

Slide 22-Orthogonality IV

MAT2040 Linear Algebra

SSE, CUHK(SZ)

Gram-Schmidt process

Note that the linearly independent set $\{\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_m\}$ may not be an orthogonal set.

Question: Can we make a linearly independent set $\{\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_m\}$ into an orthonormal set $\{\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_m\}$ while keeping the same span ($\text{Span}(\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_m) = \text{Span}(\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_m)$)?

Idea is to use the projection and project it into the subspace and the remaining vector will be orthogonal to the subspace.

Lemma 22.1 (Projection onto a subspace) Let S be a subspace of the inner product space V and $\{\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_m\}$ is the orthonormal basis for S , for any $\mathbf{x} \in V$. And let \mathbf{p} be the projection vector of \mathbf{x} onto S ($\mathbf{x} - \mathbf{p} \perp S$), then \mathbf{p} is uniquely determined by

$$\mathbf{p} = \sum_{i=1}^m \langle \mathbf{x}, \mathbf{u}_i \rangle \mathbf{u}_i$$

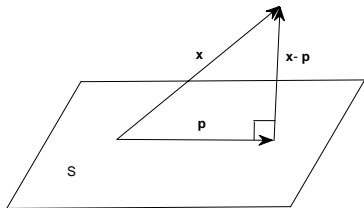


Figure: Projection of $\mathbf{x} \in V$ onto subspace S .

Proof. Since $\mathbf{p} \in S$, then write

$$\mathbf{p} = \sum_{i=1}^m c_i \mathbf{u}_i$$

In addition, $\mathbf{x} - \mathbf{p} \perp S$, thus

$$\langle \mathbf{x} - \sum_{j=1}^m c_j \mathbf{u}_j, \mathbf{u}_i \rangle = 0, \quad i = 1, \dots, m$$

$$\langle \mathbf{x}, \mathbf{u}_i \rangle - \sum_{j=1}^m c_j \langle \mathbf{u}_j, \mathbf{u}_i \rangle = 0$$

Thus

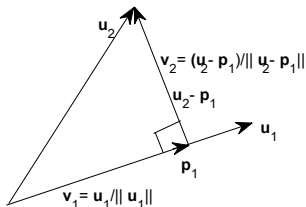
$$c_i = \langle \mathbf{x}, \mathbf{u}_i \rangle, \quad i = 1, \dots, m$$

$$\mathbf{p} = \sum_{i=1}^m \langle \mathbf{x}, \mathbf{u}_i \rangle \mathbf{u}_i$$

and $\mathbf{x} - \mathbf{p} \perp S$

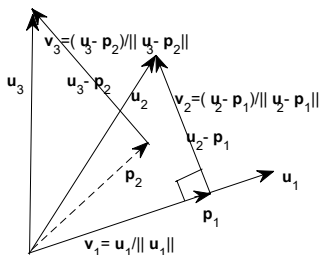
Question: Given an linearly independent set $\{\mathbf{u}_1, \dots, \mathbf{u}_m\}$ in an inner product vector space V , how can we find an orthonormal set $\{\mathbf{v}_1, \dots, \mathbf{v}_m\}$ such that $\text{Span}(\mathbf{u}_1, \dots, \mathbf{u}_m) = \text{Span}(\mathbf{v}_1, \dots, \mathbf{v}_m)$?

Thinking geometrically for $m = 2$ as the following figure:



$$\mathbf{v}_1 = \mathbf{u}_1 / \|\mathbf{u}_1\| \quad \mathbf{v}_2 = (\mathbf{u}_2 - \mathbf{p}_1) / \|\mathbf{u}_2 - \mathbf{p}_1\|$$

Thinking geometrically for $m = 3$ as following figure:



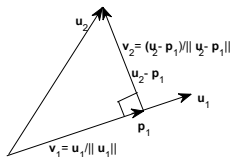
$$\begin{aligned}
 v_1 &= u_1 / \|u_1\| & p_1 &= \langle u_2, v_1 \rangle v_1 & p_2 &= \langle u_3, v_1 \rangle v_1 + \langle u_3, v_2 \rangle v_2 \\
 v_2 &= (u_2 - p_1) / \|u_2 - p_1\| & v_3 &= (u_3 - p_2) / \|u_3 - p_2\|
 \end{aligned}$$

Gram-Schmidt Process

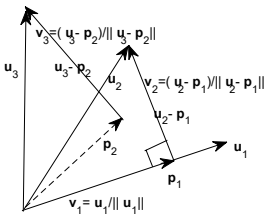
(Gram-Schmidt Process)

Step 1: normalize \mathbf{u}_1 to get \mathbf{v}_1 , i.e., $\mathbf{v}_1 = \frac{\mathbf{u}_1}{\|\mathbf{u}_1\|}$

Step 2: project \mathbf{u}_2 onto $\text{Span}(\mathbf{v}_1)$ to get $\mathbf{p}_1 = \langle \mathbf{u}_2, \mathbf{v}_1 \rangle \mathbf{v}_1$, then $\mathbf{r}_1 = \mathbf{u}_2 - \mathbf{p}_1 \perp \text{Span}(\mathbf{u}_1)$. Set $\mathbf{v}_2 = \frac{\mathbf{r}_1}{\|\mathbf{r}_1\|} = \frac{\mathbf{u}_2 - \mathbf{p}_1}{\|\mathbf{u}_2 - \mathbf{p}_1\|}$, then $\{\mathbf{v}_1, \mathbf{v}_2\}$ are orthonormal set and $\text{Span}(\mathbf{v}_1, \mathbf{v}_2) = \text{Span}(\mathbf{u}_1, \mathbf{u}_2)$.



$$\mathbf{v}_1 = \mathbf{u}_1 / \|\mathbf{u}_1\| \quad \mathbf{v}_2 = (\mathbf{u}_2 - \mathbf{p}_1) / \|\mathbf{u}_2 - \mathbf{p}_1\|$$



$$\begin{aligned}
 \mathbf{v}_1 &= \mathbf{u}_1 / \|\mathbf{u}_1\| & \mathbf{p}_1 &= \langle \mathbf{u}_2, \mathbf{v}_1 \rangle \mathbf{v}_1 & \mathbf{p}_2 &= \langle \mathbf{u}_3, \mathbf{v}_1 \rangle \mathbf{v}_1 + \langle \mathbf{u}_3, \mathbf{v}_2 \rangle \mathbf{v}_2 \\
 \mathbf{v}_2 &= (\mathbf{u}_2 - \mathbf{p}_1) / \|\mathbf{u}_2 - \mathbf{p}_1\| & \mathbf{v}_3 &= (\mathbf{u}_3 - \mathbf{p}_2) / \|\mathbf{u}_3 - \mathbf{p}_2\|
 \end{aligned}$$

Step 3: project \mathbf{u}_3 onto $\text{Span}(\mathbf{v}_1, \mathbf{v}_2)$ to get $\mathbf{p}_2 = \langle \mathbf{u}_3, \mathbf{v}_1 \rangle \mathbf{v}_1 + \langle \mathbf{u}_3, \mathbf{v}_2 \rangle \mathbf{v}_2$, then $\mathbf{u}_3 - \mathbf{p}_2 \perp \text{Span}(\mathbf{v}_1, \mathbf{v}_2)$, set $\mathbf{v}_3 = \frac{\mathbf{u}_3 - \mathbf{p}_2}{\|\mathbf{u}_3 - \mathbf{p}_2\|}$, then $\{\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3\}$ are orthonormal set and $\text{Span}(\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3) = \text{Span}(\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3)$.

\vdots

Step m : project \mathbf{u}_m onto $\text{Span}(\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_{m-1})$ to get

$$\mathbf{p}_{m-1} = \langle \mathbf{u}_m, \mathbf{v}_1 \rangle \mathbf{v}_1 + \langle \mathbf{u}_m, \mathbf{v}_2 \rangle \mathbf{v}_2 + \dots + \langle \mathbf{u}_m, \mathbf{v}_{m-1} \rangle \mathbf{v}_{m-1}$$

Then $\mathbf{r}_{m-1} = \mathbf{u}_m - \mathbf{p}_{m-1} \perp \text{Span}(\mathbf{v}_1, \dots, \mathbf{v}_{m-1})$ and set

$\mathbf{v}_m = \frac{\mathbf{r}_{m-1}}{\|\mathbf{r}_{m-1}\|} = \frac{\mathbf{u}_m - \mathbf{p}_{m-1}}{\|\mathbf{u}_m - \mathbf{p}_{m-1}\|}$. Then $\{\mathbf{v}_1, \dots, \mathbf{v}_m\}$ is an orthonormal set and $\text{Span}(\mathbf{u}_1, \dots, \mathbf{u}_m) = \text{Span}(\mathbf{v}_1, \dots, \mathbf{v}_m)$

Theorem 22.2 The set $\{\mathbf{v}_1, \dots, \mathbf{v}_m\}$ constructed by the above Gram-Schmidt process from linearly independent set $\{\mathbf{u}_1, \dots, \mathbf{u}_m\}$ is an orthonormal set and $\text{Span}(\mathbf{u}_1, \dots, \mathbf{u}_m) = \text{Span}(\mathbf{v}_1, \dots, \mathbf{v}_m)$.

Proof Skipped. See Steven's book p267.

Example 22.3 Let

$$S = \{\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3\} = \left\{ \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix}, \begin{bmatrix} -1 \\ 4 \\ 4 \\ -1 \end{bmatrix}, \begin{bmatrix} 4 \\ -2 \\ 2 \\ 0 \end{bmatrix} \right\} \subseteq \mathbb{R}^4$$

In \mathbb{R}^n , the standard inner product is the scalar product $\langle \mathbf{x}, \mathbf{y} \rangle = \mathbf{y}^T \mathbf{x}$.

Now find the orthonormal basis for $\text{Span}(\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3)$.

$$\text{Step 1: } \mathbf{v}_1 = \frac{\mathbf{u}_1}{\|\mathbf{u}_1\|} = \frac{1}{2} \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} = \begin{bmatrix} \frac{1}{2} \\ \frac{1}{2} \\ \frac{1}{2} \\ \frac{1}{2} \end{bmatrix}.$$

Step 2: calculate

$$\begin{aligned}\mathbf{u}'_2 &= \mathbf{u}_2 - \langle \mathbf{u}_2, \mathbf{v}_1 \rangle \mathbf{v}_1 \\ &= \begin{bmatrix} -1 \\ 4 \\ 4 \\ -1 \end{bmatrix} - \left(\begin{bmatrix} -1 & 4 & 4 & -1 \end{bmatrix} \begin{bmatrix} \frac{1}{2} \\ \frac{1}{2} \\ \frac{1}{2} \\ \frac{1}{2} \end{bmatrix} \right) \begin{bmatrix} \frac{1}{2} \\ \frac{1}{2} \\ \frac{1}{2} \\ \frac{1}{2} \end{bmatrix} \\ &= \begin{bmatrix} -\frac{5}{2} \\ \frac{5}{2} \\ \frac{5}{2} \\ -\frac{5}{2} \end{bmatrix}\end{aligned}$$

then

$$\mathbf{v}_2 = \frac{\mathbf{u}'_2}{\|\mathbf{u}'_2\|} = \frac{1}{5} \begin{bmatrix} -\frac{5}{2} \\ \frac{5}{2} \\ \frac{5}{2} \\ -\frac{5}{2} \end{bmatrix} = \begin{bmatrix} -\frac{1}{2} \\ \frac{1}{2} \\ \frac{1}{2} \\ -\frac{1}{2} \end{bmatrix}$$

Step3: calculate

$$\begin{aligned}\mathbf{u}'_3 &= \mathbf{u}_3 - \langle \mathbf{u}_3, \mathbf{v}_1 \rangle \mathbf{v}_1 - \langle \mathbf{u}_3, \mathbf{v}_2 \rangle \mathbf{v}_2 \\ &= \begin{bmatrix} 4 \\ -2 \\ 2 \\ 0 \end{bmatrix} - \left(\begin{bmatrix} 4 & -2 & 2 & 0 \end{bmatrix} \begin{bmatrix} \frac{1}{2} \\ \frac{1}{2} \\ \frac{1}{2} \\ \frac{1}{2} \end{bmatrix} \right) \begin{bmatrix} \frac{1}{2} \\ \frac{1}{2} \\ \frac{1}{2} \\ \frac{1}{2} \end{bmatrix} \\ &\quad - \left(\begin{bmatrix} 4 & -2 & 2 & 0 \end{bmatrix} \begin{bmatrix} -\frac{1}{2} \\ \frac{1}{2} \\ \frac{1}{2} \\ -\frac{1}{2} \end{bmatrix} \right) \begin{bmatrix} -\frac{1}{2} \\ \frac{1}{2} \\ \frac{1}{2} \\ -\frac{1}{2} \end{bmatrix} = \begin{bmatrix} 2 \\ -2 \\ 2 \\ -2 \end{bmatrix}\end{aligned}$$

then

$$\mathbf{v}_3 = \frac{\mathbf{u}'_3}{\|\mathbf{u}'_3\|} = \frac{1}{4} \begin{bmatrix} 2 \\ -2 \\ 2 \\ -2 \end{bmatrix} = \begin{bmatrix} \frac{1}{2} \\ -\frac{1}{2} \\ \frac{1}{2} \\ -\frac{1}{2} \end{bmatrix}$$

QR decomposition

Theorem 22.5 (QR decomposition) Let $A \in \mathbb{R}^{m \times n}$ be an $m \times n$ real matrix and $\text{rank}(A)=n$ (column vectors are linearly independent), then A can be factorized as $A = QR$, where Q is an $m \times n$ matrix with orthonormal column vectors and R is an upper triangular $n \times n$ matrix with all positive diagonal elements.

Proof. Suppose that $A = [\mathbf{a}_1, \dots, \mathbf{a}_n]$ and $\{\mathbf{q}_1, \dots, \mathbf{q}_n\}$ is the orthonormal set obtained from $\{\mathbf{a}_1, \dots, \mathbf{a}_n\}$ by the following Gram-Schmidt process (see step 1 and step 2).

Gram-Schmidt process

Step 1: $\mathbf{q}_1 = \frac{\mathbf{a}_1}{\|\mathbf{a}_1\|}$, $\mathbf{q}_1^T \mathbf{a}_1 = \langle \mathbf{a}_1, \mathbf{q}_1 \rangle = \|\mathbf{a}_1\| > 0$

QR decomposition

Step 2: For $j = 2, \dots, n$

1. Let

$$\mathbf{r}_{j-1} = \mathbf{a}_j - \mathbf{p}_{j-1}$$

where $\mathbf{p}_{j-1} = \langle \mathbf{a}_j, \mathbf{q}_1 \rangle \mathbf{q}_1 + \dots + \langle \mathbf{a}_j, \mathbf{q}_{j-1} \rangle \mathbf{q}_{j-1}$ is the projection of \mathbf{a}_j onto $\text{Span}\{\mathbf{q}_1, \dots, \mathbf{q}_{j-1}\} = \text{Span}\{\mathbf{a}_1, \dots, \mathbf{a}_{j-1}\}$

2. Let $\mathbf{q}_j = \frac{\mathbf{r}_{j-1}}{\|\mathbf{r}_{j-1}\|}$, then

$$\mathbf{a}_j = \langle \mathbf{a}_j, \mathbf{q}_1 \rangle \mathbf{q}_1 + \dots + \langle \mathbf{a}_j, \mathbf{q}_{j-1} \rangle \mathbf{q}_{j-1} + \|\mathbf{r}_{j-1}\| \mathbf{q}_j.$$

QR decomposition

The above relations can be rewritten as

$$\mathbf{a}_1 = \|\mathbf{a}_1\| \mathbf{q}_1$$

$$\mathbf{a}_2 = \langle \mathbf{a}_2, \mathbf{q}_1 \rangle \mathbf{q}_1 + \|\mathbf{r}_1\| \mathbf{q}_2$$

$$\mathbf{a}_3 = \langle \mathbf{a}_3, \mathbf{q}_1 \rangle \mathbf{q}_1 + \langle \mathbf{a}_3, \mathbf{q}_2 \rangle \mathbf{q}_2 + \|\mathbf{r}_2\| \mathbf{q}_3$$

$$\vdots$$

$$\mathbf{a}_n = \langle \mathbf{a}_n, \mathbf{q}_1 \rangle \mathbf{q}_1 + \cdots + \langle \mathbf{a}_n, \mathbf{q}_{n-1} \rangle \mathbf{q}_{n-1} + \|\mathbf{r}_{n-1}\| \mathbf{q}_n$$

Thus,

$$\mathbf{q}_j^T \mathbf{a}_j = \langle \mathbf{a}_j, \mathbf{q}_j \rangle = \|\mathbf{r}_{j-1}\| > 0 \quad (j = 2, \dots, n).$$

and

$$\mathbf{q}_j \perp \text{Span}(\mathbf{q}_1, \dots, \mathbf{q}_{j-1}) = \text{Span}(\mathbf{a}_1, \dots, \mathbf{a}_{j-1}), \quad (j = 2, \dots, n)$$

QR decomposition

$$A = [\mathbf{a}_1, \mathbf{a}_2, \dots, \mathbf{a}_n] = [\mathbf{q}_1, \mathbf{q}_2, \dots, \mathbf{q}_n] \begin{bmatrix} \|\mathbf{a}_1\| & \langle \mathbf{q}_1, \mathbf{a}_2 \rangle & \dots & \langle \mathbf{q}_1, \mathbf{a}_n \rangle \\ 0 & \|\mathbf{r}_1\| & \dots & \langle \mathbf{q}_2, \mathbf{a}_n \rangle \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \|\mathbf{r}_{n-1}\| \end{bmatrix}$$
$$\triangleq QR$$

Here $Q = [\mathbf{q}_1, \mathbf{q}_2, \dots, \mathbf{q}_n]$, and

$$R = \begin{bmatrix} \mathbf{q}_1^T \mathbf{a}_1 & \mathbf{q}_1^T \mathbf{a}_2 & \dots & \mathbf{q}_1^T \mathbf{a}_n \\ 0 & \mathbf{q}_2^T \mathbf{a}_2 & \dots & \mathbf{q}_2^T \mathbf{a}_n \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \mathbf{q}_n^T \mathbf{a}_n \end{bmatrix}$$

since $\mathbf{q}_1^T \mathbf{a}_1 = \langle \mathbf{a}_1, \mathbf{q}_1 \rangle = \|\mathbf{a}_1\|$, $\mathbf{q}_j^T \mathbf{a}_j = \langle \mathbf{a}_j, \mathbf{q}_j \rangle = \|\mathbf{r}_{j-1}\| > 0$ ($j = 2, \dots, n$).

QR decomposition

In fact, from $A = QR$, one has

$$\begin{aligned} R = Q^T A &= \begin{bmatrix} \mathbf{q}_1^T \mathbf{a}_1 & \mathbf{q}_1^T \mathbf{a}_2 & \cdots & \mathbf{q}_1^T \mathbf{a}_n \\ \mathbf{q}_2^T \mathbf{a}_1 & \mathbf{q}_2^T \mathbf{a}_2 & \cdots & \mathbf{q}_2^T \mathbf{a}_n \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{q}_n^T \mathbf{a}_1 & \mathbf{q}_n^T \mathbf{a}_2 & \cdots & \mathbf{q}_n^T \mathbf{a}_n \end{bmatrix} \\ &= \begin{bmatrix} \mathbf{q}_1^T \mathbf{a}_1 & \mathbf{q}_1^T \mathbf{a}_2 & \cdots & \mathbf{q}_1^T \mathbf{a}_n \\ 0 & \mathbf{q}_2^T \mathbf{a}_2 & \cdots & \mathbf{q}_2^T \mathbf{a}_n \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \mathbf{q}_n^T \mathbf{a}_n \end{bmatrix} \end{aligned}$$

where

$$\mathbf{q}_j \perp \text{Span}(\mathbf{q}_1, \cdots, \mathbf{q}_{j-1}) = \text{Span}(\mathbf{a}_1, \cdots, \mathbf{a}_{j-1}), (j = 2, \cdots, n)$$

are used.

Theorem: If A is an $m \times n$ matrix of rank n , then the least square solution of $A\mathbf{x} = \mathbf{b}$ is given by $\hat{\mathbf{x}} = R^{-1}Q^T\mathbf{b}$, where Q and R are the matrices obtained from the QR decomposition of A .

Proof. Since $A = QR$, then $A^T A \hat{\mathbf{x}} = A^T \mathbf{b}$. $A^T A = R^T Q^T Q R = R^T R$, $A^T \mathbf{b} = R^T Q^T \mathbf{b}$.

$A\mathbf{x} = \mathbf{b}$ is equivalent to

$$R^T R \hat{\mathbf{x}} = R^T Q^T \mathbf{b}$$

Since R is invertible, thus

$$R \hat{\mathbf{x}} = Q^T \mathbf{b}$$

Then

$$\hat{\mathbf{x}} = R^{-1}Q^T \mathbf{b}$$

Appendix: Gram-Schmidt Process on a functional space (an inner product space)

Example 22.7 For subspace $\mathbf{Span}\{1, x, x^2\} \subseteq C[-1, 1]$, find the orthonormal basis for $\mathbf{Span}\{1, x, x^2\}$, where the inner product and norm is defined as:

$$\langle f, g \rangle = \int_{-1}^1 f(x)g(x)dx, \quad \|f\|^2 = \int_{-1}^1 |f(x)|^2 dx$$

Now it can be verify that

$$\langle 1, x \rangle = 0, \quad \langle x, x^2 \rangle = 0, \quad \langle 1, x^2 \rangle = \frac{2}{3}$$

$$p_1 = x - \frac{\langle x, 1 \rangle}{\langle 1, 1 \rangle} = x$$

$$p_2 = x^2 - \frac{\langle x^2, 1 \rangle}{\langle 1, 1 \rangle} - \frac{\langle x^2, x \rangle}{\langle x, x \rangle} x = x^2 - \frac{1}{3}$$

$$\mathbf{q}_1 = \frac{1}{\|1\|} = \frac{1}{\sqrt{2}}$$

$$\mathbf{q}_2 = \frac{\mathbf{p}_1}{\|\mathbf{p}_1\|} = \frac{x}{\sqrt{\frac{2}{3}}}$$

$$\mathbf{q}_3 = \frac{\mathbf{p}_2}{\|\mathbf{p}_2\|} = \frac{x^2 - \frac{1}{3}}{\sqrt{\frac{8}{45}}}$$

$\left\{ \frac{1}{\sqrt{2}}, \frac{x}{\sqrt{\frac{2}{3}}}, \frac{x^2 - \frac{1}{3}}{\sqrt{\frac{8}{45}}} \right\}$ are the orthonormal basis for **Span** $\{1, x, x^2\}$.