

Gram-Schmidt and QR Decomposition Example

Suppose that

$$\mathbf{X}_{4 \times 3} = \begin{pmatrix} 1 & 1 & 1 \\ 2 & 1 & 2 \\ 3 & 2 & 2 \\ 4 & 2 & 1 \end{pmatrix}$$

As on the slides, let

\mathbf{X}_l = the matrix made of the first l columns of \mathbf{X}

and consider replacing \mathbf{X} with $\mathbf{Z}_{4 \times 3}$ having orthogonal columns for which $\mathcal{C}(\mathbf{Z}_l) = \mathcal{C}(\mathbf{X}_l)$ for all l .

Take as the first column of \mathbf{Z}

$$\mathbf{z}_1 = \mathbf{x}_1 = \begin{pmatrix} 1 \\ 2 \\ 3 \\ 4 \end{pmatrix}$$

Then take

$$\mathbf{z}_2 = \mathbf{x}_2 - \frac{\langle \mathbf{x}_2, \mathbf{z}_1 \rangle}{\langle \mathbf{z}_1, \mathbf{z}_1 \rangle} \mathbf{z}_1 = \begin{pmatrix} 1 \\ 1 \\ 2 \\ 2 \end{pmatrix} - \frac{17}{30} \begin{pmatrix} 1 \\ 2 \\ 3 \\ 4 \end{pmatrix} = \begin{pmatrix} \frac{13}{30} \\ -\frac{4}{30} \\ \frac{9}{30} \\ -\frac{8}{30} \end{pmatrix}$$

Note that

$$\langle \mathbf{z}_1, \mathbf{z}_2 \rangle = \frac{13 - 8 + 27 - 32}{30} = 0$$

and that \mathbf{x}_1 and \mathbf{x}_2 are both linear combinations of $\mathbf{z}_1, \mathbf{z}_2$, i.e. $\mathcal{C}(\mathbf{Z}_2) = \mathcal{C}(\mathbf{X}_2)$.

Then take

$$\begin{aligned} \mathbf{z}_3 &= \mathbf{x}_3 - \left(\frac{\langle \mathbf{x}_3, \mathbf{z}_1 \rangle}{\langle \mathbf{z}_1, \mathbf{z}_1 \rangle} \mathbf{z}_1 + \frac{\langle \mathbf{x}_3, \mathbf{z}_2 \rangle}{\langle \mathbf{z}_2, \mathbf{z}_2 \rangle} \mathbf{z}_2 \right) \\ &= \begin{pmatrix} 1 \\ 2 \\ 2 \\ 1 \end{pmatrix} - \left(\frac{15}{30} \begin{pmatrix} 1 \\ 2 \\ 3 \\ 4 \end{pmatrix} + \frac{(15/30)}{(330/900)} \begin{pmatrix} \frac{13}{30} \\ -\frac{4}{30} \\ \frac{9}{30} \\ -\frac{8}{30} \end{pmatrix} \right) = \begin{pmatrix} -\frac{2}{22} \\ \frac{26}{22} \\ \frac{2}{22} \\ -\frac{14}{22} \end{pmatrix} \end{aligned}$$

It is easy to see that $\langle \mathbf{z}_1, \mathbf{z}_3 \rangle = 0$ and $\langle \mathbf{z}_2, \mathbf{z}_3 \rangle = 0$ and with

$$\mathbf{Z} = \begin{pmatrix} 1 & \frac{13}{30} & -\frac{2}{22} \\ 2 & -\frac{4}{30} & \frac{26}{22} \\ 3 & \frac{9}{30} & \frac{2}{22} \\ 4 & -\frac{8}{30} & -\frac{14}{22} \end{pmatrix}$$

$\mathcal{C}(\mathbf{Z}_3) = \mathcal{C}(\mathbf{Z}) = \mathcal{C}(\mathbf{X}) = \mathcal{C}(\mathbf{X}_3)$.

Notice that for

$$\gamma_{kj} = \begin{cases} 1 & \text{if } j = k \\ \frac{\langle \mathbf{z}_k, \mathbf{x}_j \rangle}{\langle \mathbf{z}_k, \mathbf{z}_k \rangle} & \text{if } j > k \\ 0 & \text{otherwise} \end{cases}$$

and

$$\mathbf{\Gamma} = (\gamma_{kj}) = \begin{pmatrix} 1 & \frac{17}{30} & \frac{15}{30} \\ 0 & 1 & \frac{15}{11} \\ 0 & 0 & 1 \end{pmatrix}$$

one has

$$\mathbf{X} = \begin{pmatrix} 1 & \frac{13}{30} & -\frac{2}{22} \\ 2 & -\frac{4}{30} & \frac{26}{22} \\ 3 & \frac{9}{30} & \frac{2}{22} \\ 4 & -\frac{8}{30} & -\frac{14}{22} \end{pmatrix} \begin{pmatrix} 1 & \frac{17}{30} & \frac{15}{30} \\ 0 & 1 & \frac{15}{11} \\ 0 & 0 & 1 \end{pmatrix} = \mathbf{Z}\mathbf{\Gamma}$$

Further, with

$$\mathbf{D} = \mathbf{diag} \left(\langle \mathbf{z}_1, \mathbf{z}_1 \rangle^{1/2}, \langle \mathbf{z}_2, \mathbf{z}_2 \rangle^{1/2}, \langle \mathbf{z}_3, \mathbf{z}_3 \rangle^{1/2} \right) = \mathbf{diag} \left(\sqrt{30}, \sqrt{11/30}, \sqrt{20/11} \right)$$

one has

$$\mathbf{X} = \mathbf{Z}\mathbf{D}^{-1}\mathbf{D}\mathbf{\Gamma} = \mathbf{Q}\mathbf{R}$$

for $\mathbf{Q} = \mathbf{Z}\mathbf{D}^{-1}$ and $\mathbf{R} = \mathbf{D}\mathbf{\Gamma}$. The matrix

$$\mathbf{Q} = \begin{pmatrix} 1 & \frac{13}{30} & -\frac{2}{22} \\ 2 & -\frac{4}{30} & \frac{26}{22} \\ 3 & \frac{9}{30} & \frac{2}{22} \\ 4 & -\frac{8}{30} & -\frac{14}{22} \end{pmatrix} \begin{pmatrix} \frac{1}{\sqrt{30}} & 0 & 0 \\ 0 & \sqrt{\frac{30}{11}} & 0 \\ 0 & 0 & \sqrt{\frac{11}{20}} \end{pmatrix} = \left(\frac{1}{\sqrt{30}}\mathbf{z}_1, \sqrt{\frac{30}{11}}\mathbf{z}_2, \sqrt{\frac{11}{20}}\mathbf{z}_3 \right)$$

is a version of \mathbf{Z} with columns of norm 1 (that thus form an orthonormal basis for $\mathcal{C}(\mathbf{X})$).

For any vector of responses/targets \mathbf{Y} , $\{\mathbf{q}_j\}$ the columns of \mathbf{Q} , and $\hat{\mathbf{Y}}$ the projection of \mathbf{Y} onto $\mathcal{C}(\mathbf{X})$,

$$\hat{\mathbf{Y}} = \sum_{j=1}^3 \langle \mathbf{Y}, \mathbf{q}_j \rangle \mathbf{q}_j = \mathbf{Q}\mathbf{Q}'\mathbf{Y}$$

since

$$\mathbf{Q}'\mathbf{Y} = \begin{pmatrix} \langle \mathbf{Y}, \mathbf{q}_1 \rangle \\ \langle \mathbf{Y}, \mathbf{q}_2 \rangle \\ \langle \mathbf{Y}, \mathbf{q}_3 \rangle \end{pmatrix}$$

Thus

$$\hat{\mathbf{Y}} = \mathbf{Q}\mathbf{Q}'\mathbf{Y} = \mathbf{Q}\mathbf{R}\mathbf{R}^{-1}\mathbf{Q}'\mathbf{Y} = \mathbf{X}\mathbf{R}^{-1}\mathbf{Q}'\mathbf{Y}$$

which means that the ordinary least squares coefficient vector is

$$\hat{\boldsymbol{\beta}}^{\text{OLS}} = \mathbf{R}^{-1}\mathbf{Q}'\mathbf{Y}$$

and the OLS predictor of y for an arbitrary input \mathbf{x} is $\hat{f}(\mathbf{x}) = \hat{\mathbf{y}}^{\text{OLS}} = \mathbf{x}'\hat{\boldsymbol{\beta}}^{\text{OLS}} = \mathbf{x}'\mathbf{R}^{-1}\mathbf{Q}'\mathbf{Y}$.