Machine Learning Lab 4EII - IA course

1- **Introduction**

This lab aim at using simple **machine learning** classifiers via sklearn Python module for a classification problem of recognizing handwritten digits. We consider ten digits 0 to 9 from MNIST dataset, with using some machine learning algorithms, i.e. **Decision Trees**, **Random Forest** and **svm** used as **classifiers**.

In this lab you will learn to:

- Use the sklearn machine learning library
- Use different machine learning algorithms to classify 10 digits from MNIST dataset
- Study the performance and hyper-parameters of these classifiers
- Display graph results using the matplotlib module and confusion matrix

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 Fashion-MNIST dataset
```

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()

  class Dataset:
    def __init__(self, data, size=0):
      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.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):
        for i in range(self.length):
            self.digits.append(Digit(self.data[i], self.targets[i]))

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

        self.X_train, self.X_test, self.y_train, self.y_test = train_test_split(self.da
        # data normalization
        self.X_train = self.X_train/255;
        self.X_test  = self.X_test/255;
        print('Size of training set : ' + str(len(self.y_train)) + ' / ' + str(len(sel
        print('Size of testing set : ' + str(len(self.y_test))+ ' / ' + str(len(self.da

      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, botto

        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

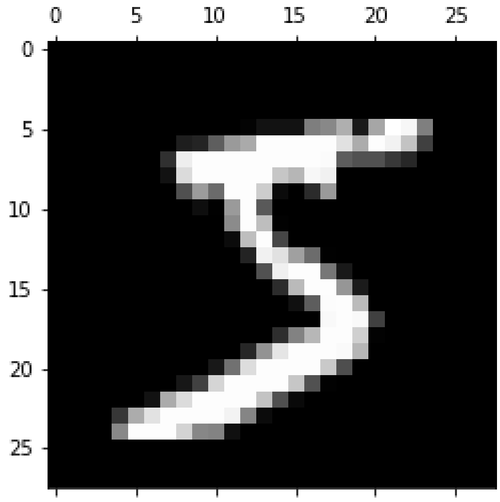
samples is the number of considered samples (sub-set) over 700000 of MNIST dataset, it enables faster training and testing

```
samples = 20000;
#TO BE COMPLETED
training_set = Dataset(mnist, samples)
```

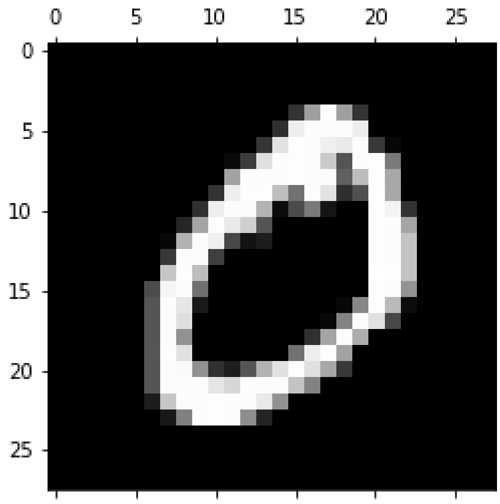
2. Display some digist with corresponding features

```
samples_to_diplay = 10#TO BE COMPLETED
for i in range(samples_to_diplay):
  training_set.digits[i].print()
```

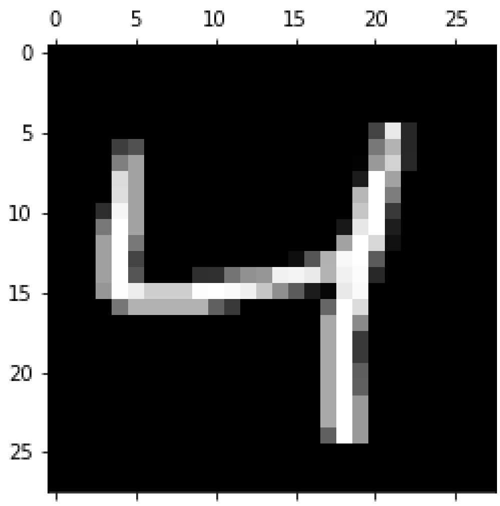
```
Digit target: 5
Digit target size: 28x28| mean : 35.11| var : 6343.94| std :79.65| entropy :1
Digit image:
<Figure size 432x288 with 0 Axes>
```




```
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>
```

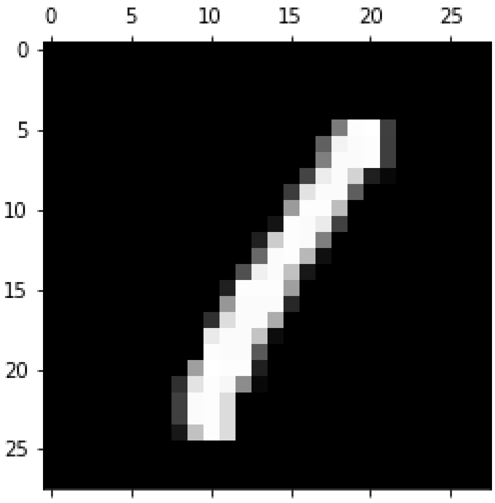



```
Digit target: 4
Digit target size: 28x28| mean : 24.8| var : 4300.7| std :65.58| entropy :1.4
Digit image:
<Figure size 432x288 with 0 Axes>
```

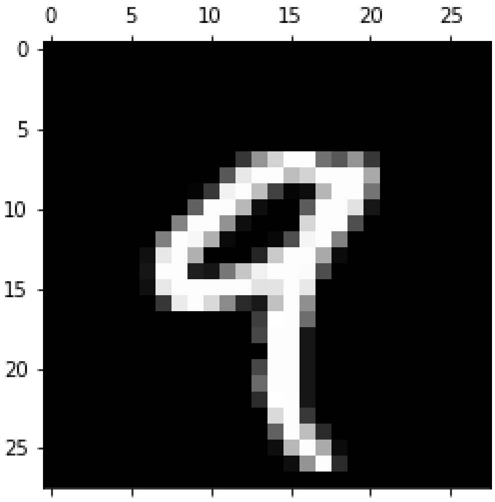



```
Digit target: 1
Digit target size: 28x28| mean : 21.86| var : 4366.42| std :66.08| entropy :1
Digit image:
<Figure size 432x288 with 0 Axes>
```

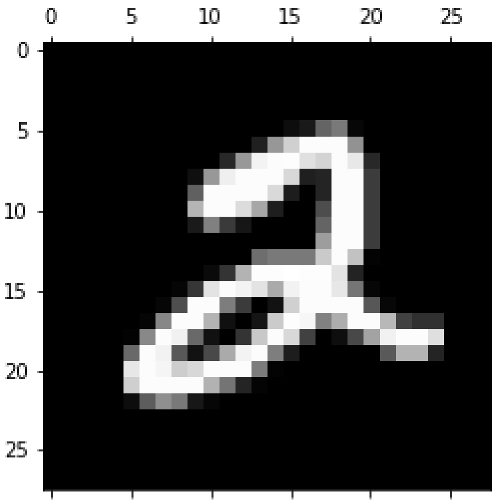
<Figure size 432x288 with 0 Axes>



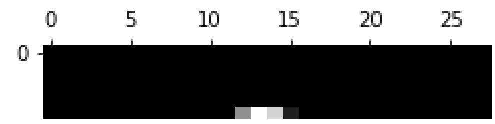

```
Digit target: 9
Digit target size: 28x28| mean : 29.61| var : 5531.09| std :74.37| entropy :1
Digit image:
```
<Figure size 432x288 with 0 Axes>

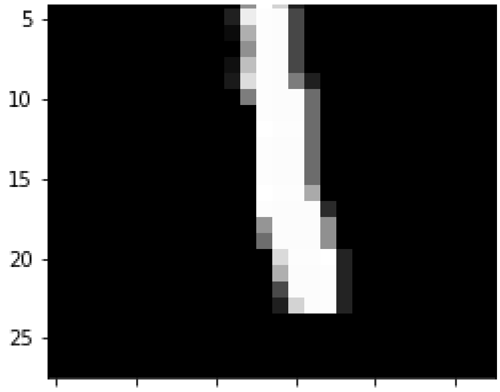



```
Digit target: 2
Digit target size: 28x28| mean : 37.76| var : 6577.97| std :81.1| entropy :2.
Digit image:
```
<Figure size 432x288 with 0 Axes>

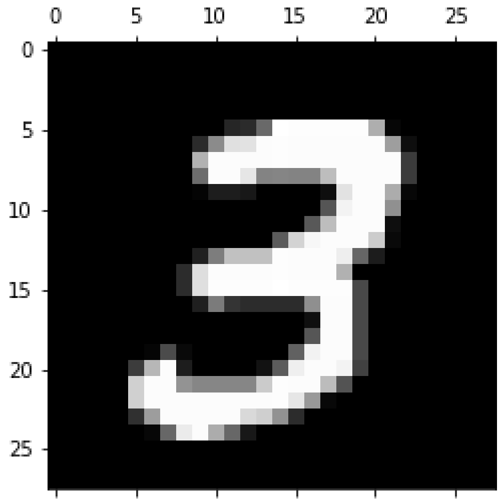



```
Digit target: 1
Digit target size: 28x28| mean : 22.51| var : 4602.49| std :67.84| entropy :0
Digit image:
```
<Figure size 432x288 with 0 Axes>






```
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>
```




```
Digit target: 1
Digit target size: 28x28| mean : 13.87| var : 2768.36| std :52.62| entropy :0
```

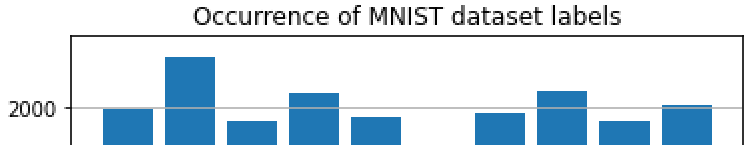
3. Display digits repartitions with *printInfo* function of *Dataset* class

- Is the dataset well balanced ?

> *As we can see, there is a smooth discrepancy related to the label '1', but nothing relevant enough to invalid the dataset.*


```
training_set.printInfo()
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:70: MatplotlibDe
```



4 - **Dataset preparation**

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

0 1 2 3 4 5 6 7 8 9

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;
#TO BE COMPLETED
training_set.separate_train_test(test_ratio)
```

```
Size of training set : 16000 / 20000
Size of testing set : 4000 / 20000
```

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

```
#TO BE COMPLETED
training_set.display_train_test()
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:111: MatplotlibD
```

> *Since we have 20000 samples for label '0' and the test ratio is 25%, we should have 4000 test samples selected, which can be noticed through the graph above. The proportion is maintained for the rest of the dataset as well.*

5 - **Classifier Training and testing**

5.a - Training and testing the Decision Tree (DT) model

> In this section, you will have to initialize a Decision Tree classifier and train it with the generated training set.

> Decision Trees (DTs) are a non-parametric supervised learning method used for classification and regression. The goal is to create a model that predicts the value of a target variable by learning simple decision rules inferred from the data features.

> *Useful functions ⇒ DecisionTreeClassifier and DecisionTreeClassifier.fit()*

> For more details, you can refer to the sklearn documentation [Decision Tree]

```
from sklearn.tree import DecisionTreeClassifier
depth = 5;
clf = DecisionTreeClassifier(random_state=0, max_depth=depth)

clf.fit(training_set.X_train, training_set.y_train)
print ("Accuracy on training set " + str(round(clf.score(training_set.X_train, tra
print ("Accuracy on testing set " + str(round(clf.score(training_set.X_test, train
```

```
Accuracy on training set 0.69
Accuracy on testing set 0.68
```

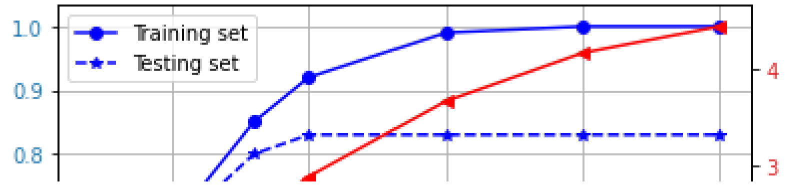
5.b - Hyper-parameters optimisation of the Decision Tree (DT) model

> In this section you will train the DT model with different depths and select the one that enables the best performance in terms of trade-off between accuracy on the testing test and complexity while avoiding over-fitting

```
from sklearn.tree import DecisionTreeClassifier

depths = [2,5,8,10,15,20, 25]
score_training = [0.0 for i in range(len(depths))]
```

```
    score_training = [0.0 for i in range(len(depths))]
    score_testing  = [0.0 for i in range(len(depths))]
    time_train  = [0.0 for i in range(len(depths))]
    time_test  = [0.0 for i in range(len(depths))]
    idx=0;
    bar = progressbar.ProgressBar(maxval=len(depths)).start()

    for d in depths:
      clf = DecisionTreeClassifier(random_state=0, max_depth=d)
      t = time.process_time()
      #TO BE COMPLETED perform training
      clf.fit(training_set.X_train, training_set.y_train)
      time_train[idx] = time.process_time() - t
      score_training[idx] = round(clf.score(training_set.X_train, training_set.y_train
      score_testing[idx] = round(clf.score(training_set.X_test, training_set.y_test),2
      time_test[idx] = time.process_time() - t - time_train[idx]
      idx +=1;
      bar.update(idx)


    plt.figure(figsize=(8,4))
    fig, ax1 = plt.subplots()

    color = 'tab:blue'
    ax1.set_xlabel('Depth', fontsize=15,)
    ax1.set_ylabel('Accuracy', color=color)
    ax1.plot(depths, score_training, '-bo', label='Training set')
    ax1.plot(depths, score_testing, '--b*', label='Testing set')
    ax1.tick_params(axis='y', labelcolor=color)
    plt.grid()
    plt.legend(loc='upper left')
    ax2 = ax1.twinx()  # instantiate a second axes that shares the same x-axis
    color = 'tab:red'

    ax2.set_ylabel('time (s)', color=color)
    ax2.plot(depths, time_train, '-r<', label='Training set')  # we already handled the
    ax2.plot(depths, time_test, '--r>', label='Testing set')  # we already handled the
    ax2.tick_params(axis='y', labelcolor=color)
    fig.tight_layout()  # otherwise the right y-label is slightly clipped


    plt.show()
    plt.savefig('perf.png')
```

```
100% (7 of 7) |##########################| Elapsed Time: 0:00:20 ETA:  00:00:
<Figure size 576x288 with 0 Axes>
```

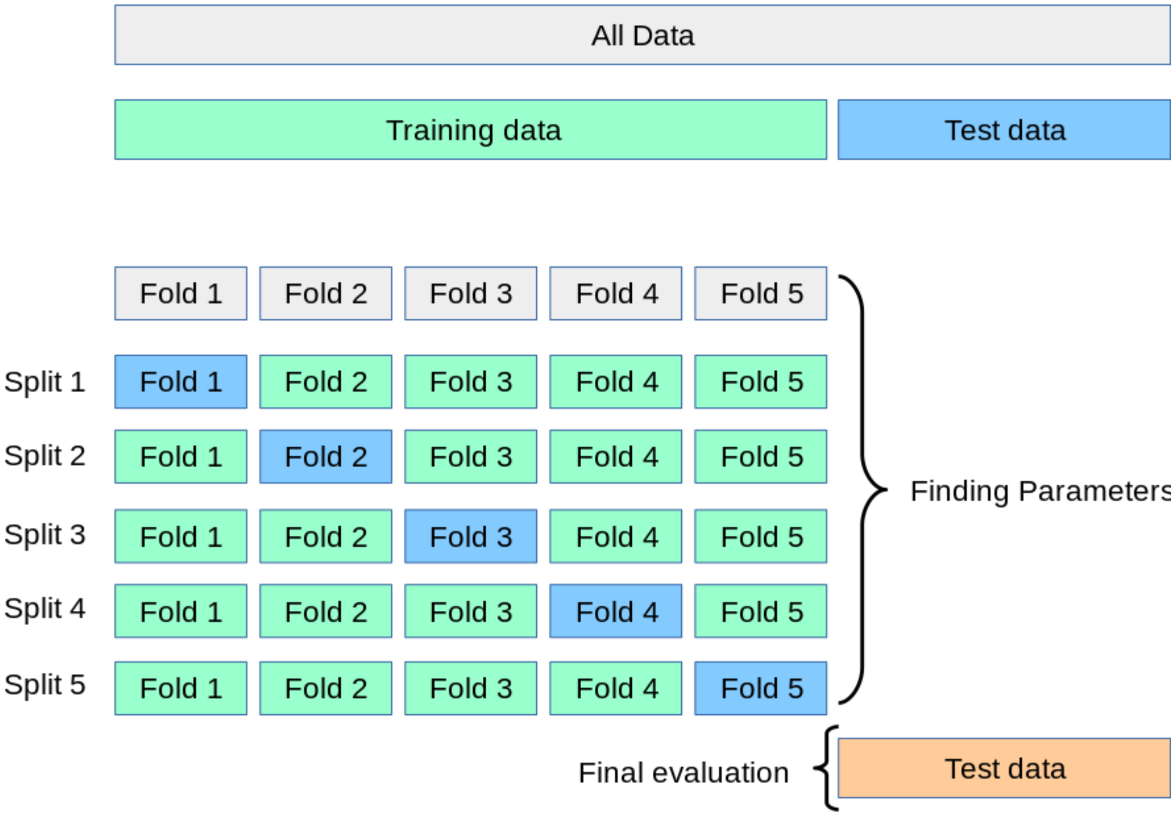


5.c - Cross-validation of the best performing solution

In this section you will test the best performing DT configuration in cross-validation approach.

> The cross-validation will split the training set in k non-overlapping sub-sets. Then the model is trained on (k-1) sub-sets and tested on the remaining sub-set. This process is performed k times on k different testing sub-sets and take the average accuracy with confidence interval (CI).

> Illustration of the cross validation repartition.



> Is the performance on testing set accurate and valid ?

```
from sklearn.model_selection import cross_val_score
best_depth = 15#TO BE COMPLETED
k = 3#TO BE COMPLETED Number of sub-sets < 4
clf = DecisionTreeClassifier(random_state=0, max_depth=best_depth)
clf.fit(training_set.X_train, training_set.y_train)
print ('Accuracy on training set= ' +  str(round(clf.score(training_set.X_train, t
scores = cross_val_score(clf, training_set.X_train, training_set.y_train, cv=k, sc
print (scores)
print("Accuracy: %0.2f (CI : +/- %0.2f)" % (scores.mean(), scores.std() * 2))
```

```
print ('Accuracy on test set= ' +  str(round(clf.score(training_set.X_test, trainin
```

```
Accuracy on training set= 0.99
[0.82133483 0.79823739 0.81511344]
Accuracy: 0.81 (CI : +/- 0.02)
Accuracy on test set= 0.83
```

> *Considering the simplicity of the classifier, we can say that a score of 0.83% is accurate. Although, we expect higher accuracy on a reliable classifier.*

5.d - Display the confusion matrix

By definition a confusion matrix C is such that Cij is equal to the number of observations known to be in group i and predicted to be in group j.

1. *plot_confusion_matrix* function enables to display a confusion matrix *cm*

```
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:
```

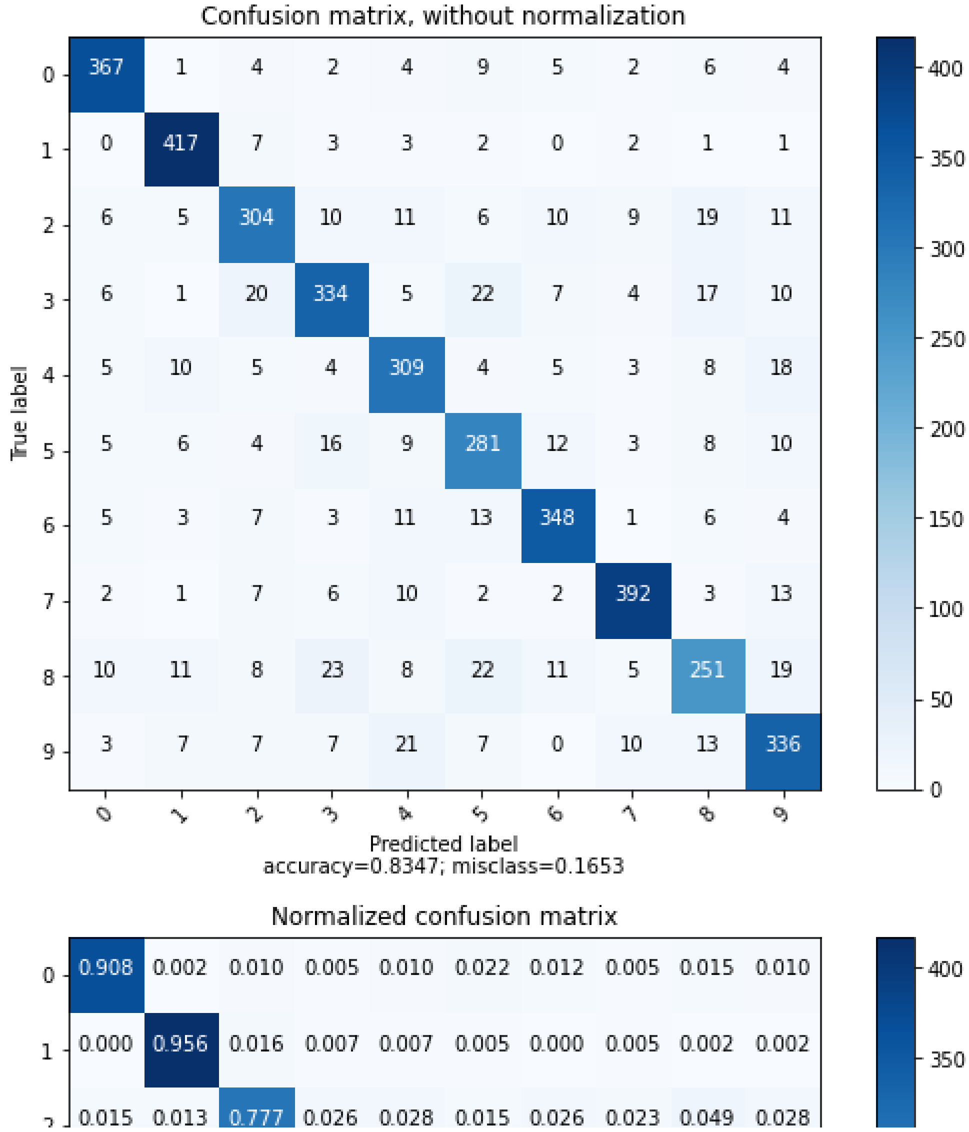
```
    plt.text(j, i, "{:,}".format(cm[i, j]),
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")
  plt.tight_layout()
  plt.ylabel('True label')
  plt.xlabel('Predicted label\naccuracy={:0.4f}; misclass={:0.4f}'.format(accuracy
  plt.show()
```

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

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

```
# Plot non-normalized confusion matrix
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)]
y_hat = clf.predict(training_set.X_test);

#TO BE COMPLETED use confusion matrix function to create conf_mx
conf_mx = confusion_matrix(training_set.y_test, y_hat)

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)
```

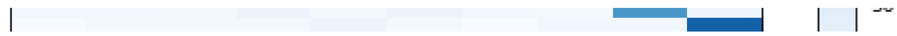
```
<Figure size 720x432 with 0 Axes>
```



> *The most difficult digit to label for this classifier was '8', since we have the lowest percentage (68.2%) of correct classifications. In contradiction, the digit '1' was the easiest to classify.*

6 - **Testing other ML models**

This section you will test the performance (section 5) of other ML classifiers such as random forest and SVM.



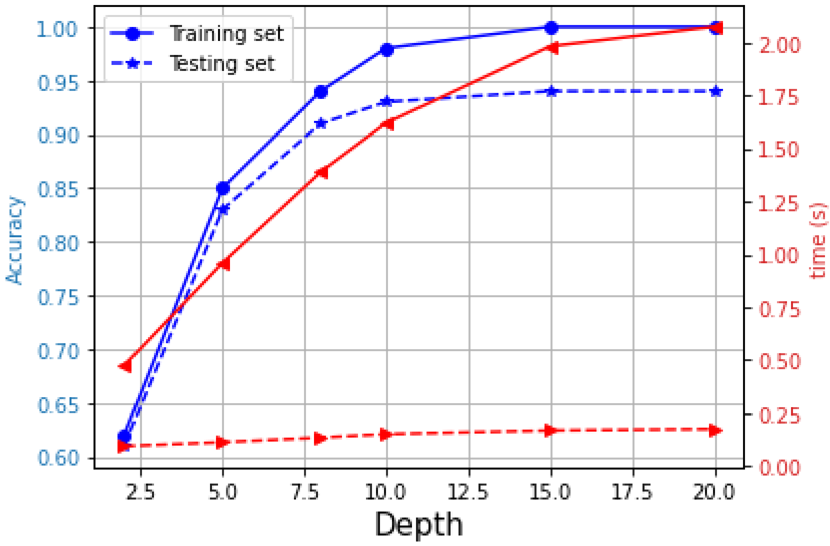
6.a Random Forest classifier

A random forest is a meta estimator that fits a number of decision tree classifiers on various sub-samples of the dataset and uses averaging to improve the predictive accuracy and control over-fitting.
Initialize the model with *RandomForestClassifier(n_estimators=50,max_depth=7, random_state=0)*
The hyper-parameters are the number of trees (n_estimators) and maximum depth (max_depth).

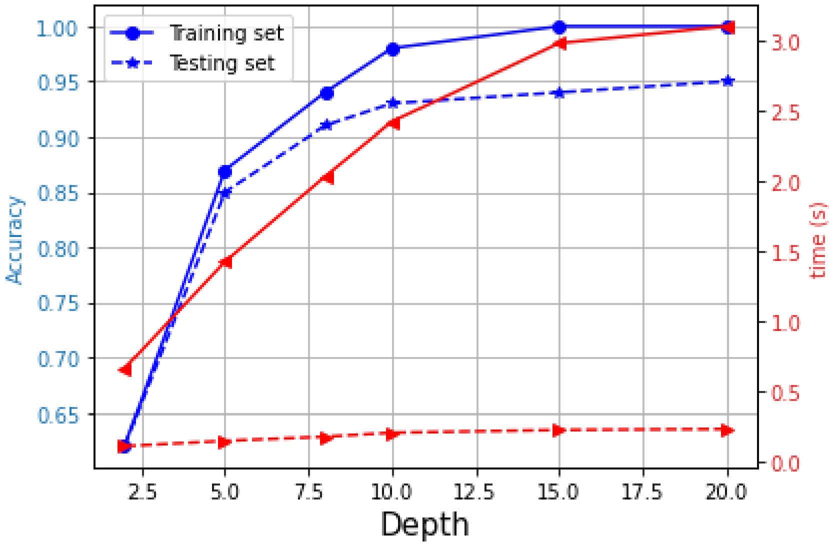
For more details on Random Forest classifier in sklearn, you can refer to [Random Forest classifier]

```
from sklearn.ensemble import RandomForestClassifier

depths = [2,5,8,10,15,20]
trees = [1, 10, 20, 30, 40]


for s in trees:
  idx = 0;
  score_training = [0.0 for i in range(len(depths))]
  score_testing  = [0.0 for i in range(len(depths))]
  time_train  = [0.0 for i in range(len(depths))]
  time_test  = [0.0 for i in range(len(depths))]
  print ("Number of trees of : " + str(s))
  bar = progressbar.ProgressBar(maxval=len(depths)).start()
  for d in depths:
    #TO BE COMPLETED initialize the RF model
    clf = RandomForestClassifier(n_estimators=s, max_depth=d)
    t = time.process_time()
    #TO BE COMPLETED run the training
    clf.fit(training_set.X_train, training_set.y_train)
    time_train[idx] = time.process_time() - t
    score_training[idx] = round(clf.score(training_set.X_train, training_set.y_tra
    time_test[idx] = time.process_time() - t - time_train[idx]
    score_testing[idx] = round(clf.score(training_set.X_test, training_set.y_test)
    idx +=1;
    bar.update(idx)


  plt.figure(figsize=(8,4))
  fig, ax1 = plt.subplots()

  color = 'tab:blue'
  ax1.set_xlabel('Depth', fontsize=15,)
  ax1.set_ylabel('Accuracy', color=color)
  ax1.plot(depths, score_training, '-bo', label='Training set')
  ax1.plot(depths, score_testing, '--b*', label='Testing set')
  ax1.tick_params(axis='y', labelcolor=color)
  plt.legend(loc='upper left')
  plt.grid()
  ax2 = ax1.twinx()  # instantiate a second axes that shares the same x-axis
  color = 'tab:red'

  ax2.set_ylabel('time (s)', color=color)
  ax2.plot(depths, time_train, '-r<', label='Training set')  # we already handled
  ax2.plot(depths, time_test, '--r>', label='Testing set')  # we already handled t
  ax2.tick_params(axis='y', labelcolor=color)
  fig.tight_layout()  # otherwise the right y-label is slightly clipped


  plt.show()
```

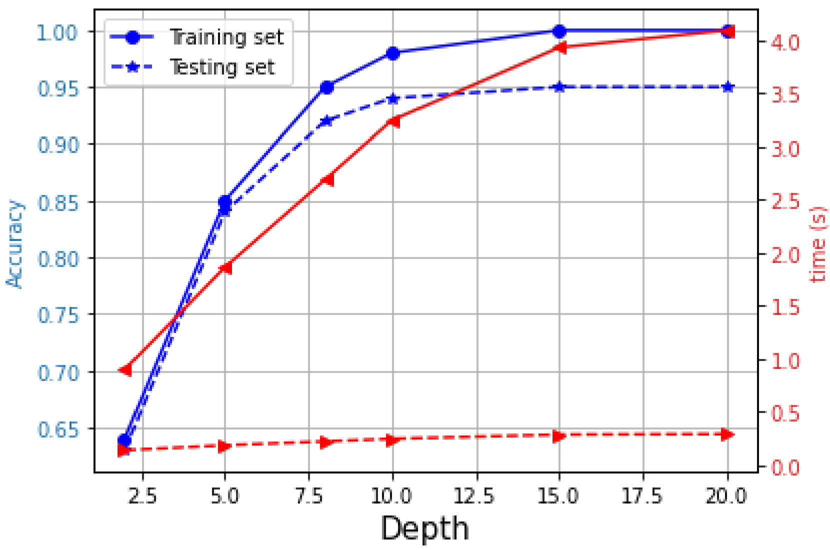
```
N/A% (0 of 6) |                          | Elapsed Time: 0:00:00 ETA:  --:-
100% (6 of 6) |##########################| Elapsed Time: 0:00:09 ETA:  00:0
<Figure size 576x288 with 0 Axes>
```




```
N/A% (0 of 6) |                          | Elapsed Time: 0:00:00 ETA:  --:-
100% (6 of 6) |##########################| Elapsed Time: 0:00:14 ETA:  00:0
<Figure size 576x288 with 0 Axes>
```




```
N/A% (0 of 6) |                          | Elapsed Time: 0:00:00 ETA:  --:-
100% (6 of 6) |##########################| Elapsed Time: 0:00:18 ETA:  00:0
<Figure size 576x288 with 0 Axes>
```



6.b SVM classifier with diffrent kernels

Initialize the SVM model by *svm.SVC(kernel='')* and test different kernels :

1. linear
2. poly (Polynomial) hyper-parameters: Optional degree=3-8 / gamma='scale'/auto
3. rbf (Radial Basis Function / Gaussian): Optional gamma='scale'/auto
4. sigmoid: Optional gamma='scale'/auto

For more details on svm classifier in sklearn, you can refer to [SVC classifier].

Compare your results with the performance reported on [MNIST] web site.

```
from sklearn import svm
kernels = ['linear', 'poly', 'rbf', 'sigmoid']
bar = progressbar.ProgressBar(maxval=len(kernels)).start()
idx = 0;
for ker in kernels:
  print('\nKernel: ' + ker)
```

```
  #TO BE COMPLETED initialize the model
  clf = svm.SVC(kernel=ker)
  t = time.process_time()
  #TO BE COMPLETED run the training
  clf.fit(training_set.X_train, training_set.y_train)
  print ( 'processing time : ' + str (round((time.process_time() - t),2)))
  print ('Accuracy on training set= ' +  str(round(clf.score(training_set.X_train,
  print ('Accuracy on testing set= ' +  str(round(clf.score(training_set.X_test, t
  idx +=1;
  bar.update(idx)
```

```
N/A% (0 of 4) |                          | Elapsed Time: 0:00:00 ETA:  --:--:
Kernel: linear
processing time : 47.48
Accuracy on training set= 0.99
 25% (1 of 4) |######                    | Elapsed Time: 0:02:23 ETA:   0:07:

Kernel: poly
processing time : 78.92
Accuracy on training set= 0.99
 50% (2 of 4) |#############             | Elapsed Time: 0:05:27 ETA:   0:06:

Kernel: rbf
processing time : 75.61
Accuracy on training set= 0.99
 75% (3 of 4) |###################       | Elapsed Time: 0:09:01 ETA:   0:03:

Kernel: sigmoid
processing time : 84.64
Accuracy on training set= 0.8
100% (4 of 4) |##########################| Elapsed Time: 0:13:10 ETA:  00:00:
```

> *We obtained better perfomance comparing 0.04 with the errors of 0.68, 0.68 e 0.56 for Virtual SVM deg-9 poly results.*

7 - Test the performance of different classifiers with Fashion-MNIST dataset

> You can find [here]() the benchmark of different classifiers on Fashion-MNIST dataset

```
fashionMnist = fetch_openml('Fashion-MNIST') #You can also use and test Fashion-MN
```

```
samples = 15000
training_set = Dataset(fashionMnist, samples)
```

```
samples_to_diplay = 10#TO BE COMPLETED
for i in range(samples_to_diplay):
  training_set.digits[i].print()
```