymbol{u}\cdot\boldsymbol{u}$

     We get: $c\boldsymbol{u}\cdot\boldsymbol{u} = \boldsymbol{y}\cdot\boldsymbol{u} - \boldsymbol{z}\cdot\boldsymbol{u} = \boldsymbol{y}\cdot\boldsymbol{u}$ ($\boldsymbol{z}$ is orthogonal to $\boldsymbol{u}$!) ➔ $c = \frac{\boldsymbol{y}\cdot\boldsymbol{u}}{\boldsymbol{u}\cdot\boldsymbol{u}}$

     So we also get: $\hat{\boldsymbol{y}} = c\boldsymbol{u} = \frac{\boldsymbol{y}\cdot\boldsymbol{u}}{\boldsymbol{u}\cdot\boldsymbol{u}}\boldsymbol{u}$ $\xrightarrow{\ \boldsymbol{z}\cdot\boldsymbol{u}\ } 0$

Project $\boldsymbol{y} = \begin{bmatrix}7\\6\end{bmatrix}$ onto vector $\boldsymbol{u} = \begin{bmatrix}2\\1\end{bmatrix}$, and sketch $\hat{\boldsymbol{y}}$.



W

$L = Span(k\vec{a})$

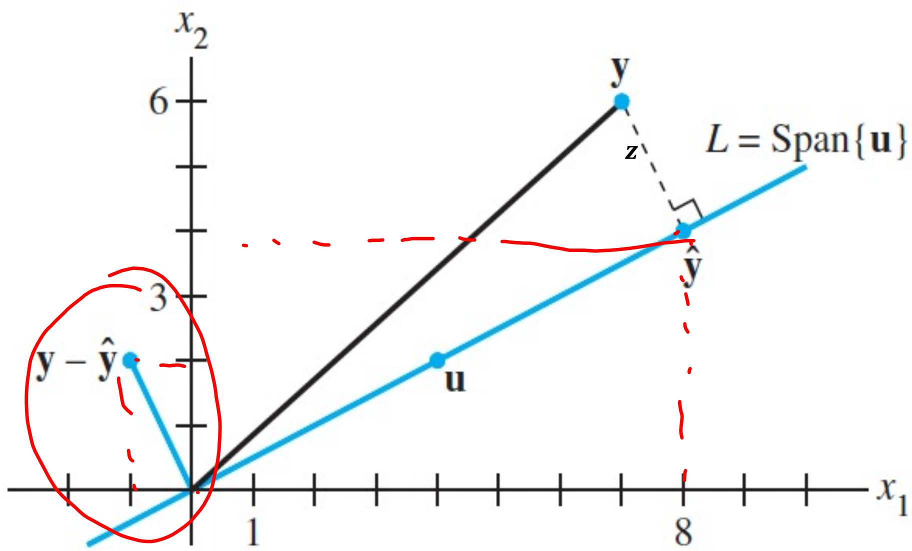
$L = Span(\frac{\vec{u}}{\|u\|})$

$L_{x_1} = Span\begin{bmatrix}1\\0\end{bmatrix}$

$L_{x_2} = Span\begin{bmatrix}0\\1\end{bmatrix}$

Example

Project $\boldsymbol{y} = \begin{bmatrix} 7 \\ 6 \end{bmatrix}$ onto vector $\boldsymbol{u} = \begin{bmatrix} 2 \\ 1 \end{bmatrix}$



$$\hat{y} = \text{Proj}_{\vec{u}}\, \vec{y} = \frac{\vec{y}\cdot\vec{u}}{\vec{u}\cdot\vec{u}}\,\vec{u} =$$

$$= \frac{\begin{bmatrix} 7 & 6 \end{bmatrix}\begin{bmatrix} 2 \\ 1 \end{bmatrix}}{\begin{bmatrix} 2 & 1 \end{bmatrix}\begin{bmatrix} 2 \\ 1 \end{bmatrix}}\begin{bmatrix} 2 \\ 1 \end{bmatrix} = \frac{20}{5}\begin{bmatrix} 2 \\ 1 \end{bmatrix} = 4\begin{bmatrix} 2 \\ 1 \end{bmatrix} = \begin{bmatrix} 8 \\ 4 \end{bmatrix}$$

$$\vec{z} = \vec{y} - \hat{y} = \begin{bmatrix} 7 \\ 6 \end{bmatrix} - \begin{bmatrix} 8 \\ 4 \end{bmatrix} = \begin{bmatrix} -1 \\ 2 \end{bmatrix}$$

Revision

Key points – 6.2.3 Orthogonal Decomposition

$W = \text{Span}\{\vec{u}_1, \vec{u}_2, \ldots \vec{u}_p\}$

$W = \text{Span}\left(\frac{\vec{u}_1}{\|u_1\|}, \frac{\vec{u}_2}{\|u_2\|}, \ldots\right)$

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

$$\boldsymbol{y} = \widehat{\boldsymbol{y}} + \boldsymbol{z}$$

where $\widehat{\boldsymbol{y}}$ is in W and residual $\boldsymbol{z}$ is in $W^{\perp}$. If $\{\boldsymbol{u}_1, \boldsymbol{u}_2 \cdots \boldsymbol{u}_p\}$ is any orthogonal basis of W, then

$$\widehat{\boldsymbol{y}} = Proj_W \boldsymbol{y} = \frac{\boldsymbol{y}\cdot\boldsymbol{u}_1}{\boldsymbol{u}_1\cdot\boldsymbol{u}_1}\boldsymbol{u}_1 + \cdots + \frac{\boldsymbol{y}\cdot\boldsymbol{u}_p}{\boldsymbol{u}_p\cdot\boldsymbol{u}_p}\boldsymbol{u}_p$$

- Explain:
  - Since $\widehat{\boldsymbol{y}}$ is in the subspace W spanned by $\{\boldsymbol{u}_1, \boldsymbol{u}_2 \cdots \boldsymbol{u}_p\}$, we can write

$$\widehat{\boldsymbol{y}} = \boldsymbol{y} - \boldsymbol{z} = c_1\boldsymbol{u}_1 + c_2\boldsymbol{u}_2 + \cdots + c_p\boldsymbol{u}_p$$

Take dot product with $\boldsymbol{u}_i$ on both sides:

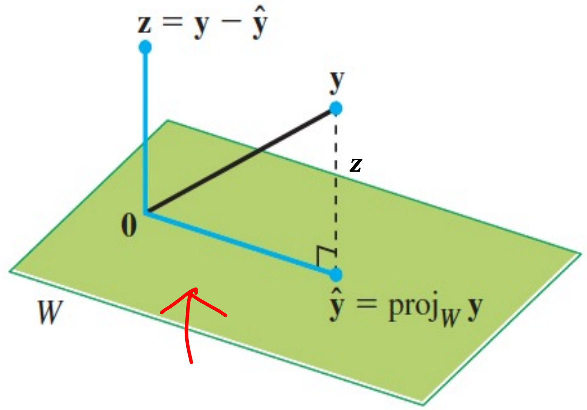
$$(\boldsymbol{y} - \boldsymbol{z}) \cdot \boldsymbol{u}_i = (c_1\boldsymbol{u}_1 + c_2\boldsymbol{u}_2 + \cdots + c_p\boldsymbol{u}_p) \cdot \boldsymbol{u}_i,\ i = 1, \cdots, p$$

Since $\boldsymbol{u}_i \cdot \boldsymbol{u}_j = 0, if\ i \neq j$, and $\boldsymbol{z} \cdot \boldsymbol{u}_i = 0$, so we have

$$c_i\boldsymbol{u}_i \cdot \boldsymbol{u}_i = (\boldsymbol{y} - \boldsymbol{z}) \cdot \boldsymbol{u}_i = \boldsymbol{y} \cdot \boldsymbol{u}_i - \boldsymbol{z} \cdot \boldsymbol{u}_i = \boldsymbol{y} \cdot \boldsymbol{u}_i$$

$\therefore \quad c_i = \frac{\boldsymbol{y}\cdot\boldsymbol{u}_i}{\boldsymbol{u}_i\cdot\boldsymbol{u}_i}$

Finally: $\widehat{\boldsymbol{y}} = c_1\boldsymbol{u}_1 + c_2\boldsymbol{u}_2 + \cdots + c_p\boldsymbol{u}_p = \frac{\boldsymbol{y}\cdot\boldsymbol{u}_1}{\boldsymbol{u}_1\cdot\boldsymbol{u}_1}\boldsymbol{u}_1 + \frac{\boldsymbol{y}\cdot\boldsymbol{u}_2}{\boldsymbol{u}_2\cdot\boldsymbol{u}_2}\boldsymbol{u}_2 + \cdots + \frac{\boldsymbol{y}\cdot\boldsymbol{u}_p}{\boldsymbol{u}_p\cdot\boldsymbol{u}_p}\boldsymbol{u}_p$



Key points – 6.2.4 Orthonormal Sets

- Definition
  - If $\{\boldsymbol{u}_1, \boldsymbol{u}_2 \cdots \boldsymbol{u}_p\}$ is called an **orthonormal basis** for subspace W if the basis vectors are orthogonal with unit length ($\boldsymbol{u}_i \cdot \boldsymbol{u}_j = 0, if\ i \neq j$, and $\|\boldsymbol{u}\| = 1$)
  - Let $U_{n\times p} = [\boldsymbol{u}_1\ \boldsymbol{u}_2 \cdots \boldsymbol{u}_p]$, $\boldsymbol{u}_i \in R^n$

    Then, $U^T U = I$ (I is a $p\times p$ identify matrix).

    1

    Explain: $U^T = \begin{bmatrix} \boldsymbol{u}_1{}^T \\ \vdots \\ \boldsymbol{u}_p{}^T \end{bmatrix}$ is a $p\times n$ matrix, So $U^T U = \begin{bmatrix} \boldsymbol{u}_1{}^T \\ \vdots \\ \boldsymbol{u}_p{}^T \end{bmatrix} [\boldsymbol{u}_1\ \boldsymbol{u}_2 \cdots \boldsymbol{u}_p] = \begin{bmatrix} \boldsymbol{u}_1{}^T\boldsymbol{u}_1 & \cdots & \boldsymbol{u}_1{}^T\boldsymbol{u}_p \\ \vdots & \ddots & \vdots \\ \boldsymbol{u}_p{}^T\boldsymbol{u}_1 & \cdots & \boldsymbol{u}_p{}^T\boldsymbol{u}_p \end{bmatrix} = \begin{bmatrix} 1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 1 \end{bmatrix} = I$ $-\ p\times p$

    $U^T = \begin{bmatrix} \vec{u}_1 \\ \vec{u}_2 \\ \vec{u}_p \end{bmatrix}$. $U = [\vec{u}_1\ \vec{u}_2 \cdots \vec{u}_p]$

- Properties
  - a. $\|U\boldsymbol{x}\| = \|\boldsymbol{x}\|$ (preserve the length of vector)
  - b. $\cancel{U\boldsymbol{x}\cdot U\boldsymbol{y} = \boldsymbol{x}\cdot\boldsymbol{y}}$
  - c. $\cancel{U\boldsymbol{x}} \cdot \cancel{U}\boldsymbol{y} = \boldsymbol{0}$, if and only if $\boldsymbol{x}\cdot\boldsymbol{y} = \boldsymbol{0}$

  $\|Ux\|^2 = (U\vec{x})\cdot(Ux) = (Ux)^T(Ux) = x^T U^T U x = x^T x = \vec{x}\cdot\vec{x} = \|x\|^2$ $\quad p\times p$

  $xU^TUy = x\cdot y = 0$

- Re-write projection equation using U: $\hat{\boldsymbol{y}} = Proj_W\boldsymbol{y} = UU^T\boldsymbol{y}$

  Explain: $\hat{\boldsymbol{y}} = Proj_W\boldsymbol{y} = \frac{\boldsymbol{y}\cdot\boldsymbol{u}_1}{\boldsymbol{u}_1\cdot\boldsymbol{u}_1}\boldsymbol{u}_1 + \cdots + \frac{\boldsymbol{y}\cdot\boldsymbol{u}_p}{\boldsymbol{u}_p\cdot\boldsymbol{u}_p}\boldsymbol{u}_p = (\boldsymbol{y}\cdot\boldsymbol{u}_1)\boldsymbol{u}_1 + \cdots + (\boldsymbol{y}\cdot\boldsymbol{u}_p)\boldsymbol{u}_p$

  $= (\boldsymbol{u}_1{}^T\boldsymbol{y})\boldsymbol{u}_1 + \cdots + (\boldsymbol{u}_p{}^T\boldsymbol{y})\boldsymbol{u}_p = [\boldsymbol{u}_1\ \boldsymbol{u}_2 \cdots \boldsymbol{u}_p]\begin{bmatrix} \boldsymbol{u}_1{}^T\boldsymbol{y} \\ \vdots \\ \boldsymbol{u}_p{}^T\boldsymbol{y} \end{bmatrix} = [\boldsymbol{u}_1\ \boldsymbol{u}_2 \cdots \boldsymbol{u}_p]\begin{bmatrix} \boldsymbol{u}_1{}^T \\ \vdots \\ \boldsymbol{u}_p{}^T \end{bmatrix}\boldsymbol{y} = UU^T\boldsymbol{y}$

  $c_1\vec{u}_1 + c_2\vec{u}_2 + \cdots + c_p\vec{u}_p$ $\quad A\vec{x}$ $\quad U^{-1} = U^T$

- Note: if U is a square, it is called "**orthogonal matrix**". In this case, $U^{-1} = U^T$

$$\begin{bmatrix} u_1^T y \\ \vdots \\ u_p^T \cdot y \end{bmatrix} = \begin{bmatrix} u_1^T \\ \vdots \\ u_p^T \end{bmatrix} \cdot y$$

Explain: $\hat{\boldsymbol{y}} = Proj_W \boldsymbol{y} = \frac{\boldsymbol{y}\cdot\boldsymbol{u}_1}{\boldsymbol{u}_1\cdot\boldsymbol{u}_1}\boldsymbol{u}_1 + \cdots + \frac{\boldsymbol{y}\cdot\boldsymbol{u}_p}{\boldsymbol{u}_p\cdot\boldsymbol{u}_p}\boldsymbol{u}_p = (\boldsymbol{y}\cdot\boldsymbol{u}_1)\boldsymbol{u}_1 + \cdots + (\boldsymbol{y}\cdot\boldsymbol{u}_p)\boldsymbol{u}_p$

$$= (\boldsymbol{u}_1{}^T\boldsymbol{y})\boldsymbol{u}_1 + \cdots + (\boldsymbol{u}_p{}^T\boldsymbol{y})\boldsymbol{u}_p = [\boldsymbol{u}_1\ \boldsymbol{u}_2 \cdots \boldsymbol{u}_p]\begin{bmatrix} \boldsymbol{u}_1{}^T\boldsymbol{y} \\ \vdots \\ \boldsymbol{u}_p{}^T\boldsymbol{y} \end{bmatrix} = [\boldsymbol{u}_1\ \boldsymbol{u}_2 \cdots \boldsymbol{u}_p]\begin{bmatrix} \boldsymbol{u}_1{}^T \\ \vdots \\ \boldsymbol{u}_p{}^T \end{bmatrix}\boldsymbol{y} = UU^T\boldsymbol{y}$$

- Note: if U is a square, it is called "**orthogonal matrix**". In this case, $U^{-1} = U^T$

$$c_1 u_1 + c_2 u_2 + \cdots c_p u_p.$$

$$[u_1\ u_2 \cdots u_p]\begin{bmatrix} c_1 \\ c_2 \\ \vdots \\ c_p \end{bmatrix}$$

$$= [u_1 \cdots u_p]\begin{bmatrix} u_1^T y \\ u_2^T y \end{bmatrix}$$

$$Ax = b$$

$$[u_1\ u_2\ \ u_p]\begin{bmatrix} x_1 \\ \vdots \\ x_p \end{bmatrix} = b$$

$$x_1 u_1 + x_2 u_2 + \cdots + x_p u_p$$

Key points – 6.2.5 Orthogonal Decomposition.

- Geometric interpretation of the orthogonal projection (see figure right-top)
- The best approximation theorem (see figure right-bottom)

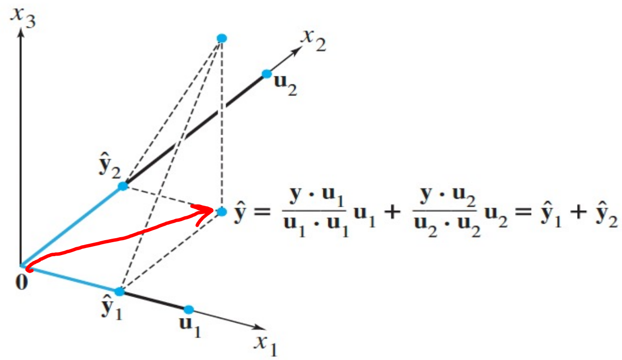
$$\|\boldsymbol{y}-\hat{\boldsymbol{y}}\| < \|\boldsymbol{y}-\boldsymbol{v}\|$$

$\hat{\boldsymbol{y}}$ is the orthogonal projection of $\boldsymbol{y}$ onto W. $\boldsymbol{v}$ is any vector in W **distinct** from $\hat{\boldsymbol{y}}$.

Explain: $\boldsymbol{y}-\boldsymbol{v} = (\boldsymbol{y}-\hat{\boldsymbol{y}}) + (\hat{\boldsymbol{y}}-\boldsymbol{v})$,

So, according to Pythagorean theorem: $\|\boldsymbol{y}-\boldsymbol{v}\|^2 = \|\boldsymbol{y}-\hat{\boldsymbol{y}}\|^2 + \|\hat{\boldsymbol{y}}-\boldsymbol{v}\|^2$ ➔ $\|\boldsymbol{y}-\hat{\boldsymbol{y}}\|^2 = \|\boldsymbol{y}-\boldsymbol{v}\|^2 - \|\hat{\boldsymbol{y}}-\boldsymbol{v}|$

Therefore we have: $\|\boldsymbol{y}-\hat{\boldsymbol{y}}\| < \|\boldsymbol{y}-\boldsymbol{v}\|$

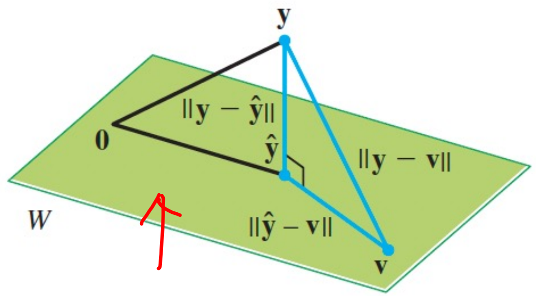


- Example: $\boldsymbol{u}_1 = \begin{bmatrix}3\\1\\1\end{bmatrix}, \boldsymbol{u}_2 = \begin{bmatrix}-1\\2\\1\end{bmatrix}, \boldsymbol{y} = \begin{bmatrix}3\\0\\1\end{bmatrix}$

$W = \mathrm{Span}(\vec{u}_1, \vec{u}_2)$

$\vec{u}_1 \cdot \vec{u}_2 = 0$

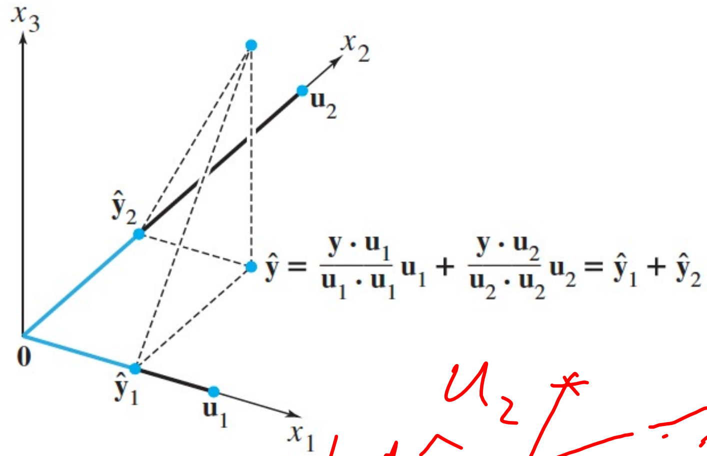
  - $\boldsymbol{u}_1$ and $\boldsymbol{u}_2$ are orthogonal?
  - $\hat{\boldsymbol{y}} = \frac{[3\ 0\ 1]\begin{bmatrix}3\\1\\1\end{bmatrix}}{9+1+1}\boldsymbol{u}_1 + \frac{[3\ 0\ 1]\begin{bmatrix}-1\\2\\1\end{bmatrix}}{1+4+1}\boldsymbol{u}_2 = \frac{9+0+1}{11}\boldsymbol{u}_1 + \frac{-3+0+1}{1+4+1}\boldsymbol{u}_2 = \frac{10}{11}\begin{bmatrix}3\\1\\1\end{bmatrix} - \frac{1}{3}\begin{bmatrix}-1\\2\\1\end{bmatrix} = \begin{bmatrix}101/33\\8/33\\19/33\end{bmatrix}$

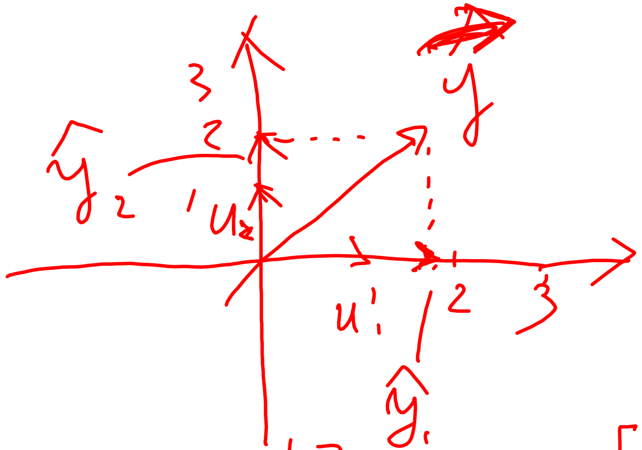


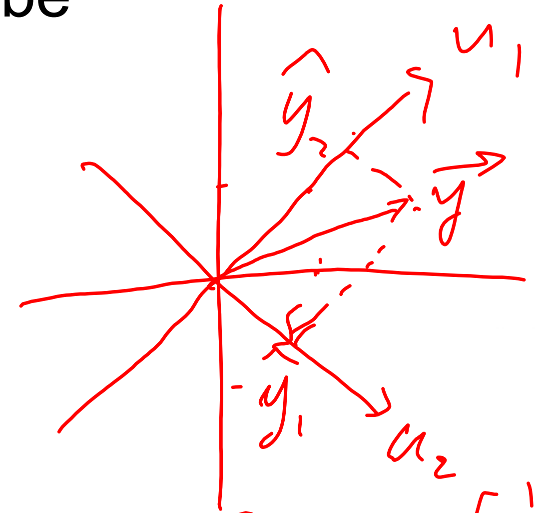
- What if $p = n$? That is, when W is the full space, what will be $\hat{\boldsymbol{y}} = Proj_W\boldsymbol{y}$?

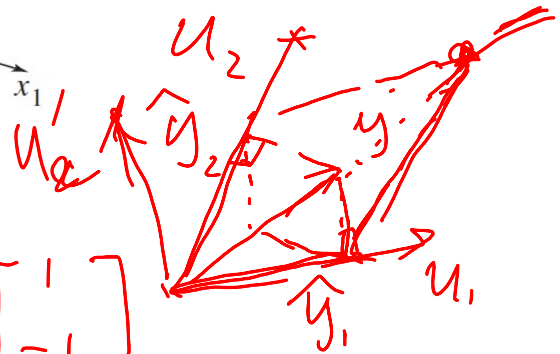
$\mathbb{R}^n$ $n=3$

What if $p = n$? That is, when W is the full space, what will be $\hat{\boldsymbol{y}} = Proj_W \boldsymbol{y}$?









① $u_1 = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$, $u_2 = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$,

$\vec{y} = \hat{y}_1 + \hat{y}_2$

② $u_1 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$, $u_2 = \begin{bmatrix} 1 \\ -1 \end{bmatrix}$

$\vec{y} = \hat{y}_1 + \hat{y}_2$

$\hat{y} = UU^T\vec{y} = I \cdot \vec{y} = \vec{y}$

$\hat{y}_1 + \hat{y}_2 \neq \vec{y}$

$u_1 \cdot u_2 \neq 0$

Key points – 6.3.1 QR Factorization (why)

- Definition of QR factorization
  - Given an $m \times n$ matrix A
  - A can be factorized as $A = QR$,
    - Q $(m \times n$) has orthonormal columns (meaning $Q^T Q = I$)
    - R $(n \times n)$ is an "up-triangle" square matrix
- Why QR factorization is useful
  - After factorize A into Q and R, we can easily find the solution for system: $A\boldsymbol{x} = \boldsymbol{b}$ using back substitute only
    - Explain: $A\boldsymbol{x} = \boldsymbol{b}$ ➔ $QR\boldsymbol{x} = \boldsymbol{b}$ ➔ $Q^T QR\boldsymbol{x} = Q^T\boldsymbol{b}$ ➔ $R\boldsymbol{x} = Q^T\boldsymbol{b} = \boldsymbol{y}$

$$R\boldsymbol{x} = \boldsymbol{y}: \begin{bmatrix} r_{11} & r_{12} & r_{13} \\ 0 & r_{22} & r_{23} \\ 0 & 0 & r_{33} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix},$$

$r_{33}\, x_3 = y_3$ ➔ $x_3 = y_3 / r_{33}$

$r_{22}\, x_2 + r_{23}\, x_3 = y_2$ ➔ $x_2 = (y_2 - r_{23}\, x_3)\, /\, r_{22}$

$r_{11}\, x_1 + r_{12}\, x_2 + r_{13}\, x_3 = y_1$ ➔ $x_1 = (y_1 - r_{12}\, x_2 - r_{13}\, x_3)\, /\, r_{11}$

  - **$\boldsymbol{QR}$ factorization is an important tool for finding a Least Square solution ($\hat{\boldsymbol{x}} = R^{-1} Q^T \boldsymbol{b}$, in week 10)**

Key points – 6.3.2 QR Factorization (how)

- How do we find Q and R from A – Gram–Schmidt Approach
  - Given any set of p independent columns (basis of non-zero subspace W in R^n): $\{\boldsymbol{x}_1, \boldsymbol{x}_2 \cdots \boldsymbol{x}_p\} \in R^n$ $(A = [\boldsymbol{x}_1\ \boldsymbol{x}_2 \cdots \boldsymbol{x}_p])$
  - Define the following orthogonal set$\{\boldsymbol{v}_1, \boldsymbol{v}_2 \cdots \boldsymbol{v}_p\}$:

$$\boldsymbol{v}_1 = \boldsymbol{x}_1$$

$$\boldsymbol{v}_2 = \boldsymbol{x}_2 - \frac{\boldsymbol{x}_2 \cdot \boldsymbol{v}_1}{\boldsymbol{v}_1 \cdot \boldsymbol{v}_1}\boldsymbol{v}_1 \text{ (so } \boldsymbol{v}_2 \text{is orthogonal to } \boldsymbol{v}_1\text{)}$$

$$\boldsymbol{v}_3 = \boldsymbol{x}_3 - \frac{\boldsymbol{x}_3 \cdot \boldsymbol{v}_1}{\boldsymbol{v}_1 \cdot \boldsymbol{v}_1}\boldsymbol{v}_1 - \frac{\boldsymbol{x}_3 \cdot \boldsymbol{v}_2}{\boldsymbol{v}_2 \cdot \boldsymbol{v}_2}\boldsymbol{v}_2 \text{ (so } \boldsymbol{v}_3 \text{is orthogonal to } \boldsymbol{v}_2, \boldsymbol{v}_1\text{)}$$

$$\vdots$$

$$\boldsymbol{v}_p = \boldsymbol{x}_p - \sum_{i=1}^{p-1} \frac{\boldsymbol{x}_p \cdot \boldsymbol{v}_i}{\boldsymbol{v}_i \cdot \boldsymbol{v}_i}\boldsymbol{v}_i \text{ (so } \boldsymbol{v}_3 \text{is orthogonal to } \boldsymbol{v}_{p-1}, \cdots, \boldsymbol{v}_2, \boldsymbol{v}_1\text{)}$$

  - Form a orthonormal basis from $\{\boldsymbol{v}_1, \boldsymbol{v}_2, \cdots, \boldsymbol{v}_p\}$
    - $Q = [\boldsymbol{u}_1\ \boldsymbol{u}_2 \cdots \boldsymbol{u}_p] = [\frac{\boldsymbol{v}_1}{\|\boldsymbol{v}_1\|}\ \frac{\boldsymbol{v}_2}{\|\boldsymbol{v}_2\|} \cdots \frac{\boldsymbol{v}_2}{\|\boldsymbol{v}_2\|}]$

  - Finally, find R
    - Since $A = QR$ and $Q^TQ = I$, from $Q^TA = Q^TQR$, we find $R = Q^TA$
    - $R = [\boldsymbol{u}_1\ \boldsymbol{u}_2 \cdots \boldsymbol{u}_p]^T[\boldsymbol{x}_1\ \boldsymbol{x}_2 \cdots \boldsymbol{x}_p]$

$$= \begin{bmatrix} \boldsymbol{u}_1{}^T \\ \vdots \\ \boldsymbol{u}_p{}^T \end{bmatrix} [\boldsymbol{x}_1 \cdots \boldsymbol{x}_p]$$

$$= \begin{bmatrix} \boldsymbol{u}_1{}^T\boldsymbol{x}_1 & \cdots & \boldsymbol{u}_1{}^T\boldsymbol{x}_p \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \boldsymbol{u}_p{}^T\boldsymbol{x}_p \end{bmatrix}$$

Key points – 6.3.2 QR Factorization (how)

- Example: $A = \begin{bmatrix} 3 & 8 \\ 0 & 5 \\ -1 & -6 \end{bmatrix}$

$\boldsymbol{x}_1 = \begin{bmatrix} 3 \\ 0 \\ -1 \end{bmatrix}$, $\boldsymbol{x}_2 = \begin{bmatrix} 8 \\ 5 \\ -6 \end{bmatrix}$, $\boldsymbol{x}_1$and $\boldsymbol{x}_2$ are independent

Find $\boldsymbol{v}_i$: $\boldsymbol{v}_1 = \boldsymbol{x}_1 = \begin{bmatrix} 3 \\ 0 \\ -1 \end{bmatrix}$, $\boldsymbol{v}_2 = \boldsymbol{x}_2 - \frac{\boldsymbol{x}_2 \cdot \boldsymbol{v}_1}{\boldsymbol{v}_1 \cdot \boldsymbol{v}_1} \boldsymbol{v}_1 = \begin{bmatrix} 8 \\ 5 \\ -6 \end{bmatrix} - \frac{[8 \quad 5 \quad -6] \cdot \begin{bmatrix} 3 \\ 0 \\ -1 \end{bmatrix}}{9+1} \begin{bmatrix} 3 \\ 0 \\ -1 \end{bmatrix} = \begin{bmatrix} -1 \\ 5 \\ -3 \end{bmatrix}$

Verify: $\boldsymbol{v}_1 \cdot \boldsymbol{v}_2 = [3 \quad 0 \quad -1] \cdot \begin{bmatrix} -1 \\ 5 \\ -3 \end{bmatrix} = 0$

Normalize $\boldsymbol{v}_1$ and $\boldsymbol{v}_2$: $\|\boldsymbol{v}_1\| = \sqrt{10}$, $\|\boldsymbol{v}_2\| = \sqrt{35}$,

So we get $\boldsymbol{u}_1 = \frac{\boldsymbol{v}_1}{\|\boldsymbol{v}_1\|} = \begin{bmatrix} 3/\sqrt{10} \\ 0 \\ -1/\sqrt{10} \end{bmatrix}$,$\boldsymbol{u}_2 = \frac{\boldsymbol{v}_2}{\|\boldsymbol{v}_2\|} = \begin{bmatrix} -1/\sqrt{35} \\ 5/\sqrt{35} \\ -3/\sqrt{35} \end{bmatrix}$ ➔ $Q = \begin{bmatrix} 3/\sqrt{10} & -1/\sqrt{35} \\ 0 & 5/\sqrt{35} \\ -1/\sqrt{10} & -3/\sqrt{35} \end{bmatrix}$

Finally, find R: $R = Q^T A = \begin{bmatrix} 3/\sqrt{10} & 0 & -1/\sqrt{10} \\ -1/\sqrt{35} & 5/\sqrt{35} & -3/\sqrt{35} \end{bmatrix} \begin{bmatrix} 3 & 8 \\ 0 & 5 \\ -1 & -6 \end{bmatrix} = \begin{bmatrix} 10/\sqrt{10} & 30/\sqrt{10} \\ 0 & 35/\sqrt{35} \end{bmatrix}$ ➔ $R = \begin{bmatrix} \sqrt{10} & 3\sqrt{10} \\ 0 & \sqrt{35} \end{bmatrix}$

Key points – 6.3.2 QR Factorization Properties

- Properties of QR factorization
  1) $Q^TQ = I$
  2) Columns of Q is equivalent to columns of A
     1) W =span $\{\boldsymbol{u}_1, \boldsymbol{u}_2 \cdots \boldsymbol{u}_p\}$ = span $\{\boldsymbol{x}_1, \boldsymbol{x}_2 \cdots \boldsymbol{x}_p\}$
     2) Q forms an orthonormal basis to span the same subspace W
  3) QQ^T is the projection matrix onto W (spanned by columns of A or Q)
  4) If A has independent columns, R is invertible, and all the values on the diagonal of R is positive
  5) If A has any dependent columns, simply skip it in Q

End