

MACHINE LEARNING

Software Project 2, Component 1

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PROBLEM DEFINITION

The task to solve in this second software project will be a simple supervised binary classification problem. Specifically, the task at hand will be to determine whether a given banknote is authentic given a number of measures taken from a photograph.

PROBLEM SPECIFICATION

Input data and preconditions

The input data we will use is a labeled dataset provided by the UC Irvine Machine Learning Repository at <https://archive.ics.uci.edu/dataset/267/banknote+authentication>. It consists of 1372 instances with 4 input features each, and a fifth class feature that can either be 0 (authentic banknote) or 1 (unauthentic). The dataset is simple, with a low number of features for each data instance, but sizable enough so that it can be used. Furthermore, there are no missing values.

Output and postconditions

The output will be a trained model which will then be used on a test dataset (cross-validation). The model will output a classification for each of the instances within said dataset, either 0 or 1.

SPECIFICATION OF THE LEARNING TASK

Task: To categorize each banknote, represented by 4 input features each, into either authentic or unauthentic.

Performance measure: Percentage of correctly classified instances within the tested dataset.

Experience: Training via gradient descent given a labeled dataset.

ML TECHNIQUE: PERCEPTRON

The perceptron is a simple supervised machine learning algorithm and one of the earliest neural network architectures, introduced by Frank Rosenblatt in the late 1950s. A perceptron maps a set of training examples (of d -dimensional input vectors) onto binary output values using a $d - 1$ dimensional hyperplane.

The perceptron is a very simple neural network. Given a dataset $\{(x_1, y_1), \dots, (x_n, y_n)\}$ where x_i is a d -dimensional input vector (x_{i1}, \dots, x_{id}) of feature values for that data instance and y_i the binary target variable, the perceptron has a real-valued weight vector $\mathbf{w} = (w_1, \dots, w_d)$ and a real-valued bias b .

The gradient descent algorithm used for training consists of the following steps:

1. Firstly, the weight vector and bias are initialized to all zeros.
2. A linear combination of the input features and weights is computed using a matrix X of (number of instances, number of features) proportions that holds all training examples through the following operation: $\mathbf{a} = X \cdot \mathbf{w} + b$.
3. The Heaviside activation function is applied to the resulting vector from the previous step to convert the real values into binary values: $\underline{y}_i = 1$ if $a_i \geq 0$, else $\underline{y}_i = 0$.
4. The weights and bias updates are computed as follows: $\Delta \mathbf{w} = \eta X^T \cdot (\underline{\mathbf{y}} - \mathbf{y})$, $\Delta b = \eta(\underline{\mathbf{y}} - \mathbf{y})$, where η is the learning rate, a scalar value that determines the magnitude of the update to the weights in each iteration.
5. The weights and biases are updated: $\mathbf{w} = \mathbf{w} + \Delta \mathbf{w}$, $b = b + \Delta b$.