Impact of the variation of hyper-parameters in artificial neural networks

Anthony Sébert [1] , october 2018

Abstract

The recent global interest in the artificial intelligence domain bring with him a whole area of interesting new challenges and techniques. With the power of bayesian inferences, powerful statistical methods, machine learning appears as one of the key domains to solve tomorrow's problems in a world where AIs will be part of everyday's life, hidden from our eyes yet monitoring and operating our environment. This paper will discuss the impact on the results of the variation of the **hyper-parameters** in supervised learning using an **Artificial Neural Network** [2] . The implementation will be written in Python 3.7 [3] , widely adopted in scientific computing in general and in artificial intelligence in particular [4] [5] , and the 2D plotting library matplotlib [6] to visualize the results.

Categories and subject Descriptors

Computing methodologies~Neural networks Computing methodologies~Supervised learning by classification Computing methodologies~Supervised learning by regression

Comparative study setup

To complete this study, two datasets were selected :

- MNIST [7] dataset (commonly used in machine learning)
  - **task** : recognise handwritten digits
  - **key properties** : 60.000 entries for the *training set*, 10.000 entries for the *testing set*, each one being a label and an array of 28x28 bytes (a byte representing a pixel of the digit's image)
  - **strategy**
    - the *training set* and *testing set* are already provided
- "Red and White Wine Quality EDA" [8] [9] dataset
  - **task** : determine the influence of each chemical properties on the mark of a wine
  - **key properties** : 1.500 entries, each containing 11 chemical properties and three marks from 0 to 10
  - **strategy**
    - since the datasets contain an important number of entries, we can consider the statistical noise very low, and hence perform a min-max scaling (normalisation) on the data (for all properties, $value_{min} = 0$ and $value_{max} = 10$)
    - we split the file into two datasets : *training set* and *testing set* with a **80:20** split ratio

Neural network

Implementation

See [src/ann.ipynb#Implementation] for the implementation of the artificial neural network.

Hyperparameters

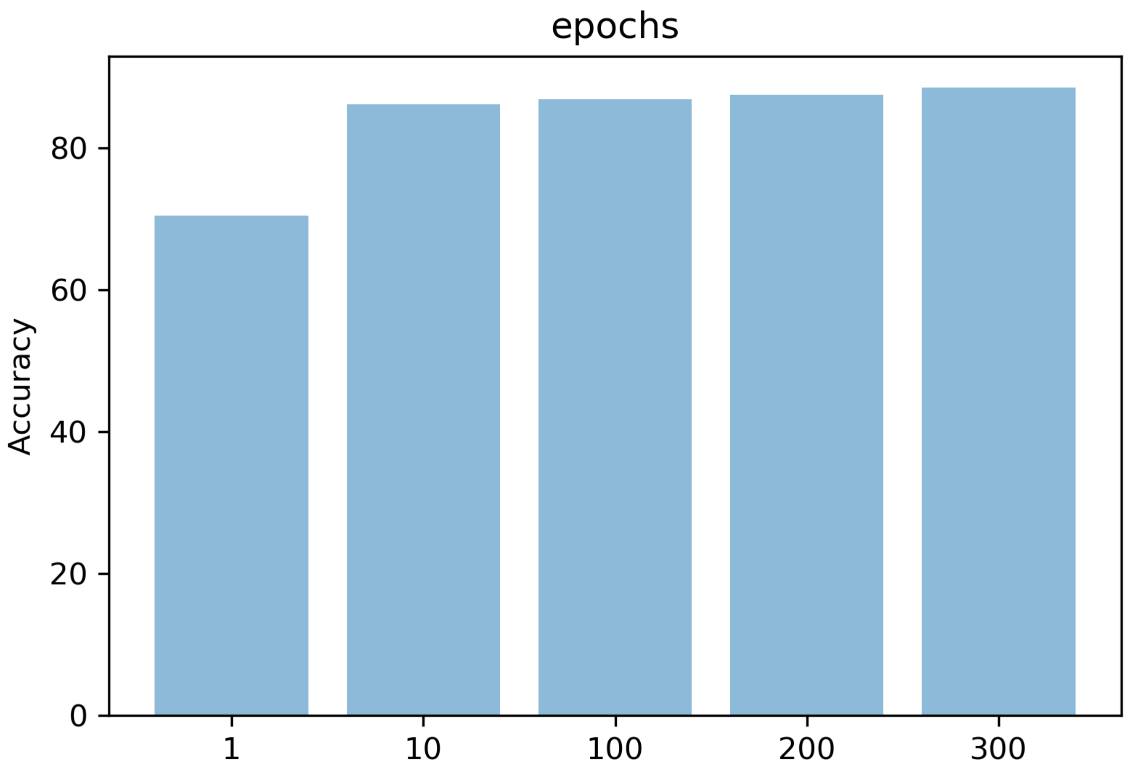
There are several hyperparameters that impact the performance of an artificial neural network. The number of *epochs* is closely linked to the neural network accuracy : the higher it is, the more correct will be the results, but the more time it will take. Concerning the *batch size*, its increase is supposed reduce the number of errors, but increase the memory space needed as well. Since the network topology is quite simple, it does not have to be trained a lot, so the *learning rate* can be low, ensuring as well to avoid overshooting. Other variants of SGD have been considered (AdaGrad or AdaDelta), but will not be part of this coursework due to a lack of time and experience [10] [11] [12].

MNIST dataset

See [src/ann.ipynb#MNIST dataset] for the implementation of the tests. The figures below have been directly exported from the code.

Epochs

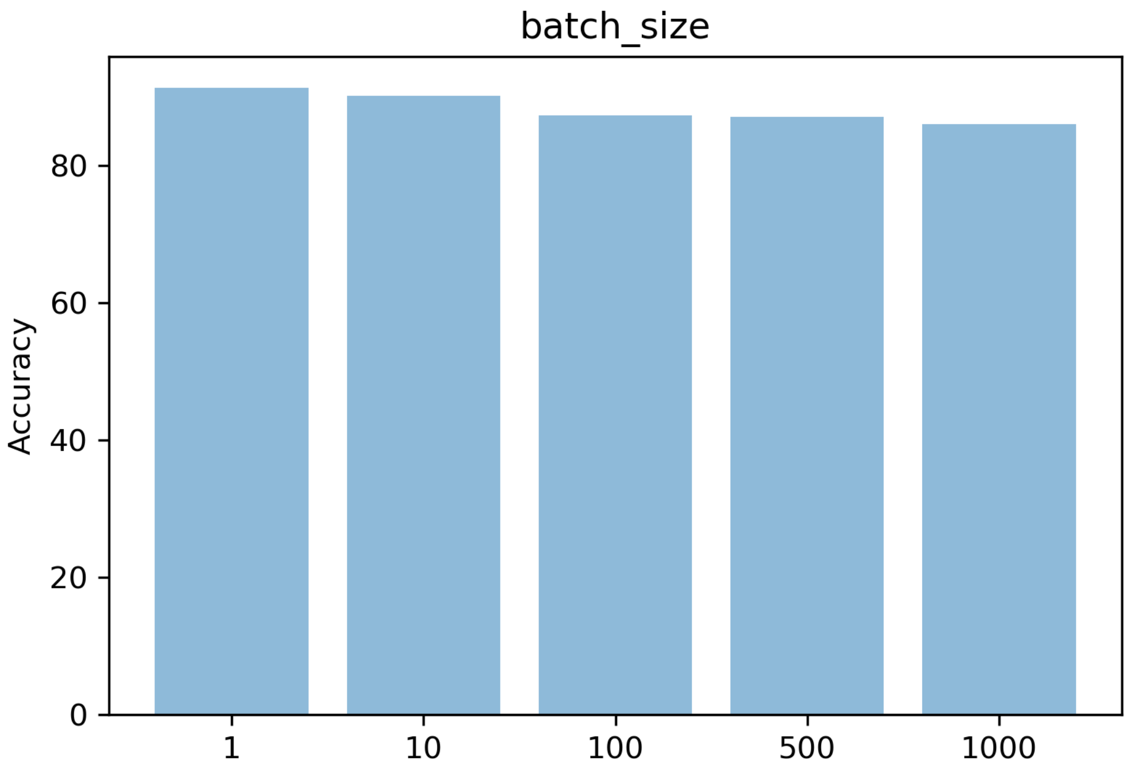
The study will be carried upon the following values (with the default value in bold) : 1, 10, **100**, 200, 300



Batch size

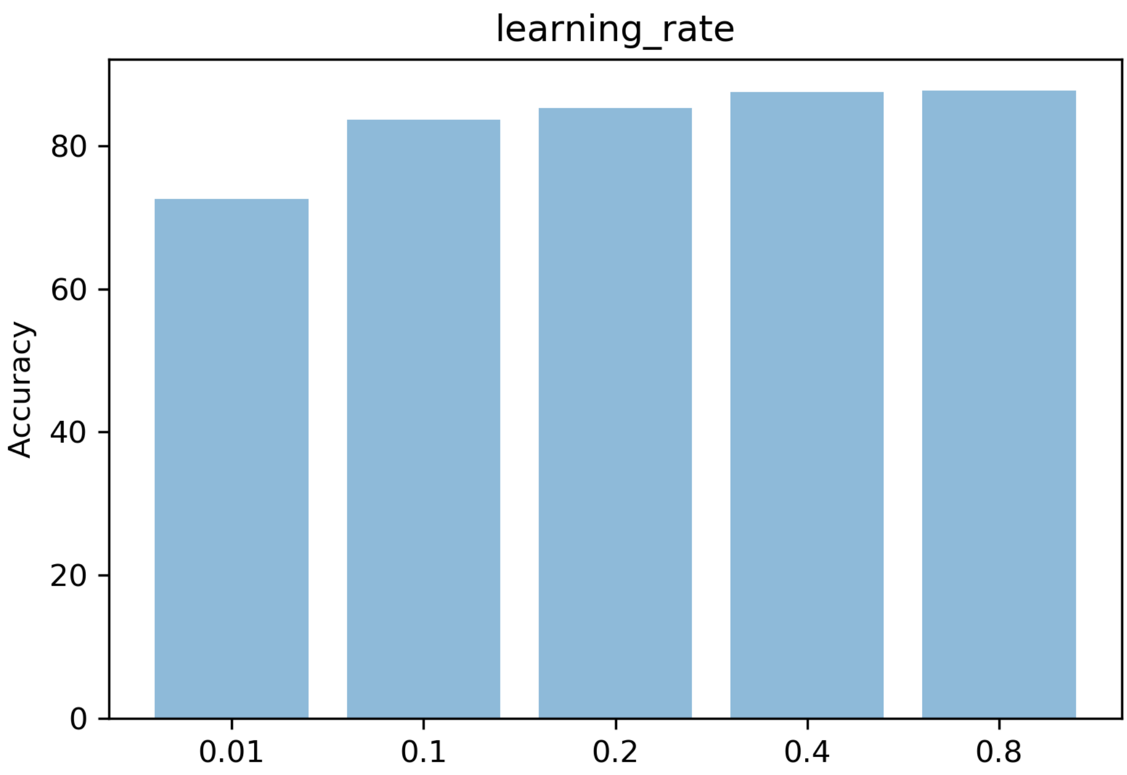
The study will be carried upon the following values (with the default value in bold) : 1, 10, **100**, 500, len(mnist_train_list)

Note The selected values have covered the approaches *Stochastic Gradient Descent*, *mini_batch* and *Gradient Decent*.



Learning rate

The study will be carried upon the following values (with the default value in bold) : 0.01, 0.1, **0.2**, 0.4, 0.8



"Red and White Wine Quality EDA" dataset

See [src/ann.ipynb#"Red and White Wine Quality EDA" dataset]() for the implementation of the tests. The figures below have been directly exported from the code.

Epochs

The study will be carried upon the following values (with the default value in bold) : 1, 10, **100**, 200, 300

epoch hyperparameter results

Batch size

The study will be carried upon the following values (with the default value in bold) : 1, 10, **100**, 200, len(mnist_train_list)

Note The selected values have covered the approaches *Stochastic Gradient Descent*, *mini_batch* and *Gradient Decent*.

batch size hyperparameter results

Learning rate

The study will be carried upon the following values (with the default value in bold) : 0.01, 0.1, **0.2**, 0.4, 0.8

learning rate hyperparameter results

Discussion of results

As we can see, the neural network is quite *learning rate*-sensitive, since there is a significant correlation between its value and the total accuracy. Of course, very low values such as *0.01* produce a poorly result. Moreover, the number of epochs seems to have a deep impact on the overall accuracy : the higher it is, the more the neural network is able to guess right, even if it increases the computation time linearly (which in this case quickly becomes problematic). Note that this parameter seems to have a "*log(n)*" impact : at some point, the network becomes insensitive. Considering the batch size, it seems that the stochastic gradient descent is the best approach, ensuring as well a low memory footprint.

References

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