1

Page No.
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ML Lab Assignment 2

Title: Implement KNN classifier for given data

Aim: Implement KNN (K-nearest neighbours) algorithm to classify Iris flower based on their sepal and petal measurements.

Objective: To understand the KNN classifier.

FAQ's.

Q1) In K-NN, what does 'K' stand for, and how does its value affect the algorithm's predictions? Explain why using too few or too many neighbours can be problematic.

→ In K-NN, K stands for the number of nearest neighbors used for predictions. The choice of 'K' significantly impacts the algos performance. When 'K' is too small the model may overfit due to sensitivity to noise and outliers.
When 'K' is too large the model oversmooths ignoring local patterns. Predictions become overly generalized.

Q2) How does K-NN compare the similarity between data points? Discuss different distance (e.g: Euclidean, Manhattan) and their suitability for various types of data.

→ ~~Kn~~ KNN compares data point similarity by measuring distances, often using metrics like Euclidean and Manhattan distance.

1. Euclidean Distance:
Measures straight line distance, suitable for continous data with equal feature importance but sensitive to scaling differences.

2. Manhattan Distance:
Sums absolute feature differences, suitable for high dimensional or categorical data, robust to outliers.

Q3) Imagine you're a new data point. How does K-NN determine which other data points are your 'nearest neighbours'? Describe the steps involved in this process.

→ Steps :
1) Calculate distance: Compute distance betn new point and all existing data points.
2) Sort distance: Arrange distances in ascending order to find the closest points.
3) Select Neighbours: Chose the 'k' closest data point as the nearest neighbors.
4) Make Predictions: Use a voting mechanism or weighted avg among neighbors to predict new points label or value.
5) Handle Ties: Employ additional rules if there are ties in voting or averaging to resolve and finalize the prediction.

Q4) How does K-NN use the information from its nearest neighbors to make predictions for new data points? Explain the different appraoches for classification and regression tasks.

→ In K-NN, for both classification and regression tasks:

Classification:

1. Voting Mechanism: Majority class among the 'K' nearest neighbours determines the predictions.
2. Weighted Voting: Proximity-based weights assigned to neighbors influence the prediction.

Regression:

1. Simple average: Mean of target value from 'K' nearest neighbors predicts the value.
2. Weighted average: Proximity-based weights assigned to neighbors influence the prediction.

Q5) What are some key advantages and limitations of the K-NN algorithm? Discuss scenarios where it might be a good choice or where other algo's might be more suitable.

→ Advantages of K-NN:

1. Simple to understand
2. No training phase
3. Adaptability to different data.

Limitations:

1. Computational cost.
2. Sensitivity to noise and outliers.
3. Scaling and Normalization Dependency.

Scenario's :

Good choice : Suitable for small to medium-sized data--sets with few features.

More Suitable Algorithms: Other algo's like decision trees or neural networks might be preferred for large datasets. or when computational efficiency is critical.

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February 8, 2024

[1]:
```python
import pandas as pd
from sklearn.datasets import load_iris
iris = load_iris()
```

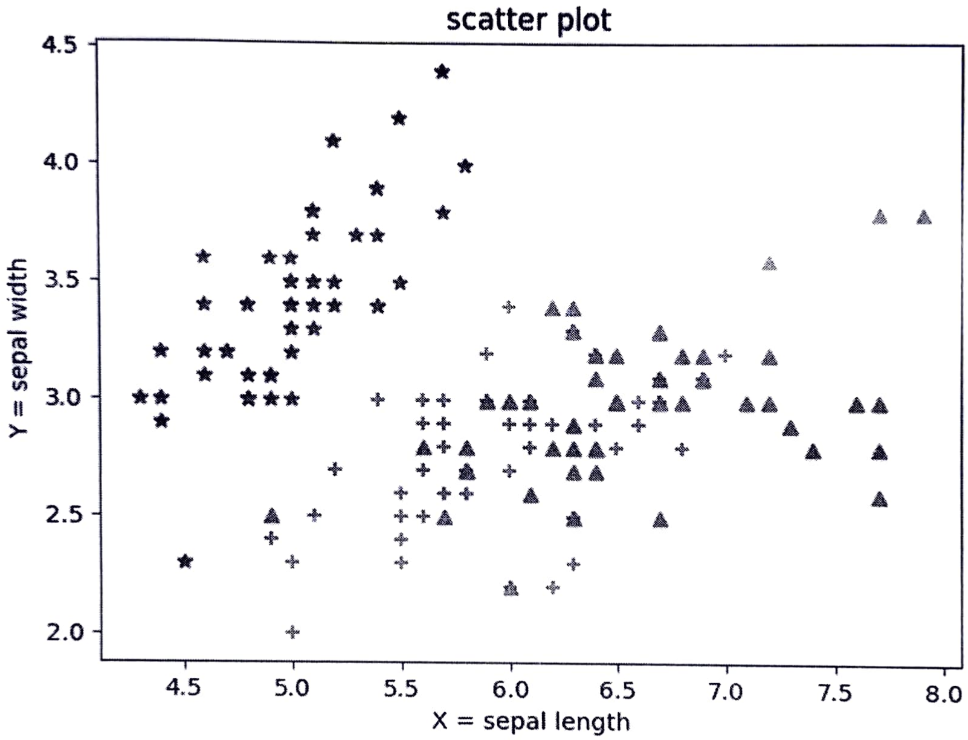
[2]:
```python
iris.target_names
df = pd.DataFrame(iris.data , columns=iris.feature_names)
df_target = pd.DataFrame(iris.target_names)
print("Features: \n", df.head())

print(" \nIris Dataset: \n", df_target)
```

```
Features:
    sepal length (cm)  sepal width (cm)  petal length (cm)  petal width (cm)
0                5.1               3.5                1.4               0.2
1                4.9               3.0                1.4               0.2
2                4.7               3.2                1.3               0.2
3                4.6               3.1                1.5               0.2
4                5.0               3.6                1.4               0.2

Iris Dataset:
              0
0      setosa
1  versicolor
2   virginica
```

[3]:
```python
import matplotlib.pyplot as plt
df0=df[:50]
df1=df[50:100]
df2=df[100:150]

plt.title("scatter plot")
plt.xlabel('X = sepal length')
plt.ylabel('Y = sepal width')
plt.scatter(df0['sepal length (cm)'],df0['sepal width (cm)'], color = 'blue',␣
 ↪marker='+')
plt.scatter(df1['sepal length (cm)'],df1['sepal width (cm)'], color = "red",␣
 ↪marker = "+")
```

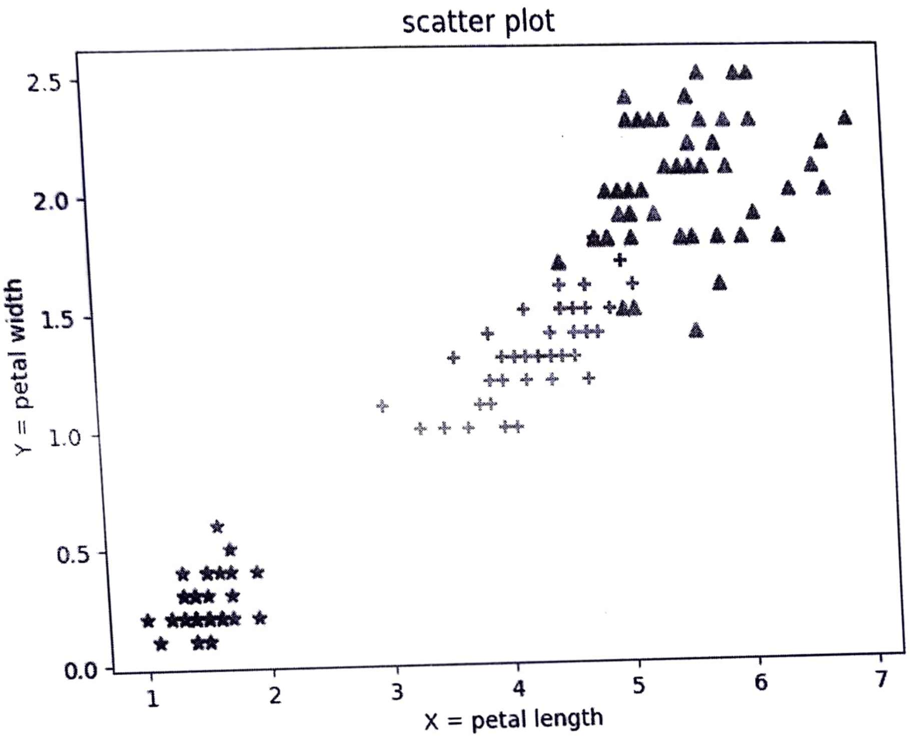
```
plt.scatter(df2['sepal length (cm)'],df2['sepal width (cm)'],color = "green",␣
↪marker ="^")
```

[3]: <matplotlib.collections.PathCollection at 0x7fab95aab070>



[4]:
```
import matplotlib.pyplot as plt
df0=df[:50]
df1=df[50:100]
df2=df[100:150]

plt.title("scatter plot")
plt.xlabel('X = petal length')
plt.ylabel('Y = petal width')
plt.scatter(df0['petal length (cm)'],df0['petal width (cm)'], color = 'blue',␣
↪marker='*')
plt.scatter(df1['petal length (cm)'],df1['petal width (cm)'], color = "red",␣
↪marker = "+")
plt.scatter(df2['petal length (cm)'],df2['petal width (cm)'],color = "green",␣
↪marker ="^")
```

[4]: <matplotlib.collections.PathCollection at 0x7fab9594f100>




```
[5]: from sklearn.neighbors import KNeighborsClassifier
     from sklearn.model_selection import train_test_split
     # Load the Iris dataset
     X = df
     y = iris.target
     # Split the dataset into training and testing sets
     X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33,␣
      ↪random_state=42)

     print(X_train)
     print(X_test)
     print(y_train)
     print(y_test)
```

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)
96	5.7	2.9	4.2	1.3
105	7.6	3.0	6.6	2.1
66	5.6	3.0	4.5	1.5

```
0                    5.1               3.5                1.4               0.2
122                  7.7               2.8                6.7               2.0
..                   ...               ...                ...               ...
71                   6.1               2.8                4.0               1.3
106                  4.9               2.5                4.5               1.7
14                   5.8               4.0                1.2               0.2
92                   5.8               2.6                4.0               1.2
102                  7.1               3.0                5.9               2.1

[100 rows x 4 columns]
     sepal length (cm)  sepal width (cm)  petal length (cm)  petal width (cm)
73                 6.1               2.8                4.7               1.2
18                 5.7               3.8                1.7               0.3
118                7.7               2.6                6.9               2.3
78                 6.0               2.9                4.5               1.5
76                 6.8               2.8                4.8               1.4
31                 5.4               3.4                1.5               0.4
64                 5.6               2.9                3.6               1.3
141                6.9               3.1                5.1               2.3
68                 6.2               2.2                4.5               1.5
82                 5.8               2.7                3.9               1.2
110                6.5               3.2                5.1               2.0
12                 4.8               3.0                1.4               0.1
36                 5.5               3.5                1.3               0.2
9                  4.9               3.1                1.5               0.1
19                 5.1               3.8                1.5               0.3
56                 6.3               3.3                4.7               1.6
104                6.5               3.0                5.8               2.2
69                 5.6               2.5                3.9               1.1
55                 5.7               2.8                4.5               1.3
132                6.4               2.8                5.6               2.2
29                 4.7               3.2                1.6               0.2
127                6.1               3.0                4.9               1.8
26                 5.0               3.4                1.6               0.4
128                6.4               2.8                5.6               2.1
131                7.9               3.8                6.4               2.0
145                6.7               3.0                5.2               2.3
108                6.7               2.5                5.8               1.8
143                6.8               3.2                5.9               2.3
45                 4.8               3.0                1.4               0.3
30                 4.8               3.1                1.6               0.2
22                 4.6               3.6                1.0               0.2
15                 5.7               4.4                1.5               0.4
65                 6.7               3.1                4.4               1.4
11                 4.8               3.4                1.6               0.2
42                 4.4               3.2                1.3               0.2
146                6.3               2.5                5.0               1.9
51                 6.4               3.2                4.5               1.5
```

27	5.2	3.5	1.5	0.2
4	5.0	3.6	1.4	0.2
32	5.2	4.1	1.5	0.1
142	5.8	2.7	5.1	1.9
85	6.0	3.4	4.5	1.6
86	6.7	3.1	4.7	1.5
16	5.4	3.9	1.3	0.4
10	5.4	3.7	1.5	0.2
81	5.5	2.4	3.7	1.0
133	6.3	2.8	5.1	1.5
137	6.4	3.1	5.5	1.8
75	6.6	3.0	4.4	1.4
109	7.2	3.6	6.1	2.5

```
[1 2 1 0 2 1 0 0 0 1 2 0 0 0 1 0 1 2 0 1 2 0 2 2 1 1 2 1 0 1 2 0 0 1 1 0 2
 0 0 1 1 2 1 2 2 1 0 0 2 2 0 0 0 1 2 0 2 2 0 1 1 2 1 2 0 2 1 2 1 1 1 0 1 1
 0 1 2 2 0 1 2 2 0 2 0 1 2 2 1 2 1 1 2 2 0 1 2 0 1 2]
[1 0 2 1 1 0 1 2 1 1 2 0 0 0 0 1 2 1 1 2 0 2 0 2 2 2 2 2 0 0 0 0 1 0 0 2 1
 0 0 0 2 1 1 0 0 1 2 2 1 2]
```

[6]:
```
# Initialize and train the KNN classifier
#importing the knn model
from sklearn.neighbors import KNeighborsClassifier
neigh = KNeighborsClassifier(n_neighbors=10)
```

[7]:
```
#fitting the model
neigh.fit(X_train, y_train)
```

[7]: KNeighborsClassifier(n_neighbors=10)

[8]:
```
#Seeing the score of the model
neigh.score(X_test,y_test)
```

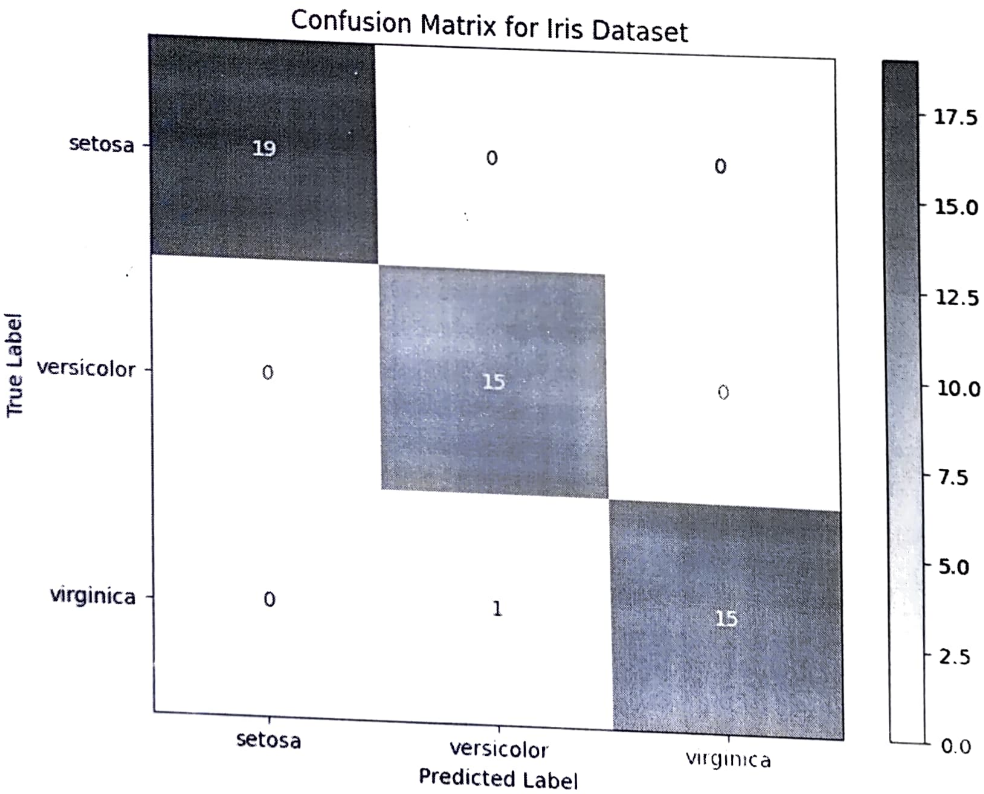
[8]: 0.98

[9]:
```
#predicting the model
neigh.predict(X_test)
```

[9]:
```
array([1, 0, 2, 1, 1, 0, 1, 2, 1, 1, 2, 0, 0, 0, 0, 1, 2, 1, 1, 2, 0, 2,
       0, 2, 2, 2, 2, 2, 0, 0, 0, 0, 1, 0, 0, 2, 1, 0, 0, 0, 2, 1, 1, 0,
       0, 1, 1, 2, 1, 2])
```

[12]:
```
#predicting and generating the confusion matrix
from sklearn.metrics import confusion_matrix
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
import matplotlib.pyplot as plt
y_pred = neigh.predict(X_test)
cm = confusion_matrix(y_test, y_pred)
```

```
cm
# Plot confusion matrix
fig, ax = plt.subplots(figsize=(8, 6))
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=iris.
  ↪target_names)
disp.plot(ax=ax, cmap=plt.cm.Blues)
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title('Confusion Matrix for Iris Dataset')
plt.show()
```




```
[ ]: # Generate and print the classification report

from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import classification_report
```

```
print("Classification Report:")
print(classification_report(y_test, y_pred, target_names=iris.target_names))
```

```
Classification Report:
              precision    recall  f1-score   support

      setosa       1.00      1.00      1.00        19
  versicolor       0.94      1.00      0.97        15
   virginica       1.00      0.94      0.97        16

    accuracy                           0.98        50
   macro avg       0.98      0.98      0.98        50
weighted avg       0.98      0.98      0.98        50
```

Pankaj
15/02/24