

The Interpolative Decomposition (ID)

Let \mathbf{A} be an $m \times n$ matrix of exact rank k . Then \mathbf{A} admits three “structure preserving” factorizations that sacrifice orthonormality to gain faithfulness to the original data:

$$\begin{aligned}
 \text{(Column ID)} \quad & \mathbf{A} = \mathbf{C} \mathbf{Z} \\
 & \begin{matrix} m \times n & m \times k & k \times n \end{matrix} \\
 \text{(Row ID)} \quad & = \mathbf{X} \mathbf{R} \\
 & \begin{matrix} m \times k & k \times n \end{matrix} \\
 \text{(Double-Sided ID)} \quad & = \mathbf{X} \mathbf{A}_{\text{skel}} \mathbf{Z} \\
 & \begin{matrix} m \times k & k \times k & k \times n \end{matrix}
 \end{aligned}$$

where

- I_s and J_s are index vectors marking the chosen rows and columns, respectively.
- $\mathbf{C} = \mathbf{A}(:, J_s)$ holds k columns of \mathbf{A} .
- \mathbf{Z} contains a $k \times k$ identity matrix, $\mathbf{Z}(:, J_s) = \mathbf{I}_k$ and $\max_{i,j} |\mathbf{Z}(i, j)| \leq 1$.
- $\mathbf{R} = \mathbf{A}(I_s, :)$ is a set of k rows of \mathbf{A} .
- \mathbf{X} contains a $k \times k$ identity matrix, $\mathbf{X}(I_s, :) = \mathbf{I}_k$ and $\max_{i,j} |\mathbf{X}(i, j)| \leq 1$.
- $\mathbf{A}_{\text{skel}} = \mathbf{A}(I_s, J_s)$

1. ADVANTAGES/DISADVANTAGES OF ID

1.1. Advantages.

- If \mathbf{A} is sparse, then so are \mathbf{C} and \mathbf{R} .
- If \mathbf{A} is non-negative, then so are \mathbf{C} and \mathbf{R} , etc.
- Data Interpretation
- Storage Efficient (Huge saving for sparse matrices, small saving for dense matrices)

1.2. Disadvantages.

- Your basis is no longer orthonormal.
- For matrices of approximate rank k , the ID can be less optimal than the SVD (approximation error is generally the same as the QR).

2. ID AND THE COLUMN-PIVOTED QR ARE CLOSELY RELATED

2.1. **Column/Row ID.** Let \mathbf{A} be $m \times n$ and $\text{rank}(\mathbf{A}) = k < \min(m, n)$. Lets compute the CPQR of \mathbf{A} :

$$(1) \quad \mathbf{A}(:, J) = \mathbf{Q} \mathbf{R}$$

$m \times n$ $m \times k$ $k \times n$

Partition $J = \begin{bmatrix} J_s & J_r \\ k & n-k \end{bmatrix}$ where s stand for the skeleton and r stands for the residual. J_s points to the k pivot vectors that were chosen and $\mathbf{R} = \begin{bmatrix} \mathbf{R}_{11} & \mathbf{R}_{12} \\ k \times k & k \times (n-k) \end{bmatrix}$. We rewrite (1) as:

$$[\mathbf{A}(:, J_s) \quad \mathbf{A}(:, J_r)] = [\mathbf{Q}_1 \mathbf{R}_{11} \quad \mathbf{Q}_1 \mathbf{R}_{12}].$$

We now see that

$$\begin{aligned}
 \mathbf{A}(:, J_s) &= \mathbf{Q}_1 \mathbf{R}_{11} =: \mathbf{C} \\
 \mathbf{A}(:, J_r) &= \mathbf{Q}_1 \mathbf{R}_{12} = \mathbf{Q}_1 \mathbf{R}_{11} \mathbf{R}_{11}^{-1} \mathbf{R}_{12} = \mathbf{C} \mathbf{T}
 \end{aligned}$$

where $\mathbf{T} := \mathbf{R}_{11}^{-1} \mathbf{R}_{12}$ Write (1) as $\mathbf{A} \mathbf{P} = \mathbf{Q} \mathbf{R}$ and then we get:

$$\begin{aligned}
 \mathbf{A} &= \mathbf{Q}_1 \mathbf{R} \mathbf{P}^* = \mathbf{Q}_1 [\mathbf{R}_{11} \quad \mathbf{R}_{12}] \mathbf{P}^* \\
 &= \mathbf{Q} \mathbf{R}_{11} \begin{bmatrix} \mathbf{I}_k \mathbf{R}_{11}^{-1} & \mathbf{R}_{12} \end{bmatrix} \mathbf{P}^* = \mathbf{C} [\mathbf{I}_k \quad \mathbf{T}] \mathbf{P}^* = \mathbf{C} \mathbf{Z}
 \end{aligned}$$

where $\mathbf{Z} = [\mathbf{I}_k \ \mathbf{T}] \mathbf{P}^*$.

Now consider a matrix of approximate rank k . Then:

$$\begin{aligned} \mathbf{AP} &= [\mathbf{Q}_1 \ \mathbf{Q}_2] \begin{bmatrix} \mathbf{R}_{11} & \mathbf{R}_{12} \\ 0 & \mathbf{R}_{22} \end{bmatrix} \\ \Rightarrow \mathbf{A} &= \mathbf{Q}_1 [\mathbf{R}_{11} \ \mathbf{R}_{12}] \mathbf{P}^* + \mathbf{Q}_2 [0 \ \mathbf{R}_{22}] \mathbf{P}^* \end{aligned}$$

The first term can be written as:

$$\mathbf{Q}_1 [\mathbf{R}_{11} \ \mathbf{R}_{12}] \mathbf{P}^* = \mathbf{Q}_1 \mathbf{R}_{11} [\mathbf{I} \ \mathbf{R}_{11}^{-1} \mathbf{R}_{12}] \mathbf{P}^* = \mathbf{CZ}$$

where $\mathbf{C} = \mathbf{Q}_1 \mathbf{R}_{11}$ and $\mathbf{Z} = [\mathbf{I} \ \mathbf{R}_{11}^{-1} \mathbf{R}_{12}] \mathbf{P}^*$ while the second term is the remainder term. Then:

$$\mathbf{A} - \mathbf{CZ} = \mathbf{Q}_2 [0 \ \mathbf{R}_{12}] \mathbf{P}^*$$

which produces exactly the same error as in the truncated QR. In practice, just take k steps of the Gram-Schmidt. Then:

$$\mathbf{AP} = \mathbf{Q}_1 [\mathbf{R}_{11} \ \mathbf{R}_{12}] + \begin{bmatrix} 0 & \mathbf{B} \\ & \mathbf{I}_{n-k} \end{bmatrix}$$

Stop when $\|\mathbf{B}\|_{Fro} \leq \epsilon$. Note that $\|\mathbf{B}\| = \|\mathbf{Q}_2 \mathbf{R}_{22} \tilde{\mathbf{P}}\| = \|\mathbf{R}_{22}\|$.

To obtain the row ID, perform the Gram-Schmidt on the rows of \mathbf{A} instead of the columns (same as doing the QR factorization of \mathbf{A}^*).

2.2. Double-Sided ID.

Step 1: Perform the column ID, $\mathbf{A} \approx \mathbf{CZ}$.

Step 2: Execute the row ID on \mathbf{C} (which is much smaller than \mathbf{A})! Since $\mathbf{C} = \mathbf{XC}(I_s, :)$ is an exact factorization and using $\mathbf{C} = \mathbf{A}(:, J_s)$, we have $\mathbf{C}(I_s, :) = \mathbf{A}(I_s, J_s)$. So:

$$\mathbf{A} \approx \mathbf{CZ} = \mathbf{XC}(I_s, :)\mathbf{Z} = \mathbf{XA}(I_s, J_s)\mathbf{Z}$$

where $\mathbf{A}(I_s, J_s) = \mathbf{A}_{\text{skel}}$.

You can also perform the Double-Sided ID using the row ID first (conduct the Gram-Schmidt on the smaller dimension for a more optimal solution).

REFERENCES