

Ex 1 How would you get an orthonormal basis of \mathbf{X} ?

Solution: Just take any basis and orthonormalize it with Gram-Schmidt or Householder QR.



Ex 2 Show how you can get a decomposition in which \mathbf{C} is lower (or upper) triangular, from the above factorization.

Solution: You first get any factorization in the form shown in Page 9-7 – Then to get an upper triangular \mathbf{C} you use the QR factorization $\mathbf{C} = \mathbf{Q}\mathbf{R}$. Then \mathbf{U} is replaced by

$$\mathbf{U}_{new} = \mathbf{U} \times \begin{pmatrix} \mathbf{Q} & \mathbf{0} \\ \mathbf{0} & \mathbf{I} \end{pmatrix}$$

and \mathbf{C} is replaced by \mathbf{R} . To get a lower triangular \mathbf{C} you can use the same trick applied to \mathbf{A}^T and transpose the final result.

Ex 3 How can you get the ULV decomposition by using only the Householder QR factorization (possibly with pivoting)?

Solution: You first get the Householder QR factorization $\mathbf{A} = \mathbf{Q}_1\mathbf{R}_1$ of the matrix \mathbf{A} . The second step is to perform a Householder QR factorization of the matrix \mathbf{R}_1^T , so you will get: $\mathbf{R}_1^T = \mathbf{Q}_2\mathbf{R}_2$. The final step is to write:

$$\mathbf{A} = \mathbf{Q}_1 * \mathbf{R}_2^T * \mathbf{Q}_2^T \equiv \mathbf{URV}^T$$

where $\mathbf{U} = \mathbf{Q}_1 \in \mathbb{R}^{m \times m}$; $\mathbf{V} = \mathbf{Q}_2 \in \mathbb{R}^{n \times n}$; $\mathbf{R} = \mathbf{R}_2 \in \mathbb{R}^{m \times n}$ \square

Ex 4 In the proof of the SVD decomposition, define \mathbf{U}, \mathbf{V} as single Householder reflectors.

Solution: We deal with \mathbf{U} only [proceed similarly with \mathbf{V}]. We need a matrix $\mathbf{P} = \mathbf{I} - 2\mathbf{w}\mathbf{w}^T$ such that the first column of \mathbf{A} is \mathbf{u}_1 and all columns are orthonormal. The second requirement is satisfied by default since \mathbf{P} is unitary. Note that what if \mathbf{P} is available we will have $\mathbf{P}\mathbf{u}_1 = \mathbf{e}_1$ because $\mathbf{P}^2 = \mathbf{I}$. Therefore, the wanted \mathbf{w} is simply the vector that transforms the vector \mathbf{u}_1 into $\alpha\mathbf{e}_1$ \square

Ex 5 How can you obtain the thin SVD from the QR factorization of \mathbf{A} and the SVD of an $n \times n$ matrix?

Solution: We first get the thin QR factorization of \mathbf{A} , namely $\mathbf{A} = \mathbf{QR}$ where $\mathbf{Q} \in \mathbb{R}^{m \times n}$ and $\mathbf{R} \in \mathbb{R}^{n \times n}$; Then we can get the SVD $\mathbf{R} = \mathbf{U}_R \mathbf{\Sigma}_R \mathbf{V}_R^T$ of \mathbf{R} and this yields:

$$\mathbf{A} = \mathbf{Q} \times \mathbf{U}_R \mathbf{\Sigma}_R \mathbf{V}_R^T \rightarrow \mathbf{A} = \mathbf{U} \mathbf{\Sigma} \mathbf{V}^T, \quad \text{with } \mathbf{U} = \mathbf{Q} \times \mathbf{U}_R; \quad \mathbf{\Sigma} = \mathbf{\Sigma}_R; \quad \mathbf{V} = \mathbf{V}_R.$$