FYS-STK3155/4155 Applied Data Analysis and Machine Learning - Project 2: Classification and Regression

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https://github.com/liseanh/FYS-STK4155-project2/

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Abstract

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1 Introduction

Classification in statistical analysis is a useful tool, e.g. for predicting outcomes of various situations or classifying and sorting large amounts of data.

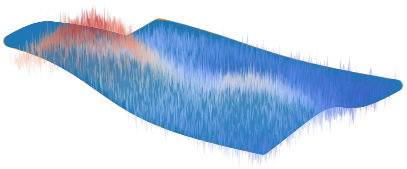

Figure 1: TEST FIGURE AS PLACEHOLDER, PLEASE REMOVE FROM FINAL VERSION

The aim of this project is to study classification and regression problems through our own implementation of logistic regression and a multilayer perceptron (MLP) in Python. This particular data set has been used in a prior research paper by Yeh, I. C. et al about data mining techniques [2], and can be downloaded from the UCI Machine Learning Repository [1]. We will use these methods to classify data of credit card clients' default payment from a Taiwanese bank. Additionally, we will use the MLP to solve a regression problem on the Franke function and compare the result with prior regression analysis results of the function using standard least squares.

2 Theory

2.1 Stochastic Gradient Descent (SGD)

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2.2 Logistic Regression (LR)

2.3 Artificial Neural Networks (ANN)

In an artificial neural network, something something nodes. The output of the nodes in each layer is given by the value of a chosen activation function $f(z)$.

2.3.1 Multilayer perceptron

The multilayer perceptron is a feedforward neural network.

The activation of the jth neuron of layer l is defined as

$$z_j^l = \sum_{i=1}^{M_{l-1}} w_{ij}^l a_j^{l-1} + b_j^l, \tag{1}$$

where b_j^l and w_{ij}^l are the biases and weights at layer l, and $a_j^l = f(z_j^l)$.

To calculate the optimal biases and weights for the problem, we initialize the gradients of the cost function $\mathcal{C}$ with respect to the weights W and biases b at the output layer $l = L$ and the output error δ_L as

$$\frac{\partial \mathcal{C}}{\partial w_{jk}^L} = \delta_j^L a_k^{L-1}, \tag{2}$$

$$\frac{\partial \mathcal{C}}{\partial b_j^L} = \delta_j^L, \tag{3}$$

$$\delta_j^L = f'(z_j^L) \frac{\partial \mathcal{C}}{\partial a_j^L}, \tag{4}$$

before propagating backwards through the hidden layers using the general equations

$$\frac{\partial \mathcal{C}}{\partial w_{jk}^l} = \delta_j^l a_k^{l-1}, \tag{5}$$

$$\frac{\partial \mathcal{C}}{\partial b_j^l} = \delta_j^l, \tag{6}$$

$$\delta_j^l = \sum_k \delta_k^{l+1} w_{kj}^{l+1} f'(z_j^l). \tag{7}$$

Looking at these equations, it is clear that the chosen cost function $\mathcal{C}$ should be differentiable.

3 Data

In this paper we are using credit card payment data from a Taiwanese bank downloaded from the UCI Machine Learning Repository. The response variable is a binary variable of default payment with Yes = 1, No = 0. The original data set consists of 30 000 observations, with X amount of observations with default payments. There are 23 explanatory variables, cited from the original paper they are described as [2]:

- X1: Amount of the given credit (NT dollar): it includes both the individual consumer credit and his/her family (supplementary) credit.
- X2: Gender (1 = male; 2 = female).
- X3: Education (1 = graduate school; 2 = university; 3 = high school; 4 = others).
- X4: Marital status (1 = married; 2 = single; 3 = others).
- X5: Age (year).
- X6 - X11: History of past payment. We tracked the past monthly payment records (from April to September, 2005) as follows: X6 = the repayment status in September, 2005; X7 = the repayment status in August, 2005; . . .;X11 = the repayment status in April, 2005. The measurement scale for the repayment status is: -1 = pay duly; 1 = payment delay for one month; 2 = payment delay for two months; . . .; 8 = payment delay for eight months; 9 = payment delay for nine months and above.
- X12-X17: Amount of bill statement (NT dollar). X12 = amount of bill statement in September, 2005; X13 = amount of bill statement in August, 2005; . . .; X17 = amount of bill statement in April, 2005.
- X18-X23: Amount of previous payment (NT dollar). X18 = amount paid in September, 2005; X19 = amount paid in August, 2005; . . .;X23 = amount paid in April, 2005.

4 Model evaluation

4.1 Regression

To evaluate the performance of our regression model, we consider the R^2 score, given

by

$$R^2(\boldsymbol{y}, \hat{\boldsymbol{y}}) = 1 - \frac{\sum_{i=0}^{n-1}(y_i - \hat{y}_i)^2}{\sum_{i=0}^{n-1}(y_i - \bar{y})^2}, \qquad (8)$$

where $\boldsymbol{y}$ is the given data, $\hat{\boldsymbol{y}}$ is the model and $\bar{y}$ is the mean value of $\boldsymbol{y}$.

4.2 Classification

To evaluate the performance of our classification model, we consider the accuracy score, given by

$$\text{accuracy} = \frac{\sum_{i=1}^{n} I(t_i = y_i)}{n}, \qquad (9)$$

where t_i is the target, y_i is the model output, n is the number of samples and I is the indicator function,

$$I = \begin{cases} 1, & t_i = y_i \\ 0, & t_i \neq y_i \end{cases}.$$

5 Method

6 Results

7 Discussion

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8 Conclusion

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References

[1] UCI Machine Learning Repository. Default of credit card clients Data Set. `https://archive.ics.uci.edu/ml/datasets/default+of+credit+card+clients`. Retrieved: 08-10-2019.

[2] I-Cheng Yeh and Che-hui Lien. The comparisons of data mining techniques for the predictive accuracy of probability of default of credit card clients. *Expert Systems with Applications*, 36(2):2473–2480, 2009.