Minimum-norm OLS estimator with intercept

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1 Context and notation

Consider the minimum norm OLS estimator in the underdetermined case:

$$\min_{w,w_0} \frac{1}{2} (w^T w + \gamma w_0^2)$$
s.t. $Xw + w_0 1_n = y$ (1)

- X holds the input feature values and has shape (n, p);
- y is the column vector has shape (n, 1);
- n is the number of samples;
- *p* is the number of features;
- w is a column vector of trainable parameter shape (p, 1);
- w_0 is an extra scalar trainable parameter ("the intercept");
- 1_n , 1_p are column vectors of ones of shape (n,1) and (p,1);
- \overline{X} is the column vector of the mean of each column of X;
- \overline{y} is the mean of y;
- X_c is the centered version of X such that $X_c = X 1_n \overline{X}^T$;
- y_c is the centered version of y such that $y_c = y \overline{y} 1_n$;
- $\gamma \in \{0,1\}$ makes it possible decide whether we want to include the intercept in the computation of the norm or not.

Setting $\gamma=1$ would yield the standard formulation which is equivalent to concatenating a column of 1 to X to avoid having to handle a separate intercept coefficient. In this case we solve as in the standard presentations that omit the intercept such as [1].

However here are interested in the $\gamma=0$ to compute the minimum norm OLS estimator where the magnitude of the intercept does not participate in the computation of the norm, to be consistent with the choice to not penalize the intercept in ridge regression for instance, and ensure the continuity of the solutions when $\alpha \to 0$.

2 Solving for $\gamma = 0$ with the method of Lagrange multipliers

Consider the centered data:

$$X = X_c + 1_n \overline{X}^T \tag{2}$$

$$y = y_c + \overline{y}1_n \tag{3}$$

We can rewrite the generic formulation of the problem in Equation 1 as:

$$\begin{split} & \min_{\boldsymbol{w}, \boldsymbol{w}_0} \frac{1}{2} (\boldsymbol{w}^T \boldsymbol{w} + \gamma \boldsymbol{w}_0^2) \\ \text{s.t.} \ & \boldsymbol{X}_c \boldsymbol{w} + \boldsymbol{1}_n \overline{\boldsymbol{X}}^T \boldsymbol{w} + \boldsymbol{w}_0 \boldsymbol{1}_n = \boldsymbol{y}_c + \overline{\boldsymbol{y}} \boldsymbol{1}_n \end{split} \tag{4}$$

Let's introduce Langrange multipliers λ to define our unconstrained objective function:

$$L(w, w_0, \lambda) = \frac{1}{2} w^T w + \frac{\gamma}{2} w_0^2$$

$$+ \lambda^T X_c w + \left(\lambda^T 1_n\right) \left(\overline{X}^T w\right) + w_0 \lambda^T 1_n$$

$$- \lambda^T y_c - \overline{y} \lambda^T 1_n$$

$$(5)$$

The minimizer of this objective function is a critical point:

 • $\nabla L_w(w,w_0,\lambda)=\mathbf{0}_p$ yields:

$$w + X_c^T \lambda + (\lambda^T 1_n) \overline{X} = 0_p \tag{6}$$

• $\nabla L_{w_0}(w,w_0,\lambda)=0$ yields:

$$\gamma w_0 + \lambda^T \mathbf{1}_n = 0 \tag{7}$$

$$X_c w + \left(\overline{X}^T w\right) 1_n + w_0 1_n = y_c + \overline{y} 1_n \tag{8}$$

Right-multiplying Equation 8 by $\mathbf{1}_n^T$ yields:

$$\mathbf{1}_n^T X_c w + \left(\mathbf{1}_n^T \mathbf{1}_n\right) \left(\overline{X}^T w\right) + w_0 \left(\mathbf{1}_n^T \mathbf{1}_n\right) = \mathbf{1}_n^T y_c + \overline{y} \mathbf{1}_n^T \mathbf{1}_n \tag{9}$$

Since $\mathbf{1}_n^T\mathbf{1}_n=n$, $\mathbf{1}_n^TX_c=\mathbf{0}_p$ and $\mathbf{1}_n^Ty_c=\mathbf{0}$ we recover the usual:

$$w_0 = \overline{y} - \overline{X}^T w \tag{10}$$

Note that Equation 10 holds for any value of γ .

For the case where $\gamma = 0$, then Equation 7 becomes:

$$\lambda^T \mathbf{1}_n = 0 \tag{11}$$

and Equation 6 yields:

$$w = -X_c^T \lambda \tag{12}$$

and therefore:

$$w_0 = \overline{y} + \overline{X}^T X_c^T \lambda \tag{13}$$

Let's subtitute in w_0 and w in Equation 8:

$$-X_{c}X_{c}^{T}\lambda-\left(\overline{X}^{T}X_{c}^{T}\lambda\right)\mathbf{1}_{n}+\left(\overline{y}+\overline{X}^{T}X_{c}^{T}\lambda\right)\mathbf{1}_{n}=\boldsymbol{y}_{c}+\overline{y}\mathbf{1}_{n}\tag{14}$$

Hence, after simplification, and assuming $X_c X_c^T$ is invertible:

$$\lambda = -\left(X_c X_c^T\right)^{-1} y_c \tag{15}$$

and therefore the solution is:

$$\hat{w} = -X_c^T \left(X_c X_c^T \right)^{-1} y_c$$

$$\hat{w}_0 = \overline{y} - \overline{X}^T \hat{w}$$
(16)

The minimum norm solution for the centered problem without intercept is also the minimum norm solution for the original problem (with intercept).

Bibliography

[1] Stephen Boyd, "Least-norm solutions of undetermined equations," 2007. [Online]. Available: https://see.stanford.edu/materials/lsoeldsee263/08-min-norm.pdf