2020

K-Nearest Neighbor (HW5)

CAP5610-HW5

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1. Importing IRIS Dataset

```
df=pd.read_csv(r'C:\Users\chat2\Downloads\Iris.csv')
df1=df.copy()
```

```
df.shape
df.head()
```

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	1	5.1	3.5	1.4	0.2	Iris-setosa
1	2	4.9	3.0	1.4	0.2	Iris-setosa
2	3	4.7	3.2	1.3	0.2	Iris-setosa
3	4	4.6	3.1	1.5	0.2	Iris-setosa
4	5	5.0	3.6	1.4	0.2	Iris-setosa

2. IMPLEMENTING KFOLD CROSS VALIDATION, SPLITTING TRAIN AND TEST DATA

Implementing a custom Kfold Cross Validation Algorithm:

1. Shuffle the dataset initially
2. use array_split() to split the data into k equal parts
3. append each folds (splits) to a list
4. split train and test data from each fold
    - 4.1.1. Include the first fold data in loop as test dataset
    - 4.1.2 Append the rest fold data together provided the test data is not included
    - 4.1.3 Append the new dataset as Train dataset.
5. Slice the dataset for predictor and Response variable respectively.

```
def kfold(input_dataframe,k):
    Datasets=[]

    input_dataframe1=input_dataframe.sample(frac=1)
    fold1,fold2,fold3,fold4,fold5=np.array_split(input_dataframe1,k)
    Datasets.append(fold1)
    Datasets.append(fold2)
    Datasets.append(fold3)
    Datasets.append(fold4)
    Datasets.append(fold5)
    return Datasets

splits=kfold(input_dataframe=df1,k=5)
train=[]
test=[]
for i in range(0,len(splits)):
    test.append(splits[i])
    train.append(pd.DataFrame(np.concatenate(splits[:i]+splits[i+1:])))
train[0].iloc[:,1:5]
print(train[0].iloc[:,1:5].shape)
print(test[0].iloc[:,1:5].shape)
```

```
(120, 4)
(30, 4)
```

- Once the Train and Test dataset is obtained for various folds, We tend to fit the KNN Model from sklearn and find the accuracy of each model for each Fold.
- We find the Average of accuracy to determine the overall performance of the model.
- Average Accuracy of KNN Model from 5 different Folds – 0.9667

```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score
from sklearn.tree import DecisionTreeClassifier
```

```
knn={'KNN accuracy':[]}
acc_sum=0
k=5
for i in range(0,len(train)):

    neigh = KNeighborsClassifier(n_neighbors=k)
    neigh.fit(train[i].iloc[:,1:5],train[i].iloc[:,-1:])
    predict_neigh=neigh.predict(test[i].iloc[:,1:5])
    acc=accuracy_score(test[i].iloc[:,-1:],predict_neigh)
    #print(predict_neigh)
    #print(test[i].iloc[:9,-1:])
    knn['KNN accuracy'].append(acc)
    acc_sum=acc+acc_sum

print(knn)
aggreagate_accuracy_knn=acc_sum/len(train)
print("Average KNN Accuracy: "+str(aggreagate_accuracy_knn))
```

```
{'KNN accuracy': [0.9333333333333333, 1.0, 0.9666666666666667, 0.9333333333333333, 1.0]}
Average KNN Accuracy: 0.9666666666666666
```

- Decision Tree model is fit on the various folds of data.
- Sklearn DecisionTreeClassifier() is used for fitting model.
- Average Accuracy of Decision Tree Model for various fold is 0.9466

```
DT={'DecissionTree accuracy':[]}
acc_sum_dt=0
for i in range(0,len(train)):

    decision_tree = DecisionTreeClassifier()
    decision_tree.fit(train[i].iloc[:,1:5],train[i].iloc[:,-1:])
    predict_tree=decision_tree.predict(test[i].iloc[:,1:5])
    acc_DT=accuracy_score(test[i].iloc[:,-1:],predict_tree)
#     print(predict_tree)
#     print(test[i].iloc[:9,-1:])
    DT['DecissionTree accuracy'].append(acc_DT)
    acc_sum_dt=acc_DT+acc_sum_dt

print(DT)
aggreagate_accuracy_dt=acc_sum_dt/len(train)

print("Average DecissionTree Accuracy: "+str(aggreagate_accuracy_dt))
```

```
{'DecissionTree accuracy': [0.9, 1.0, 0.9, 0.9333333333333333, 1.0]}
Average DecissionTree Accuracy: 0.9466666666666667
```

3.EFFECT OF K on ACCURACY:

1. We tend to determine the various accuracy for different K values.
2. Each fold must be tested for each K value
3. Run a For loop for each fold
4. Run an inside for loop for each value of K
5. We obtain a lists of list which contains Each folds and accuracy for each K value ranging from 1 to 15.
6. We group and sum each accuracy based on the K value for different folds
7. For E.g.: adding up K value=1 for Fold1, Fold2,Fold3,Fold4,Fold5 and taking an average.
8. We finally arrive average accuracy for each K value ranging from 1-15 grouped Folds.

```
import warnings
warnings.filterwarnings('ignore')
knn_diff=[]

k_value=16
for i in range(0,len(train)):
    g=[]
    k=[]
    z=str(i)

    for j in range(1,k_value):
        y=str(j)
        acc_sum_k=0
        neigh = KNeighborsClassifier(n_neighbors=j)
        neigh.fit(train[i].iloc[:,1:5],train[i].iloc[:,-1:])
        predict_neigh=neigh.predict(test[i].iloc[:,1:5])
        acc=accuracy_score(test[i].iloc[:,-1:],predict_neigh)
        #print(predict_neigh)
        #print(test[i].iloc[:9,-1:])

        k.append(acc)

    knn_diff.append(k)
print(knn_diff)

sum_k = np.sum(knn_diff,0)

avg_k=sum_k/len(knn_diff)

#print(avg_k)
```

```
[[0.9333333333333333, 0.9, 0.9666666666666667, 0.9, 0.9333333333333333, 0.9, 0.9666666666666667, 0.9333333333333333, 0.9666666666666667, 0.9666666666666667, 0.9666666666666667, 0.9666666666666667, 0.9666666666666667, 0.9666666666666667, 0.9666666666666667], [0.9666666666666667, 0.9666666666666667, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0], [0.9333333333333333, 0.9, 0.9666666666666667, 0.9666666666666667, 0.9666666666666667, 1.0, 0.9666666666666667, 1.0, 0.9666666666666667, 1.0, 0.9666666666666667, 0.9666666666666667, 1.0, 1.0, 0.9666666666666667], [0.9, 0.9, 0.9333333333333333, 0.9333333333333333, 0.9333333333333333, 0.9666666666666667, 0.9666666666666667, 0.9666666666666667, 0.9666666666666667, 0.9666666666666667, 0.9333333333333333, 0.9666666666666667, 0.9333333333333333, 0.9666666666666667, 0.9666666666666667], [1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0]]
```

Calculating Average accuracy of each K value for grouped by Folds.

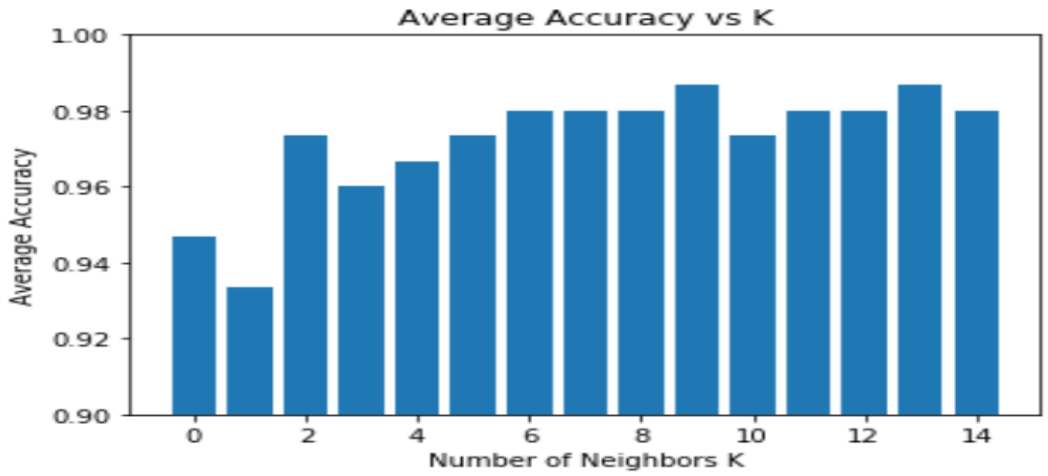
```
        acc=accuracy_score(test[i].iloc[:,-1:],predict_neigh)
        #print(predict_neigh)
        #print(test[i].iloc[:9,-1:])

        k.append(acc)

    knn_diff.append(k)
#print(knn_diff)

sum_k = np.sum(knn_diff,0)

avg_k=sum_k/len(knn_diff)

print(avg_k)
```

```
[0.94666667 0.93333333 0.97333333 0.96       0.96666667 0.97333333
 0.98       0.98       0.98       0.98666667 0.97333333 0.98
 0.98       0.98666667 0.98      ]
```

3. EVALUATING IMPACT OF K ON ACCURACY

- We use histogram to represent the Different accuracy level for Different K values.

```
import matplotlib.pyplot as plt
plt.bar([y for y in range(k_value-1)], avg_k)
plt.ylim([0.9,1])
plt.xlabel("Number of Neighbors K")
plt.ylabel("Average Accuracy")
plt.title("Average Accuracy vs K")
plt.show()
```



- The maximum Accuracy 0.986 is found when K value is 9

```
print(avg_k.max())
max=np.argmax(avg_k)
max
```

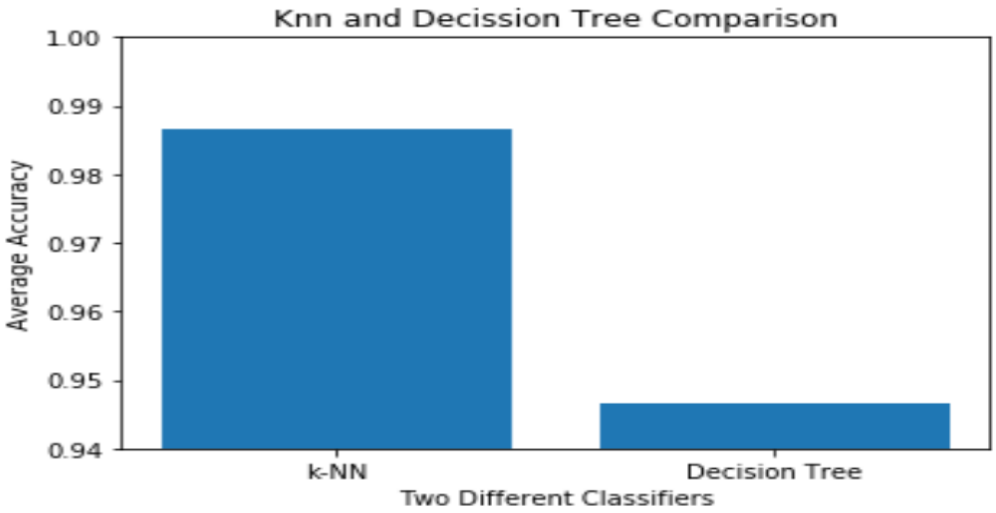
```
0.9866666666666667
9
```

- We could see the trend that for low K values the accuracy is quite low but it attains a standard state once the K value more than 6, Out of which 9 had maximum accuracy.

4. COMPARISON OF KNN AND DECISSION TREE

Comparing the accuracy of Decision Tree and KNN model we Infer from Histogram that KNN performs well for k =9 and has higher accuracy than Decision Tree Algorithm

```
obj = ('k-NN', 'Decision Tree')
ypos=np.arange(len(obj))
plt.bar(np.arange(2), [avg_k[9],aggreagate_accuracy_dt])
plt.ylim([0.94,1])
plt.xlabel("Two Different Classifiers")
plt.ylabel("Average Accuracy")
plt.title("Knn and Decission Tree Comparison")
plt.xticks(ypos, obj)
plt.show()
```



CODELINK:

https://github.com/bhuvaneshkj/CAP5610-MachineLearning-Assignment