TDT4173 – Assignment 4

Silius Mortensønn Vandeskog (siliusmv)

12 april 2018

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 124^{th} 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` *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.