

Regression formula

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The problem

Suppose that we have a system of $n + 1$ vectors: $\mathbf{x}, \mathbf{v}^{(j)}$ ($1 \leq j \leq n$) and that the $\mathbf{v}^{(j)}$ are predictors of \mathbf{x} , such that the following:

$$\sum_{j=1}^{n-1} \mathbf{L}^{(j)} \mathbf{v}^{(j)} + \mathbf{v}^{(n)}$$

is as close as possible to \mathbf{x} , such that the difference

$$\mathbf{d} = \sum_{j=1}^{n-1} \mathbf{L}^{(j)} \mathbf{v}^{(j)} + \mathbf{v}^{(n)} - \mathbf{x}$$

is as small as possible given the population. We ask the question: what set of regression matrices, $\mathbf{L}^{(j)}$, achieves this? We may solve the problem using the method of least squares.

Cost function

Define a cost function, J , that is a function of $\mathbf{L}^{(1)}, \dots, \mathbf{L}^{(n-1)}$:

$$\begin{aligned} J[\mathbf{L}^{(1)}, \dots, \mathbf{L}^{(n-1)}] &= \mathbf{d}^T \mathbf{d}, \\ &= \left(\sum_{j=1}^{n-1} \mathbf{L}^{(j)} \mathbf{v}^{(j)} + \mathbf{v}^{(n)} - \mathbf{x} \right)^T \left(\sum_{j'=1}^{n-1} \mathbf{L}^{(j')} \mathbf{v}^{(j')} + \mathbf{v}^{(n)} - \mathbf{x} \right), \\ &= \sum_{j,j'=1}^{n-1} \mathbf{v}^{(j)T} \mathbf{L}^{(j)T} \mathbf{L}^{(j')} \mathbf{v}^{(j')} + \sum_{j=1}^{n-1} \mathbf{v}^{(j)T} \mathbf{L}^{(j)T} (\mathbf{v}^{(n)} - \mathbf{x}) + \sum_{j'=1}^{n-1} (\mathbf{v}^{(n)} - \mathbf{x})^T \mathbf{L}^{(j')} \mathbf{v}^{(j')} \\ &\quad + (\mathbf{v}^{(n)} - \mathbf{x})^T (\mathbf{v}^{(n)} - \mathbf{x}). \end{aligned}$$

Expanding the notation into its components:

$$\begin{aligned} J[\mathbf{L}^{(1)}, \dots, \mathbf{L}^{(n-1)}] &= \frac{1}{2} \left\{ \sum_{j,j'=1}^{n-1} \sum_{a,b,c} \mathbf{v}_a^{(j)} \mathbf{L}_{ba}^{(j)} \mathbf{L}_{bc}^{(j')} \mathbf{v}_c^{(j')} + \sum_{j=1}^{n-1} \sum_{a,b} \mathbf{v}_a^{(j)} \mathbf{L}_{ba}^{(j)} (\mathbf{v}_b^{(n)} - \mathbf{x}_b) \right. \\ &\quad \left. + \sum_{j'=1}^{n-1} \sum_{a,b} (\mathbf{v}_b^{(n)} - \mathbf{x}_b) \mathbf{L}_{ba}^{(j')} \mathbf{v}_a^{(j')} + \sum_b (\mathbf{v}_b^{(n)} - \mathbf{x}_b)^2 \right\}. \end{aligned}$$

The minimum of the cost function with respect to the regression matrices

Differentiating J with respect to an arbitrary component of an arbitrary regression operator, $\mathbf{L}_{\alpha\beta}^{(p)}$, and assuming $p < n$ gives:

$$\begin{aligned}
\frac{\partial J}{\partial \mathbf{L}_{\alpha\beta}^{(p)}} &= \frac{1}{2} \left\{ \sum_{j,j'=1}^{n-1} \sum_{a,b,c} \mathbf{v}_a^{(j)} \delta_{\alpha b} \delta_{\beta a} \delta_{pj} \mathbf{L}_{bc}^{(j')} \mathbf{v}_c^{(j')} \right. \\
&\quad + \sum_{j,j'=1}^{n-1} \sum_{a,b,c} \mathbf{v}_a^{(j)} \mathbf{L}_{ba}^{(j)} \delta_{\alpha b} \delta_{\beta c} \delta_{pj'} \mathbf{v}_c^{(j')} \\
&\quad + \sum_{j=1}^{n-1} \sum_{a,b} \mathbf{v}_a^{(j)} \delta_{\alpha b} \delta_{\beta a} \delta_{pj} \left(\mathbf{v}_b^{(n)} - \mathbf{x}_b \right) \\
&\quad \left. + \sum_{j'=1}^{n-1} \sum_{a,b} \left(\mathbf{v}_b^{(n)} - \mathbf{x}_b \right) \delta_{\alpha b} \delta_{\beta a} \delta_{pj'} \mathbf{v}_a^{(j')} \right\}, \\
&= \frac{1}{2} \left\{ \sum_{j'=1}^{n-1} \sum_c \mathbf{v}_\beta^{(p)} \mathbf{L}_{\alpha c}^{(j')} \mathbf{v}_c^{(j')} + \sum_{j=1}^{n-1} \sum_a \mathbf{v}_a^{(j)} \mathbf{L}_{\alpha a}^{(j)} \mathbf{v}_\beta^{(p)} \right. \\
&\quad \left. + \mathbf{v}_\beta^{(p)} \left(\mathbf{v}_\alpha^{(n)} - \mathbf{x}_\alpha \right) + \left(\mathbf{v}_\alpha^{(n)} - \mathbf{x}_\alpha \right) \mathbf{v}_\beta^{(p)} \right\}.
\end{aligned}$$

In the first term on the penultimate line we can relabel the dummy variables $j' \rightarrow j$, and $c \rightarrow a$:

$$\begin{aligned}
\frac{\partial J}{\partial \mathbf{L}_{\alpha\beta}^{(p)}} &= \sum_{j=1}^{n-1} \sum_a \mathbf{v}_a^{(j)} \mathbf{L}_{\alpha a}^{(j)} \mathbf{v}_\beta^{(p)} + \left(\mathbf{v}_\alpha^{(n)} - \mathbf{x}_\alpha \right) \mathbf{v}_\beta^{(p)}, \\
&= \sum_{j=1}^{n-1} \sum_a \mathbf{L}_{\alpha a}^{(j)} \mathbf{v}_a^{(j)} \mathbf{v}_\beta^{(p)} + \left(\mathbf{v}_\alpha^{(n)} - \mathbf{x}_\alpha \right) \mathbf{v}_\beta^{(p)}.
\end{aligned}$$

This is the (α, β) element of the following matrix expression:

$$\sum_{j=1}^{n-1} \mathbf{L}^{(j)} \left(\mathbf{v}^{(j)} \mathbf{v}^{(p)\top} \right) + \left(\mathbf{v}^{(n)} - \mathbf{x} \right) \mathbf{v}^{(p)\top}.$$

Setting this to zero for the optimum gives:

$$\sum_{j=1}^{n-1} \mathbf{L}^{(j)} \left(\mathbf{v}^{(j)} \mathbf{v}^{(p)\top} \right) + \left(\mathbf{v}^{(n)} - \mathbf{x} \right) \mathbf{v}^{(p)\top} = 0.$$

There are $n - 1$ such equations ($1 \leq p < n$).

Solving for the regression matrices

The outer products are covariance matrices and can be estimated from a population of \mathbf{x} and $\mathbf{v}^{(j)}$ vectors:

$$\begin{aligned}
\mathbf{v}^{(j)} \mathbf{v}^{(p)\top} &\equiv \mathbf{C}^{(jp)}, \\
\mathbf{x} \mathbf{v}^{(p)\top} &\equiv \mathbf{C}^{(xp)}.
\end{aligned}$$

Assembling all $n - 1$ systems together gives:

$$\left(\mathbf{L}^{(1)} \quad \dots \quad \mathbf{L}^{(n-1)} \right) \begin{pmatrix} \mathbf{C}^{(1,1)} & \dots & \mathbf{C}^{(1,n-1)} \\ \vdots & \ddots & \vdots \\ \mathbf{C}^{(n-1,1)} & \dots & \mathbf{C}^{(n-1,n-1)} \end{pmatrix} = \left(\mathbf{C}^{(x,1)} \quad \dots \quad \mathbf{C}^{(x,n-1)} \right) - \left(\mathbf{C}^{(n,1)} \quad \dots \quad \mathbf{C}^{(n,n-1)} \right)$$

Assuming that different $\mathbf{v}^{(j)}$ -vectors are uncorrelated means that $\mathbf{v}^{(j)}\mathbf{v}^{(p)\text{T}} \equiv \mathbf{C}^{(jp)}\delta_{pj}$, which makes the above into:

$$\left(\mathbf{L}^{(1)} \quad \dots \quad \mathbf{L}^{(n-1)} \right) \begin{pmatrix} \mathbf{C}^{(1,1)} & & \\ & \ddots & \\ & & \mathbf{C}^{(n-1,n-1)} \end{pmatrix} = \left(\mathbf{C}^{(x,1)} \quad \dots \quad \mathbf{C}^{(x,n-1)} \right)$$

If all vectors are of equal size then the regression matrices emerge:

$$\mathbf{L}^{(i)} = \mathbf{C}^{(x,i)}\mathbf{C}^{(i,i)^{-1}}$$