Coursework 2 - ECMM445 Learning from Data

Candidate number: 087074

Task 1: KNN

In [1]:
```
# Import the appropriate packages into Python

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import math
import random
import sklearn

# Task 1
from sklearn import preprocessing
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import KFold
from sklearn.metrics import accuracy_score
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split #

# Task 2
from sklearn.tree import DecisionTreeClassifier
from sklearn.neural_network import MLPClassifier
import warnings # Because a warning occurs for the neural network - "c
warnings.simplefilter(action='ignore', category=Warning)
```

In [2]:
```
# Load the diabetes database, break it down into source and target var

task1_diabetes = pd.read_csv("task1_diabetes.txt")
source = task1_diabetes.iloc[:,:-1]
normalised_source = source.copy() # Normalise the source variables usi
scaler = MinMaxScaler()
normalised_source[:] = scaler.fit_transform(normalised_source[:])

target = task1_diabetes.iloc[:,-1:]
y_train = target['class'].to_list()

normalised_data = normalised_source.copy() # Create a normalised datas
normalised_data['class'] = target
```

In [3]:
```
# A function that calculates the Euclidean distance between two points
# of three random characteristics

def distance_cw2(x,y):
    m = 3 # As required, m = 3
    total = 0
    char_compared = [] # Ensure that the same characteristic isn't com
    for i in range(0,m):
        random_char = random.randint(0,(len(x)-1))
        while random_char in char_compared:
            random_char = random.randint(0,(len(x)-1))
        char_compared.append(random_char)
        total += (x[random_char]-y[random_char])**2
    Euclidean = math.sqrt(total)
    return(Euclidean)
```

In [4]:
```
# A function that, using the input of a distance metric and the number
# trains a K Nearest Neighbor using 10-fold validation. The ouput is t
# of the accuracy from the 10-fold validation.

def KNN(user_metric, k):
    acc_scores = []
    X = normalised_data.copy()
    kf = KFold(n_splits=10)
    for train_index, test_index in kf.split(X): # Iterate over each fo
        # Create appropriate train and test sets
        X_train, X_test = normalised_source.iloc[train_index], normali
        y_train, y_test = target.iloc[train_index], target.iloc[test_i
        y_train_copy = y_train['class'].to_list()
        y_test_copy = y_test['class'].to_list()

        # Apply the K Nearest Neighbor algorithm
        knn = KNeighborsClassifier(n_neighbors=k, metric=user_metric)
        knn.fit(X_train, y_train_copy)
        y_predict = knn.predict(X_test)
        ACC = accuracy_score(y_test_copy, y_predict)
        acc_scores.append(ACC) # Append the accuracy of that fold
    # Get the average accuracy and standard deviation
    mean_acc = np.mean(acc_scores)
    std_acc = np.std(acc_scores)
    return mean_acc, std_acc
```

In [5]:

```
# This creates a dataframe with the average mean ± standard deviation
# for k = 1,3,5,7

k_list = [1,3,5,7]
columns = ['Distance_cw2', 'Euclidean', 'Manhattan', 'Chebyshev']
dataframe_accuracy = pd.DataFrame(index=k_list, columns=columns)
dataframe_accuracy['k'] = k_list
dataframe_accuracy.set_index('k', inplace=True)
mean_accuracies_d = []
mean_accuracies_e = []
mean_accuracies_m = []
mean_accuracies_c = []

for k in k_list:
    random.seed(k) # Set random seed to ensure the reproducability of
    mean_acc_d, std_acc_d = KNN(distance_cw2, k)
    mean_acc_e, std_acc_e = KNN('euclidean', k) # Applying the KNN fun
    mean_acc_m, std_acc_m = KNN('manhattan', k)
    mean_acc_c, std_acc_c = KNN('chebyshev', k)

    mean_std_d = str(mean_acc_d.round(2)) + '±' + str(std_acc_d.round(
    mean_std_e = str(mean_acc_e.round(2)) + '±' + str(std_acc_e.round(
    mean_std_m = str(mean_acc_m.round(2)) + '±' + str(std_acc_m.round(
    mean_std_c = str(mean_acc_c.round(2)) + '±' + str(std_acc_c.round(
    mean_stds = [mean_std_d, mean_std_e, mean_std_m, mean_std_c]
    dataframe_accuracy.loc[k] = mean_stds

    # Store data in lists so a graph can be plotted
    mean_accuracies_d.append(mean_acc_d)
    mean_accuracies_e.append(mean_acc_e)
    mean_accuracies_m.append(mean_acc_m)
    mean_accuracies_c.append(mean_acc_c)

dataframe_accuracy
```

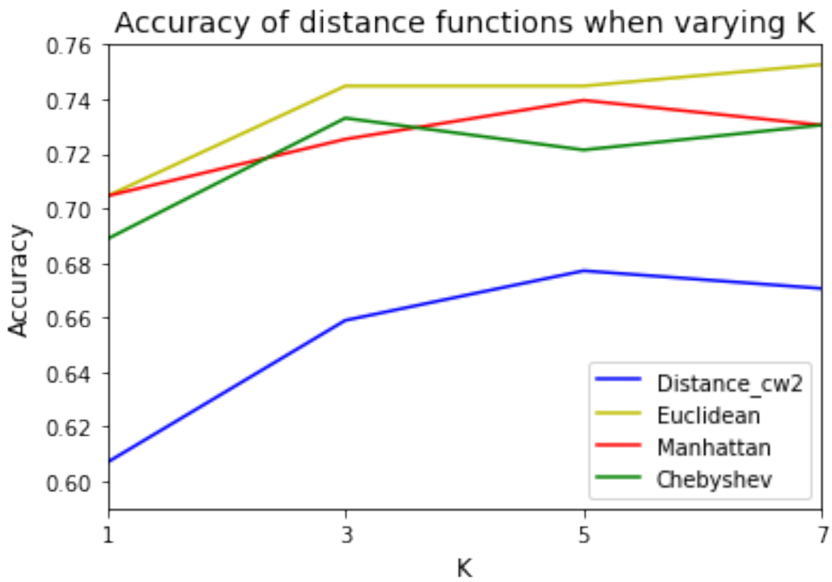
Out[5]:

k	Distance_cw2	Euclidean	Manhattan	Chebyshev
1	0.61±0.06	0.7±0.06	0.7±0.06	0.69±0.07
3	0.66±0.05	0.74±0.05	0.73±0.05	0.73±0.05
5	0.68±0.05	0.74±0.06	0.74±0.05	0.72±0.04
7	0.67±0.05	0.75±0.06	0.73±0.05	0.73±0.06

In [6]:
```
# Create a plot of the accuracy of each distance metric when varying t

# Create the graph with suitable axes and labels
plt.title("Accuracy of distance functions when varying K", fontsize=14
plt.xlabel("K", fontsize=12)
plt.ylabel("Accuracy", fontsize=12)
plt.xticks(np.arange(1, 8, step=2))
axes = plt.gca()
axes.set_xlim([1,7])
axes.set_ylim([0.59,0.76])

plt.plot(k_list,mean_accuracies_d, "-b", label="Distance_cw2") # Plot
plt.plot(k_list,mean_accuracies_e, "-y", label="Euclidean")
plt.plot(k_list,mean_accuracies_m, "-r", label="Manhattan")
plt.plot(k_list,mean_accuracies_c, "-g", label="Chebyshev")
plt.legend(loc="lower right") # Set legend to bottom right
plt.show()
```



Task 2: Impact of Noise

In [7]:
```
# Load the training set, break it down into source and target variable

task2_train = pd.read_csv("task2_train.txt")

scaler = MinMaxScaler() # Use Min-Max technique
source_train = task2_train.iloc[:,:-1]
normalised_source_train = source_train.copy()
normalised_source_train[:] = scaler.fit_transform(normalised_source_tr

target_train = task2_train.iloc[:,-1:]
y_train = target_train['class'].to_list()
```

In [8]:
```
# Load the testing set, break it down into source and target variables
task2_test = pd.read_csv("task2_test.txt")

source_test = task2_test.iloc[:,:-1]
normalised_source_test = source_test.copy()
normalised_source_test[:] = scaler.fit_transform(normalised_source_tes

target_test = task2_test.iloc[:,-1:]
y_test = target_test['class'].to_list()
```

In [9]:
```
# A function that requires the input of the target values of a dataset
# The specified percentage of noise is then added and the noisy datase

def add_noise(target, percent):
    noisy_target = target.copy()
    table_length = len(noisy_target['class'])
    one_percent = math.floor(table_length/100) # Calculate the number
    num_of_rows = one_percent*percent
    random_rows = []
    for i in range(0, num_of_rows):
        random_row = random.randint(0,table_length-1)
        if noisy_target.loc[random_row,'class'] == 1: # Ensure the sam
            noisy_target.loc[random_row,'class'] = 0
        else:
            noisy_target.loc[random_row,'class'] = 1
    return(noisy_target)
```

In [*]:
```
# This trains three different models on the noisy datasets (ranging fr
# their accuracy at predicting the results of the test set. For each m
# times and the average accuracy is taken.

accuracy_NN = [] # Creat empty lists that store the accuracy of each m
accuracy_KNN = []
accuracy_DT = []
noise = []

for i in range(0,30,2): # Iterate from 0%-30% of noise
    acccuracy_of_NN = [] # Create empty lists to store the 50 iteratio
    acccuracy_of_KNN = [] # The average will be taken
    acccuracy_of_DT = []
    for h in range(0,50):
        random.seed(h) # Set random seed equal to h to ensure reporodu
        noisy_target = add_noise(target_train,i)
        y_train = noisy_target['class'].to_list()

        Neural_network = MLPClassifier(hidden_layer_sizes=(8,3), rando
        Neural_network.fit(normalised_source_train, y_train) # Train a
        y_predict_NN = Neural_network.predict(normalised_source_test)
        ACC_NN = accuracy_score(y_predict_NN,y_test)
        acccuracy_of_NN.append(ACC_NN) # Store the accuracy

        knn = KNeighborsClassifier(n_neighbors = 5, weights = 'distanc
        knn.fit(normalised_source_train, y_train) # Train a K nearest 
        y_predict_KNN = knn.predict(normalised_source_test)
        ACC_KNN = accuracy_score(y_predict_KNN,y_test)
        acccuracy_of_KNN.append(ACC_KNN)

        DT_model = DecisionTreeClassifier(max_depth = 2) # Set max_dep
        DT_model = DT_model.fit(normalised_source_train, y_train) # Tr
        y_predict_DT = DT_model.predict(normalised_source_test)
        ACC_DT = accuracy_score(y_predict_DT,y_test)
        acccuracy_of_DT.append(ACC_DT)

    accuracy_NN.append(np.mean(acccuracy_of_NN)) # Take the average ac
    accuracy_KNN.append(np.mean(acccuracy_of_KNN)) # for each model.
    accuracy_DT.append(np.mean(acccuracy_of_DT))
    noise.append(i)
```

In [*]:
```
# Plot the accuracy of the models for different noise levels

plt.title("Accuracy of different classifiers when varying the level of
plt.xlabel("Noise (%)", fontsize=12)
plt.ylabel("Accuracy", fontsize=12)
axes = plt.gca()
axes.set_xlim([0,30])
axes.set_ylim([0.58,0.75])

plt.plot(noise, accuracy_NN, "-b", label="Neural Network")
plt.plot(noise, accuracy_KNN, "-g", label="K Nearest Neighbor")
plt.plot(noise, accuracy_DT,  "-r", label="Decision Tree")
plt.legend(loc="top right") # Set legend to bottom right
plt.show()
```

Task 3: Reflection

Task 1

Task 1 is to analyse the performance of the K Nearest Neighbour (KNN) classification algorithm on the “diabetes.txt” dataset using different distance metrics and values of k. I made the distance metric “distance_cw2” that calculates the Euclidean distance between two observations based on three randomly chosen characteristics. The distance_cw2 metric and the built-in “Euclidean”, “Manhattan” and “Chebyshev” metrics were used to train and test a KNN model on the dataset using the 10-fold validation method. The performance of these different metrics was analysed when the number of nearest neighbours, k, was varied over values 1, 3, 5, 7.

The built-in functions all increased in accuracy from around 0.70 to 0.74 as k increased, whereas distance_cw2 increased in accuracy from 0.61 to 0.67. Therefore, the experiment showed that the built-in Euclidean, Manhattan and Chebyshev metrics are more effective than the handmade distance_cw2 metric.

The experiment could be improved by calculating the run time of the KNN algorithm when using the different metrics. Therefore, we could see if the better performance of different metrics is at the expense of higher computation levels.

Task 2

Task 2 is to compare the performance of K Nearest Neighbour (KNN), Decision Tree (DT) and Neural Network (NN) classification models when trained on a noisy dataset. To do this, the level of noise in the “task2_train.txt” was increased from 0% to 30% and the KNN, DT and NN models were trained on the dataset at each level of noise. Their ability to accurately predict the classifications of the test dataset, “task2_test.txt” was then measured. This was repeated 50 times to get the average accuracy of each model at each noise level.

At a level of 0% noise, the NN has a 73% accuracy rate, the DT a 68% accuracy rate and the KNN a 66% accuracy rate. As the level of noise increased, the accuracy of all three models reduced by around 5%. Overall, the NN outperformed the other two models by 5%, proving it to be the best classifier model in this scenario.

Currently, the performance of models is only being analysed using pre-determined parameters. The value of these parameters is very important and can massively affect the performance of the models. Therefore, to improve the experiment, the parameters of the models could be varied to determine the parameters that maximise their model’s performance levels. These parameters could then be used in the experiment.