

HW2

Deadline: NOV 17th

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About submission:

• File's naming format:

For Homeworks: "HWX Student NO."

Exe: HW2 _400613198.pdf

For MATLAB Homeworks: "PRJX Student NO."

Exe: PRJ1 _400613198.pdf

• About late submissions: %10 of daily reduction of the HW mark.

Exercise 7.2 Multi-output linear regression

(Source: Jaakkola.)

When we have multiple independent outputs in linear regression, the model becomes

$$p(\mathbf{y}|\mathbf{x}, \mathbf{W}) = \prod_{j=1}^{M} \mathcal{N}(y_j | \mathbf{w}_j^T \mathbf{x}_i, \sigma_j^2)$$

Since the likelihood factorizes across dimensions, so does the MLE. Thus

$$\hat{\mathbf{W}} = [\hat{\mathbf{w}}_1, \dots, \hat{\mathbf{w}}_M]$$

where
$$\hat{\mathbf{w}}_j = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{Y}_{:,j}$$
.

In this exercise we apply this result to a model with 2 dimensional response vector $\mathbf{y}_i \in \mathbb{R}^2$. Suppose we have some binary input data, $x_i \in \{0,1\}$. The training data is as follows:

$$\begin{array}{c|cc} \mathbf{x} & \mathbf{y} \\ \hline \mathbf{0} & (-1,-1)^T \\ \mathbf{0} & (-1,-2)^T \\ \mathbf{0} & (-2,-1)^T \\ \mathbf{1} & (1,1)^T \\ \mathbf{1} & (1,2)^T \\ \mathbf{1} & (2,1)^T \\ \end{array}$$

Let us embed each x_i into 2d using the following basis function:

$$\phi(0) = (1,0)^T, \ \phi(1) = (0,1)^T$$

The model becomes

$$\hat{\mathbf{y}} = \mathbf{W}^T \boldsymbol{\phi}(x)$$

where ${\bf W}$ is a 2×2 matrix. Compute the MLE for ${\bf W}$ from the above data.

Exercise 7.3 Centering and ridge regression

Assume that $\bar{\mathbf{x}} = 0$, so the input data has been centered. Show that the optimizer of

$$J(\mathbf{w}, w_0) = (\mathbf{y} - \mathbf{X}\mathbf{w} - w_0 \mathbf{1})^T (\mathbf{y} - \mathbf{X}\mathbf{w} - w_0 \mathbf{1}) + \lambda \mathbf{w}^T \mathbf{w}$$

is

$$egin{array}{lll} \hat{w}_0 & = & \overline{y} \ \mathbf{w} & = & (\mathbf{X}^T\mathbf{X} + \lambda \mathbf{I})^{-1}\mathbf{X}^T\mathbf{y} \end{array}$$

Exercise 7.5 MLE for the offset term in linear regression

Linear regression has the form $\mathbb{E}[y|\mathbf{x}] = w_0 + \mathbf{w}^T \mathbf{x}$. It is common to include a column of 1's in the design matrix, so we can solve for the offset term w_0 term and the other parameters \mathbf{w} at the same time using the normal equations. However, it is also possible to solve for \mathbf{w} and w_0 separately. Show that

$$\hat{w}_0 = \frac{1}{N} \sum_i y_i - \frac{1}{N} \sum_i \mathbf{x}_i^T \mathbf{w} = \overline{y} - \overline{\mathbf{x}}^T \mathbf{w}$$

So \hat{w}_0 models the difference in the average output from the average predicted output. Also, show that

$$\hat{\mathbf{w}} = (\mathbf{X}_c^T \mathbf{X}_c)^{-1} \mathbf{X}_c^T \mathbf{y}_c = \left[\sum_{i=1}^N (\mathbf{x}_i - \overline{\mathbf{x}}) (\mathbf{x}_i - \overline{\mathbf{x}})^T \right]^{-1} \left[\sum_{i=1}^N (y_i - \overline{y}) (\mathbf{x}_i - \overline{\mathbf{x}}) \right]$$

where \mathbf{X}_c is the centered input matrix containing $\mathbf{x}_i^c = \mathbf{x}_i - \overline{\mathbf{x}}$ along its rows, and $\mathbf{y}_c = \mathbf{y} - \overline{\mathbf{y}}$ is the centered output vector. Thus we can first compute $\hat{\mathbf{w}}$ on centered data, and then estimate w_0 using $\overline{y} - \overline{\mathbf{x}}^T \hat{\mathbf{w}}$.

Q4) Prove that each of these distributions belong to the exponential family

- a) Normal
- b) Poisson
- c) Gamma
- d) Binomial with certain number f trials
- e) Chi-squared