MACHINE LEARNING LAB - TUTORIAL 7

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1. DATA PRE-PROCESSING

In [1]:
```
import pandas as pd
import numpy as np
from collections import Counter
import math
import matplotlib.pyplot as plt
```

D1 DATA - IRIS

The dataset used is the Iris dataset and the main goal of the implementation is to classify the test set to the nearest class.

In [2]:
```
missing_values = ['-','na','Nan','nan','n/a','?']
column_names_iris = ['Sepal length in cm','Sepal width in cm','Peta
l length in cm','Petal width in cm','Class']
D1 = pd.read_csv("iris.data", sep=',', na_values = missing_values,
names=column_names_iris)
D1.head()
```

Out[2]:

	Sepal length in cm	Sepal width in cm	Petal length in cm	Petal width in cm	Class
0	5.1	3.5	1.4	0.2	Iris-setosa
1	4.9	3.0	1.4	0.2	Iris-setosa
2	4.7	3.2	1.3	0.2	Iris-setosa
3	4.6	3.1	1.5	0.2	Iris-setosa
4	5.0	3.6	1.4	0.2	Iris-setosa

In [3]:
```
# Check for missing or incongruent values
check = D1.empty
print('checking missing values:',check)
print('Sum of errors:',D1.isnull().sum())
```

```
checking missing values: False
Sum of errors: Sepal length in cm    0
Sepal width in cm     0
Petal length in cm    0
Petal width in cm     0
Class                 0
dtype: int64
```

SPLIT DATA 70% TRAIN 30% TEST

In [4]:
```
D1_train = D1.sample(frac=0.7, random_state=1)
D1_test = D1.drop(D1_train.index)
```

In [5]:
```
Y_train = D1_train['Class'].values
X_train = D1_train.drop(['Class'], axis=1).values
Y_test = D1_test['Class'].values
X_test = D1_test.drop(['Class'], axis=1).values
```

IMPLEMENT K-NEAREST NEIGHBOUR (KNN)

In [6]:
```
rows= []
rows_All = []
Each_row = []
k_nearest_array = []
array_k_nearest_index = []
new_class = []
final_classes = []
k = 3
scatter = []

# measuring the distance for each row of test set with each row of
training set
for index, j in enumerate(X_test):
    row = []
    for index, i in enumerate(X_train):
        count = 0
        distance = math.sqrt(sum((i - j) ** 2)) # Euclidean distanc
e.
        count += distance
        row.append((count, index))
        row.sort()
    rows_All.append(row)

# Extracting the index of each row to further select the class.
for i in range(len(rows_All)):
    k_nearest = (rows_All[i][:k])
    k_nearest_array = []
    for j in range(len(k_nearest)):
        p = (k_nearest[j][1])
        k_nearest_array.append(p)
    array_k_nearest_index.append(k_nearest_array)


# Matching each index to the respective class
assign_class = []
for j in range(len(array_k_nearest_index)):
    u = []
    classification=[]
    for h in (array_k_nearest_index[j]):
        for l in range(len(Y_train)):
            if h == l:
                clas=Y_train[l]
                u.append(clas)
    classification.append(u)

# Selecting the most common class for each row of test data.

    for p in classification:
        p2 = np.array(p).flatten()
        a = Counter(p2).most_common(1)[0][0]
        final_classes.append(a)
```

In [7]:
```
# Outcome of the exercise with the number of correctly matched clas
ses and Accuracy value
count = 0
boolean = []

for i in range(len(final_classes)):
    if final_classes[i] == Y_test[i]:
        count+=1
        answer = 'Match'
        boolean.append(answer)
    else:
        answer = 'Wrong'
        boolean.append(answer)
print('Correctly matched classes:',count)
accuracy = count/len(final_classes)
print('Accuracy of prediction:',accuracy)
```

```
Correctly matched classes: 42
Accuracy of prediction: 0.9333333333333333
```

In [8]:
```
dataset = pd.DataFrame({'Predicted Class': final_classes, 'Y test C
lass': Y_test, 'Accuracy of matches': boolean})

def not_match(val):
    color = 'red' if val == 'Wrong' else 'black'
    return 'color: %s' % color

df = dataset.style.applymap(not_match)
df
```

Out[8]:

	Predicted Class	Y test Class	Accuracy of matches
0	Iris-setosa	Iris-setosa	Match
1	Iris-setosa	Iris-setosa	Match
2	Iris-setosa	Iris-setosa	Match
3	Iris-setosa	Iris-setosa	Match
4	Iris-setosa	Iris-setosa	Match
5	Iris-setosa	Iris-setosa	Match
6	Iris-setosa	Iris-setosa	Match
7	Iris-setosa	Iris-setosa	Match
8	Iris-setosa	Iris-setosa	Match
9	Iris-setosa	Iris-setosa	Match
10	Iris-setosa	Iris-setosa	Match
11	Iris-setosa	Iris-setosa	Match
12	Iris-setosa	Iris-setosa	Match

13	Iris-setosa	Iris-setosa	Match
14	Iris-setosa	Iris-setosa	Match
15	Iris-setosa	Iris-setosa	Match
16	Iris-setosa	Iris-setosa	Match
17	Iris-versicolor	Iris-versicolor	Match
18	Iris-versicolor	Iris-versicolor	Match
19	Iris-versicolor	Iris-versicolor	Match
20	Iris-versicolor	Iris-versicolor	Match
21	Iris-versicolor	Iris-versicolor	Match
22	Iris-versicolor	Iris-versicolor	Match
23	Iris-virginica	Iris-versicolor	Wrong
24	Iris-versicolor	Iris-versicolor	Match
25	Iris-virginica	Iris-versicolor	Wrong
26	Iris-versicolor	Iris-versicolor	Match
27	Iris-versicolor	Iris-versicolor	Match
28	Iris-versicolor	Iris-versicolor	Match
29	Iris-versicolor	Iris-versicolor	Match
30	Iris-versicolor	Iris-versicolor	Match
31	Iris-versicolor	Iris-versicolor	Match
32	Iris-virginica	Iris-virginica	Match
33	Iris-versicolor	Iris-virginica	Wrong
34	Iris-virginica	Iris-virginica	Match
35	Iris-virginica	Iris-virginica	Match
36	Iris-virginica	Iris-virginica	Match
37	Iris-virginica	Iris-virginica	Match
38	Iris-virginica	Iris-virginica	Match
39	Iris-virginica	Iris-virginica	Match
40	Iris-virginica	Iris-virginica	Match
41	Iris-virginica	Iris-virginica	Match
42	Iris-virginica	Iris-virginica	Match
43	Iris-virginica	Iris-virginica	Match
44	Iris-virginica	Iris-virginica	Match

Observations

1. The measure of accuracy chosen is a division between the sum of all accurate predicted classes by the total number of entries. This measure is chosen considering the fact of a **supervised learning** algorithm where all the right classes are known. Moreover, since it is a classification model it is feasible to compare 'right match' and 'wrong match' classes. Consequently, it is an instinctive way of measuring accuracy.

DETERMINE OPTIMAL VALUE OF K IN KNN ALGORITHM.

In [9]:

```
rows= []
rows_All = []
Each_row = []
k_nearest_array = []
array_k_nearest_index = []
new_class = []
final_classes = []
accuracy_array = []
final_Accuracy = []
plot_k = []
plot_error = []
k = [2, 3, 5, 6, 7, 8, 10, 12, 13, 21]

# Iterating through each value of K
# measuring the distance for each row of test set with each row of
training set
for q in k:
    final_Accuracy = []
    print('K:',q)
    for index, j in enumerate(X_test):
        row = []
        for index, i in enumerate(X_train):
            count = 0
            distance = math.sqrt(sum((i - j) ** 2))
            count += distance
            row.append((count, index))
            row.sort()
        rows_All.append(row)

    # Extracting the index of each row to further select the class.

    for i in range(len(rows_All)):
        k_nearest = (rows_All[i][:q])
        k_nearest_array = []
        for j in range(len(k_nearest)):
            p = (k_nearest[j][1])
```

```
            k_nearest_array.append(p)
        array_k_nearest_index.append(k_nearest_array)

    # Matching each index to the respective class
    assign_class = []
    for j in range(len(array_k_nearest_index)):
        u = []
        classification=[]
        for h in (array_k_nearest_index[j]):
            for l in range(len(Y_train)):
                if h == l:
                    clas=Y_train[l]
                    u.append(clas)
        classification.append(u)


        # Selecting the most common class for each row of test data
.

        for p in classification:
            p2 = np.array(p).flatten()
            a = Counter(p2).most_common(1)[0][0]
            final_classes.append(a)

    count = 0
    boolean = []

    for i in range(len(final_classes)):

        if final_classes[i] == Y_test[i]:
            count+=1
            answer = 'Match'
            boolean.append(answer)
        else:
            answer = 'Wrong'
            boolean.append(answer)
    print('Correctly matched classes:',count)
    accuracy = count/len(final_classes)
    error = 1 - accuracy
    plot_k.append(q)
    plot_error.append(error)
    print('Accuracy of prediction:',accuracy)
    print('Error of prediction:',error)
    optimal_Results = (accuracy, q)
    accuracy_array.append(optimal_Results)
    rows= []
    rows_All = []
    Each_row = []
    k_nearest_array = []
    array_k_nearest_index = []
    new_class = []
    final_classes = []
optimum_value = max(accuracy_array)
print('\n','Higher Accuracy prediction & Optimum K:', optimum_value
```

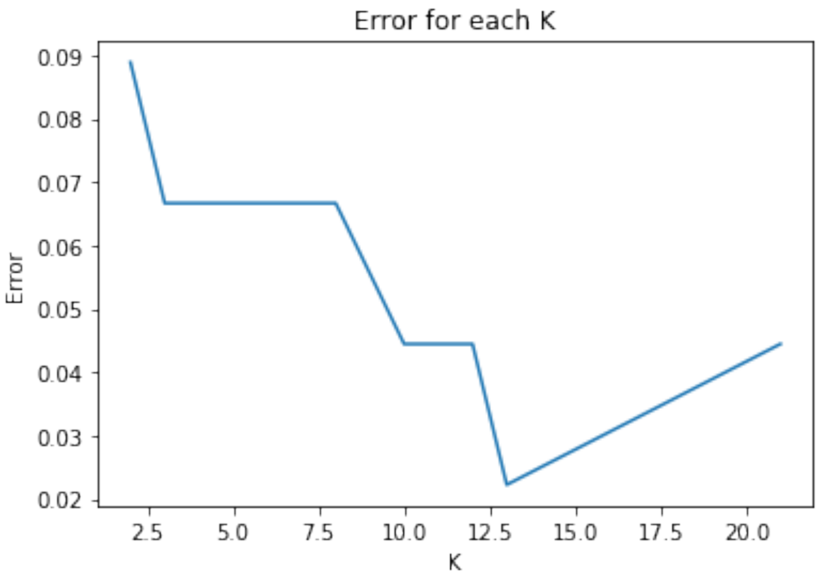
```
)
```

```
K: 2
Correctly matched classes: 41
Accuracy of prediction: 0.9111111111111111
Error of prediction: 0.0888888888888889
K: 3
Correctly matched classes: 42
Accuracy of prediction: 0.9333333333333333
Error of prediction: 0.06666666666666665
K: 5
Correctly matched classes: 42
Accuracy of prediction: 0.9333333333333333
Error of prediction: 0.06666666666666665
K: 6
Correctly matched classes: 42
Accuracy of prediction: 0.9333333333333333
Error of prediction: 0.06666666666666665
K: 7
Correctly matched classes: 42
Accuracy of prediction: 0.9333333333333333
Error of prediction: 0.06666666666666665
K: 8
Correctly matched classes: 42
Accuracy of prediction: 0.9333333333333333
Error of prediction: 0.06666666666666665
K: 10
Correctly matched classes: 43
Accuracy of prediction: 0.9555555555555556
Error of prediction: 0.0444444444444444
K: 12
Correctly matched classes: 43
Accuracy of prediction: 0.9555555555555556
Error of prediction: 0.0444444444444444
K: 13
Correctly matched classes: 44
Accuracy of prediction: 0.9777777777777777
Error of prediction: 0.022222222222222254
K: 21
Correctly matched classes: 43
Accuracy of prediction: 0.9555555555555556
Error of prediction: 0.0444444444444444

 Higher Accuracy prediction & Optimum K: (0.9777777777777777, 13)
```

Plotting the Error of each k

In [10]:
```
plt.plot(plot_k, plot_error)
plt.title('Error for each K')
plt.xlabel('K')
plt.ylabel('Error')
plt.show()
```



Observations

1. Considering the different variations of **K** selected all predictions are working with high accuracy for classifying each datapoint.

2. Cross validation is not used in this exercise because this is not a training model.

3. Surprisingly, one could say that the higher the number of K we add to the model the more accurate the model will work. That observation is partly true. Finding the optimal K value and plotting the error helps to avoid silly decisions based on partial information. Identifying the ideal value for which classification works out well means that if adding +-1 to k will decrease the accuracy.

4. There are a few number of k's with the same accuracy value. In this exercise all of them are sequentially. Therefore, in a real world application it would mislead the final classification output. It is always good to test with different values of k and specially if they are not sequentially to see the real impact of accuracy for different k's.

5. being questioning myself what would happen if for a specific k there is a tie between categories. A good practice is to use odd number of k instead of chossing a random classification from the options.

6. The model works automatically and it is possible to add more K values. The printing of each K results is done to see a better picture and compare them accordingly.