Algorithms and Data Structures

Matrix Decomposition QR Decomposition

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Learning goals

- QR decomposition
- Gram-Schmidt Pprocess \bullet

QR DECOMPOSITION

Given $A \in \mathbb{R}^{n \times n}$. We decompose A into the product of an orthogonal matrix $\mathbf{Q} \in \mathbb{R}^{n \times n}$ and an upper triangular matrix $\mathbf{R} \in \mathbb{R}^{n \times n}$

 $\mathsf{A} = \mathsf{Q}\mathsf{R}$ with $\mathsf{Q}^\top \mathsf{Q} = \mathsf{I}$,

The columns of the matrix $\boldsymbol{Q} = (\boldsymbol{q}_1, \dots, \boldsymbol{q}_n)$ form an orthonormal basis for the column space of the matrix **A** and

$$
R = \left(\begin{matrix} \langle q_1, a_1 \rangle & \langle q_1, a_2 \rangle & \langle q_1, a_3 \rangle & \cdots \\ 0 & \langle q_2, a_2 \rangle & \langle q_2, a_3 \rangle & \cdots \\ 0 & 0 & \langle q_3, a_3 \rangle & \cdots \\ \vdots & \vdots & \vdots & \ddots & \end{matrix}\right)
$$

The orthonormal basis for **A** is calculated by the Gram-Schmidt process.

GRAM-SCHMIDT PROCESS

The process takes a finite, linearly independent set of vectors and generates an orthogonal set of vectors that form an orthonormal basis $(*)$

Procedure: Projection: $\text{proj}_q a = \frac{\langle q, a \rangle}{\langle q, q \rangle} q$.

$$
u_1 = a_1
$$

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$$
u_2 = a_2 - \text{proj}_{u_1} a_2
$$

\n
$$
\vdots = \vdots
$$

\n
$$
u_k = a_k - \sum_{j=1}^{k-1} \text{proj}_{u_j} a_k
$$

\n
$$
q_k = \frac{u_k}{\|u_k\|}
$$

\n
$$
q_k = \frac{u_k}{\|u_k\|}
$$

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The vectors constructed in this way actually form an orthonormal basis of the column space of **A** (can be shown).

(∗) If the vector *aⁱ* is not independent of *a*1, ..., *ai*−1, then *uⁱ* = **0**.

GRAM-SCHMIDT PROCESS / 2

A can now be represented by the calculated orthonormal basis:

$$
\mathbf{a}_1 = \mathbf{q}_1 \langle \mathbf{q}_1, \mathbf{a}_1 \rangle
$$

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

\n
$$
\vdots = \vdots
$$

\n
$$
\mathbf{a}_k = \sum_{j=1}^k \mathbf{q}_j \langle \mathbf{q}_j, \mathbf{a}_k \rangle
$$

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Or in matrix notation:

$$
\textit{QR} = (q_1 \langle q_1, a_1 \rangle, q_1 \langle q_1, a_2 \rangle + q_2 \langle q_2, a_2 \rangle, \cdots) = \textit{A}
$$

Given: Three independent vectors a_1 , a_2 , a_3 **Aim:** Vectors of an orthonormal basis *q*1, *q*2, *q*³

- **1** a_1 serves as the first vector of the orthogonal basis (u_1) .
	-
	- $\overline{a_3}$ is projected onto $\overline{u_1}$ and $\overline{u_2}$, to obtain $\overline{u_3}$.
- u_1 , u_2 and u_3 are normalized.

https://commons.wikimedia.org/wiki/File:Gram-Schmidt_orthonormalization_process.gif

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- **3** a_3 is projected onto u_1 and u_2 , to obtain u_3 .
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- $\left(4\right)$ *u*₁, *u*₂ and *u*₃ are normalized.

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- **1** a_1 serves as the first vector of the orthogonal basis (u_1) .
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- **3** a_3 is projected onto u_1 and u_2 , to obtain u_3 .
- $\left(4\right)$ *u*₁, *u*₂ and *u*₃ are normalized.

Given: Three independent vectors *a*1, *a*2, *a*³ **Aim:** Vectors of an orthonormal basis *q*1, *q*2, *q*³

- **1** a_1 serves as the first vector of the orthogonal basis (u_1) .
- **2** a_2 is projected onto u_1 ; projection is substracted from a_2 to obtain u_2 .
- a_3 is projected onto u_1 and u_2 , to obtain u_3 .
- $\frac{1}{2}$ $\frac{u_1}{u_2}$ and $\frac{u_3}{u_3}$ are normalized.

https://commons.wikimedia.org/wiki/File:Gram-Schmidt_orthonormalization_process.gif

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- **1** a_1 serves as the first vector of the orthogonal basis (u_1) .
- **2** a_2 is projected onto u_1 ; projection is substracted from a_2 to obtain u_2 .
- a_3 is projected onto u_1 and u_2 , to obtain u_3 .
- $\frac{1}{2}$ $\frac{1}{4}$, $\frac{1}{2}$ and $\frac{1}{3}$ are normalized.

QR DECOMPOSITION: EXAMPLE

Calculation of $A = QR$ with A given by

$$
A = \begin{pmatrix} 0 & -20 & -14 \\ 3 & 27 & -4 \\ 4 & 11 & -2 \end{pmatrix}
$$

\n
$$
k = 1:
$$

\n
$$
u_1 = a_1 = \begin{pmatrix} 0 \\ 3 \\ 4 \end{pmatrix}
$$

\n
$$
q_1 = \frac{u_1}{\|u_1\|} = \frac{u_1}{\sqrt{0+9+16}} = \frac{1}{5} \begin{pmatrix} 0 \\ 3 \\ 4 \end{pmatrix}
$$

\n
$$
r_{11} = \langle q_1, a_1 \rangle = \frac{1}{5} (0^2 + 3^2 + 4^2) = 5
$$

\n
$$
r_{12} = \langle q_1, a_2 \rangle = \frac{1}{5} (0 \cdot (-20) + 3 \cdot 27 + 4 \cdot 11) = 25
$$

\n
$$
r_{13} = \langle q_1, a_3 \rangle = \frac{1}{5} (0 \cdot (-14) + 3 \cdot (-4) + 4 \cdot (-2)) = -4
$$

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QR DECOMPOSITION: EXAMPLE /2

 $k = 2$:

$$
\mathbf{u}_2 = \mathbf{a}_2 - \frac{\langle \mathbf{u}_1, \mathbf{a}_2 \rangle}{\langle \mathbf{u}_1, \mathbf{u}_1 \rangle} \mathbf{u}_1
$$

$$
= \mathbf{a}_2 - \frac{125}{25} \begin{pmatrix} 0 \\ 3 \\ 4 \end{pmatrix}
$$

$$
= \begin{pmatrix} -20 \\ 12 \\ -9 \end{pmatrix}
$$

$$
\mathbf{q}_2 = \frac{\mathbf{u}_2}{\|\mathbf{u}_2\|} = \frac{\mathbf{u}_2}{\sqrt{400 + 144 + 81}} = \frac{1}{25} \begin{pmatrix} -20 \\ 12 \\ -9 \end{pmatrix}
$$

\n
$$
r_{22} = \langle \mathbf{q}_2, \mathbf{a}_2 \rangle = \frac{1}{25} ((-20) \cdot (-20) + 12 \cdot 27 + (-9) \cdot 11) = 25
$$

\n
$$
r_{23} = \langle \mathbf{q}_2, \mathbf{a}_3 \rangle = \frac{1}{25} ((-20) \cdot (-14) + 12 \cdot (-4) + (-9) \cdot (-2)) = 10
$$

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QR DECOMPOSITION: EXAMPLE / 3

 $k = 3$:

$$
\mathbf{u}_3 = \mathbf{a}_3 - \frac{\langle \mathbf{u}_1, \mathbf{a}_3 \rangle}{\langle \mathbf{u}_1, \mathbf{u}_1 \rangle} \mathbf{u}_1 - \frac{\langle \mathbf{u}_2, \mathbf{a}_3 \rangle}{\langle \mathbf{u}_2, \mathbf{u}_2 \rangle} \mathbf{u}_2
$$
\n
$$
= \mathbf{a}_3 - \frac{-20}{25} \begin{pmatrix} 0 \\ 3 \\ 4 \end{pmatrix} - \frac{250}{625} \begin{pmatrix} -20 \\ 12 \\ -9 \end{pmatrix}
$$
\n
$$
= \begin{pmatrix} -6 \\ -6.4 \\ 4.8 \end{pmatrix}
$$
\n
$$
\mathbf{q}_3 = \frac{\mathbf{u}_3}{\|\mathbf{u}_3\|} = \frac{1}{25} \begin{pmatrix} -15 \\ -16 \\ 12 \end{pmatrix}
$$
\n
$$
r_{33} = \langle \mathbf{q}_3, \mathbf{a}_3 \rangle = \frac{1}{25} ((-15) \cdot (-14) + (-16) \cdot (-4) + 12 \cdot (-2)) = 10
$$

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QR DECOMPOSITION: EXAMPLE / 4

This results in

$$
\mathbf{Q} = \frac{1}{25} \begin{pmatrix} 0 & -20 & -15 \\ 15 & 12 & -16 \\ 20 & -9 & 12 \end{pmatrix} \text{ and } \mathbf{R} = \begin{pmatrix} 5 & 25 & -4 \\ 0 & 25 & 10 \\ 0 & 0 & 10 \end{pmatrix}.
$$

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HOUSEHOLDER AND GIVENS MATRIX

Problem in practice:

Q often not really orthogonal when using the above algorithm due to numerical reasons.

Two other methods for QR decomposition

Householder matrix:

For vector **u**, matrix $\mathbf{U} = \mathbf{I} - d\mathbf{u}\mathbf{u}^\top$ is orthogonal, if $d = 2/\mathbf{u}^\top \mathbf{u}$. Choose $\mathbf{u} = \mathbf{x} + s\mathbf{e}_1$ with $s = \mathbf{x}^\top \mathbf{x} \Rightarrow \mathbf{U} \mathbf{x} = -s\mathbf{e}_1$.

Successive elimination of column elements yields QR decomposition.

Givens matrix:

Similar to Householder, but orthogonal transformations that eliminate an element of a column vector each, and change a second vector.

For details see Carl D. Meyer *Matrix Analysis and Applied Linear Algebra*.

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PROPERTIES OF QR DECOMPOSITION

- Splitting a matrix into an orthogonal matrix **Q** and **R**
- Gram-Schmidt process is numerically unstable, but can be extended and numerically stabilized
- **Existence:** Decomposition exists for each *n* × *n* matrix and can be extended to general $m \times n$, $m \neq n$ matrices
- Runtime behavior: Numerical stable solution of Householder transformation or Givens rotation comes along with higher effort:
	- Decomposition of $n \times n$ matrix using Householder transformation: $\approx \frac{2}{3}n^3$ multiplications
	- 3 Forward and back substitution: *n* 2

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COMPARISON OF METHODS

QR DECOMPOSITION FOR *M* × *N* **MATRICES**

General $m \times n$, $m \ge n$ matrices can be decomposed as well when using QR decomposition.

$$
\textbf{A} = \textbf{Q}\textbf{R} = \textbf{Q} \begin{bmatrix} \textbf{R}_1 \\ \textbf{0} \end{bmatrix} = \begin{bmatrix} \textbf{Q}_1 & \textbf{Q}_2 \end{bmatrix} \begin{bmatrix} \textbf{R}_1 \\ \textbf{0} \end{bmatrix} = \textbf{Q}_1 \textbf{R}_1
$$

 $\mathbf{Q}_1 \in \mathbb{R}^{m \times n}$, $\mathbf{Q}_2 \in \mathbb{R}^{m \times (m-n)}$ with orthogonal columns, and $\mathbf{R} \in \mathbb{R}^{n \times n}$ upper triangular matrix.

 $\mathbf{Q}_1 \times \mathbf{R}_1$ is known as a **reduced** QR decomposition.

