Machine Learning Lab 4EII - IA course

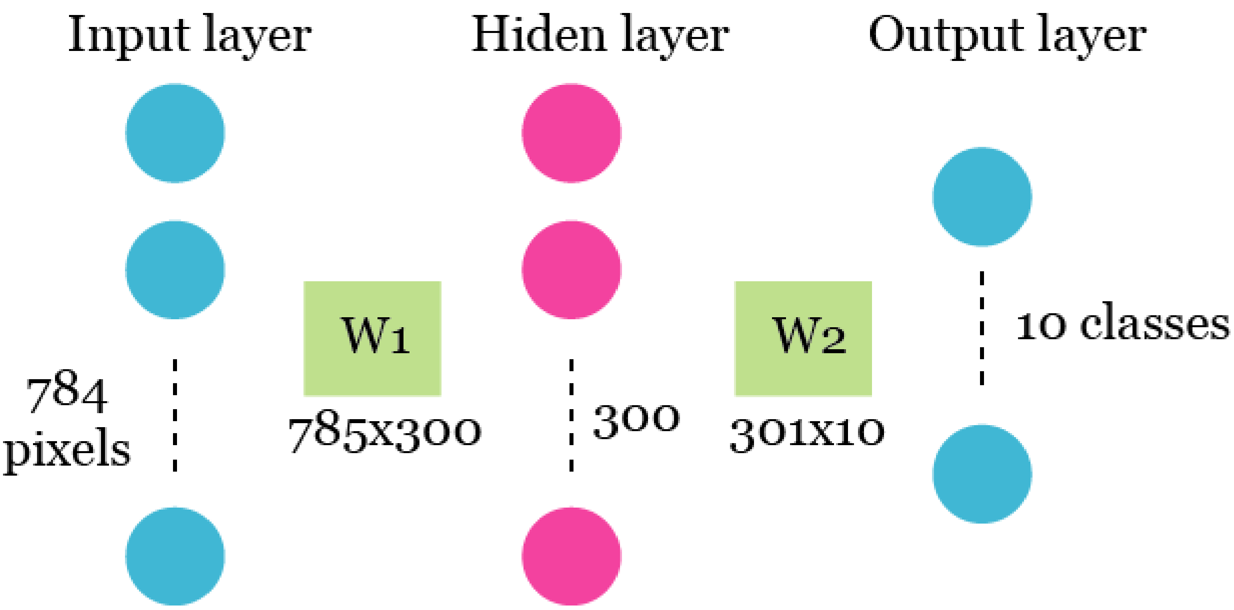
1- **Introduction**

This lab aim at using simple **deep learning** classifier only with Python (without external framework) for a classification problem of recognizing handwritten digits. We consider ten digits 0 to 9 from MNIST dataset, with using Neural Network (NN) with two layers (one hidden layer).

In this lab you will learn to:

- Build you own two layers NN with Python
- Build different steps of NN: forward, backward propagations, loss function and activation functions.
- Study the performance and hyper-parameters of NN
- Build a NN and CNN with using Keras module

The architecture and parameters of the two layers NN are shown in this figure.



2- **Module importation**

Import some useful and common python modules

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.datasets import fetch_openml
import progressbar
import time
```

3- **Download and study the the MNIST dataset**

3.a - Download the MNIST dataset

MNIST dataset contains 70000 images of handwritten digits from 0 to 9. The dataset contains images of size 28x28 pixels and the corresponding labels

```
mnist = fetch_openml('mnist_784') #You can also use and test mnist_784/Fashion-MNI
```

3.b - Create a class structure to save and analyse the dataset

```
def computeentropy(image):
    lensig=image.size
    symset=list(set(image))
    numsym=len(symset)
    propab=[np.size(image[image==i])/(1.0*lensig) for i in symset]
    ent=np.sum([p*np.log2(1.0/p) for p in propab])
    return ent;

class Digit:
    def __init__(self, data, target):
        self.width      = int(np.sqrt((len(data))))
        self.target     = target;
        self.image      = data;

        self.features   = {
                            'var'        :0.0, 'std'        :0.0,
                            'mean'       :0.0, 'entropy'    :0.0,
                          }
        self.computeFeatures()

    def computeFeatures(self):
        self.features['var'] = round(np.var(self.image),2)
        self.features['std'] = round(np.std(self.image),2)
        self.features['mean'] = round(np.mean(self.image),2)
        self.features['entropy'] = round(computeentropy(self.image),2)

    def print(self):
        print("Digit target: " + str(self.target))
        print("Digit target size: "+ str(self.width)  + "x" +str(self.width) +
              '| mean : ' + str(self.features['mean']) +
              '| var : ' + str(self.features['var']) +
              '| std :' + str(self.features['std']) +
              '| entropy :' + str(self.features['entropy']))
        print("Digit image:")
        plt.figure()
        plt.gray()
        plt.matshow(self.image.reshape(self.width, self.width))
        plt.savefig(str(self.target)+'.png', bbox_inches='tight')
        plt.show()
    def getWidth(self):
```

```
        return self.width;


class Dataset:
    def __init__(self, data, size=0, nb_classes=10):
        self.length = int((len(data['data'])))
        if size > 0 and size <  self.length:
            self.length = size;
        else:
            size = self.length;

        self.targets  = data['target'][0:size]
        self.data = data['data'][0:size];
        self.digits       = [];
        self.nb_classes = nb_classes;
        self.createDigits()
        self.X_train = [];
        self.X_test = [];
        self.y_train = [];
        self.y_test = [];

    def printInfo(self):
        from collections import Counter

        c = Counter(self.targets)
        info = "Dataset size " + str(self.length)
        key_value = {}
        for i in sorted(c.keys()):
            key_value[i] = c[i];

        plt.bar(key_value.keys(), key_value.values());
        plt.xlabel('Labels')
        plt.ylabel('Occurrence')
        plt.title('Occurrence of MNIST dataset labels')
        ax = plt.axes()
        ax.grid(which='major', axis='y')
        plt.show()
        return info

    def createDigits(self):
        bar = progressbar.ProgressBar(maxval=self.length).start()
        for i in range(self.length):
            self.digits.append(Digit(self.data[i], self.targets[i]))
            bar.update(i+1);

    def separate_train_test(self, test_size_ratio):
        from sklearn.model_selection import train_test_split
        import keras

        self.X_train, self.X_test, self.y_train, self.y_test = train_test_split(se
        # data normalization
        self.X_train = self.X_train/255;
        self.X_test  = self.X_test/255;

        self.X_train = self.X_train.astype('float32')
```

```
        self.X_test = self.X_test.astype('float32')
        print('Size of training set : ' + str(len(self.y_train)) + ' / ' + str(len
        print('Size of testing set : ' + str(len(self.y_test))+ ' / ' + str(len(se
        self.X_train  = self.X_train.reshape(len(self.X_train), self.digits[0].getW
        self.X_test   = self.X_test.reshape(len(self.X_test), self.digits[0].width
        self.X_train  = self.X_train.astype('float32')
        self.X_test   = self.X_test.astype('float32')

        self.Y_train = keras.utils.to_categorical(self.y_train, self.nb_classes)
        self.Y_test = keras.utils.to_categorical(self.y_test, self.nb_classes)

    def reshapeinImage(self):
        width = self.digits[0].width;
        self.X_train = self.X_train.reshape(self.X_train.shape[0], width, width, 1
        self.X_test  = self.X_test.reshape(self.X_test.shape[0], width, width, 1)


    def display_train_test(self):
        from collections import Counter

        test = Counter(self.y_test)
        train = Counter(self.y_train)
        info = "Dataset size " + str(self.length)

        key_value_train = {};
        key_value_test = {};

        for i in sorted(test.keys()):
            key_value_test[i] = test[i];
        for i in sorted(train.keys()):
            key_value_train[i] = train[i];

        p1 = plt.bar(key_value_train.keys(), key_value_train.values(), width=0.5);
        p2 = plt.bar( key_value_test.keys(), key_value_test.values(), width=0.5, bo

        plt.legend((p1[0], p2[0]), ('Training set', 'Test set'), loc='lower left')
        plt.xlabel('Labels')
        plt.ylabel('Occurrence')
        plt.title('Occurrence of training and testing sets')
        ax = plt.axes()
        ax.grid(which='major', axis='y')
        plt.show();
```

3.b - Load the MNIST dataset in Dataset class and analyse it:

1. Load the dataset in Dataset class

samples is the number of considered samples (sub-set) over 700000 of MNIST dataset, it enables faster training and testing

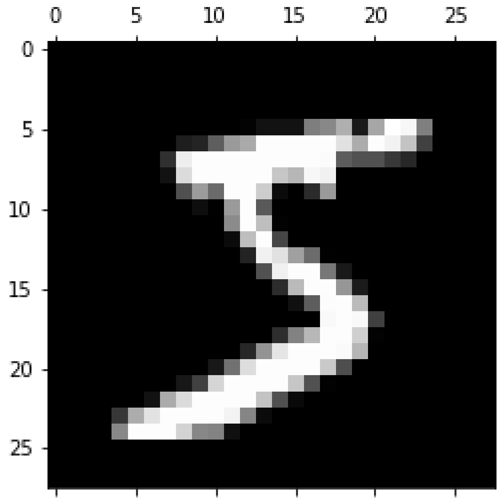
```
samples = 0; # All pictures
training_set = Dataset(mnist, samples)
```

```
99% (69986 of 70000) |################# | Elapsed Time: 0:00:42 ETA:   0:00:
```

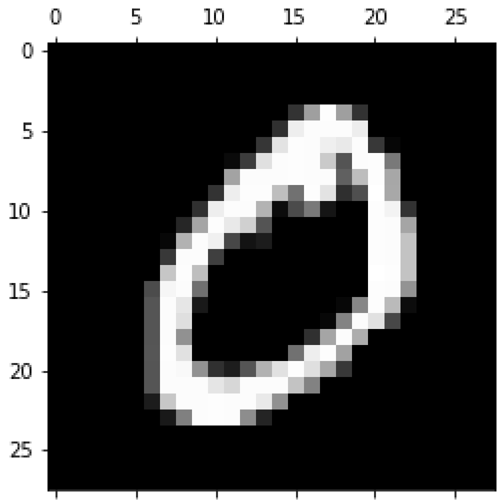
2. Display some digist with corresponding features

```
samples_to_diplay = 10;
for i in range(samples_to_diplay):
  training_set.digits[i].print()
```

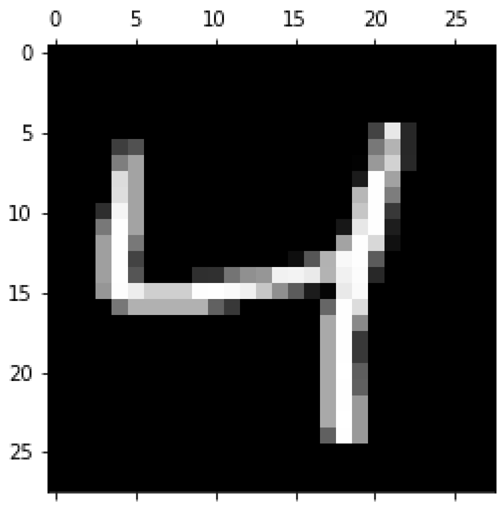
```
Digit target: 5
Digit target size: 28x28| mean : 35.11| var : 6343.94| std :79.65| entropy :1
Digit image:
<Figure size 432x288 with 0 Axes>
```



```
Digit target: 0
Digit target size: 28x28| mean : 39.66| var : 7037.06| std :83.89| entropy :1
Digit image:
<Figure size 432x288 with 0 Axes>
```

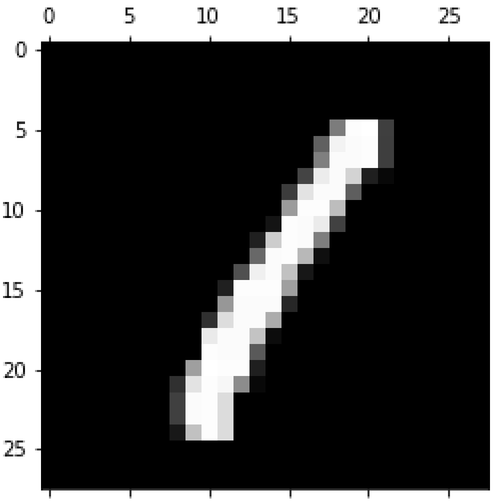


```
Digit target: 4
Digit target size: 28x28| mean : 24.8| var : 4300.7| std :65.58| entropy :1.4
Digit image:
<Figure size 432x288 with 0 Axes>
```



```
Digit target: 1
Digit target size: 28x28| mean : 21.86| var : 4366.42| std :66.08| entropy :1
Digit image:
<Figure size 432x288 with 0 Axes>
```

<Figure size 432x288 with 0 Axes>

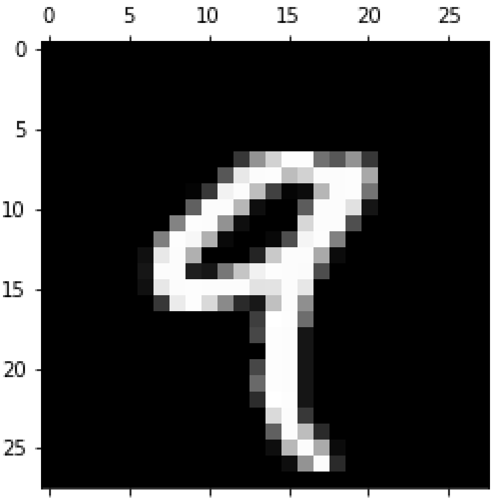


Digit target: 9

Digit target size: 28x28| mean : 29.61| var : 5531.09| std :74.37| entropy :1

Digit image:

<Figure size 432x288 with 0 Axes>

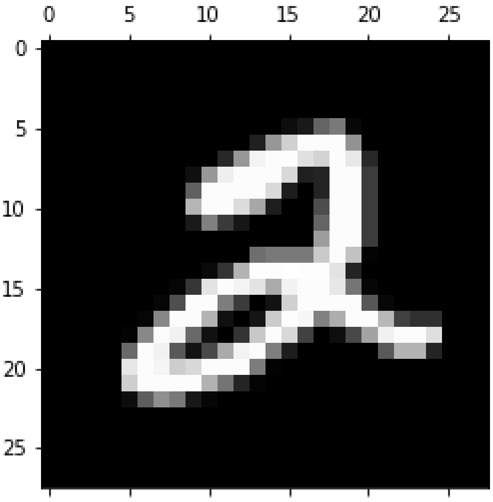


Digit target: 2

Digit target size: 28x28| mean : 37.76| var : 6577.97| std :81.1| entropy :2.

Digit image:

<Figure size 432x288 with 0 Axes>

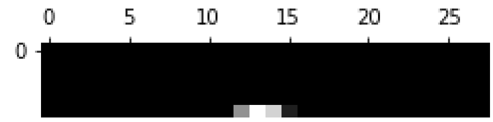


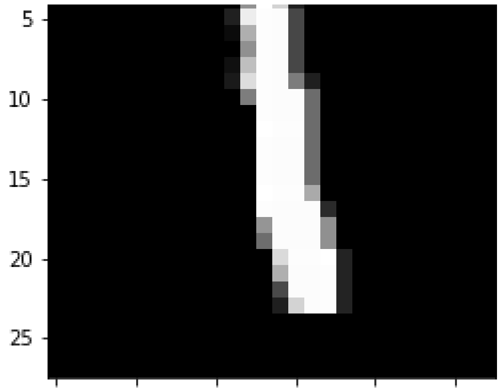
Digit target: 1

Digit target size: 28x28| mean : 22.51| var : 4602.49| std :67.84| entropy :0

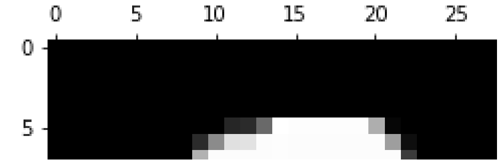
Digit image:

<Figure size 432x288 with 0 Axes>






```
Digit target: 3
Digit target size: 28x28| mean : 45.75| var : 8102.99| std :90.02| entropy :1
Digit image:
<Figure size 432x288 with 0 Axes>
```

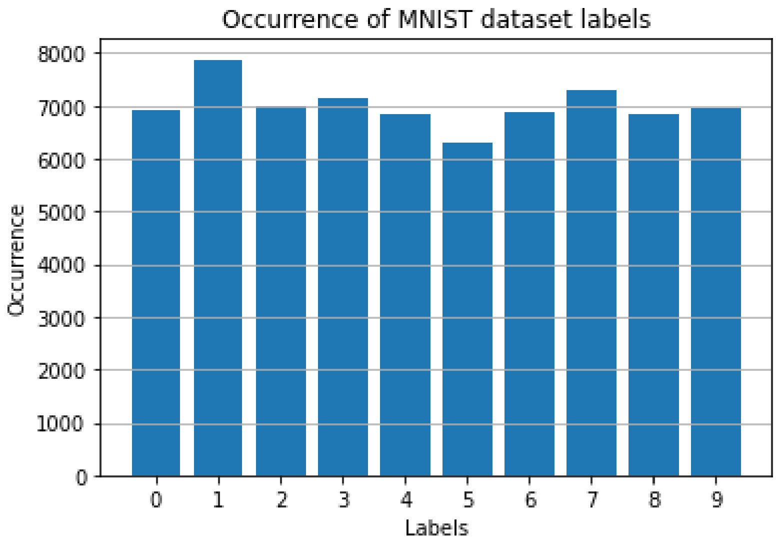


3. Display digits repartitions with *printInfo* function of *Dataset* class

- Is the dataset well balanced ?

```
training_set.printInfo()
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:75: MatplotlibDe
```




```
'Dataset size 70000'
```

> *It seems to be, except for a smooth discrepancy for the label '1'.*

```
<Figure size 432x288 with 0 Axes>
```

4 - **Dataset preparation**

> The MNIST dataset is split to training and testing sets with the corresponding labels

[redacted]

4.a - Split the the MNIST dataset in training and testing sets

- Use *separate_train_test* function with a test set split ratio as parameter
- The test and train sets will be loaded in X_train and X_test lists and the corresponding labels in y_train and y_test lists.

```
test_ratio = 0.2;
training_set.separate_train_test(test_ratio)
```

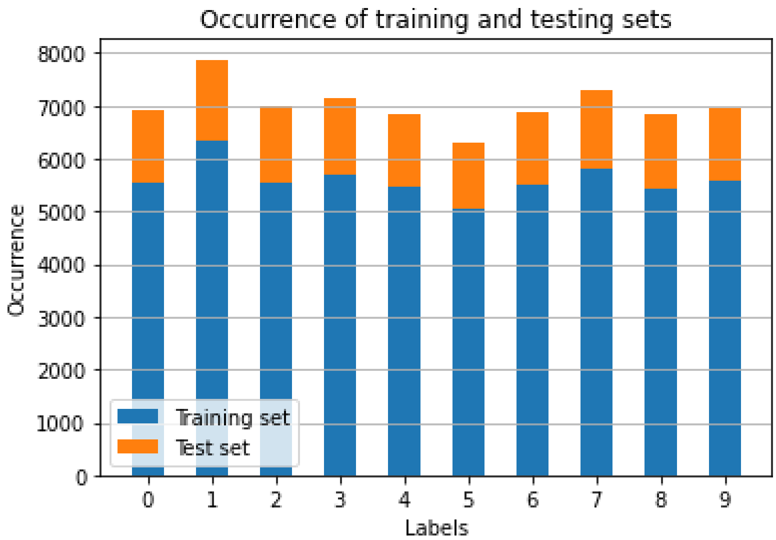
```
Size of training set : 56000 / 70000
Size of testing set : 14000 / 70000
```

4.b - Display the repartition of the digits

- Use *display_train_test* function to illustrate the digits' repartition
- Check whether the repartition ratio is correct

```
training_set.display_train_test()
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:135: MatplotlibD
```



5 - **Define the diffrent functions of the NN**

5.a - Activation fucntion

> Define the activation functions used in forward and bachward propagations

> Implement three activations functions seen in the MIT DL course: sigmoid, Hyperbolic Tangent and Rectified Linear Unit (ReLU) in forward and backward processes. Use numpy module functions such as *np.maximum* and *np.exp*

```
class myActivationFun(object):

    def softMax(x):
        '''
        always used on the last dense layers. It returns a value in the interval [(
        '''
        exps = np.exp(x - np.max(x))
        return exps / np.sum(exps, axis=0)

    def forward(x, actF):
        if(actF =='ReLu'):
            # TO DO
            return np.maximum(0, x)
        elif(actF =='Sigmoid'):
            # TO DO
            return 1/(1 + np.exp(-x))
        elif (actF =='tanh'):
            # TO DO
            return np.tanh(x)
        else:
            print('Error this activation function '+ actF + ' is not supported, we
            return np.maximum(0, x)

    def backward(x, actF):
        '''
        We just need to derivate the functions given in forward propagation.
        '''
        if(actF =='ReLu'):
            # TO DO
            return np.maximum(0, np.sign(x))
        elif(actF =='Sigmoid'):
            # TO DO
            return 1/(1+np.exp(-(x)))*(1-1/(1+np.exp(-x)));
        elif (actF =='tanh'):
            # TO DO
            return 1 - np.power(np.tanh(x), 2)
        else:
            print('Error this activation function '+ actF + ' is not supported, we
            return np.maximum(0, np.sign(x))
```

5.b - Cross entropy loss function

> Define the cross entropy loss function Use numpy module functions such as *np.multiply* and *np.log*

```
class MyCrossEntropy(object):
    def costFun(y, yt):
        return -np.sum(np.multiply(yt,np.log(y)),axis=0)
```

6 - **Build the architecture of the NN**

In this section you will build the architecture of the NN in five mains steps:

1. Initialization of the parameters
2. Forward Process
3. Backward Process
4. Train the network
5. Predict the output

6.a Parameters initialization

```
class Neural_Network:
    def __init__(self, dataset, nb_classes=10, nb_hiden_layers=1,
                 batch_size=128, hiden_layer_size=300, activFunc = "ReLu"):
        self.dataset     = dataset;
        self.nb_layers   = nb_hiden_layers+1;
        self.nb_classes  = nb_classes;
        self.output_size  = nb_classes;
        self.Mini_batch_size  = batch_size;
        self.train_set_size,self.input_size = self.dataset.X_train.shape
        self.hiden_layer_size  = hiden_layer_size;
        self.activFunc = activFunc;
        self.Initilize_NN()

    def Initilize_NN(self):
        self.sig   = 0.05;
        self.lambd = 0.01;
        self.W = [0]*self.nb_layers;

        # Initialize the weights with a normal distribution
        self.W[0] = self.sig*np.random.randn(self.hiden_layer_size, self.input_siz
        for i in range(1, self.nb_layers-1):
            self.W[i] = self.sig*np.random.randn(self.hiden_layer_size, self.hiden_
        self.W[self.nb_layers-1] = self.sig*np.random.randn(self.output_size, self

    def forward (self, ind):
        l = [];
        h  = self.dataset.X_train[ind,].T
        l.append(h);

        for i in range(self.nb_layers):
            a = np.matmul(self.W[i], np.r_[h, np.ones((1, self.Mini_batch_size))])

            if(i != self.nb_layers-1): # Aplly ReLu operation
                l.append(a);
                h = myActivationFun.forward(a, self.activFunc)
            else: # Apply SoftMax for the last layer
                h = myActivationFun.softMax(a);
```

```
            l.append(h);
        return l;

    def backward(self, l, ind, exps):
        gradW = [0]*self.nb_layers;
        stepsize = 0.1/self.Mini_batch_size;

        dJ_da  = exps - self.dataset.Y_train[ind,].T
        for i in range(self.nb_layers):
            gradW[self.nb_layers-i-1] = np.matmul(dJ_da , np.r_[l.pop(), np.ones((
            if(i != self.nb_layers-1):
                dJ_da = np.matmul(self.W[self.nb_layers-i-1][:,0:self.hiden_layer_
            self.W[self.nb_layers-i-1] = self.W[self.nb_layers-i-1] - stepsize*grad

    def train(self, nb_epoch=50):
        t0=time.time()
        nb_ite_max = int(np.round(nb_epoch*self.train_set_size/self.Mini_batch_siz
        bar = progressbar.ProgressBar(maxval=nb_ite_max).start()
        idx = 0;
        for itr in range(nb_ite_max):
            ind = np.random.choice(np.arange(self.train_set_size),self.Mini_batch_
            l = NN.forward(ind);
            exps = l.pop();
            err = MyCrossEntropy.costFun(exps, self.dataset.Y_train[ind,].T);
            #print(np.sum(err))
            NN.backward(l, ind, exps);
            idx +=1;
            bar.update(idx)
        print('total computing time: '+str(time.time()-t0))


    def predict(self):
        test_set_size,p = self.dataset.X_test.shape;
        y = self.dataset.X_test.T;

        for i in range(self.nb_layers):
            h = np.matmul(self.W[i], np.r_[y, np.ones((1,test_set_size))])
            if(i != self.nb_layers-1): # Aplly ReLu operation
                # TO DO
                y = myActivationFun.forward(h, self.activFunc)
            else: # Apply SoftMax for the last layer
                # TO DO
                y = myActivationFun.softMax(h)

        winner = y.max(0).reshape((test_set_size,1))
        yp = (y == np.outer(np.ones((10,1)),winner)).astype(int)
        err_rate = 100*np.sum(np.abs(yp - self.dataset.Y_test.T))/test_set_size/2
        print('Error rate:  %4.2f %%'% err_rate)
```

5.d - Train the Neural Network

> Perform Neural Network training

> 1. Create an instance of Neural_Network class
> 2. Perform prediction on the testing set
> 3. Train the created Neural Network
> 4. Perform prediction again on the testing set

> Compare the performance of the NN with the benchmark on MNIST and Fashion-MNIST datasets, which one is more challenging to classify

> Test your NN with different activation functions

> Does increasing the number of hidden layers enhance the NN performance

> What is the impact of the training rate of the NN performance ?

> How many parameters are trained in this NN

> Why the performance may slighly change between two simulations

> Train the network with three layers

> 3 layers

```
NN = Neural_Network(training_set, batch_size=128, nb_hiden_layers=3, hiden_layer_s
print('Error rate before training : ')
# TO DO
NN.predict()

print('Training ------------------------------')
# TO DO
NN.train()


print('Testing ------------------------------')
# TO DO
NN.predict()
```

```
Error rate before training :
  0% (5 of 21875) |                      | Elapsed Time: 0:00:00 ETA:   0:07:
Training ------------------------------
 99% (21871 of 21875) |################# | Elapsed Time: 0:07:33 ETA:   0:00:
Testing ------------------------------
Error rate:  1.90 %
```

> Run again prediction

```
def predict(NN):
```

```
    nt,p = NN.dataset.X_test.shape;
    y = NN.dataset.X_test.T;
    for i in range(NN.nb_layers):
        h = np.matmul(NN.W[i], np.r_[y, np.ones((1,nt))])
        if(i != NN.nb_layers-1): # Aplly ReLu operation
            # TO DO
            y = myActivationFun.forward(h,"ReLu")
        else: # Apply SoftMax for the last layer
            # TO DO
            y = myActivationFun.softMax(h)

    winner = y.max(0).reshape((nt,1))
    yp = (y == np.outer(np.ones((10,1)),winner)).astype(int)
    err_rate = 100*np.sum(np.abs(yp - NN.dataset.Y_test.T))/nt/2
    print('Test error rate:  %4.2f %%'% err_rate)
    return yp;
print("3 Layers - ReLu")
y_hat = predict(NN).T;
```

```
3 Layers - ReLu
Test error rate:  1.90 %
```

2. Compute the [confusion matrix] of the selected best performing solution and display it with *plot_confusion_matrix* function

> What are the most difficult digits to predict ? Support your answer with numbers from the confusion matrix.

```
def plot_confusion_matrix(cm,
                          target_names,
                          title='Confusion matrix',
                          cmap=None,
                          normalize=True):
    import matplotlib.pyplot as plt
    import numpy as np
    import itertools

    accuracy = np.trace(cm) / float(np.sum(cm))
    misclass = 1 - accuracy

    if cmap is None:
        cmap = plt.get_cmap('Blues')
    plt.figure(figsize=(8, 6))
    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()

    if target_names is not None:
        tick_marks = np.arange(len(target_names))
        plt.xticks(tick_marks, target_names, rotation=45)
        plt.yticks(tick_marks, target_names)
```

```
    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]

    thresh = cm.max() / 1.5 if normalize else cm.max() / 2
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        if normalize:
            plt.text(j, i, "{:0.3f}".format(cm[i, j]),
                  horizontalalignment="center",
                  color="white" if cm[i, j] > thresh else "black")
        else:
            plt.text(j, i, "{:,}".format(cm[i, j]),
                    horizontalalignment="center",
                    color="white" if cm[i, j] > thresh else "black")
    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label\naccuracy={:0.4f}; misclass={:0.4f}'.format(accura
    plt.show()
```

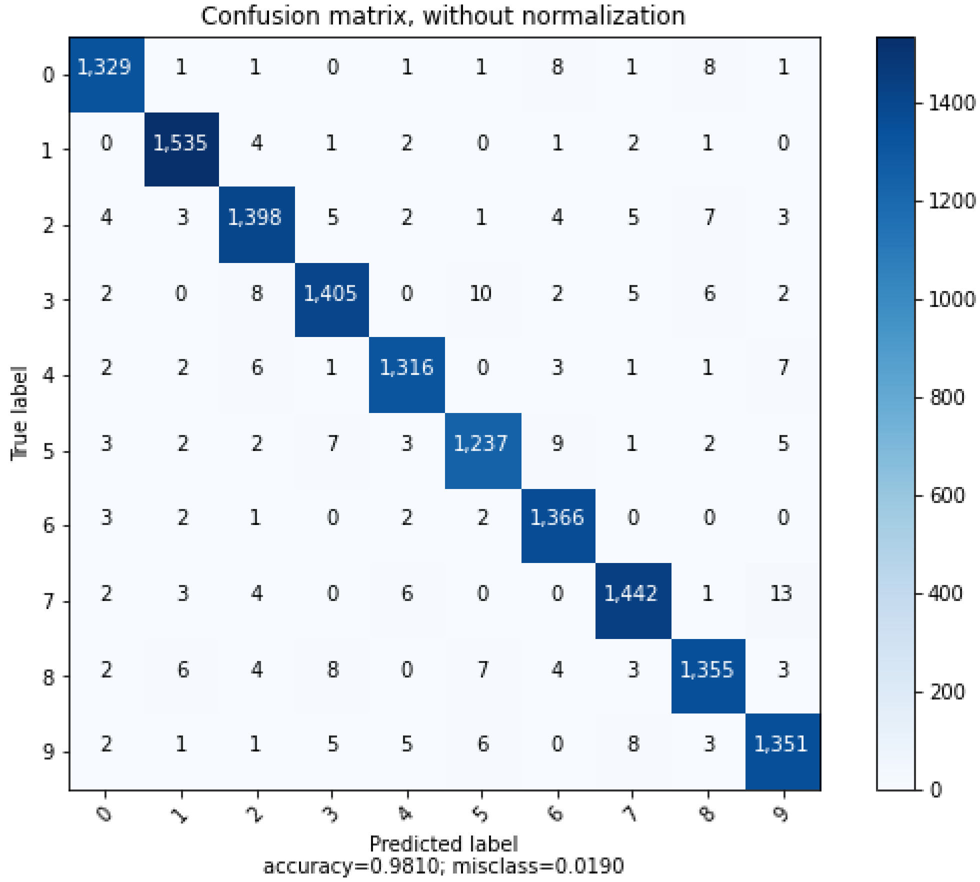
Confusion Matrix for 3 Layers Solution and ReLu activation function

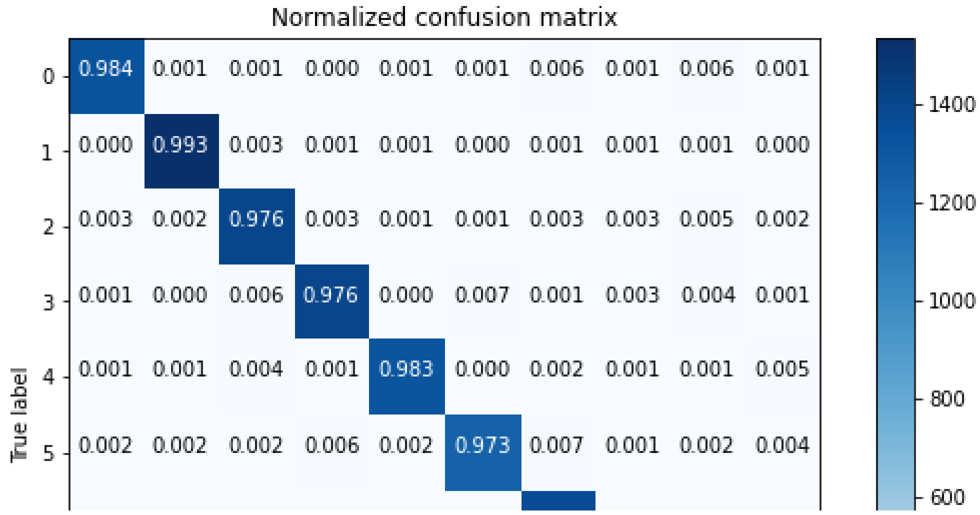
```
from sklearn.metrics import confusion_matrix
class_names = ['0', '1', '2', '3', '4', '5', '6', '7', '8', '9'];
titles_options = [("Confusion matrix, without normalization", False),
                  ("Normalized confusion matrix", True)]
```

```
n, c = y_hat.shape
y_hat1 = np.zeros(n);
y1 = np.zeros(n);
for i in range(n):
    y_hat1[i] = class_names[ int(np.where(y_hat[:][i]==1)[0]) ];
    y1[i] = class_names[ int(np.where(NN.dataset.Y_test[:][i]==1)[0]) ];

conf_mx = confusion_matrix( y1, y_hat1);
plt.figure(figsize=(10,6))
for title, normalize in titles_options:
    disp = plot_confusion_matrix(cm=conf_mx,
                                 target_names=class_names,
                                 title=title,
                                 cmap=plt.cm.Blues,
                                 normalize=normalize)
```

```
<Figure size 720x432 with 0 Axes>
```





> *As we can see, the most difficult digits to identify were '5' and '8' with a score of 0.973. The easiest one was the digit '1'.*

6- Build a NN with using Keras module

> Now, you can configure Colab to use GPU go to: Execution -> Modifier le type d'execution and select GPU. You can check the model of your GPU by running the code below

```
import tensorflow as tf
```

```
tf.test.gpu_device_name()
from tensorflow.python.client import device_lib
device_lib.list_local_devices()
```

```
[name: "/device:CPU:0"
 device_type: "CPU"
 memory_limit: 268435456
 locality {
 }
 incarnation: 11795002885212341873, name: "/device:GPU:0"
 device_type: "GPU"
 memory_limit: 14674281152
 locality {
   bus_id: 1
   links {
   }
 }
 incarnation: 4681180899647280432
 physical_device_desc: "device: 0, name: Tesla T4, pci bus id: 0000:00:04.0,
```

> Import keras related modules

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow import keras
import time
```

6-a Create a 2 layers NN rachitecture

```
NN2 = Sequential()
NN2.add(Dense(units=300, activation='relu', input_dim=784))
NN2.add(Dense(units=10, activation='softmax'))
NN2.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 300)               235500
_________________________________________________________________
dense_1 (Dense)              (None, 10)                3010
=================================================================
Total params: 238,510
Trainable params: 238,510
Non-trainable params: 0
_________________________________________________________________
```

6.b Train the NN model

```
NN2.compile(loss      = 'categorical_crossentropy',
            optimizer = keras.optimizers.SGD(),
            metrics   = ['accuracy'])
t0=time.time()
NN2.fit(training_set.X_train, training_set.Y_train, epochs=10, verbose=0)
print('')
print('total computing time: '+str(time.time()-t0))
```

```
total computing time: 23.68254041671753
```

6.c Test the NN model

```
score = NN2.evaluate(training_set.X_test, training_set.Y_test)
err = 100*(1-np.array(score))
print('Test loss: %4.3f '%score[0])
print('Test err:  %4.2f %%'% err[1])
```

```
438/438 [==============================] - 1s 2ms/step - loss: 0.1745 - accur
Test loss: 0.175
Test err:  4.98 %
```

6.d Test the 2-layers NN with diffrent optimizers

> Here you can use optimizes you have seen in the MIT course: SGD(lr=0.01, decay=1e-6, momentum=0.9, nesterov=False), Adadelta(), Adam(), Adagrad(), RMSprop(). Use more epochs for training.

> Which solver enables the best accuracy on this dataset

```
NN2.compile(loss      = 'categorical_crossentropy',
            optimizer = keras.optimizers.SGD(lr=0.01, decay=1e-6, momentum=0.9, nes
            metrics   = ['accuracy'])
t0=time.time()
NN2.fit(training_set.X_train, training_set.Y_train, epochs=10, verbose=0)
print('')
print('total computing time: '+str(time.time()-t0))
score = NN2.evaluate(training_set.X_test, training_set.Y_test)
err = 100*(1-np.array(score))
print('Test loss: %4.3f '%score[0])
print('Test err:  %4.2f %%'% err[1])
```

```
total computing time: 21.83983302116394
438/438 [==============================] - 1s 2ms/step - loss: 0.0673 - accur
Test loss: 0.067
Test err:  2.01 %
```

```
NN2.compile(loss      = 'categorical_crossentropy',
            optimizer = keras.optimizers.Adadelta(),
            metrics   = ['accuracy'])
t0=time.time()
NN2.fit(training_set.X_train, training_set.Y_train, epochs=10, verbose=0)
print('')
print('total computing time: '+str(time.time()-t0))
score = NN2.evaluate(training_set.X_test, training_set.Y_test)
err = 100*(1-np.array(score))
print('Test loss: %4.3f '%score[0])
print('Test err:  %4.2f %%'% err[1])
```

```
total computing time: 21.868603229522705
438/438 [==============================] - 1s 2ms/step - loss: 0.0652 - accur
Test loss: 0.065
Test err:  1.92 %
```

```
NN2.compile(loss      = 'categorical_crossentropy',
            optimizer = keras.optimizers.Adam(),
            metrics   = ['accuracy'])
t0=time.time()
NN2.fit(training_set.X_train, training_set.Y_train, epochs=10, verbose=0)
print('')
print('total computing time: '+str(time.time()-t0))
score = NN2.evaluate(training_set.X_test, training_set.Y_test)
err = 100*(1-np.array(score))
print('Test loss: %4.3f '%score[0])
print('Test err:  %4.2f %%'% err[1])
```

```
total computing time: 22.229887008666992
438/438 [==============================] - 1s 2ms/step - loss: 0.1118 - accur
Test loss: 0.112
Test err:  2.26 %
```

```
NN2.compile(loss      = 'categorical_crossentropy',
            optimizer = keras.optimizers.Adagrad(),
            metrics   = ['accuracy'])
t0=time.time()
NN2.fit(training_set.X_train, training_set.Y_train, epochs=10, verbose=0)
print('')
print('total computing time: '+str(time.time()-t0))
score = NN2.evaluate(training_set.X_test, training_set.Y_test)
err = 100*(1-np.array(score))
print('Test loss: %4.3f '%score[0])
print('Test err:  %4.2f %%'% err[1])
```

```
total computing time: 21.45932650566101
438/438 [==============================] - 1s 2ms/step - loss: 0.0895 - accur
Test loss: 0.090
Test err:  1.86 %
```

```
NN2.compile(loss      = 'categorical_crossentropy',
           optimizer = keras.optimizers.RMSprop(),
           metrics   = ['accuracy'])
t0=time.time()
NN2.fit(training_set.X_train, training_set.Y_train, epochs=10, verbose=0)
print('')
print('total computing time: '+str(time.time()-t0))
score = NN2.evaluate(training_set.X_test, training_set.Y_test)
err = 100*(1-np.array(score))
print('Test loss: %4.3f '%score[0])
print('Test err:  %4.2f %%'% err[1])
```

```
total computing time: 24.346070051193237
438/438 [==============================] - 1s 2ms/step - loss: 0.1250 - accur
Test loss: 0.125
Test err:  1.57 %
```

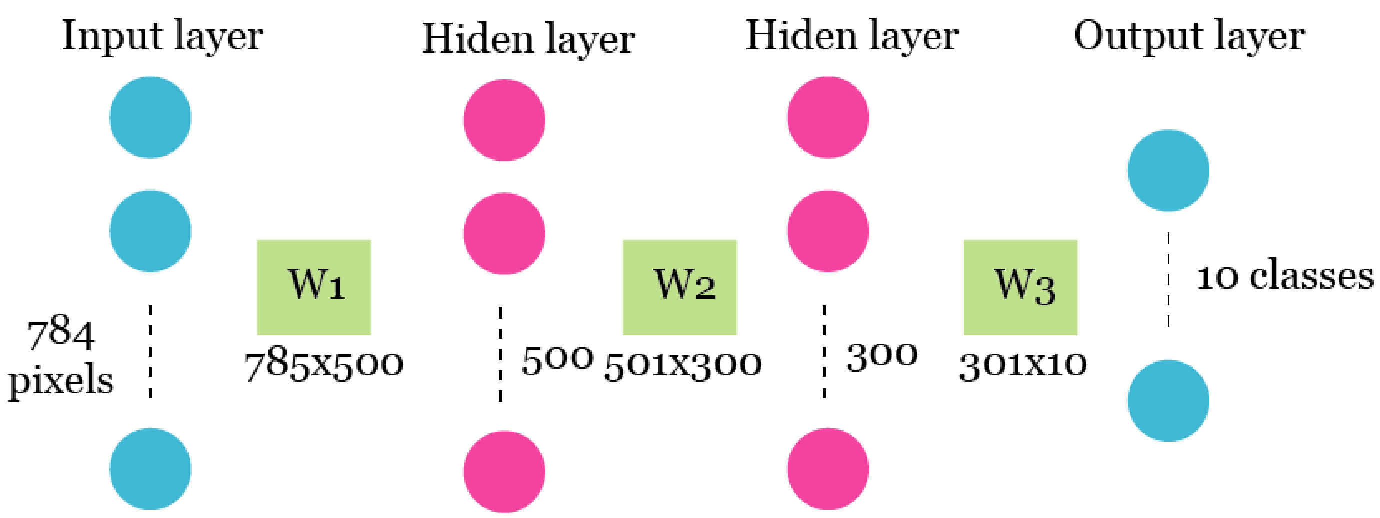
> *Following the numbers, we can see that by far RMSprop has obtained the best performance. Optmizers are very important to reach the best convergence and adjust weithgs properly after each iteration. This algorithm has been showed great performance in the last researches, so the results achieved here were expected.*

6.e - Create a 3 layers NN

> In this section you should build a new NN model with thee layers as illustrated in this Figure.

> You can test with three optimizers: SGD and Adam and Adadelta().

> Compare the performance with the 2 layers NN implemented in the previous section in terms of complexity (number of parameters and accuracy/error)



```
NN3 = Sequential()
NN3.add(Dense(units=500, activation='relu', input_dim=784))
NN3.add(Dense(units=300, activation='relu', input_dim=500))
NN3.add(Dense(units=10, activation='softmax'))
NN3.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_2 (Dense)              (None, 500)               392500
_________________________________________________________________
dense_3 (Dense)              (None, 300)               150300
_________________________________________________________________
dense_4 (Dense)              (None, 10)                3010
=================================================================
Total params: 545,810
Trainable params: 545,810
Non-trainable params: 0
_________________________________________________________________
```

```
NN3.compile(loss      = 'categorical_crossentropy',
           optimizer = keras.optimizers.SGD(lr=0.01, decay=1e-6, momentum=0.9, nes
           metrics   = ['accuracy'])
t0=time.time()
NN3.fit(training_set.X_train, training_set.Y_train, epochs=10, verbose=0)
print('')
print('total computing time: '+str(time.time()-t0))
score = NN3.evaluate(training_set.X_test, training_set.Y_test)
err = 100*(1-np.array(score))
print('Test loss: %4.3f '%score[0])
print('Test err:  %4.2f %%'% err[1])
```

```
total computing time: 24.736000776290894
438/438 [==============================] - 1s 2ms/step - loss: 0.0670 - accur
Test loss: 0.067
Test err:  1.81 %
```

```
NN3.compile(loss      = 'categorical_crossentropy',
           optimizer = keras.optimizers.Adam(),
           metrics   = ['accuracy'])
t0=time.time()
NN3.fit(training_set.X_train, training_set.Y_train, epochs=10, verbose=0)
print('')
print('total computing time: '+str(time.time()-t0))
score = NN3.evaluate(training_set.X_test, training_set.Y_test)
err = 100*(1-np.array(score))
print('Test loss: %4.3f '%score[0])
print('Test err:  %4.2f %%'% err[1])
```

```
total computing time: 24.363827228546143
438/438 [==============================] - 1s 2ms/step - loss: 0.1051 - accur
```

```
Test loss: 0.105
Test err:  2.01 %
```

```
NN3.compile(loss      = 'categorical_crossentropy',
           optimizer = keras.optimizers.Adadelta(),
           metrics   = ['accuracy'])
t0=time.time()
NN3.fit(training_set.X_train, training_set.Y_train, epochs=10, verbose=0)
print('')
print('total computing time: '+str(time.time()-t0))
score = NN3.evaluate(training_set.X_test, training_set.Y_test)
err = 100*(1-np.array(score))
print('Test loss: %4.3f '%score[0])
print('Test err:  %4.2f %%'% err[1])
```

```
total computing time: 23.483312129974365
438/438 [==============================] - 1s 2ms/step - loss: 0.1008 - accur
Test loss: 0.101
Test err:  1.91 %
```

```
NN3.compile(loss      = 'categorical_crossentropy',
           optimizer = keras.optimizers.RMSprop(),
           metrics   = ['accuracy'])
t0=time.time()
NN3.fit(training_set.X_train, training_set.Y_train, epochs=10, verbose=0)
print('')
print('total computing time: '+str(time.time()-t0))
score = NN3.evaluate(training_set.X_test, training_set.Y_test)
err = 100*(1-np.array(score))
print('Test loss: %4.3f '%score[0])
print('Test err:  %4.2f %%'% err[1])
```

```
total computing time: 26.990374326705933
438/438 [==============================] - 1s 2ms/step - loss: 0.2112 - accur
Test loss: 0.211
Test err:  1.38 %
```

> *Adding one more layer we have increased smoothly the accuracy of the neural network*

7- Create a convolutional neural Network (CNN)

> In this section you will build a convolutional Neural Networks and compare its performance in terms of complexity (number of parameter to train, training and

> testing time) and accuracy/error on the testing and training sets.

```
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Dropout, Flatten, Averag
```

> Create a CNN with two conv layers (6 filters of size 5x5 and 16 of size 5x5) followed maxPooling layers and three dense layers (of size 120, 84 and ...).

```
CNN = Sequential()
CNN.add(Conv2D(6, kernel_size=(5, 5), activation=tf.keras.layers.ReLU(), input_sha
CNN.add(MaxPooling2D(pool_size=(2, 2)))
CNN.add(Conv2D(16, (5, 5), activation=tf.keras.layers.ReLU()))
CNN.add(MaxPooling2D(pool_size=(2, 2)))
CNN.add(Flatten())
# add 3 hiden layers
# TO DO
CNN.add(Dense(units=120, activation=tf.keras.layers.ReLU()))
CNN.add(Dense(units=84, activation=tf.keras.layers.ReLU()))
CNN.add(Dense(units=10, activation='softmax'))

CNN.summary()
CNN.compile(loss=keras.losses.categorical_crossentropy, optimizer=keras.optimizers

t0=time.time()

h = CNN.fit(training_set.X_train.reshape(training_set.X_train.shape[0], 28, 28,1),

tn = time.time()-t0;
print('total computing time: '+str(tn))

score = CNN.evaluate(training_set.X_test.reshape(training_set.X_test.shape[0], 28,
err = 100*(1-np.array(score))
print('Test loss: %4.3f '%score[0])
print('Test err:  %4.2f %%'% err[1])
```

```
Model: "sequential_15"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_25 (Conv2D)           (None, 24, 24, 6)         156
_________________________________________________________________
max_pooling2d_23 (MaxPooling (None, 12, 12, 6)         0
_________________________________________________________________
conv2d_26 (Conv2D)           (None, 8, 8, 16)          2416
_________________________________________________________________
max_pooling2d_24 (MaxPooling (None, 4, 4, 16)          0
_________________________________________________________________
flatten_11 (Flatten)         (None, 256)               0
_________________________________________________________________
dense_38 (Dense)             (None, 120)               30840
_________________________________________________________________
dense_39 (Dense)             (None, 84)                10164
_________________________________________________________________
dense_40 (Dense)             (None, 10)                850
```

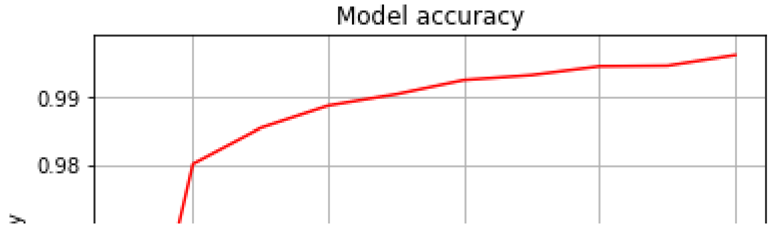
```
=================================================================
Total params: 44,426
Trainable params: 44,426
Non-trainable params: 0
_________________________________________________________________
total computing time: 32.47839021682739
438/438 [==============================] - 1s 2ms/step - loss: 0.0414 - accur
Test loss: 0.041
Test err:  1.06 %
```

> Draw some figures on train history (accuracy, loss function) by epoch

```
print('Test err:  %4.2f %%  time: %4.2f min'% (err[1],tn/60))

plt.plot(list(range(1,len(h.history['accuracy'])+1)),h.history['accuracy'],'r')
plt.title('Model accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(('Train', 'Validation', 'Test'), loc='lower right')
plt.grid()
plt.show()
plt.plot(list(range(1,len(h.history['loss'])+1)),h.history['loss'],'b')
plt.title('Model accuracy')
plt.ylabel('loss')
plt.xlabel('Epoch')
plt.legend(('Train', 'Validation', 'Test'), loc='upper right')
plt.grid()
plt.show()
```

```
Test err:  1.06 %  time: 0.54 min
```



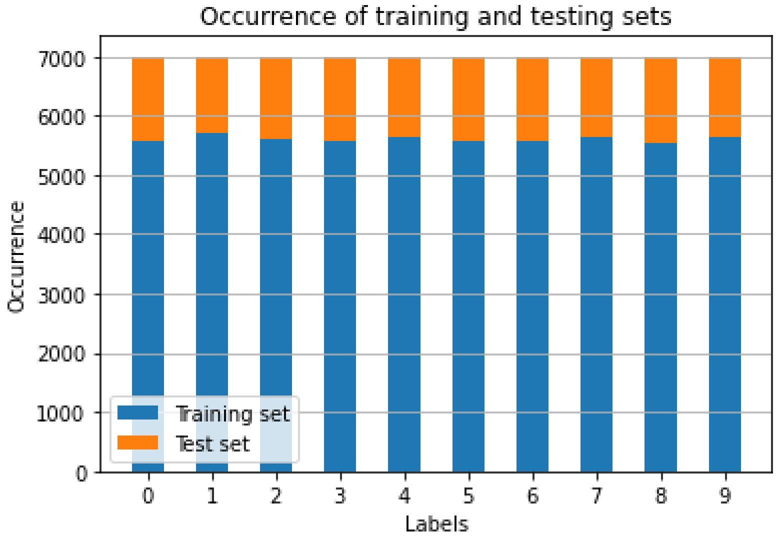
> Create you own CNN model performing better performance than the proposed one while avoiding over-fitting and huge complexity network

> Test the different networks on [MNIST]() and [Fashion-MNIST]()

> Summarize the performance of the different networks in a Table that includes : architecture Name, Number of trained parameters, used optimizer, CPU Time, GPU Time, and Accuracy/Error


```
fashionMnist = fetch_openml('Fashion-MNIST') #You can also use and test Fashion-MN
samples = 0
training_set = Dataset(fashionMnist, samples)
test_ratio = 0.2;
training_set.separate_train_test(test_ratio)
training_set.display_train_test()
```

```
100% (70000 of 70000) |##################| Elapsed Time: 0:01:07 ETA:  00:00:
Size of testing set : 14000 / 70000
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:135: MatplotlibD
```




```
CNN = Sequential()
CNN.add(Conv2D(6, kernel_size=(5, 5), activation=tf.keras.layers.LeakyReLU(), inpu
CNN.add(MaxPooling2D(pool_size=(2,2)))
CNN.add(Conv2D(16, (5, 5), activation=tf.keras.layers.LeakyReLU()))
CNN.add(MaxPooling2D(pool_size=(2,2)))
CNN.add(Conv2D(16, (3, 3), activation=tf.keras.layers.LeakyReLU()))
CNN.add(Flatten())
# add 3 hiden layers
# TO DO
```

```
# TO DO
CNN.add(Dense(units=200, activation=tf.keras.layers.LeakyReLU()))
CNN.add(Dense(units=84, activation=tf.keras.layers.LeakyReLU()))
CNN.add(Dense(units=10, activation='softmax'))

CNN.summary()
CNN.compile(loss=keras.losses.categorical_crossentropy, optimizer=keras.optimizers

t0=time.time()

h = CNN.fit(training_set.X_train.reshape(training_set.X_train.shape[0], 28, 28,1),

tn = time.time()-t0;
print('total computing time: '+str(tn))

score = CNN.evaluate(training_set.X_test.reshape(training_set.X_test.shape[0], 28,
err = 100*(1-np.array(score))
print('Test loss: %4.3f '%score[0])
print('Test err:  %4.2f %%'% err[1])
```

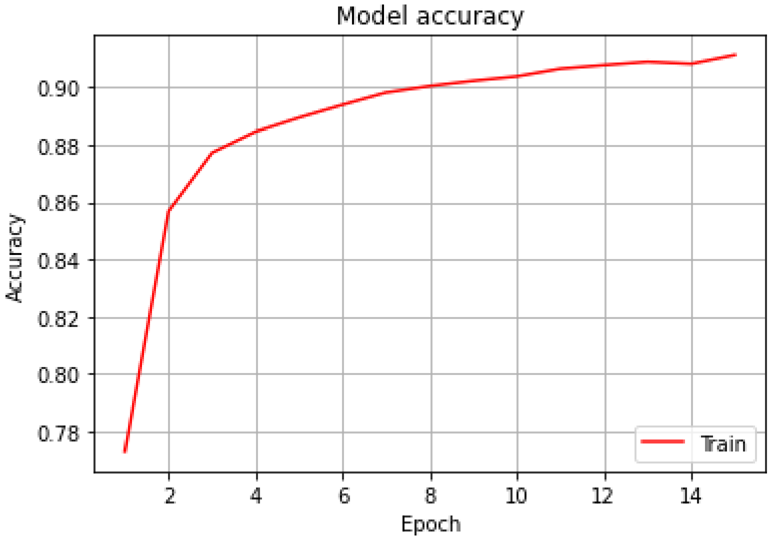
```
Model: "sequential_23"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_40 (Conv2D)           (None, 24, 24, 6)         156
_________________________________________________________________
max_pooling2d_33 (MaxPooling (None, 12, 12, 6)         0
_________________________________________________________________
conv2d_41 (Conv2D)           (None, 8, 8, 16)          2416
_________________________________________________________________
max_pooling2d_34 (MaxPooling (None, 4, 4, 16)          0
_________________________________________________________________
conv2d_42 (Conv2D)           (None, 2, 2, 16)          2320
_________________________________________________________________
flatten_16 (Flatten)         (None, 64)                0
_________________________________________________________________
dense_55 (Dense)             (None, 200)               13000
_________________________________________________________________
dense_56 (Dense)             (None, 84)                16884
_________________________________________________________________
dense_57 (Dense)             (None, 10)                850
=================================================================
Total params: 35,626
Trainable params: 35,626
Non-trainable params: 0
_________________________________________________________________
total computing time: 68.18204808235168
438/438 [==============================] - 1s 2ms/step - loss: 0.3167 - accur
Test loss: 0.317
Test err:  10.58 %
```

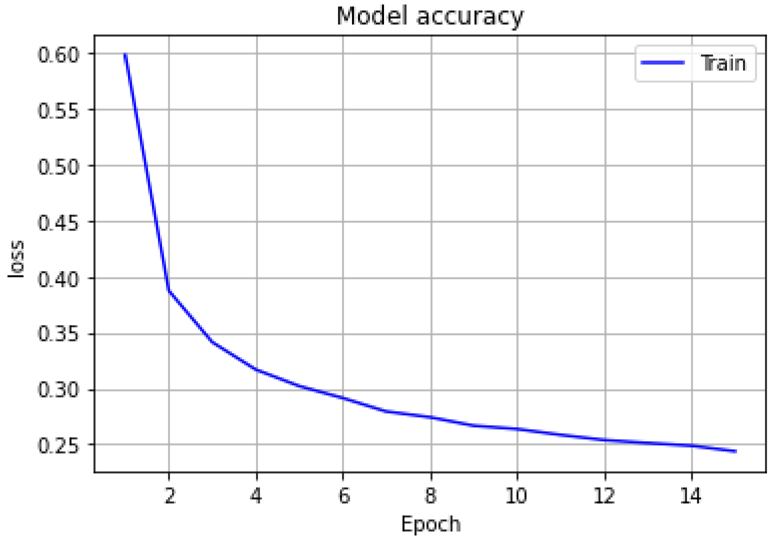
```
print('Test err:  %4.2f %%  time: %4.2f min'% (err[1],tn/60))

plt.plot(list(range(1,len(h.history['accuracy'])+1)),h.history['accuracy'],'r')
plt.title('Model accuracy')
plt.ylabel('Accuracy')
```

```
plt.xlabel('Epoch')
plt.legend(('Train', 'Validation', 'Test'), loc='lower right')
plt.grid()
plt.show()
plt.plot(list(range(1,len(h.history['loss'])+1)),h.history['loss'],'b')
plt.title('Model accuracy')
plt.ylabel('loss')
plt.xlabel('Epoch')
plt.legend(('Train', 'Validation', 'Test'), loc='upper right')
plt.grid()
plt.show()
```

```
Test err:  10.58 %  time: 1.14 min
```






```
CNN = Sequential()
CNN.add(Conv2D(6, kernel_size=(5, 5), activation=tf.keras.layers.ELU(),
               input_shape=(28,28,1)))
CNN.add(MaxPooling2D(pool_size=(2, 2)))
CNN.add(Conv2D(16, (5, 5), activation=tf.keras.layers.ELU()))
CNN.add(MaxPooling2D(pool_size=(2, 2)))
CNN.add(Flatten())
# add 4 hiden layers
# TO DO
CNN.add(Dense(units=300, activation=tf.keras.layers.ELU()))
CNN.add(Dense(units=200, activation=tf.keras.layers.ELU()))
CNN.add(Dense(units=84, activation=tf.keras.layers.ELU()))
```

```
CNN.add(Dense(units=84, activation=tf.keras.layers.ELU()))
CNN.add(Dense(units=10, activation='softmax'))

CNN.summary()
CNN.compile(loss=keras.losses.categorical_crossentropy, optimizer=keras.optimizers



t0=time.time()

h = CNN.fit(training_set.X_train.reshape(training_set.X_train.shape[0], 28, 28,1),

tn = time.time()-t0;
print('total computing time: '+str(tn))

score = CNN.evaluate(training_set.X_test.reshape(training_set.X_test.shape[0], 28,
err = 100*(1-np.array(score))
print('Test loss: %4.3f '%score[0])
print('Test err:  %4.2f %%'% err[1])
```

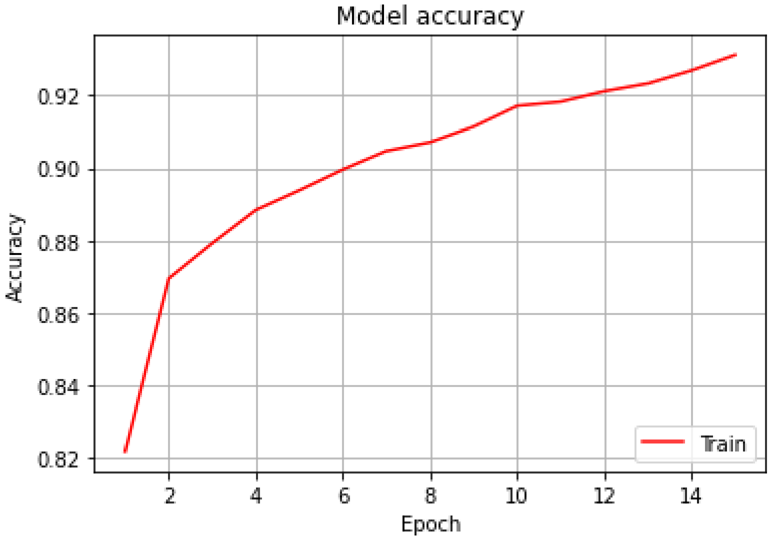
```
Model: "sequential_22"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_38 (Conv2D)           (None, 24, 24, 6)         156
_________________________________________________________________
max_pooling2d_31 (MaxPooling (None, 12, 12, 6)         0
_________________________________________________________________
conv2d_39 (Conv2D)           (None, 8, 8, 16)          2416
_________________________________________________________________
max_pooling2d_32 (MaxPooling (None, 4, 4, 16)          0
_________________________________________________________________
flatten_15 (Flatten)         (None, 256)               0
_________________________________________________________________
dense_51 (Dense)             (None, 300)               77100
_________________________________________________________________
dense_52 (Dense)             (None, 200)               60200
_________________________________________________________________
dense_53 (Dense)             (None, 84)                16884
_________________________________________________________________
dense_54 (Dense)             (None, 10)                850
=================================================================
Total params: 157,606
Trainable params: 157,606
Non-trainable params: 0
_________________________________________________________________
total computing time: 66.00361824035645
438/438 [==============================] - 1s 2ms/step - loss: 0.4031 - accur
Test loss: 0.403
Test err:  11.01 %
```

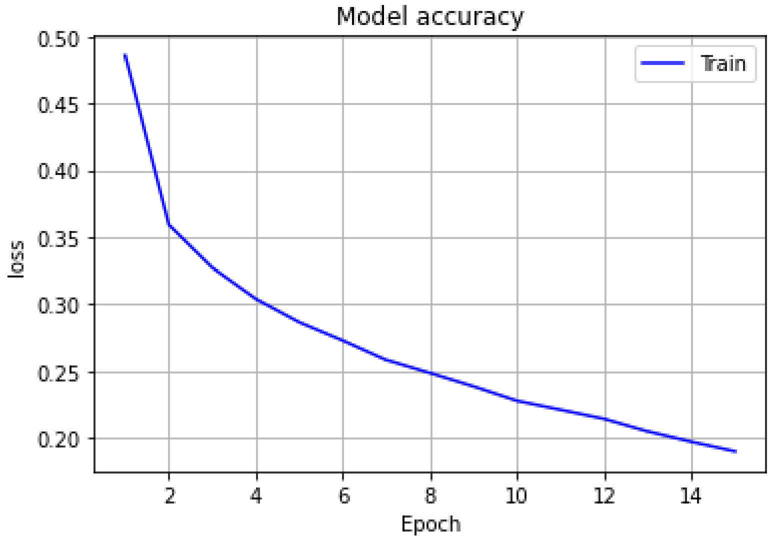
```
print('Test err:  %4.2f %%  time: %4.2f min'% (err[1],tn/60))

plt.plot(list(range(1,len(h.history['accuracy'])+1)),h.history['accuracy'],'r')
plt.title('Model accuracy')
plt.ylabel('Accuracy')
```

```
plt.xlabel('Epoch')
plt.legend(('Train', 'Validation', 'Test'), loc='lower right')
plt.grid()
plt.show()
plt.plot(list(range(1,len(h.history['loss'])+1)),h.history['loss'],'b')
plt.title('Model accuracy')
plt.ylabel('loss')
plt.xlabel('Epoch')
plt.legend(('Train', 'Validation', 'Test'), loc='upper right')
plt.grid()
plt.show()
```

```
Test err:  11.01 %  time: 1.10 min
```





0s conclusão: 23:20