

1. Introduction

- 1.1. Overview
- 1.2. Optimization Models

2. Linear Algebra

- 2.1. Vectors
- 2.2. Matrices
- 2.3. Linear Equations
- 2.4. Least-Squares
- 2.5. Eigenvalues
- 2.6 Singular Values

3. Convex Models

- 3.1. Convexity
- 3.2. LP and QP
- 3.3. SOCP
- 3.4. Robust LP
- 3.5. GP
- 3.6. SDP
- 3.7. Non-Convex Models

4. Duality

- 4.1. Weak Duality
- 4.2. Strong Duality
- 4.3. Applications

5. Case Studies

- 5.1. Senate Voting
- 5.2. Antenna Arrays
- 5.3. Localization
- 5.4. Circuit Design

# Solving linear equations via the QR decomposition

Linear Equations > Motivating example | Existence, Unicity | Solving via QR | Applications

- Basic idea
- The QR decomposition of a matrix
- Solution via full QR decomposition
- Set of solutions

## Basic idea: reduction to triangular systems of equations

Consider the problem of solving a system of linear equations  $Ax = y$ , where  $A \in \mathbf{R}^{m \times n}$  and  $y \in \mathbf{R}^m$  are given.

The basic idea in the solution algorithm starts with the observation that in the special case when  $A$  is **upper triangular**, that is,  $A_{ij} = 0$  if  $i < j$ , then the system can be easily solved by a process known as *backward substitution*. In backward substitution we simply start solving the system by eliminating the last variable first, then proceed to solve backwards. The process is illustrated in this [example](#), and described in generality [here](#).

## The QR decomposition of a matrix

The **QR decomposition** allows to express any  $m \times n$  matrix  $A$  as the product  $A = QR$  where  $Q$  is  $m \times m$  and orthogonal (that is,  $Q^T Q = I_m$ ) and  $R$  is upper triangular. For more details on this, see [here](#).

Once the QR factorization of  $A$  is obtained, we can solve the system by first pre-multiplying with  $Q$  both sides of the equation:

$$QRx = y \iff Rx = Q^T y.$$

This is due to the fact that  $Q^T Q = I_m$ . The new system  $Rx = Q^T y$  is triangular and can be solved by **backwards substitution**. For example, if  $A$  is full column rank, then  $R$  is invertible, so that the solution is unique, and given by  $x = R^{-1} Q^T y$ .

Let us detail the process now.

## Using the full QR decomposition

We start with the **full QR decomposition** of A with column permutations:

$$AP = QR = \begin{pmatrix} Q_1 & Q_2 \end{pmatrix} \begin{pmatrix} R_1 & R_2 \\ 0 & 0 \end{pmatrix}$$

where

- $Q = [Q_1, Q_2]$  is  $m \times m$  and orthogonal ( $Q^T Q = I_m$ );
- $Q_1$  is  $m \times r$ , with orthonormal columns ( $Q^T Q = I_r$ );
- $Q_2$  is  $m \times (m - r)$ , with orthonormal columns ( $Q^T Q = I_{m-r}$ );
- $r$  is the *rank* of  $A$ ;
- $R_1$  is  $r \times r$  upper triangular, and invertible;
- $R_2$  is a  $r \times (n - r)$  matrix;
- $P$  is a  $m \times m$  permutation matrix (thus,  $P^T = P^{-1}$ ).
- The zero submatrices in the bottom (block) row of  $R$  have  $m - r$  rows.

Using  $A = QRP^T$ , we can write  $Rz = Q^T y$ , where  $z := P^T x$ . Let's look at the equation in  $z$  in expanded form:

$$\begin{pmatrix} R_1 & R_2 \\ 0 & 0 \end{pmatrix} \begin{pmatrix} z_1 \\ z_2 \end{pmatrix} = \begin{pmatrix} Q_1^T y \\ Q_2^T y \end{pmatrix}.$$

We see that unless  $Q_2^T y = 0$ , there is no solution. Let us assume that  $Q_2^T y = 0$ . We have then

$$R_1 z_1 + R_2 z_2 = Q_1^T y,$$

which is a set of  $r$  linear equations in  $n$  variables.

A particular solution is obtained upon setting  $z_2 = 0$ , which leads to a triangular system in  $z_1$ , with an invertible triangular matrix  $R_1$ . Hence  $z_1 = R_1^{-1} Q_1^T y$ , which corresponds to a particular solution  $x_0$  to  $Ax = y$ :

$$x_0 := P \begin{pmatrix} R_1^{-1} Q_1^T y \\ 0 \end{pmatrix}.$$

## Set of solutions

We can also generate all the solutions, by noting that  $z_2$  is a free variable. We have

$$x = P \begin{pmatrix} R_1^{-1} Q_1^T (y - R_2 z_2) \\ 0 \end{pmatrix} = x_0 + L z_2,$$

where

$$L := -P \begin{pmatrix} R_1^{-1} Q_1^T R_2 \\ 0 \end{pmatrix}.$$

The set of solutions is the affine set  $x_0 + \text{range}(L)$ .