Assignment 1, Deep Learning Fundamentals, 2022
Perceptron Algorithm

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Abstract

*The perceptron algorithm is a classic algorithm in Machine Learning and is often used for classification problems. In this experiment, as the goal is to gain a deeper understanding of the perceptron algorithm, this algorithm will be self-implemented from scratch and trained on the **Pima Indians Diabetes** dataset. The algorithm will also be tested on different epochs and learning rates. Then, the best result will be compared with the perceptron algorithm from the sklearn library to inspect how well the self-implementation algorithm works.*

1. Introduction

Machine Learning is seen as a part of Artificial Intelligence and has recently become extremely popular in the technology community. Its algorithms and underlying architecture aim to create a model that can make predictions or decisions without being explicitly programmed to do so. This learning method is widely used to make predictions using its ability to generalise the input it has not seen before by minimising the difference between prediction and expected output from the training dataset. Machine learning can be applied in various areas, and one of its main tasks is classification [3]. In this experiment, one typical machine learning algorithm called ***Perceptron*** will be implemented to predict whether a patient has diabetes or not, using the ***Pima Indians Diabetes*** dataset. Furthermore, the perceptron algorithm will be tested and compared on different learning rates and numbers of epochs to find the optimal value that leads to the highest accuracy. The implementation code is available at: https://github.com/DoDucNhan/DL-assignment.git

2. Perceptron Alogrithm

In machine learning, the *Perceptron* is an algorithm for supervised learning of binary classifiers. This algorithm is a simplified model of a biological neuron that enables a computer to learn and processes elements in the training set one at a time to make its predictions based on a linear predictor function combining a set of weights with the feature vector [5].

2.1. Loss function

Loss functions for classification are computationally feasible, representing the price paid for the inaccuracy of predictions in classification problems (problems of identifying which category a particular observation belongs to) [2]. In the perceptron algorithm, the loss function is defined as follows:

$$l_{pern}(x, y, w) = max\{0, -y\langle x, w\rangle\} \tag{1}$$

To better understand this loss function, the first thing to notice is that the label of the data is $\{-1, 1\}$ and $y_{predict} = \langle x, w\rangle$. That means when the algorithm is misclassified, which means $y_{true} = 1, y_{predict} = -1$ or $y_{true} = -1, y_{preidict} = 1$, then the value of $-y_{true} \times y_{predict}$ will be greater than 0, and the max function will return the value of $-y_{true} \times y_{predict}$. Conversely, when the algorithm correctly predicts the label, the value of the max function returned will be 0. Therefore, this loss function can effectively record when the perceptron algorithm gives wrong predictions, and the goal of the learning problem is to minimize calculated loss.

2.2. Learning algorithm

First is the mathematics notations for the algorithm:

- T: the number of epochs
- N: the size of the dataset
- w, b: the weights and bias value for making prediction
- (x, y): the input features and the corresponding labels, $y \in \{-1, 1\}$

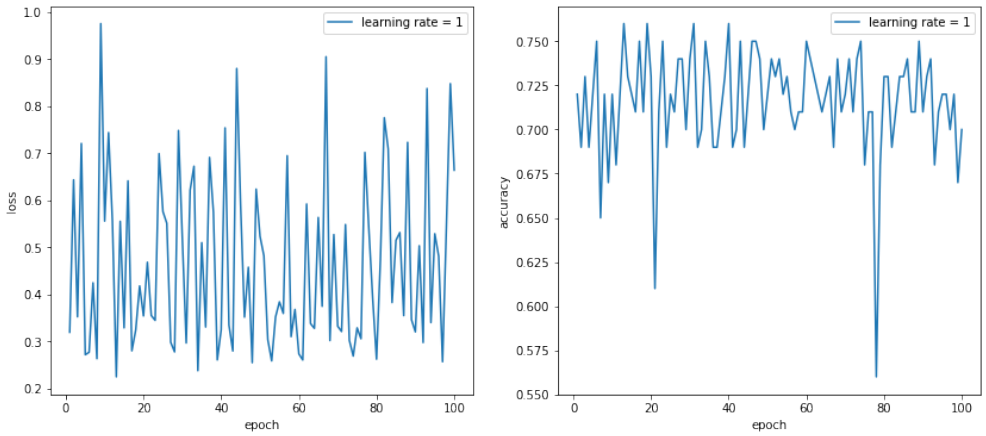


Figure 1. The *loss* and *accuracy* with no learning rate ($\alpha = 1$) after training for 100 epochs.

- α: the learning rate.

The learning process which is also known as updating weights of the perceptron algorithm is presented in the following steps:

Algorithm 1 Perceptron Algorithm

inputs: Training data $\{(x_i, y_i)\}_{i=1}^{N}$, label $y \in \{-1, 1\}$, learning rate α, number of epochs T.

initialization: initialize the $w = 0$ and $b = 0$.

procedure
  for $t := 1$ to T do: **do**
    for $i := 1$ to N do: **do**
      $y^* := \langle x_i, w \rangle$
      if $y_i \times y^* < 0$ **then**
        $w := w + \alpha(y_i \times x_i)$
        $b := b + \alpha y_i$
      end if
    end for
  end for
end procedure

output: w and b.

The class prediction of x is $\hat{y} = sign(\langle x, w \rangle)$, where $sign(z) = 1$ if $z \geq 0, -1$ otherwise.

3. Experiment

3.1. Dataset

The dataset used in this experiment is **Pima Indians Diabetes** (https://www.kaggle.com/datasets/uciml/pima-indians-diabetes-database). It consists of 768 rows and 9 columns. One column for the label, which is $\{0, 1\}$ and others are information about *Pregnancies, Glucose, BloodPressure, SkinThickness, Insulin, BMI, DiabetesPedigreeFunction, and Age*.

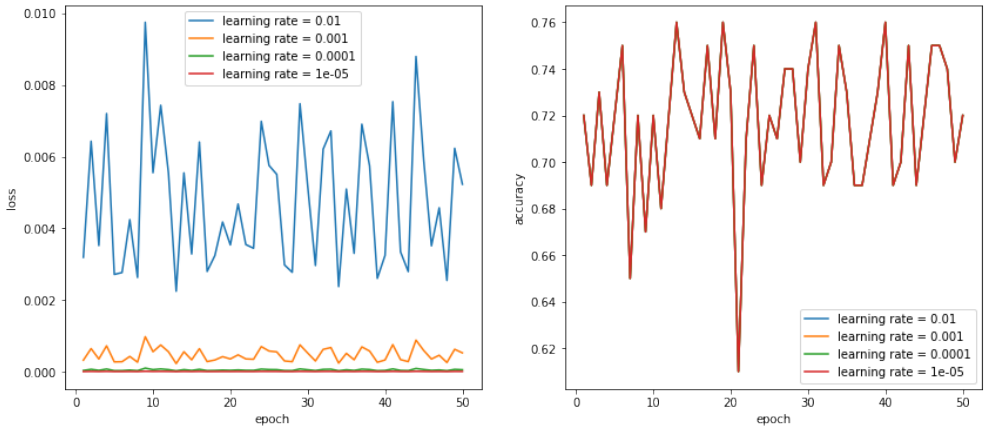
The scaled version of the dataset will be used, which is in the url: https://www.csie.ntu.edu.tw/~cjlin/libsvmtools/datasets/binary.html. The truth labels in this version are $y \in \{-1, 1\}$ indicating whether a patient has diabetes or not.

3.2. Learning rate

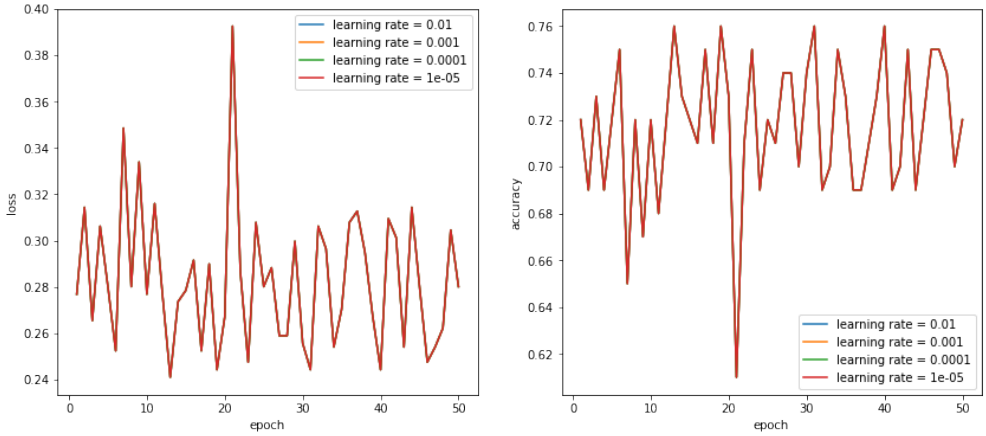
The perceptron algorithm was trained with four different learning rates, $\alpha \in \{0.01, 0.001, 0.0001, 0.00001\}$ and the same epochs of 50. After training, the low loss corresponds to a lower learning rate, but the accuracy is the same regardless of different learning rates (Fig. 2a). Therefore, the sign function was applied to $\langle x, w \rangle$ in Eq. 1 to investigate how the loss would change if the correctness of the prediction (value of $-1, 1$) was the only concerning aspect. As shown in Fig. 2b, after applying the sign function, the loss is the same even if the learning rate changes. This result shows that the learning rate only scales the output value of the inner product $\langle x, w \rangle$ and has no effect on the sign of the output value [1, 4], which is also the algorithm's predicted label value and the classification task's importance.

3.3. Number of epochs

Since the learning does not affect the perceptron algorithm's performance, the learning rate will be assigned to 1, which can be understood that there is no learning rate during training. As shown in Fig. 1, after 100 epochs, the accuracy is fluctuated and hard to identify the pattern. The simple approach to tackle this difficulty is finding the peak of the accuracy (or the the bottom of the loss record), and the epoch corresponding to that accuracy will be the best number of epochs for the training process.

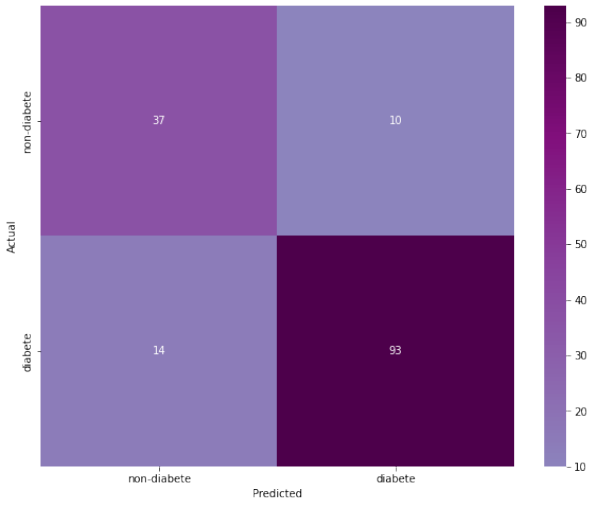


(a) The *sign* function is not applied to the output.

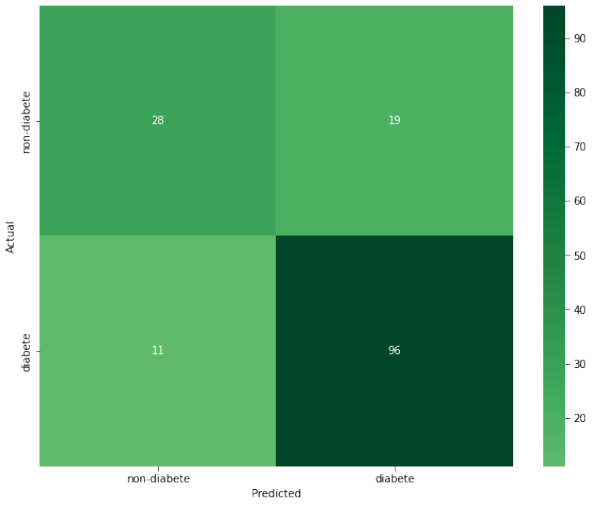


(b) The *sign* function is applied to the output.

Figure 2. The *loss* (the left side) and *accuracy* (the right side) of different learning rates when applying and not applying *sign* function to the output.



(a) The confusion matrix of the implemented perceptron.



(b) The confusion matrix of the perceptron using library.

Figure 3. The confusion matrix comparison between the implemented perceptron and the perceptron from *sklearn* library.

The perceptron algorithm from the sklearn library was used to compare with the self-implementation algorithm to evaluate whether the self-implemetation algorithm works well. After retraining with the best number of epochs found earlier, the self-implementation algorithm's accuracy after training is 84%, which is 3% more than the sklearn library (Table. 1). The confusion matrix in Fig. 3 also shows more specific predictions about the classes of the sklearn and self-implementation algorithms. Thus, this result has confirmed that determining the peak of accuracy and its matching epoch will bring promising results. In this case, just training with a small number of epochs has brought excellent results instead of continuing to train over 100 epochs, but uncertain if the accuracy is increasing.

	Precision		Accuracy
	non-diabete	diabete	
self-implementation	0.73	0.90	**0.84**
sklearn	0.72	0.83	0.81

Table 1. The precision and accuracy comparison between self-implementation percetron and *sklearn* perceptron.

4. Conclusion

Through experimentation, it can be seen that the algorithm is not affected by the learning rate because multiplying the update by any constant $(\alpha \in (0, 1])$ simply rescales the weights but never changes the sign of the prediction. In this classification problem, the best performance of the algorithm can be found through the peak of the accuracy record. However, the loss and accuracy of the algorithm are very inconsistent, so it is quite challenging to find the optimal epoch for the algorithm if training with a larger and more complex dataset. A *Logistic Regression* algorithm might be a better solution to the classification problem since the loss of the algorithm is more stable and more accessible to track by the number of epochs.

References

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[2] Loss functions for classification - wikipedia. https://en.wikipedia.org/wiki/Loss_functions_for_classification. (Accessed on 09/18/2022). 1

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