Lecture 3: Projector, Classical/Modified Gram–Schmidt orthogonalization, QR factorization



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1. Projector

• A square matrix $\mathbf{P} \in \mathbb{C}^{m \times m}$ is called a *projector* if $\mathbf{P}^2 = \mathbf{P}$. Any projector is diagonalizable. (Eigenvalues?) Example: $\mathbf{P} = \begin{bmatrix} 0 & 0 \\ \alpha & 1 \end{bmatrix}$

Theorem 1

Let **P** be a projector. Then,

- (1) for all $\mathbf{v} \in \text{range}(\mathbf{P})$, we have $\mathbf{P}\mathbf{v} = \mathbf{v}$;
- (2) range(\mathbf{P}) and null(\mathbf{P}) satisfy

$$range(\mathbf{P}) \cap null(\mathbf{P}) = \{\mathbf{0}\}, \quad range(\mathbf{P}) + null(\mathbf{P}) = \mathbb{C}^m;$$

(3) $\mathbf{I} - \mathbf{P}$ is a projector, and

$$range(\mathbf{I} - \mathbf{P}) = null(\mathbf{P}), \quad null(\mathbf{I} - \mathbf{P}) = range(\mathbf{P}).$$

(4) if $\mathbf{P} \neq \mathbf{0}$, \mathbf{I} , we have $\|\mathbf{I} - \mathbf{P}\|_2 = \|\mathbf{P}\|_2$. (See Ref. 1 and Ref. 2)

• Two subspaces $S_1, S_2 \subseteq \mathbb{C}^m$ are called *complementary subspaces* if they satisfy

$$S_1 \cap S_2 = \{\mathbf{0}\}, \qquad S_1 + S_2 = \mathbb{C}^m.$$

Theorem 2

Let S_1 and S_2 be complementary subspaces. Then there exists a unique projector \mathbf{P} with range(\mathbf{P}) = S_1 and null(\mathbf{P}) = S_2 .

Proof.

The existence is left as an exercise. Now we prove the uniqueness. Let \mathbf{e}_j denote the jth column of the identity matrix \mathbf{I} . Since \mathcal{S}_1 and \mathcal{S}_2 are complementary, we can assume $\mathbf{e}_j = \mathbf{s}_j^1 + \mathbf{s}_j^2$, where $\mathbf{s}_j^1 \in \mathcal{S}_1$, and $\mathbf{s}_j^2 \in \mathcal{S}_2$. Assume both \mathbf{P}_1 and \mathbf{P}_2 are desired projectors. Then we have

$$\forall 1 \le j \le m, \quad (\mathbf{P}_1 - \mathbf{P}_2)\mathbf{e}_j = (\mathbf{P}_1 - \mathbf{P}_2)\mathbf{s}_j^1 + (\mathbf{P}_1 - \mathbf{P}_2)\mathbf{s}_j^2$$

= $\mathbf{P}_1\mathbf{s}_i^1 - \mathbf{P}_2\mathbf{s}_i^1 = \mathbf{s}_i^1 - \mathbf{s}_i^1 = \mathbf{0}.$

Therefore, $\mathbf{P}_1 = \mathbf{P}_2$, i.e., uniqueness.

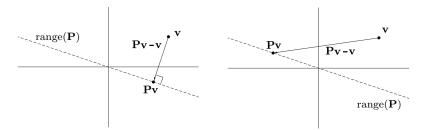
• Let S_1 and S_2 be complementary subspaces. The unique projector \mathbf{P} with range(\mathbf{P}) = S_1 and null(\mathbf{P}) = S_2 is called the *projector* onto S_1 along S_2 .

1.1. Orthogonal and oblique projectors

• For a projector **P**, if range(**P**) and null(**P**) are orthogonal, then it is called an *orthogonal* projector. Otherwise, *oblique*.

Warning: orthogonal projector "≠" orthogonal matrix!!!

• Geometric interpretation



The orthogonal projection

An oblique projection

Theorem 3

A projector \mathbf{P} is an orthogonal projector if and only if $\mathbf{P} = \mathbf{P}^*$.

• $\mathbf{P} = \begin{bmatrix} 0 & 0 \\ \alpha & 1 \end{bmatrix}$: oblique (if $\alpha \neq 0$) or orthogonal (if $\alpha = 0$) projector.

Theorem 4

Let the columns of \mathbf{Q}_r be an orthonormal basis of an r-dimensional subspace \mathcal{S} . Then the orthogonal projector onto \mathcal{S} is given by $\mathbf{Q}_r\mathbf{Q}_r^*$, and the orthogonal projector onto \mathcal{S}^{\perp} is given by $\mathbf{I} - \mathbf{Q}_r\mathbf{Q}_r^*$.

- $\bullet \ a \neq 0, \quad P_a = \frac{aa^*}{a^*a}, \quad P_{a^\perp} = I \frac{aa^*}{a^*a}$
- Let $\mathbf{A} \in \mathbb{C}^{m \times n}$. The orthogonal projector onto range(\mathbf{A}) is given by $\mathbf{U}_r \mathbf{U}_r^*$, where \mathbf{U}_r is the matrix in SVD of \mathbf{A} .
- \bullet Others: $\mathbf{A}\mathbf{A}^{\dagger}$ onto $\mathrm{range}(\mathbf{A})$, $\mathbf{A}^{\dagger}\mathbf{A}$ onto $\mathrm{range}(\mathbf{A}^{*})$

1.2. General definitions

- Suppose $\langle \cdot, \cdot \rangle$ denotes an inner product on \mathbb{C}^m . A linear mapping $\mathbf{T}: \mathbb{C}^m \mapsto \mathbb{C}^m$ is called
 - a projector if it is idempotent, i.e., if $\mathbf{T}^2 = \mathbf{T}$;
 - an orthogonal projector (with respect to $\langle \cdot, \cdot \rangle$) if for all $\mathbf{x}, \mathbf{y} \in \mathbb{C}^m$,

$$\langle \mathbf{x} - \mathbf{T}\mathbf{x}, \mathbf{T}\mathbf{y} \rangle = 0;$$

• self-adjoint (with respect to $\langle \cdot, \cdot \rangle$) if for all $\mathbf{x}, \mathbf{y} \in \mathbb{C}^m$,

$$\langle \mathbf{T}\mathbf{x}, \mathbf{y} \rangle = \langle \mathbf{x}, \mathbf{T}\mathbf{y} \rangle.$$

- It is easy to see that a projector is orthogonal (with respect to $\langle \cdot, \cdot \rangle$) if and only if it is self-adjoint (with respect to $\langle \cdot, \cdot \rangle$).
- If **T** is self-adjoint (with respect to $\langle \cdot, \cdot \rangle$) so is $\mathbf{I} \mathbf{T}$ and vice versa.
- Exercise: Prove if $\forall \mathbf{x}, \mathbf{y} \in \mathbb{C}^m$, $\langle \mathbf{x} \mathbf{T}\mathbf{x}, \mathbf{T}\mathbf{y} \rangle = 0$, then $\mathbf{T}^2 = \mathbf{T}$.

2. Gram-Schmidt orthogonalization (GS)

• For n linearly independent vectors $\{\mathbf{a}_i\}_{i=1}^n$: at the jth step, Gram–Schmidt orthogonalization finds a unit vector \mathbf{q}_j that is orthogonal to $\mathbf{q}_1, \ldots, \mathbf{q}_{j-1}$, lies in span $\{\mathbf{a}_1, \ldots, \mathbf{a}_j\}$ as follows:

$$\widetilde{\mathbf{q}}_j = \mathbf{a}_j - \sum_{i=1}^{j-1} \mathbf{q}_i^* \mathbf{a}_j \mathbf{q}_i, \quad \mathbf{q}_j = \frac{\widetilde{\mathbf{q}}_j}{\|\widetilde{\mathbf{q}}_j\|_2}.$$

More generally, for a given inner product $\langle \cdot, \cdot \rangle$,

$$\widetilde{\mathbf{q}}_j = \mathbf{a}_j - \sum_{i=1}^{j-1} \langle \mathbf{a}_j, \mathbf{q}_i \rangle \mathbf{q}_i, \quad \mathbf{q}_j = \frac{\widetilde{\mathbf{q}}_j}{\sqrt{\langle \widetilde{\mathbf{q}}_j, \widetilde{\mathbf{q}}_j \rangle}}.$$

• Gram–Schmidt orthogonalization can also be represented via orthogonal projectors. For the standard inner product, we have

$$\widetilde{\mathbf{q}}_j = \mathbf{P}_j \mathbf{a}_j, \quad \mathbf{q}_j = \widetilde{\mathbf{q}}_j / \|\widetilde{\mathbf{q}}_j\|_2,$$

where $\mathbf{P}_j = \mathbf{I} - \mathbf{Q}_{j-1} \mathbf{Q}_{j-1}^*$ and $\mathbf{Q}_{j-1} = \begin{bmatrix} \mathbf{q}_1 & \mathbf{q}_2 & \dots & \mathbf{q}_{j-1} \end{bmatrix}$.

2.1. Classical Gram-Schmidt orthogonalization (ClGS)

ClGS is based on the use of

$$\widetilde{\mathbf{q}}_j = \mathbf{a}_j - \mathbf{q}_1^* \mathbf{a}_j \mathbf{q}_1 - \mathbf{q}_2^* \mathbf{a}_j \mathbf{q}_2 \cdots - \mathbf{q}_{j-1}^* \mathbf{a}_j \mathbf{q}_{j-1}$$

and calculates \mathbf{q}_i by evaluating the following formulas in order:

$$\mathbf{q}_{j}^{(0)} = \mathbf{a}_{j},$$

$$\mathbf{q}_{j}^{(1)} = \mathbf{q}_{j}^{(0)} - \mathbf{q}_{1}^{*} \mathbf{a}_{j} \mathbf{q}_{1},$$

$$\mathbf{q}_{j}^{(2)} = \mathbf{q}_{j}^{(1)} - \mathbf{q}_{2}^{*} \mathbf{a}_{j} \mathbf{q}_{2},$$

$$\vdots \qquad \vdots$$

$$\mathbf{q}_{j}^{(j-1)} = \mathbf{q}_{j}^{(j-2)} - \mathbf{q}_{j-1}^{*} \mathbf{a}_{j} \mathbf{q}_{j-1},$$

$$\mathbf{q}_{j} = \mathbf{q}_{j}^{(j-1)} / \|\mathbf{q}_{j}^{(j-1)}\|_{2}.$$

2.2. Modified Gram-Schmidt orthogonalization (MGS)

MGS is based on the use of

$$\widetilde{\mathbf{q}}_j = \mathbf{P}_j \mathbf{a}_j = (\mathbf{I} - \mathbf{q}_{j-1} \mathbf{q}_{j-1}^*) \cdots (\mathbf{I} - \mathbf{q}_2 \mathbf{q}_2^*) (\mathbf{I} - \mathbf{q}_1 \mathbf{q}_1^*) \mathbf{a}_j$$

and calculates \mathbf{q}_i by evaluating the following formulas in order:

$$\begin{array}{rcl} \mathbf{q}_{j}^{(0)} & = & \mathbf{a}_{j}, \\ \mathbf{q}_{j}^{(1)} & = & \mathbf{q}_{j}^{(0)} - \mathbf{q}_{1}^{*} \mathbf{q}_{j}^{(0)} \mathbf{q}_{1}, \\ \mathbf{q}_{j}^{(2)} & = & \mathbf{q}_{j}^{(1)} - \mathbf{q}_{2}^{*} \mathbf{q}_{j}^{(1)} \mathbf{q}_{2}, \\ & \vdots & & \vdots \\ \mathbf{q}_{j}^{(j-1)} & = & \mathbf{q}_{j}^{(j-2)} - \mathbf{q}_{j-1}^{*} \mathbf{q}_{j}^{(j-2)} \mathbf{q}_{j-1}, \\ \mathbf{q}_{j} & = & \mathbf{q}_{j}^{(j-1)} / \|\mathbf{q}_{j}^{(j-1)}\|_{2}. \end{array}$$

2.3. ClGS and MGS algorithms

Algorithm: GS for *n* linearly independent vectors $\{\mathbf{a}_i\}_{i=1}^n$. for j = 1 to n $\mathbf{q}_i = \mathbf{a}_i$ for i = 1 to j - 1 $\begin{cases} r_{ij} = \mathbf{q}_i^* \mathbf{a}_j & \text{ClGS} \\ r_{ij} = \mathbf{q}_i^* \mathbf{q}_i & \text{MGS} \end{cases}$ $\mathbf{q}_i = \mathbf{q}_i - r_{ij}\mathbf{q}_i$ end $r_{ij} = \|\mathbf{q}_i\|_2$ $\mathbf{q}_i = \mathbf{q}_i/r_{ii}$ end

- The computational cost: $\sim 2mn^2$ (leading term) for $\mathbf{a}_i \in \mathbb{C}^m$
- ClGS and MGS are mathematically equivalent. In finite precision arithmetic, MGS introduces smaller errors than ClGS.

3. QR factorization

• Definition: Let m and n be arbitrary positive integers $(m \ge n)$ or m < n. Given $\mathbf{A} \in \mathbb{C}^{m \times n}$, not necessarily of full rank, a full QR factorization of \mathbf{A} is a factorization

$$A = QR$$

where $\mathbf{Q} \in \mathbb{C}^{m \times m}$ is unitary, and $\mathbf{R} \in \mathbb{C}^{m \times n}$ is upper triangular. For $m \geq n$, a reduced QR factorization of \mathbf{A} is a factorization

$$\mathbf{A} = \mathbf{Q}_n \mathbf{R}_n$$

where $\mathbf{Q}_n \in \mathbb{C}^{m \times n}$ has orthonormal columns, and

$$\mathbf{R}_n = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ & r_{22} & \ddots & \vdots \\ & & \ddots & \vdots \\ & & & r_{nn} \end{bmatrix}. \quad \begin{bmatrix} & & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & \\ & &$$

Theorem 5 (Existence of QR)

Every matrix $\mathbf{A} \in \mathbb{C}^{m \times n} (m \ge n)$ has a reduced QR factorization and a full QR factorization.

Proof.

• Existence of reduced QR factorization.

For the full column rank case, Gram–Schmidt orthogonalization produces a sequence of reduced QR factorizations for $\mathbf{A} \in \mathbb{C}^{m \times n}$:

$$\mathbf{A}_j := \begin{bmatrix} \mathbf{a}_1 & \mathbf{a}_2 & \dots & \mathbf{a}_j \end{bmatrix} = \mathbf{Q}_j \mathbf{R}_j, \quad j = 1 \colon n.$$

For the rank-deficient case, $\tilde{\mathbf{q}}_j = \mathbf{0}$ at one or more steps j, GS fails to produce \mathbf{q}_j . At this moment, we pick \mathbf{q}_j arbitrarily to be any unit vector orthogonal to span $\{\mathbf{q}_1, \mathbf{q}_2, \cdots, \mathbf{q}_{j-1}\}$, set $r_{jj} = 0$, and then continue the Gram–Schmidt orthogonalization until we obtain a reduced QR factorization.

• Existence of full QR factorization.

Let $\mathbf{A} = \mathbf{Q}_n \mathbf{R}_n$ be a reduced QR factorization of \mathbf{A} . A full QR factorization can be constructed via

$$\mathbf{A} = \mathbf{Q}\mathbf{R} := egin{bmatrix} \mathbf{Q}_{\mathrm{c}} \end{bmatrix} egin{bmatrix} \mathbf{R}_{n} \ \mathbf{0} \end{bmatrix},$$

where $\mathbf{Q}_{c} \in \mathbb{C}^{m \times (m-n)}$ has orthonormal columns orthogonal to span $\{\mathbf{q}_{1}, \mathbf{q}_{2}, \cdots, \mathbf{q}_{n}\}$.

Theorem 6

Every matrix $\mathbf{A} \in \mathbb{C}^{m \times n}$ $(m \ge n)$ of full column rank has a unique reduced QR factorization $\mathbf{A} = \mathbf{Q}_n \mathbf{R}_n$ with $r_{jj} > 0$.

Proof.

 $r_{11}\mathbf{q}_1 = \mathbf{a}_1$ and $r_{11} > 0 \Rightarrow r_{11}$ and \mathbf{q}_1 unique $\Rightarrow r_{12}$ and $r_{22}\mathbf{q}_2$ unique, by $r_{22} > 0 \Rightarrow r_{22}$ and \mathbf{q}_2 unique, and so on.

3.1. When vectors become continuous functions

• Replace \mathbb{C}^m by C[-1,1], a linear space of real-valued continuous functions on [-1,1] with the L^2 inner product

$$\forall f(x), g(x) \in C[-1,1], \qquad \langle f(x), g(x) \rangle_{L^2} = \int_{-1}^1 f(x)g(x)\mathrm{d}x,$$

and the norm

$$||f(x)||_{L^2} = \sqrt{\langle f(x), f(x) \rangle_{L^2}}.$$

Gram-Schmidt orthogonalization (GS) with respect to the L^2 inner product $\langle f(x), g(x) \rangle_{L^2}$ is: At step j,

$$\widetilde{q}_j(x) = a_j(x) - \sum_{i=1}^{j-1} \langle a_j(x), q_i(x) \rangle_{L^2} q_i(x),$$

$$q_j(x) = \widetilde{q}_j(x) / \|\widetilde{q}_j(x)\|_{L^2}.$$

The functions $q_i(x)$ satisfy

$$\langle q_i(x), q_j(x) \rangle_{L^2} = \int_{-1}^1 q_i(x) q_j(x) dx = \delta_{ij} = \begin{cases} 1 & \text{if } i = j, \\ 0 & \text{if } i \neq j. \end{cases}$$

Then we have "continuous QR factorization"

$$A = QR = \begin{bmatrix} q_1(x) & q_2(x) & \cdots & q_n(x) \end{bmatrix} \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ & r_{22} & & \vdots \\ & & & \ddots & \vdots \\ & & & & r_{nn} \end{bmatrix}$$

where

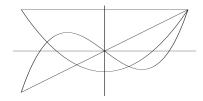
$$A = \begin{bmatrix} a_1(x) & a_2(x) & \cdots & a_n(x) \end{bmatrix}$$

and

$$r_{jj} = \|\widetilde{q}_j(x)\|_{L^2}, \qquad r_{ij} = \langle a_j(x), q_i(x) \rangle_{L^2}.$$

• Example: $a_j(x) = x^{j-1}, j = 1, 2, \dots, n$

$$\mathbf{A} = \left[\begin{array}{c|c} 1 & x & x^2 & \cdots & x^{n-1} \end{array} \right]$$



Legendre polynomials $P_j(x) = q_j(x)/q_j(1)$:

$$P_1(x) = 1$$
, $P_2(x) = x$, $P_3(x) = \frac{3}{2}x^2 - \frac{1}{2}$, $P_4(x) = \frac{5}{2}x^3 - \frac{3}{2}x$.

Experiment: Discrete Legendre polynomials

