TDT4173 – Assignment 4

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Theory

1)

The core idea of deep learning is…

2)

3)

Programming

```
# Extract data
knn_class <- read.csv("dataset/dataset/knn_classification.csv")
knn_reg <- read.csv("dataset/dataset/knn_regression.csv")
ada_train <- read.csv("dataset/dataset/adaboost_train.csv")
ada_test <- read.csv("dataset/dataset/adaboost_test.csv")
```

2.1)

We implement a k-NN algorithm from scratch. Then the program is reused in order to implement a k-NN regression and classification. The code can be seen below

```
# Euclidian distance function
eucDist <- function(all_points, point){

  res <- sweep(all_points, 2, point, "-")
  res <- res^2
  res <- apply(res, 1, sum)
  res <- sqrt(res)

  return(res)
}


# Find k nearest neighbours
findKnn <- function(all_points, point, distFunc, k, values){

  distances <- distFunc(all_points, point)

  ord <- order(distances)

  res <- list(distances = distances[1:k],
```

```r
               values = values[ord][1:k])

  return(res)

}


# Classification by voting
vote <- function(closest){

  t <- table(closest$values)

  or <- order(t, decreasing = TRUE)

  if(t[or[1]] == t[or[2]]){
    # return("You need to fix voting when two or more classes
           # are equally well represented")
    equal_votes <- t[which(t == t[or[1]])]

    for(i in 1:k){
      p <- which(names(equal_votes) == as.character(closest$values[i]))
      if(p){
        return(names(equal_votes)[p])
      }
    }
  }

  return(names(t)[or[1]])
}


knn <- function(k, data, point, type){

  all_points <- as.matrix(data[, -dim(data)[2]])
  values <- data[, dim(data)[2]]

  closest <- findKnn(all_points = all_points,
                     point = point,
                     k = k,
                     values = values,
                     distFunc = eucDist)

  if(type == "reg"){
    return(mean(closest$values))
  } else if(type == "class"){
    return(vote(closest))
  }

  return("This type is not accepted")
}
```

We now use the algorithms with $k = 10$ for the 124th example of the given data sets. As seen below, the algorithm predicts a value of 1.6 for the regression and 2 for the classification.

```r
knn(k = 10,
    data = knn_reg,
    point = as.vector(as.matrix((knn_reg[124, 1:3]))),
    type = "reg")
```

```
## [1] 1.6
```

```r
knn(k = 10,
    data = knn_class,
    point = as.vector(as.matrix((knn_class[124, 1:4]))),
    type = "class")
```

```
## [1] "2"
```

2.2)

We implement tha AdaBoost algorithm from scratch. The code can be seen in the print-out below. We use the `DecisionTreeClassifier` from `sklearn` with a miximum depth of 1 as our weak learner.

```python
# Returns classifier for some data
# using T iterations of adaBoost
def adaBoost(data, T):
    dim = data.shape

    x = data[0:dim[0], 2:(dim[1]-1)]
    y = data[0:dim[0], 1]
    classifiers = []
    all_as = []

    weight = np.ones(dim[0]) * (1. / dim[0])
    for i in range(T):

        clf = tree.DecisionTreeClassifier(max_depth = 1)
        clf = clf.fit(x, y, sample_weight = weight)
        pred = clf.predict(x)

        epsilon = sum((pred != y) * weight)
        a = (1. / 2) * np.log((1 - epsilon) / epsilon)

        nw = weight * np.e**(-a * y * pred)
        nw = nw / sum(nw)
        weight = nw

        classifiers.append(clf)
        all_as.append(a)

    return(list([classifiers, all_as]))

# Returns predictions from an
# adaBoost algorithm
def adaPred(points, classifier):

    n = len(classifier[0])
    s = np.zeros(points.shape[0])

    for i in range(n):
        s = s + classifier[0][i].predict(points) * classifier[1][i]

    return(np.sign(s))

# Misclassification error
def misClass(pred, y):
    return(sum(pred != y) / float(len(y)))
# Return an error vector for iteration 1 through max_iter
def testAdaBoost(max_iter, train_data, test_data):

    test_dim = test_data.shape
    x_test = test_data[0:test_dim[0], 2:(test_dim[1]-1)]
    y_test = test_data[0:test_dim[0], 1]
    errors = []

    for i in range(max_iter):
        classifier = adaBoost(train_data, i+1)
        pred = adaPred(x_test, classifier)
        errors.append(misClass(pred, y_test))

    return(errors)
```

Firstly, we load the data and modules needed,

```
# -*- coding: utf-8 -*-
import sys
import numpy as np
import os
import sklearn
import matplotlib.pyplot as plt
cwd = os.getcwd()
sys.path.insert(0, cwd)
import ex_code as ss
knn_class = np.genfromtxt("dataset/dataset/knn_classification.csv",
delimiter=",", skip_header=1)
knn_reg = np.genfromtxt("dataset/dataset/knn_regression.csv",
delimiter=",", skip_header=1)
ada_test = np.genfromtxt("dataset/dataset/adaboost_test.csv",
delimiter=",", skip_header=1)
ada_train = np.genfromtxt("dataset/dataset/adaboost_train.csv",
delimiter=",", skip_header=1)
```

We want to test the AdaBoost algorithm for different number of iterations. Since the true target values are known we can calculate the misclassification error for AdaBoost algorithms with 1 to 15 iterations. The error rates are printed below.

```
err = ss.testAdaBoost(15, ada_train, ada_test)
for e in err:
  print("%.2f" % e)
```

```
## 0.46
## 0.46
## 0.43
## 0.43
## 0.39
## 0.39
## 0.37
## 0.37
## 0.35
## 0.35
## 0.36
## 0.33
## 0.38
## 0.32
## 0.35
```

We see that the error rate steadily declines for one to 10 iterations of the algorithm. After this, the error rate starts oscillating. This might be an indicator of overfitting. A safe value for the number of iterations with this data seems to be around 10. After this we cannot trust the algorithm any more, as the error might be much larger. It could als be smaller, but it is hard to know.

2.3)

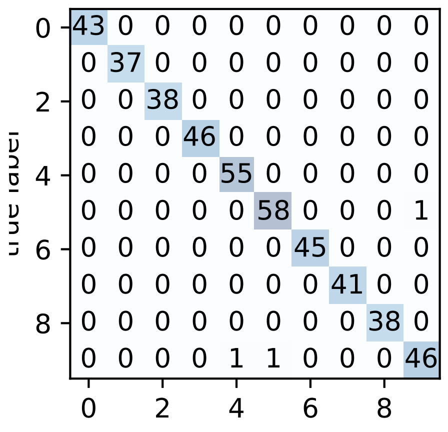
The code used for this task can be found below.

```python
# Loads data for task 2.3)
def getData():
    from sklearn.datasets import load_digits
    from sklearn.model_selection import train_test_split as TTS
    digits = load_digits()

    X_train, X_test, y_train, y_test = TTS(digits.data, digits.target, random_state=42)

    return(X_train, X_test, y_train, y_test)
X_train, X_test, y_train, y_test = ss.getData()
from sklearn.neighbors import KNeighborsClassifier as KNN
neigh = KNN()
neigh.fit(X_train, y_train)
pred_neigh = neigh.predict(X_test)
from sklearn import svm
clf = svm.SVC()
clf.fit(X_train, y_train)
pred_svm = clf.predict(X_test)
from sklearn.ensemble import RandomForestClassifier as RFC
forest = RFC()
forest.fit(X_train, y_train)
pred_forest = forest.predict(X_test)
```

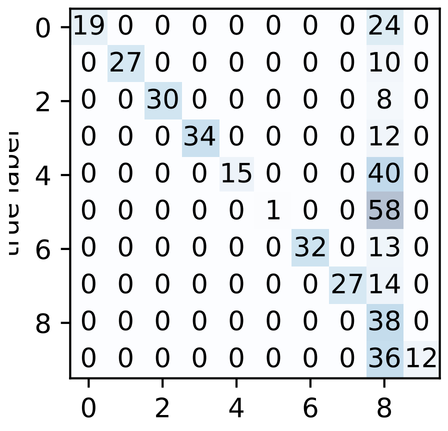
We now want to test the different predictors. To do this we create and plot the confusion matrix for each prediciton. These can be seen below. The true label is found along the y-axis ,and the predicted label is found along the x-axis.

```python
from sklearn.metrics import confusion_matrix
from mlxtend.plotting import plot_confusion_matrix
cnf_neigh = confusion_matrix(y_test, pred_neigh)
cnf_svm = confusion_matrix(y_test, pred_svm)
cnf_forest = confusion_matrix(y_test, pred_forest)
```

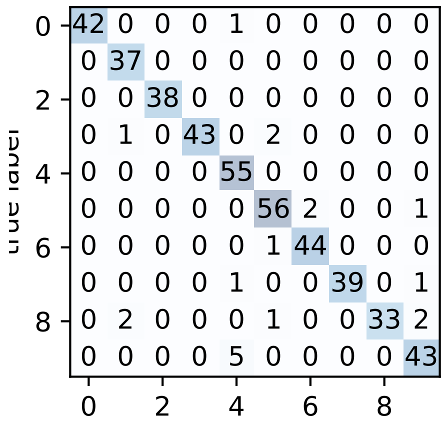
```
fig_neigh, ax = plot_confusion_matrix(conf_mat = cnf_neigh)
plt.show()
```



```
fig_svm, ax = plot_confusion_matrix(conf_mat = cnf_svm)
plt.show()
```



```
fig_forest, ax = plot_confusion_matrix(conf_mat = cnf_forest)
plt.show()
```



We can see that both the kNN and random forest implementationw worked quite well. The kNN had a lot less errors than the random forest, though. We see that the SVM algorithm faultily classifies extremely many of the labels as 8, thus making it perform very poorly. There was not any similar patterns for the other algorithms. Apart from the predictions of the label 8, all other predictions from the SVM method are correct, though. This will of course change when we change the parameters in the three methods. It is very hard to compare the methods with unlimited possible parameter values, though. This is the reason why we useed the "standard" parameters defined in `sklearn` for all the methods.