Machine Learning

Exercise Sheet 3

Winter Term 2023/2024 Prof. Dr. Niels Landwehr Dr. Ujjwal Available: 16.11.2023 Hand in until: 23.11.2023 11:59am Exercise sessions: 27.11.2023/29.11.2023

Task 1 – Logistic Regression

[25 points]

In this exercise, we study a binary logistic regression model with two-dimensional input of the form

$$f_{\theta}(\mathbf{x}) = \sigma(\theta_0 + \theta_1 x_1 + \theta_2 x_2) \tag{1}$$

$$= \sigma(\theta_0 x_0 + \theta_1 x_1 + \theta_2 x_2) \tag{2}$$

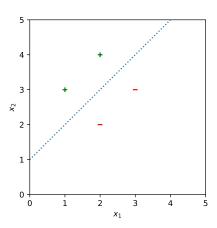
$$= \sigma(\mathbf{x}^\mathsf{T}\boldsymbol{\theta}) \tag{3}$$

where $x_1, x_2 \in \mathbb{R}$ are the two input features and as discussed in the lecture on linear regression we use an additional constant "dummy" feature $x_0 = 1$ to conveniently include the offset term θ_0 in the model. The model outputs the probability for the positive class, that is, $f_{\theta}(\mathbf{x}) = p(y = 1|\mathbf{x}, \theta)$.

Consider the following set of N=4 data points for this model given in matrix form:

$$\mathbf{X} = \begin{pmatrix} 1 & 1 & 3 \\ 1 & 2 & 4 \\ 1 & 2 & 2 \\ 1 & 3 & 3 \end{pmatrix} \qquad \mathbf{y} = \begin{pmatrix} 1 \\ 1 \\ 0 \\ 0 \end{pmatrix} \tag{4}$$

where the rows of **X** contain the instances $\mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3, \mathbf{x}_4$ and **y** contains the targets y_1, y_2, y_3, y_4 . We can visualize the data (ignoring the dummy attribute x_0) in a two-dimensional plot as follows:



In the figure, we have already included a possible linear decision boundary that correctly separates these four instances. The proposed decision boundary is characterized by running through the points $x_1 = 0$, $x_2 = 1$ and $x_1 = 4$, $x_2 = 5$.

a) Determine model parameters $\boldsymbol{\theta}^* = (\theta_1^*, \theta_2^*, \theta_3^*)$ for the logistic regression model given by Equation 1 such that the model has the decision boundary proposed in the figure. Confirm that your model parameters correctly classify all instances. Compute the logarithmic likelihood of the data \mathbf{X}, \mathbf{y} given this model.

b) Characterize the space of all model parameters θ that would result in the same decision boundary and predictions as given by your model θ^* . That is, characterize the space

$$\Theta = \{ \boldsymbol{\theta} | \forall \mathbf{x} \in \mathcal{X} : sign(\mathbf{x}^\mathsf{T} \boldsymbol{\theta}) = sign(\mathbf{x}^\mathsf{T} \boldsymbol{\theta}^*) \}$$

where

$$sign(z) = \begin{cases} 1 & \text{if } z > 0 \\ 0 & \text{if } z = 0 \\ -1 & \text{if } z < 0 \end{cases}$$
 (5)

From the space Θ , find model parameters θ_+^* that have a higher logarithmic likelihood than the original model θ^* , and parameters θ_-^* that have a lower logarithmic likelihood.

Task 2 – Binary and Multiclass Logistic Regression

[15 points]

Assume a multiclass logistic regression model for T=2 classes of the form

$$f_{\mathbf{B}}(\mathbf{x}) = softmax(\mathbf{B}\mathbf{x}) \tag{6}$$

where $\mathbf{B} \in \mathbb{R}^{2 \times M}$ and we have left out the offset terms **b** because an offset can easily be incorporated by using a "dummy" feature that is constantly one as in Task 1. As explained in the lecture, the output of the model is a vector $f_{\mathbf{B}}(\mathbf{x}) \in \mathbb{R}^2$ of probabilities for the two classes.

- a) From the matrix **B**, construct a parameter vector $\boldsymbol{\theta} \in \mathbb{R}^M$ for a binary logistic regression model such that the probability $p(y=1|\mathbf{x},\boldsymbol{\theta}) = \sigma(\mathbf{x}^{\mathsf{T}}\boldsymbol{\theta})$ obtained from the binary logistic regression is identical to the probability $p(y=1|\mathbf{x},\boldsymbol{\theta})$ obtained as the second element of the output vector $f_{\mathbf{B}}(\mathbf{x})$ of the multiclass logistic regression model. Here, we are assuming for the multiclass model that the second class is the positive class.
- b) Construct a matrix $\mathbf{B} \in \mathbb{R}^{2\times 3}$ such that for any input the class membership probabilities returned by the multiclass logistic regression model are identical to the class membership probabilities returned by the model $\boldsymbol{\theta}^*$ from Task 1 a).