Lab-02_2

November 16, 2021

1 Lab 2: Nearest Neighbour

6252320 Leon Debnath

[31]:
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

from numpy.random import random
from sklearn.metrics import accuracy_score
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
```

[32]:
```python
# Class of k-Nearest Neigbor Classifier


class kNN():
    def __init__(self, k = 3, exp = 2, normalise=False):
        self.k = k
        self.exp = exp
        self.normalise = normalise

    def fit(self, X_train, Y_train):
        if self.normalise:
            self.X_train = self.normalise_data(X_train)
        else:
            self.X_train = X_train
        self.Y_train = Y_train

    def getDiscreteClassification(self, X_test):

        if self.normalise:
            X_test = self.normalise_data(X_test)

        Y_pred_test = []

        for i in range(len(X_test)):
            test_instance = X_test.iloc[i]
```

```
        # Store distances in a dataframe. The dataframe has the index of
        # Y_train in order to keep the correspondence with the classes
        # of the training instances
        distances = []

        for j in range(len(self.X_train)):
            train_instance = self.X_train.iloc[j]
            distance = self.Minkowski_distance(test_instance,␣
↪train_instance)
            distances.append(distance)


        df_dists = pd.DataFrame(data=distances, columns=['dist'], index =␣
↪self.Y_train.index)

        # Sort distances, and only consider the k closest points in the
        # new dataframe df_knn
        df_nn = df_dists.sort_values(by=['dist'], axis=0)
        df_knn =  df_nn[:self.k]

        # Note that the index df_knn.index of df_knn contains indices
        # in Y_train of the k-closed training instances to the i-th test
        # instance. Thus, the dataframe self.Y_train[df_knn.index]
        # contains the classes of those k-closed training instances.
        # Method value_counts() computes the counts (no. occurencies)
        # for each class in self.Y_train[df_knn.index] in predictions.
        predictions = self.Y_train[df_knn.index].value_counts()

        # the first element of the index predictions.index contains the
        # class with the highest count; i.e. the prediction y_pred_test.
        y_pred_test = predictions.index[0]

        # add the prediction y_pred_test to the prediction vector
        # Y_pred_test for all the test instances in X_test
        Y_pred_test.append(y_pred_test)

    return Y_pred_test


def Minkowski_distance(self, x1, x2):
    '''
    Computes the Minkowski distance of x1 and x2 for two
    labeled instances (x1,y1) and (x2,y2)
    '''
    distance = 0
```

```python
        for i in range(len(x1)):
            distance = distance + abs(x1[i] - x2[i])**self.exp

        distance = distance**(1/self.exp)

        return distance


    #########
    # PART B
    #########
    def normalise_data(self, X) -> pd.DataFrame:
        '''
        NB:  this has been put INSIDE the class becuase that is what is
        specified in the lab spec. I believe his would probably provide
        more accurate results if the entire dataset was normalised outside
        of the class and then split into a train/test split.
        '''
        scaler = StandardScaler()
        X_scaled = scaler.fit_transform(X)
        return pd.DataFrame(X_scaled)


    #########
    # PART C
    #########
    def get_class_probs(self, X_test) -> pd.DataFrame:

        class_probs, columns = self.create_probs(X_test)

        for i in range(len(X_test)):
            test_instance = X_test.iloc[i]
            distances = []

            for j in range(len(self.X_train)):
                train_instance = self.X_train.iloc[j]
                distance = self.Minkowski_distance(test_instance,
                                                   train_instance)
                distances.append(distance)

            df_dists = pd.DataFrame(data=distances,
                                    columns=['dist'],
                                    index = self.Y_train.index)

            df_nn = df_dists.sort_values(by=['dist'], axis=0)
            df_knn =  df_nn[:self.k]
```

```
            row = self.set_probs(self.Y_train[df_knn.index].value_counts(),
                                 columns)
            class_probs.loc[i] = row

        return class_probs


    def create_probs(self, X_test):
        '''
        Create a new dataframe that holds all of the values for the
        number of instances per column
        '''
        class_columns = []
        classes = self.Y_train.value_counts()

        for index, value in classes.items():
            class_columns.append(index)
            class_probs = pd.DataFrame(columns=class_columns)

        return class_probs, class_columns


    def set_probs(self, classifications, columns):
        ''' Set the probabilities for each classification in the row '''
        row = [0]*len(columns)

        for classification, count in classifications.items():

            for column in columns:
                index = columns.index(classification)
                row[index] = count / self.k

        return row

    #########
    # PART D
    #########
    def get_predictions(self, X) -> pd.DataFrame:
        '''
        For every row in the DataFrame, get the classification
        probabilities and compute the regression cost for each element
        '''
        predictions = pd.DataFrame(columns = ['Reg Price'])
        class_probs = self.get_class_probs(X)

        for i in class_probs.index:
```

```
            row = class_probs.loc[i]
            cost = self.compute_cost(row)
            predictions.loc[i] = cost

        return predictions


    def compute_cost(self, row):
        '''
        For element in the row, compute the regression cost as
        the cost * the probability
        '''
        regression_cost = 0

        for cost, probability in row.iteritems():
            regression_cost += cost * probability

        return [regression_cost]
```

K Experiment Method

[33]:
```
def k_experiment(csv_file_name, normalise=False):
    '''
    Runs the experiment on the datatset in the named file
    for a range of k values
    '''
    data = pd.read_csv(csv_file_name)
    data.head()
    Y = data['class']
    X = data.drop(['class'],axis=1)

    X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.34,␣
 ↪random_state=10)

    # range for the values of parameter k for kNN
    k_range = [1, 3, 5, 7, 9, 11, 13, 15, 17, 19, 21, 23, 25, 27, 29, 31]

    trainAcc = np.zeros(len(k_range))
    testAcc = np.zeros(len(k_range))

    index = 0
    for k  in  k_range:
        clf = kNN(k, normalise=normalise)
        clf.fit(X_train, Y_train)
        Y_predTrain = clf.getDiscreteClassification(X_train)
        Y_predTest = clf.getDiscreteClassification(X_test)
        trainAcc[index] = accuracy_score(Y_train, Y_predTrain)
```

```
        testAcc[index] = accuracy_score(Y_test, Y_predTest)
        index += 1

    plt.plot(k_range,trainAcc,'ro-',k_range,testAcc,'bv--')
    plt.legend(['Training Accuracy','Test Accuracy'])
    plt.xlabel('k')
    plt.ylabel('Accuracy')

    if normalise:
        title = csv_file_name + ' normalised'
    else:
        title = csv_file_name + ' un-modified'
    plt.title(title)
```

Exp Experiment Method

[34]:
```
def exp_experiment(csv_file_name, normalise=False):
    '''
    Runs the experiment on the datatset in the named file for
    a range of exp values
    '''

    data = pd.read_csv(csv_file_name)
    data.head()
    Y = data['class']
    X = data.drop(['class'],axis=1)

    X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.34,␣
 ↪random_state=10)

    exp_range = [2,  100, 10000]

    trainAcc = np.zeros(len(exp_range))
    testAcc = np.zeros(len(exp_range))

    index = 0
    for exp  in  exp_range:
        clf = kNN(k=3, exp=exp, normalise=normalise)
        clf.fit(X_train, Y_train)
        Y_predTrain = clf.getDiscreteClassification(X_train)
        Y_predTest = clf.getDiscreteClassification(X_test)
        trainAcc[index] = accuracy_score(Y_train, Y_predTrain)
        testAcc[index] = accuracy_score(Y_test, Y_predTest)
        index += 1

    plt.plot(exp_range,trainAcc,'ro-',exp_range,testAcc,'bv--')
    plt.legend(['Training Accuracy','Test Accuracy'])
```

```
    plt.xscale('log')
    plt.xlabel('exp')
    plt.ylabel('Accuracy')

    if normalise:
        title = csv_file_name + ' normalised'
    else:
        title = csv_file_name + ' un-modified'
    plt.title(title)
```

1.1 Part B

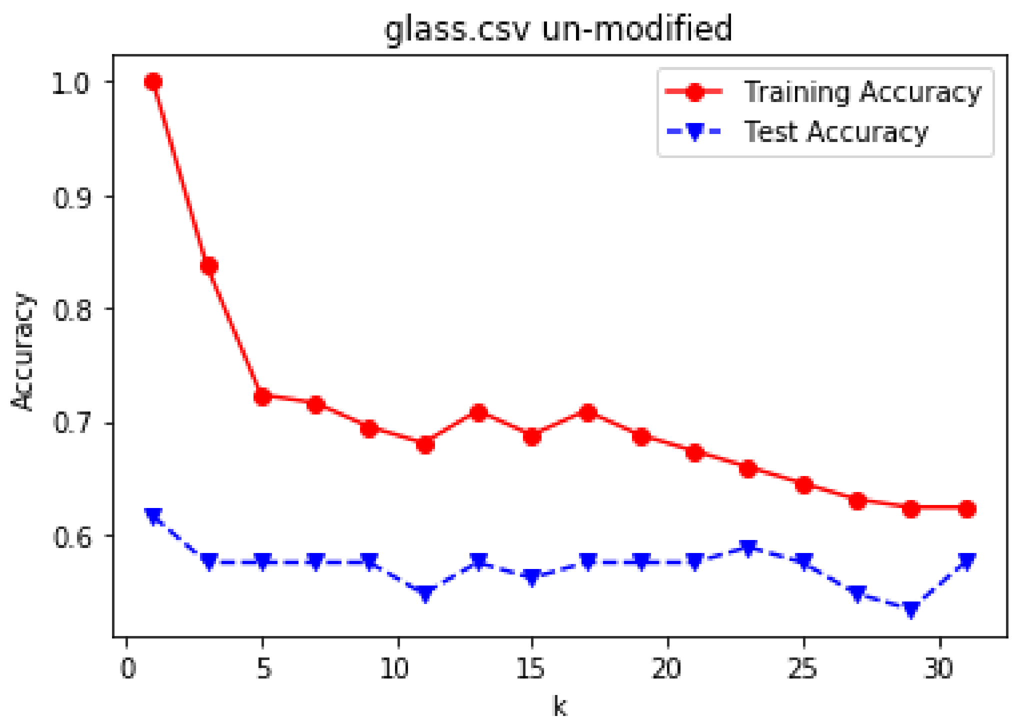
Test the kNN classifier on the diabetis and glass classification data sets (see Appendix A) for the case when the data is not normalized and the case when the data is normalized. Indicate whether the training and hold-out accuracy rates improve with normalization.

For testing the kNN classifier you might use the script provided in the Jupiter notebook. The script provides a plot with training and hold-out accuracy rates in function of parameter k of the kNN classifier.

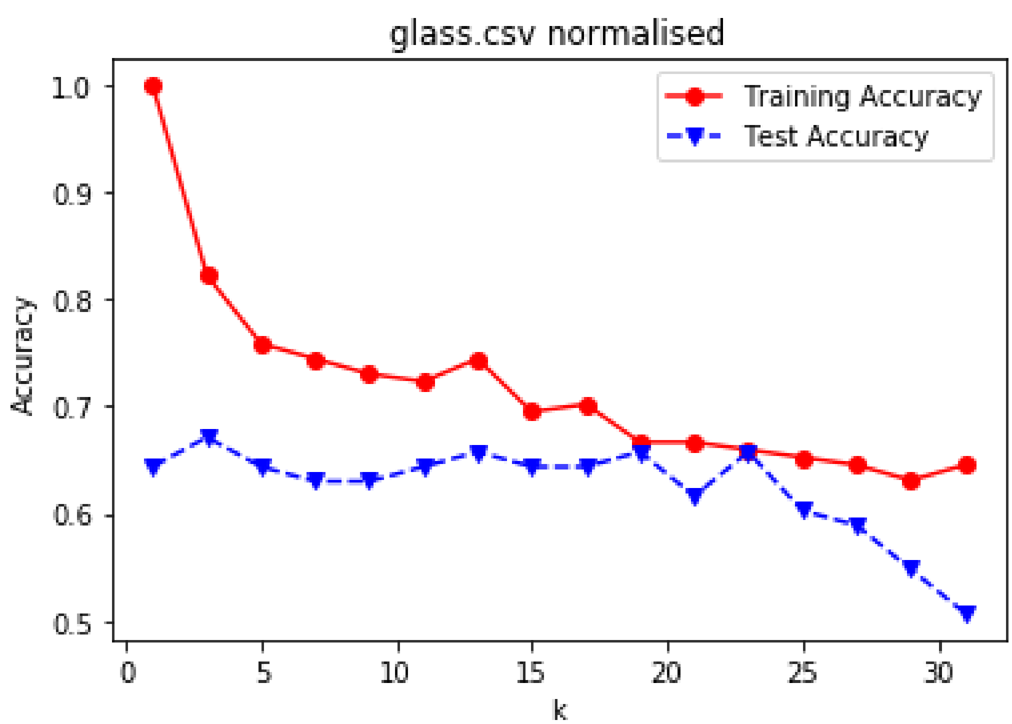
Test the kNN classifier on the glass classification data sets the data is normalized for different values of the exp parameter of the Minkowski distance. Indicate whether the training and hold-out accuracy rates changes due to exp. For this task you might use the second testing script provided in the Jupiter note.

[37]:
```
#################################
# Test that this shit still works
#################################

data = pd.read_csv('glass.csv')
data.head()
Y = data['class']
X = data.drop(['class'],axis=1)

X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.34,␣
 ↪random_state=10)

clf = kNN(k=3, normalise=True)
clf.fit(X_train, Y_train)
```

[20]:
```
k_experiment('glass.csv', normalise=False)
```



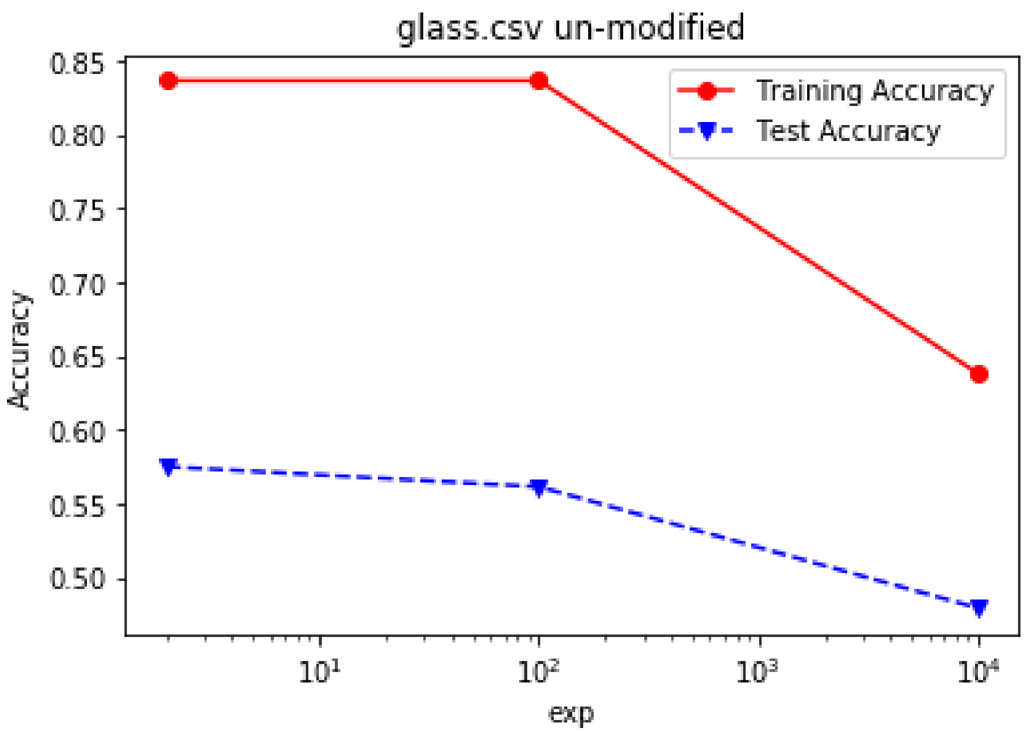
[23]:
```
k_experiment('glass.csv', normalise=True)
```



We can see that the normalised data performs far better than the un-normalised data for the Glass dataset. With higher values for K (between 20 - 25) providing almost the same training and test accuracy and a higher average value (above 0.6) for the normalised data compared to a below 0.5 average for the standard dataset.

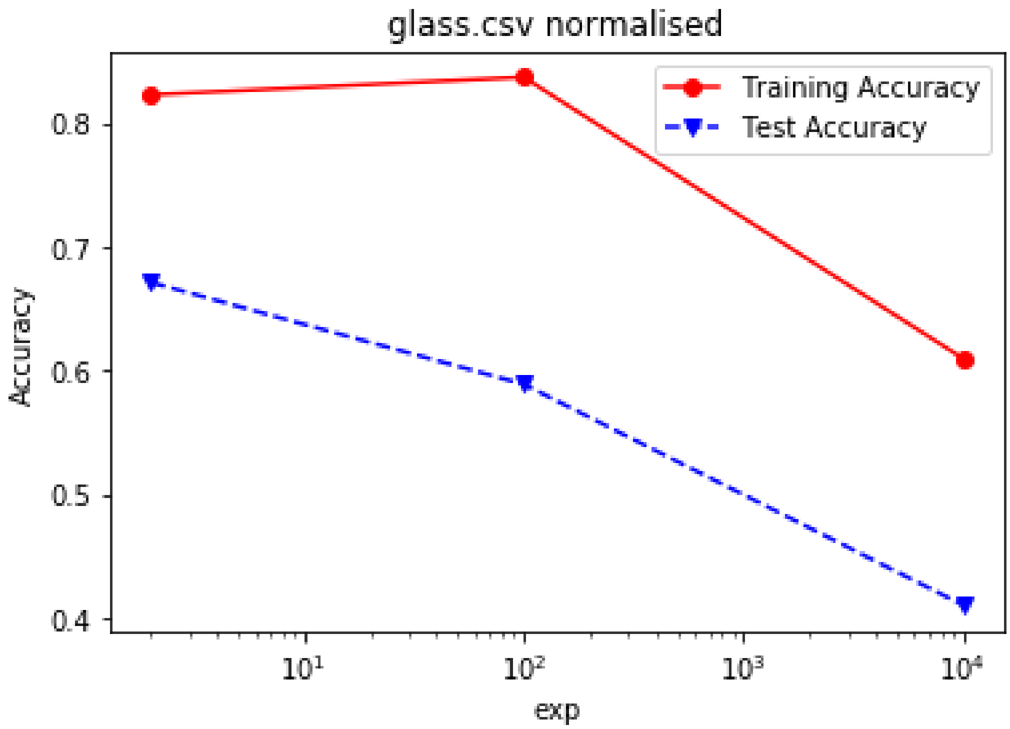
[9]:
```
exp_experiment('glass.csv', normalise=False)
```

```
/home/leon/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:74:
RuntimeWarning: overflow encountered in double_scalars
```



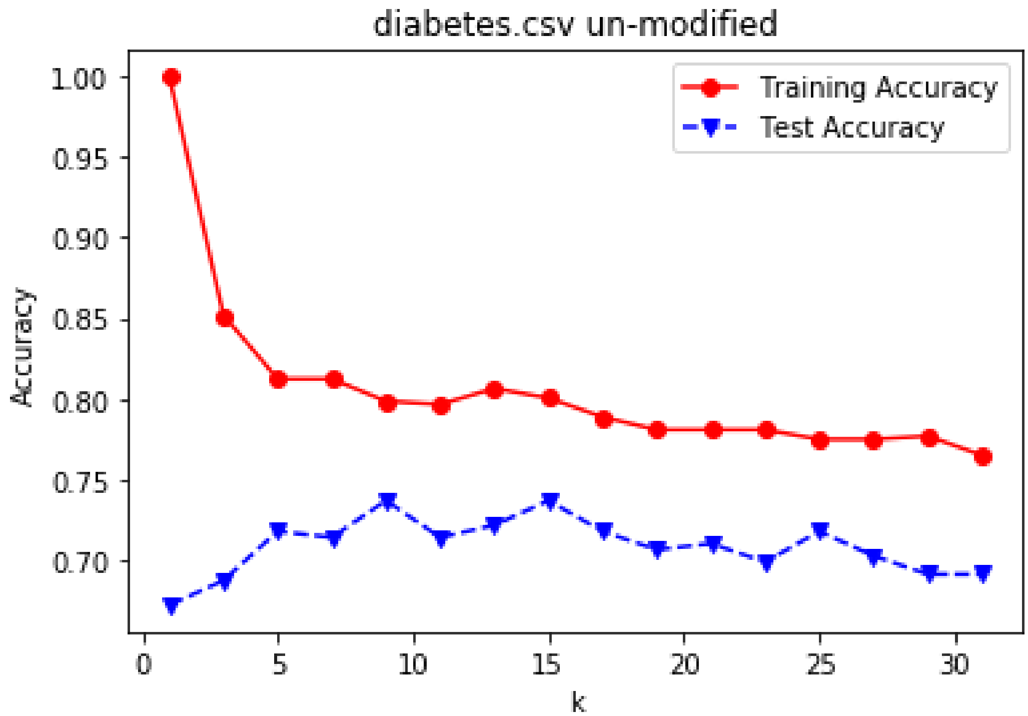
[10]:
```
exp_experiment('glass.csv', normalise=True)
```

```
/home/leon/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:74:
RuntimeWarning: overflow encountered in double_scalars
/home/leon/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:74:
RuntimeWarning: overflow encountered in double_scalars
```

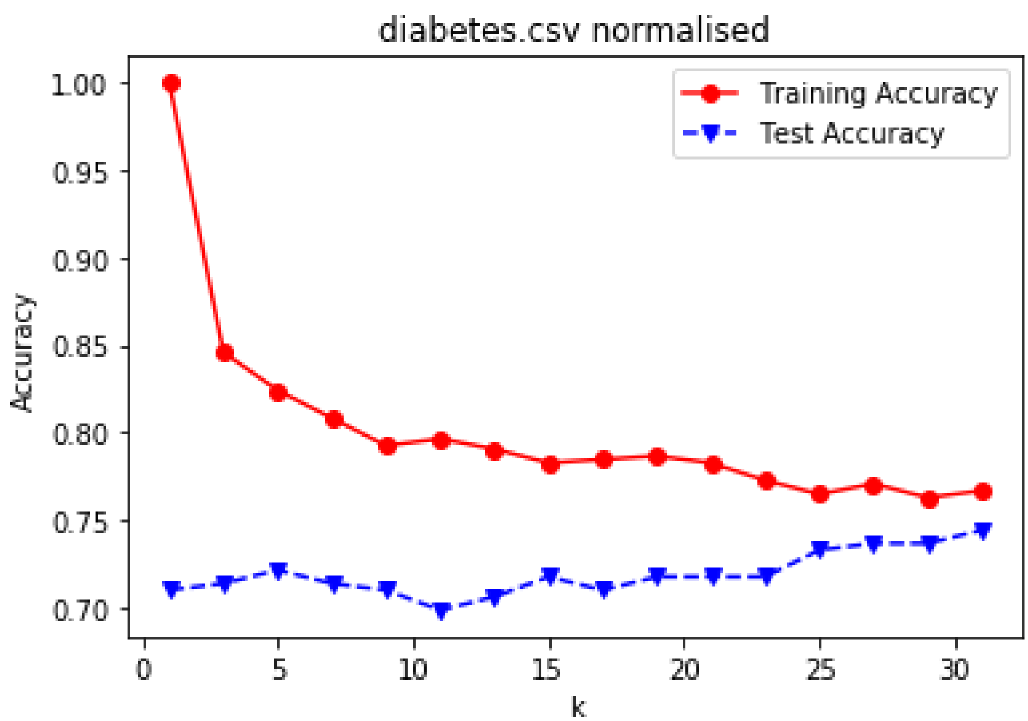


The exp experiment for the Glass dataset provides similar results with a higher accuracy rate for the normalised dataset.

[39]:
```
k_experiment('diabetes.csv', normalise=False)
```



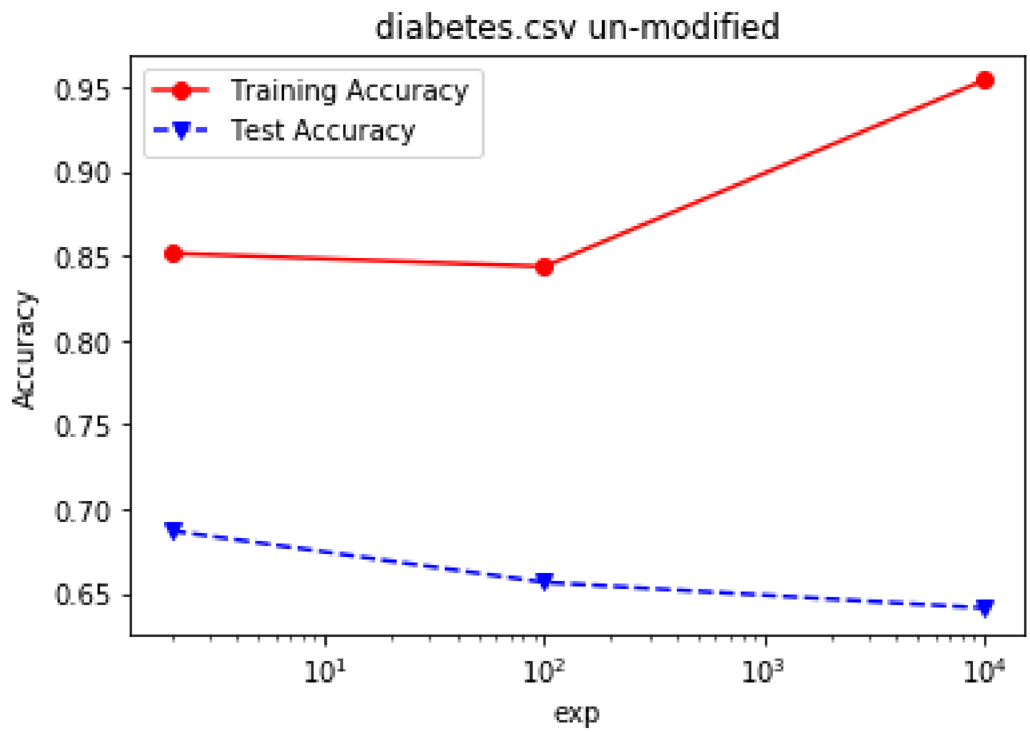
[40]:
```
k_experiment('diabetes.csv', normalise=True)
```



We can see that the normalised data also performs better than the un-normalised data for the Diabetes dataset, especiallu at higher values of K.

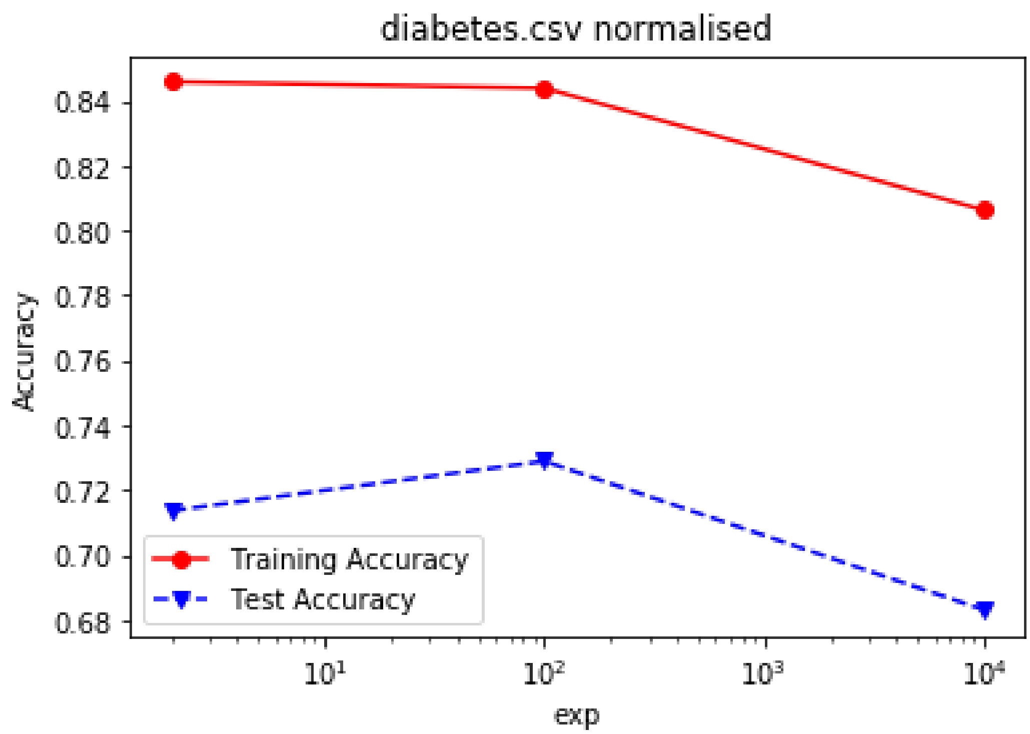
[41]:
```
exp_experiment('diabetes.csv', normalise=False)
```

```
/home/leon/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:74:
RuntimeWarning: overflow encountered in double_scalars
```



[43]:
```
exp_experiment('diabetes.csv', normalise=True)
```

```
/home/leon/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:74:
RuntimeWarning: overflow encountered in double_scalars
/home/leon/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:74:
RuntimeWarning: overflow encountered in double_scalars
```



Interestingly the normalised values for the exp experiment provide a lower value for training accuracy at exp=10000, however the test accuracy is improved for the normalised data.

1.2 Part C

Add to class `kNN` method `get_class_probs` that computes for all the test instances in `X_test` the posterior class probabilities. This means that the method computes for each row (instance) in `X_test` a row with probability of class 1, probability of class 2, and probability of class n. Combine the rows of the posterior class probabilities in `pandas.DataFrame` object that will be the output of the method `get_class_probs`.

[24]:
```
data = pd.read_csv('glass.csv')
data.head()
Y = data['class']
X = data.drop(['class'],axis=1)

X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.34,␣
 ↪random_state=10)

clf = kNN()
clf.fit(X_train, Y_train)
clf.get_class_probs(X_test)
```

```
[24]:    'build wind non-float'  'build wind float'  headlamps  'vehic wind float'  \
      0                0.000000            0.666667   0.000000            0.333333
      1                0.000000            1.000000   0.000000            0.000000
      2                0.000000            0.000000   0.666667            0.000000
      3                0.666667            0.333333   0.000000            0.000000
      4                0.000000            1.000000   0.000000            0.000000
      ..                    …                   …         …                   …
      68               0.000000            0.333333   0.000000            0.666667
      69               0.333333            0.000000   0.333333            0.333333
      70               0.333333            0.000000   0.333333            0.000000
      71               1.000000            0.000000   0.000000            0.000000
      72               0.666667            0.333333   0.000000            0.000000

         containers  tableware
      0    0.000000   0.000000
      1    0.000000   0.000000
      2    0.333333   0.000000
      3    0.000000   0.000000
      4    0.000000   0.000000
      ..        …         …
      68   0.000000   0.000000
      69   0.000000   0.000000
      70   0.000000   0.333333
      71   0.000000   0.000000
      72   0.000000   0.000000

      [73 rows x 6 columns]
```

1.3 Part D

Add to class kNN method `get_prediction` that computes for all the test instances in `X_test` regression values for the output attribute. This means that the method computes for each instance (row) in `X_test` a regression value equal to the average of y values in `Y_train` of the k-nearest neighbors of the instance in `X_train`. Combine the computed regression values for all the instances in `X_test` in `pandas.DataFrame` object that will be the output of the method `get_prediction`.

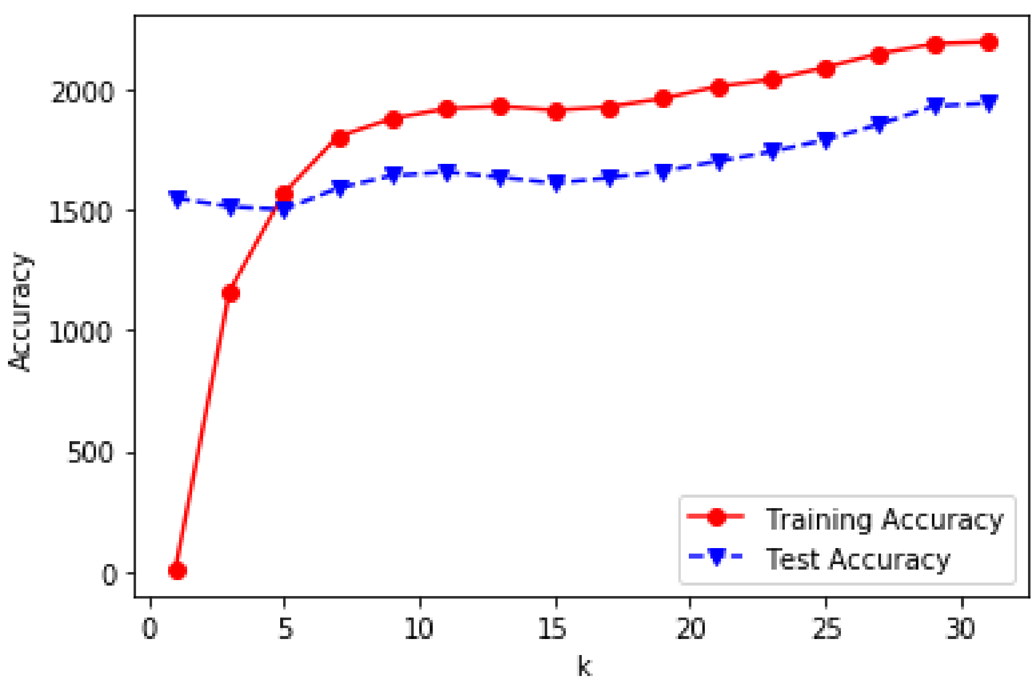
Test the method `get_prediction` on the autoprice data set which is a regression data set (see Appendix A). For that purpose you can adapt the test script that you have already used for Task B. Please use mean absolute error as the main metric for estimating regression performance instead of the accuracy rate. To compute the mean absolute error you can use method `mean_absolute_error` from `sklearn.metrics`.

```
[36]: def regression(csv_file_name):

          data = pd.read_csv(csv_file_name)
          data.head()
          Y = data['class']
          X = data.drop(['class'],axis=1)
```

```
    X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.34,␣
↪random_state=10)

    k_range = [1, 3, 5, 7, 9, 11, 13, 15, 17, 19, 21, 23, 25, 27, 29, 31]

    trainAcc = np.zeros(len(k_range))
    testAcc = np.zeros(len(k_range))

    index = 0
    for k  in  k_range:
        clf = kNN(k)
        clf.fit(X_train, Y_train)
        Y_predTrain = clf.get_predictions(X_train)
        Y_predTest = clf.get_predictions(X_test)
        trainAcc[index] = mean_absolute_error(Y_train, Y_predTrain)
        testAcc[index] = mean_absolute_error(Y_test, Y_predTest)
        index += 1

    plt.plot(k_range,trainAcc,'ro-',k_range,testAcc,'bv--')
    plt.legend(['Training Accuracy','Test Accuracy'])
    plt.xlabel('k')
    plt.ylabel('Accuracy')
```

[38]:

```
regression('autoprice.csv')
```



```
[ ]:
```