Andrew Vu - CS156_HW2

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1 CS156 (Introduction to AI), Spring 2022

2 Homework 2 submission

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Any special notes or anything you would like to communicate to me about this homework submission goes in here.

2.1 References and sources

List all your references and sources here. This includes all sites/discussion boards/blogs/posts/etc. where you grabbed some code examples.

From files section of Canvas page:
knn.synthetic_data
kmeans.synthetic_data

https://machinelearningmastery.com/tutorial-to-implement-k-nearest-neighbors-in-python-from-scratch/
https://towardsdatascience.com/how-to-build-knn-from-scratch-in-python-5e22b8920bd2
https://www.askpython.com/python/examples/k-nearest-neighbors-from-scratch
https://medium.com/analytics-vidhya/knn-implementation-from-scratch-96-6-accuracy-python-machine-learning-31ba66958644
https://medium.com/analytics-vidhya/implementing-k-nearest-neighbours-knn-without-using-scikit-learn-3905b4decc3c

2.2 Solution

Load libraries and set random number generator seed

[237]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from scipy.spatial import distance
from scipy.stats import mode
from sklearn.metrics import accuracy_score
```

[238]:

```
np.random.seed(42)
```

Code the solution

2.2.1 KNN FUNCTION

[239]:

```
# newObservation is a point in the test data set
# referenceData is the training data set

def knn(newObservation, referenceData, k=3):
    distances_from_newdata = []  # array to store distances
    k_shortest_distances = []    # array for the k shortest distances

    # compute the distance between each point in the reference data and the␣
↪newObservation point
    for i in range(len(referenceData)):
        dist = distance.euclidean(referenceData.iloc[i], newObservation)
        distances_from_newdata.append([dist, i]) # add this computed distance␣
↪to the distances_from_newdata array with its index
    distances_from_newdata.sort()
    k_shortest_distances = (distances_from_newdata)[0:k]

    return k_shortest_distances # returns the array of the k shortest distances␣
↪with their respective row number
```

2.2.2 PREDICTIONS FUNCTION

[240]:

```
def predictions(X_test, ref_data, Y_train):
    labels = [] # output
    for i in range(len(X_test)):
        modelabels = [] # create a separate array for determining the majority␣
↪of the labels
        distance_indexes = knn(X_test.iloc[i], ref_data, k=3)
        for j in range(len(distance_indexes)): # for however many distances␣
↪there are in the return value of knn
            modelabels.append(Y_train[distance_indexes[j][1]]) # append that␣
↪distance's Y_train label value to a separate array
        lab = mode(modelabels) # returns an array of the majority of the labels␣
↪as well as the count of how many
        lab = lab.mode[0]       # returns specifically the mode
        labels.append(lab)      # adds this label to the real labels
    return labels
```

2.3 Generate 2D Data

[241]:
```
n = 100 # n = data points

# loc = mean or mass of gravity in which the generated data centers around this␣
↪value
# scale = standard deviation
# size = how many data points you want

# CLASS 0
X0 = np.random.normal(loc = -2.0, scale = 2.0, size = int(n/2))
Y0 = np.random.normal(loc = 0.0, scale = 1.0, size = int(n/2))

# CLASS 1
X1 = np.random.normal(loc = 2.0, scale = 2.0, size = int(n/2))
Y1 = np.random.normal(loc = 0.0, scale = 1.0, size = int(n/2))

X = np.concatenate((X0, X1), axis = 0)
Y = np.concatenate((Y0, Y1), axis = 0)
```

2.3.1 Generate Labels for 2D

[242]:
```
l1 = [0]*int(n/2)
l2 = [1]*int(n/2)
labels2D = l1+l2
```

2.3.2 Visualize the generated data

[243]:
```
dt = pd.DataFrame({'X':X, 'Y':Y}, columns=['X', 'Y'])
dt.head()
```

[243]:

	X	Y
0	-1.006572	0.324084
1	-2.276529	-0.385082
2	-0.704623	-0.676922
3	1.046060	0.611676
4	-2.468307	1.031000

[244]:
```
X_train, X_test, Y_train, Y_test = train_test_split(dt, labels2D, test_size=0.
↪2, random_state=0)
# X_train = data for training set
# X_test = data for test set
# Y_train = labels 0/1 for training set
# Y_test = labels 0/1 or test set
# 80% training, 20% test split
print(X_train)
```

```
            X         Y
43 -2.602207 -0.327662
62  2.120460  1.158596
3   1.046060  0.611676
71  0.181225 -0.815810
45 -3.439688 -1.463515
..       …        …
96 -0.473901 -0.883857
67 -0.337356  1.896793
64  1.615278  0.963376
47  0.114244  0.261055
44 -4.957044 -0.392108

[80 rows x 2 columns]
```

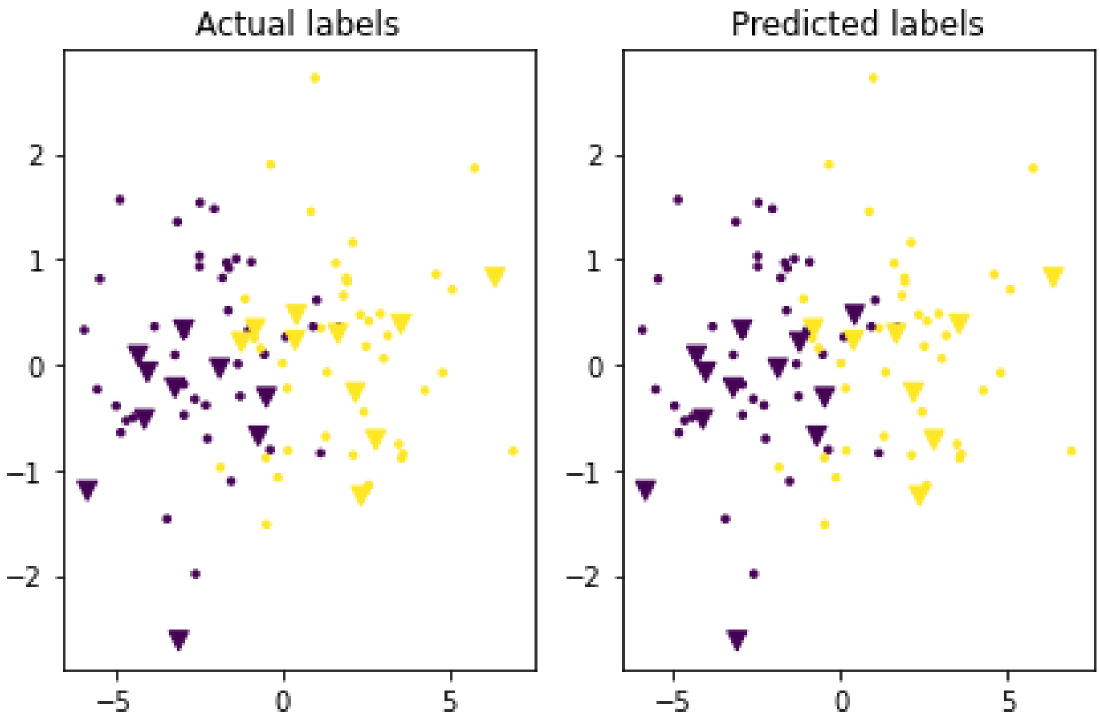
2.3.3 ACCURACY FOR 2D

[245]:
```python
prediction_results = predictions(X_test, X_train, Y_train)
print(Y_test)
print(prediction_results)
print("Accuracy of the predictions on the 2D test dataset is " +
 ↪str(accuracy_score(Y_test, prediction_results)))
```

```
[0, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0]
[0, 0, 0, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0]
Accuracy of the predictions on the 2D test dataset is 0.9
```

2.3.4 ACTUAL VS PREDICTED LABELS VISUALIZATION

[246]:
```python
plt.subplot(1, 2, 1)
plt.scatter(X_train.iloc[:,0],X_train.iloc[:,1], s=25, c=Y_train, marker=".")
plt.scatter(X_test.iloc[:,0],X_test.iloc[:,1], s=50, c=Y_test, marker="v")
plt.title("Actual labels")

plt.subplot(1, 2, 2)
plt.scatter(X_train.iloc[:,0],X_train.iloc[:,1], s=25, c=Y_train, marker=".")
plt.scatter(X_test.iloc[:,0],X_test.iloc[:,1], s=50, c=prediction_results,
 ↪marker="v")
plt.title("Predicted labels")

plt.tight_layout()
plt.show()
```



2.4 Generate 3-D data

[247]:
```
n = 1000 # n data points

# CLASS 0
X0 = np.random.normal(loc = 0, scale = 3, size = int(n/4))
Y0 = np.random.normal(loc = -3, scale = 1, size = int(n/4))
Z0 = np.random.normal(loc = -1, scale = 1, size = int(n/4))
# CLASS 1
X1 = np.random.normal(loc = 0, scale = 3, size = int(n/4))
Y1 = np.random.normal(loc = 1, scale = 2, size = int(n/4))
Z1 = np.random.normal(loc = 1, scale = 1, size = int(n/4))
# CLASS 2
X2 = np.random.normal(loc = 0, scale = 3, size = int(n/4))
Y2 = np.random.normal(loc = 3, scale = 1, size = int(n/4))
Z2 = np.random.normal(loc = 4, scale = 1, size = int(n/4))
# CLASS 3
X3 = np.random.normal(loc = 0, scale = 3, size = int(n/4))
Y3 = np.random.normal(loc = 5, scale = 3, size = int(n/4))
Z3 = np.random.normal(loc = -3, scale = 1, size = int(n/4))

X = np.concatenate((X0, X1, X2, X3), axis = 0)
Y = np.concatenate((Y0, Y1, Y2, Y3), axis = 0)
```

```
Z = np.concatenate((Z0, Z1, Z2, Z3), axis = 0)
```

[248]:
```
l1 = [0]*int(n/4)
l2 = [1]*int(n/4)
l3 = [2]*int(n/4)
l4 = [3]*int(n/4)
labels3D = l1+l2+l3+l4
```

[249]:
```
dt = pd.DataFrame({'X':X, 'Y':Y, 'Z':Z}, columns=['X', 'Y', 'Z'])
dt.head()
```

[249]:

	X	Y	Z
0	1.073362	-3.062679	-1.522723
1	1.682354	-2.044858	0.049009
2	3.249154	-3.985726	-1.704344
3	3.161406	-2.495953	-2.408461
4	-4.133008	-3.530258	-2.556629

[250]:
```
X_train, X_test, Y_train, Y_test = train_test_split(dt, labels3D, test_size=0.
↪2, random_state=0)
print(X_train)
```

```
            X         Y         Z
687  1.272183  4.549020  3.075767
500  1.051890  1.226968  5.804348
332  1.197669  2.416217  1.323168
979 -0.790345  7.956349 -2.484372
817 -6.657901  6.364223 -5.832156
..        …         …         …
835 -0.885270  3.944236 -2.553127
192 -3.960700 -3.259591  0.066675
629  0.056549  2.549811  4.849102
559  3.944743  3.937570  4.198948
684 -0.079217  2.645959  4.032797

[800 rows x 3 columns]
```

2.5 ACCURACY FOR 3D

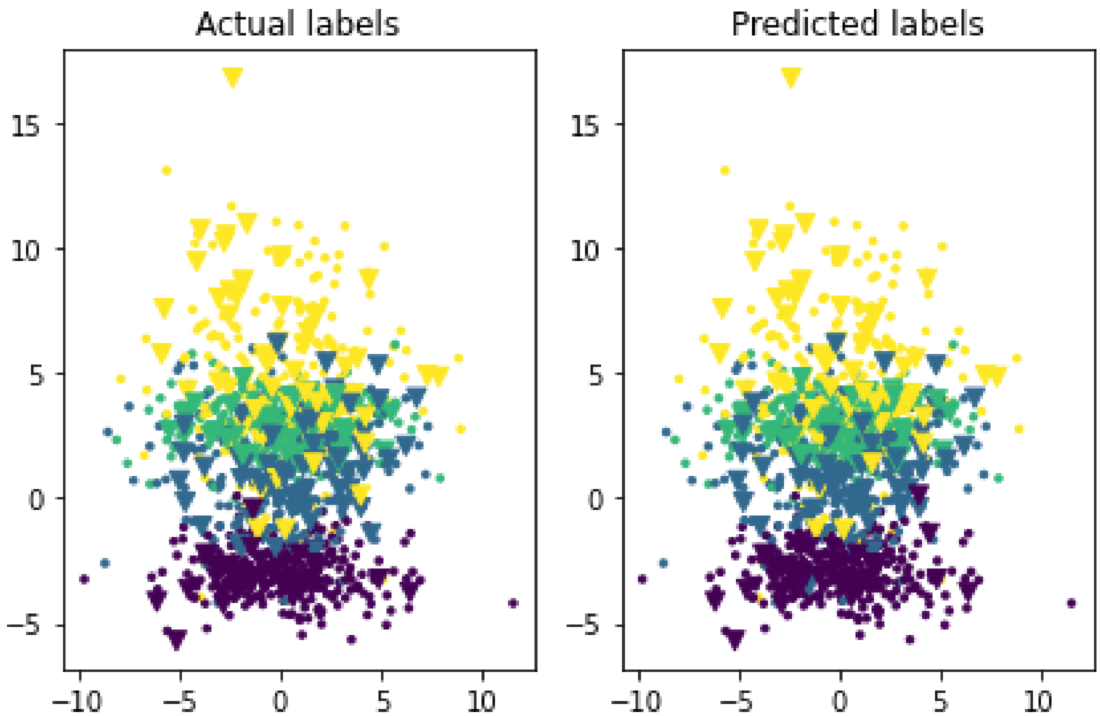
[251]:
```
prediction_results = predictions(X_test, X_train, Y_train)
print(Y_test)
print("\n")
print(prediction_results)
print("Accuracy of the predictions on the 3D test dataset is " +␣
↪str(accuracy_score(Y_test, prediction_results)))
```

```
[3, 3, 1, 2, 2, 3, 0, 0, 1, 2, 1, 2, 3, 0, 2, 0, 3, 0, 0, 0, 0, 1, 1, 1, 3, 3,
0, 0, 3, 0, 3, 2, 2, 3, 1, 2, 3, 1, 3, 1, 0, 3, 2, 2, 1, 3, 3, 0, 1, 2, 1, 1, 1,
```

```
1, 3, 2, 1, 1, 3, 1, 2, 2, 0, 0, 1, 0, 1, 2, 1, 2, 2, 1, 2, 0, 3, 1, 1, 3, 2, 2,
1, 1, 1, 3, 3, 2, 0, 2, 1, 3, 1, 1, 3, 1, 2, 1, 2, 0, 1, 2, 3, 3, 0, 3, 1, 2, 2,
3, 3, 0, 0, 2, 1, 2, 1, 1, 2, 1, 1, 2, 3, 3, 0, 3, 0, 3, 1, 1, 3, 2, 1, 2, 2, 2,
3, 2, 1, 0, 2, 3, 0, 2, 2, 0, 1, 1, 1, 1, 0, 0, 1, 0, 1, 3, 3, 3, 1, 1, 3, 1, 2,
3, 2, 3, 3, 1, 1, 3, 1, 1, 3, 3, 0, 3, 1, 3, 0, 2, 3, 0, 3, 3, 1, 1, 3, 3, 2, 1,
3, 0, 3, 3, 1, 0, 3, 2, 2, 0, 2, 0]


[3, 3, 1, 2, 2, 3, 0, 0, 2, 2, 1, 1, 3, 0, 2, 1, 3, 0, 0, 0, 0, 1, 1, 1, 3, 3,
0, 0, 3, 0, 3, 2, 2, 3, 0, 2, 3, 1, 3, 1, 0, 3, 2, 2, 1, 3, 3, 0, 1, 2, 1, 1, 1,
1, 3, 2, 1, 1, 3, 2, 2, 2, 0, 0, 1, 0, 1, 2, 1, 2, 2, 1, 2, 0, 3, 1, 1, 3, 2, 2,
1, 0, 1, 3, 3, 2, 0, 2, 1, 3, 1, 1, 3, 1, 2, 2, 2, 0, 1, 1, 3, 1, 0, 3, 1, 2, 2,
3, 3, 0, 0, 2, 1, 2, 1, 1, 2, 1, 1, 2, 3, 3, 0, 3, 0, 3, 1, 1, 3, 2, 1, 2, 2, 2,
3, 2, 1, 0, 2, 3, 0, 2, 2, 0, 1, 2, 1, 0, 0, 0, 1, 0, 1, 3, 3, 3, 1, 3, 3, 1, 1,
3, 2, 3, 3, 0, 2, 3, 1, 1, 3, 3, 0, 3, 1, 3, 0, 2, 3, 0, 3, 0, 1, 1, 3, 3, 2, 1,
3, 1, 3, 3, 1, 0, 3, 2, 2, 0, 2, 0]
Accuracy of the predictions on the 3D test dataset is 0.915
```

2.5.1 ACTUAL VS PREDICTED LABELS VISUALIZATION

[252]:
```python
plt.subplot(1, 2, 1)
plt.scatter(X_train.iloc[:,0],X_train.iloc[:,1], s=25, c=Y_train, marker=".")
plt.scatter(X_test.iloc[:,0],X_test.iloc[:,1], s=50, c=Y_test, marker="v")
plt.title("Actual labels")

plt.subplot(1, 2, 2)
plt.scatter(X_train.iloc[:,0],X_train.iloc[:,1], s=25, c=Y_train, marker=".")
plt.scatter(X_test.iloc[:,0],X_test.iloc[:,1], s=50, c=prediction_results,
 ↪marker="v")
plt.title("Predicted labels")

plt.tight_layout()
plt.show()
```


Actual labels
Predicted labels
15
10
5
0
−5
−10
−5
0
5
10