CX1104: Linear Algebra for Computing

$$\underbrace{\begin{bmatrix} a_{11} & a_{12} & a_{13} & \dots & a_{1n} \\ a_{21} & a_{22} & a_{23} & \dots & a_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & a_{m3} & \dots & a_{mn} \end{bmatrix}}_{A} \underbrace{\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \\ x_n \end{bmatrix}}_{n \times n} = \underbrace{\begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_m \end{bmatrix}}_{m \times 1}$$

Chap. No: **6.3.3**

Lecture: Orthogonality

Topic: Gram-Schmidt Process

Concept: Using GS Process for QR Factorisation

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The application of the Gram-Schmidt process to the column vectors of a full column rank matrix yields the QR decomposition.

QR decomposition helps in solving linear least squares problem (next chapter).

If $A \in \mathbb{R}^{m \times n}$ has full column rank, i.e, A has linearly independent columns, A can be factored as follows:

$$A = QR$$

$$A = [q_1 \ q_2 \ \cdots \ q_n] \begin{bmatrix} R_{11} \ R_{12} \ \cdots \ R_{2n} \\ 0 \ R_{22} \ \cdots \ R_{2n} \\ \vdots \ \vdots \ \ddots \ \vdots \\ 0 \ 0 \ \cdots \ R_{nn} \end{bmatrix}$$

The *Q* Factor:

- Q is $m \times n$ with orthonormal columns $(Q^T Q = I)$
- If A is square (m = n), then Q is orthogonal, i.e, $Q^TQ = QQ^T = I$

The R Factor:

- R is $n \times n$ upper triangular, with nonzero diagonal elements
- R is nonsingular (diagonal elements are nonzero)

- Vectors q_1, q_2, \dots, q_n are orthonormal m-vectors: $||q_i|| = 1$ and $q_i^T q_j = 0$ if $i \neq j$
- Diagonal elements R_{ii} are nonzero. NOTE:

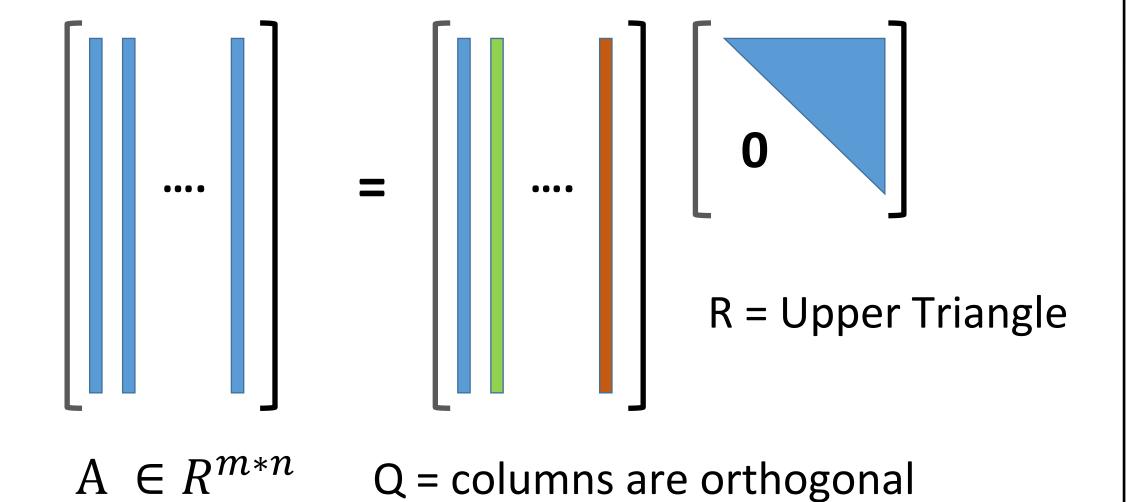
Q is obtained by performing GS Process on A^{2}

THEOREM 12

The QR Factorization

If A is an $m \times n$ matrix with linearly independent columns, then A can be factored as A = QR, where Q is an $m \times n$ matrix whose columns form an orthonormal basis for Col A and R is an $n \times n$ upper triangular invertible matrix with positive entries on its diagonal.

$$A = [\mathbf{x}_1 \quad \cdots \quad \mathbf{x}_n] = [Q\mathbf{r}_1 \quad \cdots \quad Q\mathbf{r}_n] = QR$$



```
% Gram Schmit - Chng Eng Siong, for QR decomposition
 % 20 May 2020
= function [Q,R] = my GS(A)
 [m,n] = size(A);
 Q=zeros(m,n);
 R=zeros(n,n);
        = A(:,1);
 x1
 Q(:,1) = x1/norm(x1);
 R(1,1) = norm(x1);
     for i=2:n
         x i = A(:,i);
         v i = x i;
         for j=1:i-1
             v j = Q(:,j);
             RVal = (x_i'*v_j)/(v_j'*v_j);
             v i = v i - RVal*v j;
             R(j,i) = RVal;
         end % of for j
         Q(:,i) = v_i/norm(v_i);
         R(i,i) = norm(v_i);
     end % of for i
 end % of funcyion
```

Consider a full column rank matrix A:

$$A = [x_1, x_2, x_3, ..., x_n]$$

$$\text{Proj}_{v} x = \frac{\langle v, x \rangle}{\langle v, v \rangle} v$$

$$v_1 = x_1$$

$$v_2 = x_2 - \operatorname{Proj}_{v_1} x_2$$

$$v_3 = x_3 - \operatorname{Proj}_{v_1} x_3 - \operatorname{Proj}_{v_2} x_3$$

$$v_i = x_i - \sum_{j=1}^{i-1} \text{Proj}_{v_j} x_i$$

$$e_1 = \frac{v_1}{||v_1||}$$

$$e_i = \frac{v_i}{||v_i||}$$

We can now express the \mathbf{a}_i s over our newly computed orthonormal basis:

$$x_1 = \langle e_1, x_1 \rangle e_1$$

 $x_2 = \langle e_1, x_2 \rangle e_1 + \langle e_2, x_2 \rangle e_2$
 $x_3 = \langle e_1, x_3 \rangle e_1 + \langle e_2, x_3 \rangle e_2 + \langle e_3, x_3 \rangle e_3$
:

$$x_n = \sum_{j=1}^n \langle e_j, x_n \rangle e_j$$

This can be written in matrix form:

$$A = QR$$

where:

$$Q = [e_1, e_2, e_3, ..., e_n]$$

and

$$R = \begin{pmatrix} < e_1, x_2 > < e_1, x_3 > \dots \\ 0 & < e_2, x_2 > < e_2, x_3 > \dots \\ 0 & 0 & < e_3, x_3 > \dots \\ \vdots & \vdots & \vdots & \ddots \end{pmatrix}$$

Example [edit]

Consider the decomposition of

$$A = egin{pmatrix} 12 & -51 & 4 \ 6 & 167 & -68 \ -4 & 24 & -41 \end{pmatrix}.$$

Recall that an orthonormal matrix Q has the property

$$Q^{\mathsf{T}} \ Q = I.$$

Then, we can calculate Q by means of Gram–Schmidt as follows:

$$U = (\mathbf{u}_1 \quad \mathbf{u}_2 \quad \mathbf{u}_3) = \begin{pmatrix} 12 & -69 & -58/5 \\ 6 & 158 & 6/5 \\ -4 & 30 & -33 \end{pmatrix};$$

$$Q = \left(\frac{\mathbf{u}_1}{\|\mathbf{u}_1\|} \quad \frac{\mathbf{u}_2}{\|\mathbf{u}_2\|} \quad \frac{\mathbf{u}_3}{\|\mathbf{u}_3\|} \right) = \begin{pmatrix} 6/7 & -69/175 & -58/175 \\ 3/7 & 158/175 & 6/175 \\ -2/7 & 6/35 & -33/35 \end{pmatrix} \times \begin{pmatrix} 14 & 21 & -14 \\ 0 & 175 & -70 \\ 0 & 0 & 35 \end{pmatrix}$$

$$Q = \begin{pmatrix} \mathbf{u}_1 & \mathbf{u}_2 & \mathbf{u}_3 & \mathbf$$

Thus, we have

$$Q^{\mathsf{T}} A = Q^{\mathsf{T}} Q \, R = R; \ R = Q^{\mathsf{T}} A = egin{pmatrix} 14 & 21 & -14 \ 0 & 175 & -70 \ 0 & 0 & 35 \end{pmatrix}$$

Hence,

$$A = \begin{pmatrix} 12 & -51 & 4 \\ 6 & 167 & -68 \\ -4 & 24 & -41 \end{pmatrix} =$$

$$\begin{pmatrix} 6/7 & -69/175 & -58/175 \\ 3/7 & 158/175 & 6/175 \\ -2/7 & 6/35 & -33/35 \end{pmatrix} \mathbf{X} \begin{pmatrix} 14 & 21 & -14 \\ 0 & 175 & -70 \\ 0 & 0 & 35 \end{pmatrix}$$

Q: Orthogonal Matrix

R: Upper Triangular Matrix