

Dense QR factorization and its error analysis

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Direct methods of factorization

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- Block QR factorization

Plan

Direct methods of factorization

- QR factorization

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The QR factorization

Given a matrix $A \in \mathbb{R}^{m \times n}$, $m \geq n$, its QR factorization is

$$A = QR = (Q_1 \quad Q_2) \begin{pmatrix} R_1 \\ 0 \end{pmatrix} = Q_1 R_1$$

where $Q \in \mathbb{R}^{m \times m}$ is orthogonal and $R \in \mathbb{R}^{m \times n}$ is upper triangular.

If A has full rank, the factorization $Q_1 R_1$ is essentially unique (modulo signs of diagonal elements of R).

- $A^T A = R_1^T R_1$ is a Cholesky factorization and $A = A R_1^{-1} R_1$ is a QR factorization.
- $A = Q_1 D \cdot D R_1$, $D = \text{diag}(\pm 1)$ is a QR factorization.

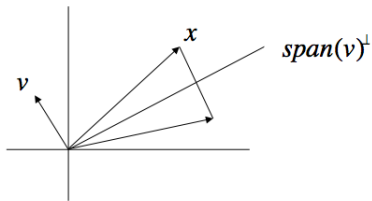
Householder transformation

The Householder matrix

$$P = I - \frac{2}{v^T v} v v^T$$

has the following properties:

- is symmetric and orthogonal,
 $P^2 = I$,
- is independent of the scaling of v ,
- it reflects x about the hyperplane $\text{span}(v)^\perp$



$$Px = x - \frac{2v^T x}{v^T v} v = x - \alpha v$$

Presentation of Householder transformations and stability analysis from [N.J.Higham, 2002].

Householder for the QR factorization

We look for a Householder matrix that allows to annihilate the elements of a vector x , except first one.

$$Px = y, \quad \|x\|_2 = \|y\|_2, \quad y = \sigma e_1, \quad \sigma = \pm \|x\|_2$$

With the choice of sign made to avoid cancellation when computing $v_1 = x_1 - \sigma$, we have

$$\begin{aligned}v &= x - y = x - \sigma e_1, \\ \sigma &= -\text{sign}(x_1) \|x\|_2, \quad v = x - \sigma e_1, \\ P &= I - \beta vv^T, \quad \beta = \frac{2}{v^T v}\end{aligned}$$

Householder based QR factorization

$$A = \begin{pmatrix} x & x & x \\ x & x & x \\ x & x & x \end{pmatrix} = P_1 \begin{pmatrix} x & x & x \\ 0 & x & x \\ 0 & x & x \end{pmatrix} = P_1 \begin{pmatrix} 1 & & \\ & \tilde{P}_2 & \end{pmatrix} \begin{pmatrix} x & x & x \\ 0 & x & x \\ 0 & 0 & x \end{pmatrix} = R$$

So we have

$$\begin{aligned} Q^T A &= P_n P_{n-1} \dots P_1 A = R, \\ Q &= (I - \beta_1 v_1 v_1^T) \dots (I - \beta_{n-1} v_{n-1} v_{n-1}^T) (I - \beta_n v_n v_n^T) \end{aligned}$$

$$\#flops = 2n^2(m - n/3)$$

Error analysis of Householder transformations

Lemma (Lemma 19.1 in [N.J.Higham, 2002])

Consider the computation of $P = I - \beta vv^T$, where $Px = \sigma e_1$, $v \in \mathbb{R}^m$, as

1: $v = x$

2: $s = \text{sign}(x_1) \|x\|_2$, $\% \sigma = -s$

3: $v_1 = v_1 + s$

4: $\beta = 1/(sv_1)$

Then we have

$$\begin{aligned}\hat{v}(2:n) &= v(2:n) \\ \hat{\beta} &= \beta(1 + \tilde{\theta}_m), \quad \hat{v}_1 = v_1(1 + \tilde{\theta}_m), \quad \text{where } |\tilde{\theta}_m| \leq \tilde{\gamma}_m\end{aligned}$$

Proof based on the fact that $fl(x^T x) = (1 + \theta_m)x^T x$. The result can be re-written as

$$\hat{v} = v + \Delta v, \quad |\Delta v| \leq \tilde{\gamma}_m |v|$$

In the following results, the Householder matrix is $I - vv^T$, hence $v = \sqrt{\beta}v$, $\beta = 1$, and so $\|v\|_2 = \sqrt{2}$.

Error analysis of Householder transformations

Lemma (Lemma 19.2 in [N.J.Higham, 2002])

Consider the computation $y = \hat{P}b = (I - \hat{v}\hat{v}^T)b$, where $b, \hat{v} \in \mathbb{R}^m$. Then

$$\hat{y} = (P + \Delta P)b, \quad \|\Delta P\|_F \leq \tilde{\gamma}_m. \quad (1)$$

Proof.

$$\begin{aligned} \hat{w} &= fl(\hat{v}(\hat{v}^T b)) = (\hat{v} + \Delta\hat{v})(\hat{v}^T(b + \Delta b)), \quad |\Delta\hat{v}| \leq u|\hat{v}| \text{ and } |\Delta b| \leq \gamma_m|b| \\ &= (v + \Delta v + \Delta\hat{v})(v + \Delta v)^T(b + \Delta b) \end{aligned}$$

Hence

$$\hat{w} = v(v^T b) + \Delta w, \quad \text{where } |\Delta w| \leq \tilde{\gamma}_m|v||v^T||b|$$



Error analysis of Householder transformations

Continued proof of the previous lemma. We obtain

$$\hat{y} = fl(b - \hat{w}) = b - v(v^T b) - \Delta w + \Delta y_1, \quad |\Delta y_1| \leq u|b - \hat{w}|$$

Since

$$|-\Delta w + \Delta y_1| \leq u|b| + \tilde{\gamma}_m |v| |v^T| |b|$$

we obtain

$$\hat{y} = Pb + \Delta y, \quad \|\Delta y\|_2 \leq \tilde{\gamma}_m \|b\|_2$$

Finally, with $\Delta P = \Delta y b^T / b^T b$, we have

$$\hat{y} = (P + \Delta P)b, \quad \|\Delta P\|_F = \|\Delta y\|_2 / \|b\|_2 \leq \tilde{\gamma}_m$$

Error analysis of a sequence of transformations

Lemma ([N.J.Higham, 2002])

Let $Q = P_r P_{r-1} \dots P_1$ and let $A_{r+1} = Q^T A$, $A \in \mathbb{R}^{m \times n}$. We have

$$\hat{A}_{r+1} = Q^T (A + \Delta A), \quad \|\Delta a_j\|_2 \leq r \tilde{\gamma}_m \|a_j\|_2, \quad j = 1 : n$$

Sketch of the proof: Let a_j be the j -th column of A .

$$\hat{a}_j^{(r+1)} = (P_r + \Delta P_r) \dots (P_1 + \Delta P_1) a_j, \quad \|\Delta P_k\|_F \leq \tilde{\gamma}_m, \quad k = 1 : r$$

We obtain

$$\begin{aligned} \hat{a}_j^{(r+1)} &= Q^T (a_j + \Delta a_j), \\ \|\Delta a_j\|_2 &\leq ((1 + \tilde{\gamma}_m)^r - 1) \|a_j\|_2 \leq \frac{r \tilde{\gamma}_m}{1 - r \tilde{\gamma}_m} \|a_j\|_2 = r \tilde{\gamma}'_m \|a_j\|_2 \end{aligned}$$

Error analysis of the QR factorization

The following result follows

Theorem ([N.J.Higham, 2002])

Let $\hat{R} \in \mathbb{R}^{m \times n}$ be the computed factor of $A \in \mathbb{R}^{m \times n}$ obtained by using Householder transformations. Then there is an orthogonal $Q \in \mathbb{R}^{m \times m}$ such that

$$A + \Delta A = Q\hat{R}, \text{ where } \|\Delta a_j\|_2 \leq \tilde{\gamma}_{mn} \|a_j\|_2, \quad j = 1 : n$$

Householder-QR factorization

Require: $A \in \mathbb{R}^{m \times n}$

1: Let $R \in \mathbb{R}^{n \times n}$ be initialized with zero matrix

2: **for** $k = 1$ to n **do**

3: \triangleright Compute Householder matrix $P_k = I - \beta_k v_k v_k^T$ s.t.

$$P_k A(k:m, k) = \pm \|A(k:m, k)\|_2 e_1. \text{ Store } v_k \text{ in } Y(k) \text{ and } \beta_k \text{ in } \mathcal{T}(k)$$

4: $R(k, k) = -\text{sgn}(A(k, k)) \cdot \|A(k:m, k)\|_2$

5: $\mathcal{T}(k) = \frac{R(k, k) - A(k, k)}{R(k, k)}$

6: $Y(k+1:m, k) = \frac{1}{R(k, k) - A(k, k)} \cdot A(k+1:m, k)$

7: \triangleright Update trailing matrix

8: $A(k:m, k+1:n) = (I - Y(k+1:m, k)\mathcal{T}(k)Y(k+1:m, k)^T) \cdot A(k:m, k+1:n)$

9: $R(k, k+1:n) = A(k, k+1:n)$

10: **end for**

Assert: $A = QR$, where $Q = P_1 \dots P_n = (I - \beta_1 v_1 v_1^T) \dots (I - \beta_n v_n v_n^T)$, the Householder vectors v_k are stored in Y and \mathcal{T} is an array of size n .

Computational complexity

■ Flops per iterations

- Dot product $w = v_k^T A(k : m, k + 1 : n) : 2(m - k)(n - k)$
- Outer product $v_k w : (m - k)(n - k)$
- Subtraction $A(k : m, k + 1 : n) - \dots : (m - k)(n - k)$

■ Flops of Householder-QR

$$\begin{aligned}\sum_{k=1}^n 4(m - k)(n - k) &= 4 \sum_{k=1}^n (mn - k(m + n) + k^2) \\ &\approx 4mn^2 - 4(m + n)n^2/2 + 4n^3/3 = 2mn^2 - 2n^3/3\end{aligned}$$

Algebra of block QR

Storage efficient representation for Q [Schreiber and Loan, 1989]

$$Q = Q_1 Q_2 \dots Q_k = (I - \beta_1 v_1 v_1^T) \dots (I - \beta_k v_k v_k^T) = I - YTY^T$$

Example for $k = 2$

$$Y = (v_1 | v_2), \quad T = \begin{pmatrix} \beta_1 & -\beta_1 v_1^T v_2 \beta_2 \\ 0 & \beta_2 \end{pmatrix}$$

Example for combining two compact representations

$$Q = (I - Y_1 T_1 Y_1^T)(I - Y_2 T_2 Y_2^T)$$
$$T = \begin{pmatrix} T_1 & -T_1 Y_1^T Y_2 T_2 \\ 0 & T_2 \end{pmatrix}$$

Block algorithm for computing the QR factorization

Partitioning of matrix A of size $m \times n$

$$A = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix}$$

where A_{11} is of size $b \times b$, A_{21} is of size $(m - b) \times b$, A_{12} is of size $b \times (n - b)$ and A_{22} is of size $(m - b) \times (n - b)$.

Block QR algebra

The first step of the block QR factorization algorithm computes:

$$Q_1^T A = \begin{pmatrix} R_{11} & R_{12} \\ & A^1 \end{pmatrix}$$

The algorithm continues recursively on the trailing matrix A^1 .

Algebra of block QR factorization

$$A = \begin{pmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{pmatrix} = Q_1 \begin{pmatrix} R_{11} & R_{12} \\ & A^1 \end{pmatrix}$$

Block QR algebra

1. Compute the factorization

$$\begin{pmatrix} A_{11} \\ A_{12} \end{pmatrix} = Q_1 R_{11}$$

2. Compute the compact representation $Q_1 = I - YTY^T$
3. Apply Q_1^T on the trailing matrix

$$(I - YTY^T) \begin{pmatrix} A_{12} \\ A_{22} \end{pmatrix} = \begin{pmatrix} A_{12} \\ A_{22} \end{pmatrix} - Y \left(T^T \left(Y^T \begin{pmatrix} A_{12} \\ A_{22} \end{pmatrix} \right) \right)$$

4. The algorithm continues recursively on the trailing matrix A^1 .

Parallel implementation of the QR factorization

QR factorization on a $P = P_r \times P_c$ grid of processors

For $ib = 1$ to $n-1$ step b

1. Compute panel factorization on P_r processors

$$\begin{pmatrix} A_{11} \\ A_{12} \end{pmatrix} = Q_1 R_{11} = (I - YTY^T)R_{11}$$

2. The P_r processors broadcast along the rows their parts of Y and T
3. Apply Q_1^T on the trailing matrix:

- All processors compute their local part of

$$W_l = Y_l^T (A_{12l}; A_{22l})$$

- The processors owning block row ib compute the sum over W_l , that is

$$W = Y^T (A_{12}; A_{22})$$

and then compute $W' = T^T W$

- The processors owning block row ib broadcast along the columns their part of W'
4. All processors compute

$$(A_{12}^1; A_{22}^1) = (A_{12}; A_{22}) - (A_{12}; A_{22}) * W'$$

Cost of parallel QR factorization

$$\begin{aligned} & \gamma \cdot \left(\frac{6mnb - 3n^2b}{2p_r} + \frac{n^2b}{2p_c} + \frac{2mn^2 - 2n^3/3}{p} \right) \\ + & \beta \cdot \left(nb \log p_r + \frac{2mn - n^2}{p_r} + \frac{n^2}{p_c} \right) \\ + & \alpha \cdot \left(2n \log p_r + \frac{2n}{b} \log p_c \right). \end{aligned}$$

Solving least squares problems

Given matrix $A \in \mathbb{R}^{m \times n}$, $\text{rank}(A) = n$, vector $b \in \mathbb{R}^{m \times 1}$, the unique solution to $\min_x \|Ax - b\|_2$ is

$$x = A^+ b, \quad A^+ = (A^T A)^{-1} A^T$$

Using the QR factorization of A

$$A = QR = \begin{pmatrix} Q_1 & Q_2 \end{pmatrix} \begin{pmatrix} R_1 \\ 0 \end{pmatrix} \quad (2)$$

We obtain




$$\begin{aligned} \|r\|_2^2 &= \|b - Ax\|_2^2 = \|b - (Q_1 \quad Q_2) \begin{pmatrix} R_1 \\ 0 \end{pmatrix} x\|_2^2 \\ &= \left\| \begin{pmatrix} Q_1^T \\ Q_2^T \end{pmatrix} b - \begin{pmatrix} R_1 \\ 0 \end{pmatrix} x \right\|_2^2 = \left\| \begin{pmatrix} Q_1^T b - R_1 x \\ Q_2^T b \end{pmatrix} \right\|_2^2 \\ &= \|Q_1^T b - R_1 x\|_2^2 + \|Q_2^T b\|_2^2 \end{aligned}$$

Solve $R_1 x = Q_1^T b$ to minimize $\|r\|_2$.

Acknowledgement

- Stability analysis results presented from [N.J.Higham, 2002]
- Some of the examples taken from [Golub and Van Loan, 1996]

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