

MATH 425 Lecture 18

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Project now due 4/29.

Least Squares Solutions

Least squares solutions can be found without computation of \hat{b}

$$b - \hat{b} = b - A\hat{x} \in \text{Col}A^\perp$$

Which is the same as saying:

$$b - A\hat{x} \in \text{Nul}A^T$$

as:

$$\text{Col}A^\perp = \text{Nul}A^T$$

This implies:

$$A^T(b - A\hat{x}) = 0$$

$$A^Tb - A^TA\hat{x} = 0$$

$$A^TA\hat{x} = A^Tb$$

This equation is largely more useful and does not require the computation of the orthogonal basis of A and the projection of b: \hat{b} .

This method is used in the case of an inconsistent solution.

QR decomposition

If A is an nxn matrix linearly independent columns, then A can be factored as A=QR where Q is an mxn matrix whose columns form an orthonormal basis for the column space of A and R is an nxn matrix upper triangular invertible matrix with positive entries on its diagonal.

$$A = QR$$

$$A = \begin{bmatrix} | & | & \dots & | \\ v_1 & v_2 & \dots & v_n \\ | & | & \dots & | \end{bmatrix} \begin{bmatrix} r_{11} & r_{12} & \dots & r_{1n} \\ 0 & r_{22} & \dots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & r_{nn} \end{bmatrix}$$

We can create an orthonormal basis for Col A by applying the Gram Schmidt process to Q. QQ^T is the identity matrix. therefore, :

$$Q^T A = R$$

Algorithm for QR decomposition: (Gram schmidt no shift) given A with linearly independent columns. Algorithm: Classical Gram-Schmidt:

```
def gram_schmidt(A) :
    R = np.zeros(A.shape)
    Q = np.zeros(A.shape)
    for j in range(len(A)) :
        v_j = A[j]
        for i in range(j - 1) :
            r_ij = v_j.transpose() * A[i]
            v_j = v_j - r_ij * u_i
            R[i, j] = r_ij
        r_jj = v_j.magnitude()
        u_j = v_j / r_jj
        Q[i][j] = u_j
```

least Squares with QR

If A has linearly independent columns then A can be factored as A=QR:

$$A^T A x = A^T b$$

$$A^T = (QR)^T = R^T Q^T \quad \therefore$$

$$A^T A = R^T Q^T Q R$$

$$R^T R \hat{x} = R^T Q^T b$$

$$(R^T)^{-1} R^T R \hat{x} = (R^T)^{-1} R^T Q^T b$$

$$R \hat{x} = Q^T b$$

From here we can use back substitution to solve for the solution.

Curve fitting

Given m data points $(x_1, y_1), \dots, (x_m, y_m)$ if the data points lie on the line then for the line

$$y = \beta_0 + \beta_1 x$$

we have