CSL7670 : Fundamentals of Machine Learning

Lab Report



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Chapter 1

Lab-2

1.1 Objective

The objective of this lab assignment is to get familiarity with the K-Nearest Neighbors (K-NN) algorithm. By completing the problems and exercises in this lab.

1.2 Problem-1

- 1. (Apple vs Orange) You are given a K-NN code for the Apple vs Orange problem. Please read and understand the code. Now perform the following tasks:
 - 1. Synthetically increase the dataset size to 50 samples.
 - 2. Edit the code so that random 80%, 10%, and 10% samples are used for training, testing, and validation respectively.
 - 3. Change the value of K to 3, 5, and 7 and compare the validation set and test set results.
 - 4. Write a code that draws confusion matrices for different K. Use the following link to understand about Confusion Matrix.

Solution 1:

```
# -*- coding: utf-8 -*-

"""prob-1.py

Automatically generated by Colaboratory.

Original file is located at

https://colab.research.google.com/drive/1

Sp9P_8FqwjvNQWMe5biq50100P10DWXl

"""

import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, confusion_matrix

# Sample synthetic dataset, 1=Apple, -1=Orange
data_apples = np.array([
```

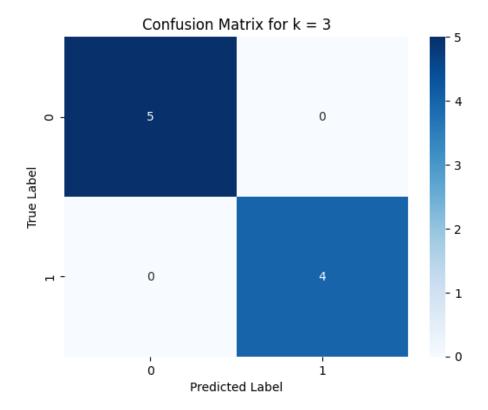
```
[250, 120, 1],
19
        [240, 110, 1],
20
        [245, 130, 1],
21
        [240, 100, 1],
        [220, 120, 1],
23
        [230, 125, 1],
24
        [255, 115, 1],
25
        [215, 110, 1],
26
        [210, 130, 1],
27
       [235, 105, 1],
28
       [240, 122, 1],
29
        [245, 125, 1],
30
        [248, 117, 1],
31
       [243, 127, 1],
32
        [225, 112, 1],
33
        [230, 118, 1],
34
       [238, 123, 1],
35
        [222, 115, 1],
36
        [248, 130, 1],
37
        [210, 100, 1],
38
        [255, 121, 1],
39
       [245, 128, 1],
40
        [240, 132, 1],
41
        [235, 120, 1],
42
        [250, 110, 1],
43
        [243, 135, 1],
44
        [227, 125, 1],
45
       [222, 132, 1],
46
       [232, 110, 1],
47
        [240, 105, 1],
48
        [238, 128, 1],
49
        [215, 118, 1],
50
       [255, 112, 1],
        [250, 125, 1],
52
        [240, 118, 1],
53
       [223, 130, 1],
54
       [232, 120, 1],
        [235, 130, 1],
56
       [245, 112, 1],
       [228, 123, 1],
        [240, 116, 1],
59
        [220, 128, 1],
60
        [255, 120, 1],
61
        [230, 130, 1],
62
       [225, 122, 1],
63
        [240, 126, 1],
64
       [233, 128, 1]
65
  ])
66
   data_oranges = np.array([
68
       [20, 91, -1],
69
       [30, 95, -1],
        [14, 84, -1],
71
       [32, 95, -1],
72
```

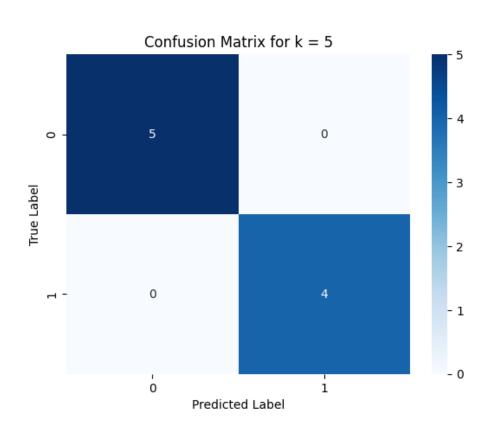
1.2. PROBLEM-1

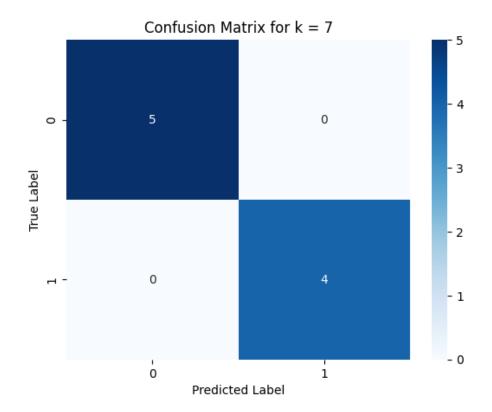
```
[18, 94, -1],
73
        [23, 90, -1],
74
        [25, 92, -1],
75
        [12, 80, -1],
76
        [29, 87, -1],
        [19, 89, -1],
78
        [22, 82, -1],
79
        [30, 88, -1],
80
        [16, 85, -1],
81
        [26, 89, -1],
82
        [28, 86, -1],
83
        [21, 83, -1],
84
        [24, 88, -1],
85
        [15, 81, -1],
86
        [17, 84, -1],
87
        [27, 91, -1],
88
        [23, 84, -1],
        [22, 88, -1],
90
        [20, 80, -1],
91
        [25, 87, -1],
92
        [18, 85, -1],
93
        [19, 82, -1],
94
        [28, 83, -1],
        [26, 81, -1],
96
        [30, 84, -1],
97
        [29, 82, -1],
        [21, 87, -1],
99
        [12, 78, -1],
100
        [27, 84, -1],
        [16, 80, -1],
        [24, 82, -1],
        [14, 88, -1],
104
        [17, 82, -1],
        [22, 80, -1],
106
        [23, 86, -1],
107
        [13, 79, -1],
108
        [19, 85, -1],
109
        [21, 89, -1],
110
        [15, 84, -1],
        [26, 87, -1],
112
        [25, 85, -1],
113
        [27, 82, -1],
114
        [28, 89, -1]
115
   ])
116
117
   \# Concatenate apple and orange data
   data = np.vstack((data_apples, data_oranges))
119
120
   # Separate features (redness and weight) and labels (fruit type)
   X = data[:, :2]
   y = data[:, 2]
123
    \textit{\# Split dataset into training, testing, and validation sets } \\
126 X_train, X_temp, y_train, y_temp = train_test_split(X, y, test_size=0.2,
```

```
→ random_state=42)
  | X_test, X_val, y_test, y_val = train_test_split(X_temp, y_temp, test_size
127
      \hookrightarrow =0.5, random_state=42)
128
   # List of k values to try
129
   k_{values} = [3, 5, 7]
130
   for k in k_values:
132
        print(f"Testing_{\sqcup}k_{\sqcup}=_{\sqcup}\{k\}")
133
134
        \# Create a KNN classifier with the current k value and L1 distance
135
           \hookrightarrow metric
        knn_classifier = KNeighborsClassifier(n_neighbors=k, p=1)
136
137
        # Train the classifier on the training data
138
        knn_classifier.fit(X_train, y_train)
139
        # Predict the fruit types for the test data
141
        y_test_pred = knn_classifier.predict(X_test)
142
143
        # Create a confusion matrix
144
        cm = confusion_matrix(y_test, y_test_pred)
145
        # Plot the confusion matrix
147
        plt.figure()
148
        sns.heatmap(cm, annot=True, fmt="d", cmap="Blues")
149
        plt.title(f"Confusion\sqcupMatrix\sqcupfor\sqcupk\sqcup=\sqcup{k}")
150
        plt.xlabel("Predicted_Label")
        plt.ylabel("True Label")
        plt.show()
154
        # Calculate the accuracy of the model on test data
155
        accuracy_test = accuracy_score(y_test, y_test_pred)
156
        print("Test \ Accuracy:", accuracy_test)
157
        print()
```

1.2. PROBLEM-1 7







1.3 Problem-2

- 2. (Handwritten Digit Classification) Use the provided code for classifying handwritten digits from the MNIST dataset. First, read and understand the code. Then, perform the following tasks:
 - 1. Modify the code so that it uses L1-distance instead of the default L2-distance (Euclidean).
 - 2. Determine the value of K that gives better performance.
 - 3. Report the accuracy achieved with the modified code.
 - 4. Display the results by showing the image, actual label, and predicted label. Identify some samples where the predicted label is incorrect.

Solution 2:

1.3. PROBLEM-2

```
# -*- coding: utf-8 -*-
  """prob-1b.ipynb
2
  Automatically generated by Colaboratory.
5
  Original file is located at
      \hookrightarrow nqJn1KDRPHxX
9
  warnings.simplefilter(action='ignore', category=FutureWarning)
10
  import numpy as np
11
12 from sklearn.datasets import fetch_openml
  from sklearn.model_selection import train_test_split
  from sklearn.neighbors import KNeighborsClassifier
  from sklearn.metrics import accuracy_score
  import matplotlib.pyplot as plt
17
  # Load MNIST dataset
18
  mnist = fetch_openml('mnist_784')
  X = mnist.data
20
  y = mnist.target
21
  # Limit to a subset of the data
23
  num_samples = 5000
  X_subset = X[:num_samples]
  y_subset = y[:num_samples]
26
27
  # Split dataset into training and testing sets
28
  X_train, X_test, y_train, y_test = train_test_split(X_subset, y_subset,
29
     → test_size=0.2, random_state=42)
  # Find the optimal value of K using cross-validation
31
  best_accuracy = 0
32
  best_k = 0
33
  k_range = range(1, 6) # Limiting the search range
34
  for k in k_range:
36
      knn_classifier = KNeighborsClassifier(n_neighbors=k, p=1) # p=1
37
         \hookrightarrow indicates L1-distance
      knn_classifier.fit(X_train, y_train)
38
      y_pred = knn_classifier.predict(X_test)
39
      accuracy = accuracy_score(y_test, y_pred)
40
41
      if accuracy > best_accuracy:
42
          best_accuracy = accuracy
43
          best_k = k
44
45
  print("Best_K:", best_k)
  print("Best_Accuracy:", best_accuracy)
47
18
  # Train the final classifier with the best K on the entire training data
  final_knn_classifier = KNeighborsClassifier(n_neighbors=best_k, p=1)
51 | final_knn_classifier.fit(X_train, y_train)
```

```
52
  \# Predict the labels for the test data
53
  y_pred = final_knn_classifier.predict(X_test)
  # Calculate the accuracy of the final model
  accuracy = accuracy_score(y_test, y_pred)
57
  print("Final \ Accuracy:", accuracy)
58
59
  # Display images, actual labels, and predicted labels for incorrect
60
     \hookrightarrow predictions
  incorrect_indices = np.where(y_pred != y_test)[0]
61
62
  for index in incorrect_indices[:5]: # Display the first 5 incorrect
63
     → predictions
       image = X_test[index, :].reshape(28, 28)
64
       actual_label = y_test[index]
65
       predicted_label = y_pred[index]
67
       plt.figure(figsize=(4, 4))
68
       plt.imshow(image, cmap='gray')
       plt.title(f"Actual: u{actual_label}, uPredicted: u{predicted_label}")
70
       plt.axis('off')
71
       plt.show()
```

OUTPUT: Best K: 1 Best Accuracy: 0.939 Final Accuracy: 0.939

