# **ARN - Report - Labo04**

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### Learning algorithm

1. What is the learning algorithm being used to optimize the weights of the neural networks? What are the parameters (arguments) being used by that algorithm? What cost function is being used? please, give the equation(s)

MLP\_from\_raw\_data.ipynb

The algorithm used is RMSprop.

The arguments used by this algorithm are: - Learning rate A Tensor, floating point value, or a schedule that is a tf.keras.optimizers.schedules.LearningRateSchedule, or a callable that takes no arguments and returns the actual value to use. The learning rate. Defaults to 0.001. - rho: Discounting factor for the history/coming gradient. Defaults to 0.9. - momentum: A scalar or a scalar Tensor. Defaults to 0.0. - epsilon: A small constant for numerical stability. This epsilon is "epsilon hat" in the Kingma and Ba paper (in the formula just before Section 2.1), not the epsilon in Algorithm 1 of the paper. Defaults to 1e-7. - centered: Boolean. If True, gradients are normalized by the estimated variance of the gradient; if False, by the uncentered second moment. Setting this to True may help with training, but is slightly more expensive in terms of computation and memory. Defaults to False. - name: Optional name prefix for the operations created when applying gradients. Defaults to "RMSprop". - \*\*kwargs: keyword arguments. Allowed arguments are clipvalue, clipnorm, global\_clipnorm. If clipvalue (float) is set, the gradient of each weight is clipped to be no higher than this value. If clipnorm (float) is set, the gradient of each weight is individually clipped so that its norm is no higher than this value. If global\_clipnorm (float) is set the gradient of all weights is clipped so that their global norm is no higher than this value.

The used cost function is the categorical crossentropy function. It's equation is:

$$ext{Loss} = -\sum_{i=1}^{ ext{output}} y_i \cdot \log \, \hat{y}_i$$

Figure 1: ARN-Labo04-CrossEntrEquation

MLP\_from\_HOG.ipynb

CNN.ipynb

## **Model Complexity**

2. Model complexity: for each experiment (shallow network learning from raw data, shallow network learning from features, CNN, and Fashion MNIST), select a neural network topology and describe the inputs, indicate how many are they, and how many outputs. Compute the number of weights of each model (e.g., how many weights between the input and the hidden layer, how many weights between each pair of layers, biases, etc...) and explain how do you get to the total number of weights.

```
MLP_from_raw_data.ipynb

MLP_from_HOG.ipynb

CNN.ipynb

Fashion_MNIST.ipynb
```

### **Deep Neural Networks**

3. Do the deep neural networks have much more "capacity" (i.e., do they have more weights?) than the shallow ones? explain with one example

```
MLP_from_raw_data.ipynb
MLP_from_HOG.ipynb
```

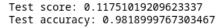
#### **Tests**

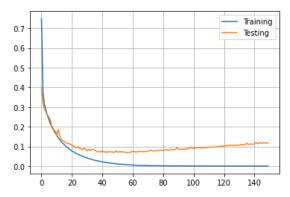
CNN.ipynb

4. Test every notebook for at least three different meaningful cases (e.g., for the MLP exploiting raw data, test different models varying the number of hidden neurons, for the feature-based model, test pix\_p\_cell 4 and 7, and number of orientations or number of hidden neurons, for the CNN, try different number of neurons in the feed-forward part) describe the model and present the performance of the system (e.g., plot of the evolution of the error, final

evaluation scores and confusion matrices). Comment the differences in results. Are there particular digits that are frequently confused?

MLP\_from\_raw\_data.ipynb





**Figure 2:** ARN-RAW-Plot-tanh-softmax\_Batch2048\_NoDropout\_Epoch150

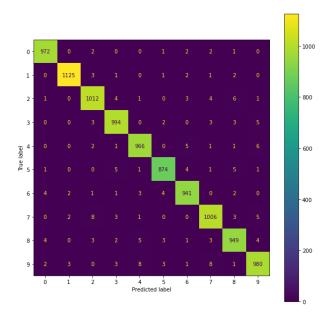


Figure 3: ARN-RAW-ConfMat-tanh-softmax\_Batch2048\_NoDropout\_Epoch150

We can see in this experiment that there's clearly an overfitting.

Test score: 0.0734260305762291 Test accuracy: 0.9796000123023987

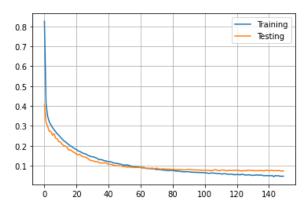


Figure 4: ARN-RAW-Plot-tanh-softmax\_Batch2048\_Dropout\_Epoch150

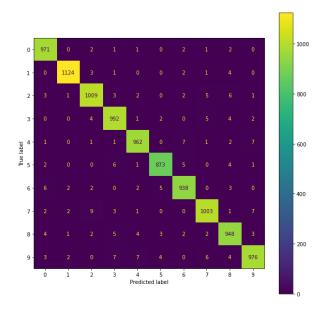
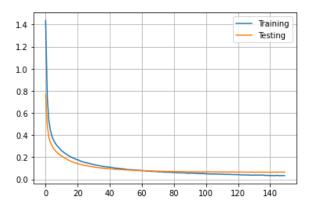


Figure 5: ARN-RAW-ConfMat-tanh-softmax\_Batch2048\_Dropout\_Epoch150

Test score: 0.06564721465110779 Test accuracy: 0.9828000068664551



**Figure 6:** ARN-RAW-Plot-sigmoid-softmax\_Batch2048\_Dropout\_Epoch150

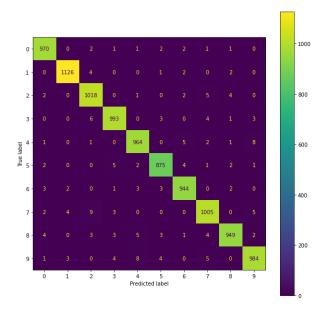


Figure 7: ARN-RAW-ConfMat-sigmoid-softmax\_Batch2048\_Droptout\_Epoch150

Test score: 0.08130748569965363 Test accuracy: 0.9761999845504761

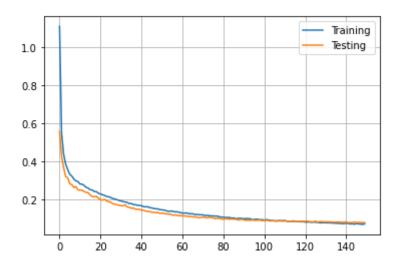


Figure 8: ARN-RAW-Plot-tanh-softmax-Neur250\_Batch4096\_Dropout\_Epoch150

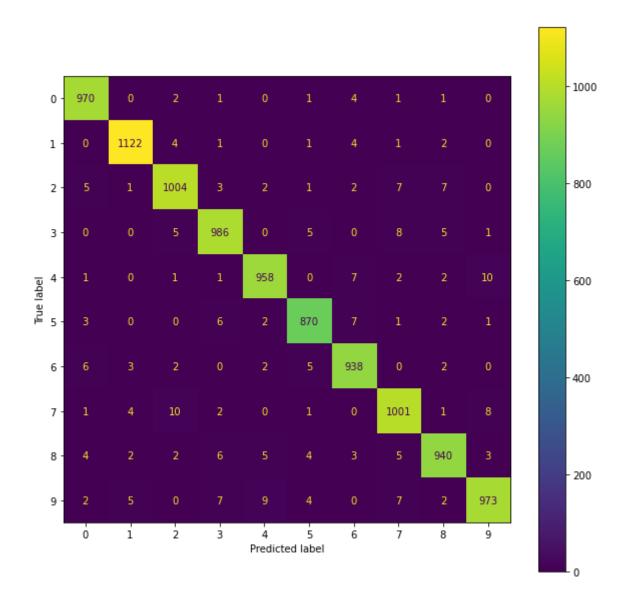
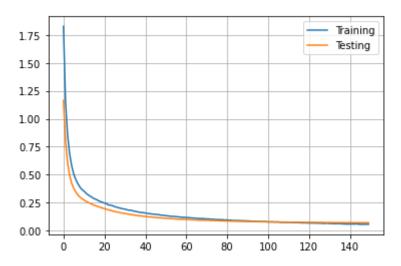


Figure 9: ARN-RAW-ConfMat-tanh-softmax-Neur250\_Batch4096\_Dropout\_Epoch150

Test score: 0.06945059448480606 Test accuracy: 0.9797000288963318



**Figure 10:** ARN-RAW-Plot-sigmoid-softmax-Neur250\_Batch4096\_Dropout\_Epoch150

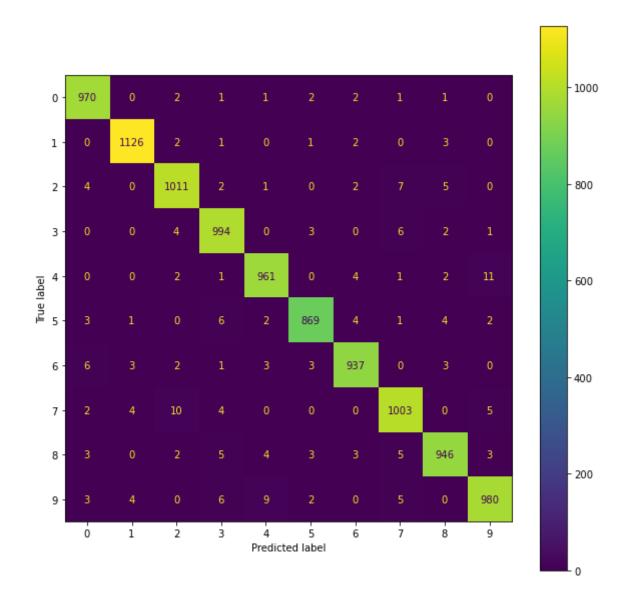


Figure 11: ARN-RAW-ConfMax-sigmoid-softmax-Neur250\_Batch4096\_Dropout\_Epoch150

Test score: 0.06911627948284149 Test accuracy: 0.983299970626831

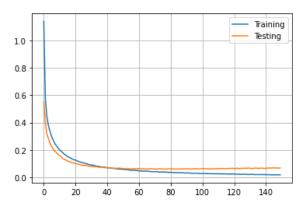


Figure 12: ARN-RAW-Plot-relu\_softmax-Neur250\_Batch4096\_Dropout\_Epoch150

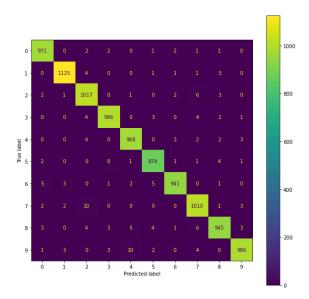


Figure 13: ARN-RAW-ConfMat-relu-softmax-Neur250\_Batch4096\_Dropout\_Epoch150

Test score: 0.07871479541063309 Test accuracy: 0.9796000123023987

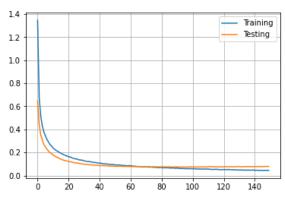


Figure 14: ARN-RAW-Plot-relu-softmax-Neur150\_Batch4096\_Dropout\_Epoch150

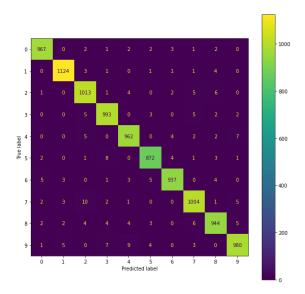
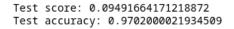


Figure 15: ARN-RAW-ConfMat-relu-softmax-Neur150\_Batch4096\_Dropout\_Epoch150



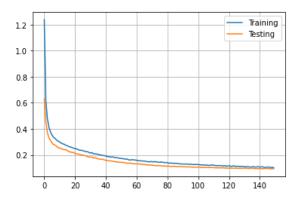


Figure 16: ARN-RAW-Plot-tanh-softmax-Neur150\_Batch4096\_Dropout\_Epoch150

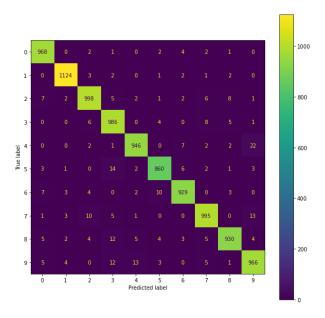
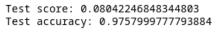


Figure 17: ARN-RAW-ConfMat-tanh-softmax-Neur150\_Batch4096\_Dropout\_Epoch150



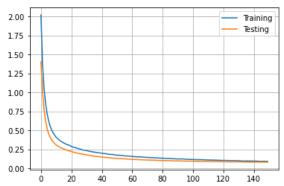


Figure 18: ARN-RAW-Plot-sigmoid-softmax-Neur150\_Batch4096\_Dropout\_Epoch150

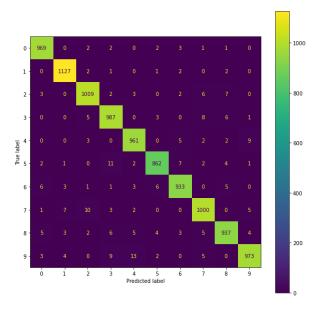


Figure 19: ARN-RAW-ConfMat-sigmoid-softmax-Neur150\_Batch4096\_Dropout\_Epoch150

MLP\_from\_HOG.ipynb

CNN.ipynb