# CS550_Week4HW1_Yixin_Cao_19536

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# 1 KNN on Iris Dataset

## 1.1 By Yixin Cao

[38]:
```
#importing the required libraries
import pandas as pd
import numpy as np
import operator
import matplotlib.pyplot as plt
```

### 1.1.1 Reading data from Drive:

Need to mount to Google Drive and Copy the file path to read

[39]:
```
#reading data from the csv file
data = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/CS550 Machine␣
↪Learning/iris.csv')
data
```

[39]:

| | sepal_length | sepal_width | petal_length | petal_width | variety |
|---|---|---|---|---|---|
| 0 | 5.1 | 3.5 | 1.4 | 0.2 | Setosa |
| 1 | 4.9 | 3.0 | 1.4 | 0.2 | Setosa |
| 2 | 4.7 | 3.2 | 1.3 | 0.2 | Setosa |
| 3 | 4.6 | 3.1 | 1.5 | 0.2 | Setosa |
| 4 | 5.0 | 3.6 | 1.4 | 0.2 | Setosa |
| .. | … | … | … | … | … |
| 145 | 6.7 | 3.0 | 5.2 | 2.3 | Virginica |
| 146 | 6.3 | 2.5 | 5.0 | 1.9 | Virginica |
| 147 | 6.5 | 3.0 | 5.2 | 2.0 | Virginica |
| 148 | 6.2 | 3.4 | 5.4 | 2.3 | Virginica |
| 149 | 5.9 | 3.0 | 5.1 | 1.8 | Virginica |

[150 rows x 5 columns]

### 1.1.2 Divide the dataset

[40]:
```python
#randomize the indices
indices = np.random.permutation(data.shape[0])
div = int(0.75 * len(indices))
development_id, test_id = indices[:div], indices[div:]
#dividing the dataset using randomized indices
development_set, test_set = data.loc[development_id,:], data.loc[test_id,:]
print("Development Set:\n", development_set, "\n\nTest Set:\n", test_set)
```

```
Development Set:
      sepal_length  sepal_width  petal_length  petal_width     variety
114           5.8          2.8           5.1          2.4   Virginica
143           6.8          3.2           5.9          2.3   Virginica
50            7.0          3.2           4.7          1.4  Versicolor
78            6.0          2.9           4.5          1.5  Versicolor
54            6.5          2.8           4.6          1.5  Versicolor
..            …          …           …          …         …
30            4.8          3.1           1.6          0.2      Setosa
66            5.6          3.0           4.5          1.5  Versicolor
38            4.4          3.0           1.3          0.2      Setosa
22            4.6          3.6           1.0          0.2      Setosa
142           5.8          2.7           5.1          1.9   Virginica

[112 rows x 5 columns]

Test Set:
      sepal_length  sepal_width  petal_length  petal_width     variety
60            5.0          2.0           3.5          1.0  Versicolor
132           6.4          2.8           5.6          2.2   Virginica
109           7.2          3.6           6.1          2.5   Virginica
71            6.1          2.8           4.0          1.3  Versicolor
36            5.5          3.5           1.3          0.2      Setosa
28            5.2          3.4           1.4          0.2      Setosa
122           7.7          2.8           6.7          2.0   Virginica
121           5.6          2.8           4.9          2.0   Virginica
104           6.5          3.0           5.8          2.2   Virginica
1             4.9          3.0           1.4          0.2      Setosa
87            6.3          2.3           4.4          1.3  Versicolor
0             5.1          3.5           1.4          0.2      Setosa
145           6.7          3.0           5.2          2.3   Virginica
72            6.3          2.5           4.9          1.5  Versicolor
57            4.9          2.4           3.3          1.0  Versicolor
116           6.5          3.0           5.5          1.8   Virginica
106           4.9          2.5           4.5          1.7   Virginica
80            5.5          2.4           3.8          1.1  Versicolor
129           7.2          3.0           5.8          1.6   Virginica
40            5.0          3.5           1.3          0.3      Setosa
```

```
81           5.5          2.4           3.7          1.0  Versicolor
144          6.7          3.3           5.7          2.5   Virginica
8            4.4          2.9           1.4          0.2      Setosa
118          7.7          2.6           6.9          2.3   Virginica
26           5.0          3.4           1.6          0.4      Setosa
49           5.0          3.3           1.4          0.2      Setosa
93           5.0          2.3           3.3          1.0  Versicolor
89           5.5          2.5           4.0          1.3  Versicolor
15           5.7          4.4           1.5          0.4      Setosa
130          7.4          2.8           6.1          1.9   Virginica
45           4.8          3.0           1.4          0.3      Setosa
105          7.6          3.0           6.6          2.1   Virginica
65           6.7          3.1           4.4          1.4  Versicolor
76           6.8          2.8           4.8          1.4  Versicolor
63           6.1          2.9           4.7          1.4  Versicolor
58           6.6          2.9           4.6          1.3  Versicolor
64           5.6          2.9           3.6          1.3  Versicolor
147          6.5          3.0           5.2          2.0   Virginica
```

### 1.1.3 Calculate set mean and standard deviation

[41]:
```
mean_development_set = development_set.mean()
print("Mean of Development set: \n",mean_development_set)
mean_test_set = test_set.mean()
print("Mean of test set: \n",mean_development_set)
std_development_set = development_set.std()
print("Standard deviation of Development set: \n",mean_development_set)
std_test_set = test_set.std()
print("Standard deviation of test set: \n",mean_development_set)
```

```
Mean of Development set:
 sepal_length    5.798214
sepal_width     3.100893
petal_length    3.678571
petal_width     1.168750
dtype: float64
Mean of test set:
 sepal_length    5.798214
sepal_width     3.100893
petal_length    3.678571
petal_width     1.168750
dtype: float64
Standard deviation of Development set:
 sepal_length    5.798214
sepal_width     3.100893
petal_length    3.678571
petal_width     1.168750
dtype: float64
```

```
Standard deviation of test set:
 sepal_length    5.798214
sepal_width     3.100893
petal_length    3.678571
petal_width     1.168750
dtype: float64
```

```
<ipython-input-41-082befa235ee>:1: FutureWarning: Dropping of nuisance columns
in DataFrame reductions (with 'numeric_only=None') is deprecated; in a future
version this will raise TypeError.  Select only valid columns before calling the
reduction.
  mean_development_set = development_set.mean()
<ipython-input-41-082befa235ee>:3: FutureWarning: Dropping of nuisance columns
in DataFrame reductions (with 'numeric_only=None') is deprecated; in a future
version this will raise TypeError.  Select only valid columns before calling the
reduction.
  mean_test_set = test_set.mean()
<ipython-input-41-082befa235ee>:5: FutureWarning: Dropping of nuisance columns
in DataFrame reductions (with 'numeric_only=None') is deprecated; in a future
version this will raise TypeError.  Select only valid columns before calling the
reduction.
  std_development_set = development_set.std()
<ipython-input-41-082befa235ee>:7: FutureWarning: Dropping of nuisance columns
in DataFrame reductions (with 'numeric_only=None') is deprecated; in a future
version this will raise TypeError.  Select only valid columns before calling the
reduction.
  std_test_set = test_set.std()
```

#### 1.1.4 Calculating the mean and standard deviation of the development set and test set for normalizing the data.

[42]:
```
test_class = list(test_set.iloc[:,-1])
dev_class = list(development_set.iloc[:,-1])
mean_development_set = development_set.mean()
print("Mean of development set: \n",mean_development_set)
mean_test_set = test_set.mean()
print("Mean of test set: \n",mean_development_set)
std_development_set = development_set.std()
print("Standard deviation of development set: \n",std_development_set)
std_test_set = test_set.std()
print("Standard deviation of test set: \n",std_test_set)
```

```
Mean of development set:
 sepal_length    5.798214
sepal_width     3.100893
petal_length    3.678571
petal_width     1.168750
dtype: float64
```

```
Mean of test set:
 sepal_length    5.798214
sepal_width     3.100893
petal_length    3.678571
petal_width     1.168750
dtype: float64
Standard deviation of development set:
 sepal_length    0.788656
sepal_width     0.422668
petal_length    1.752344
petal_width     0.767238
dtype: float64
Standard deviation of test set:
 sepal_length    0.933298
sepal_width     0.454353
petal_length    1.806053
petal_width     0.750059
dtype: float64
```

```
<ipython-input-42-a713a9759383>:3: FutureWarning: Dropping of nuisance columns
in DataFrame reductions (with 'numeric_only=None') is deprecated; in a future
version this will raise TypeError.  Select only valid columns before calling the
reduction.
  mean_development_set = development_set.mean()
<ipython-input-42-a713a9759383>:5: FutureWarning: Dropping of nuisance columns
in DataFrame reductions (with 'numeric_only=None') is deprecated; in a future
version this will raise TypeError.  Select only valid columns before calling the
reduction.
  mean_test_set = test_set.mean()
<ipython-input-42-a713a9759383>:7: FutureWarning: Dropping of nuisance columns
in DataFrame reductions (with 'numeric_only=None') is deprecated; in a future
version this will raise TypeError.  Select only valid columns before calling the
reduction.
  std_development_set = development_set.std()
<ipython-input-42-a713a9759383>:9: FutureWarning: Dropping of nuisance columns
in DataFrame reductions (with 'numeric_only=None') is deprecated; in a future
version this will raise TypeError.  Select only valid columns before calling the
reduction.
  std_test_set = test_set.std()
```

### 1.1.5 Functions for distance metric:

- euclidean distance
- normalized euclidean distance
- cosine similarity

[43]:
```
def euclideanDistance(data_1, data_2, data_len):
    dist = 0
```

```
    for i in range(data_len):
        dist = dist + np.square(data_1[i] - data_2[i])
    return np.sqrt(dist)

def normalizedEuclideanDistance(data_1, data_2, data_len, data_mean, data_std):
    n_dist = 0
    for i in range(data_len):
        n_dist = n_dist + (np.square(((data_1[i] - data_mean[i])/data_std[i]) -␣
 ↪((data_2[i] - data_mean[i])/data_std[i])))
    return np.sqrt(n_dist)

# Title: Cosine Similarty between 2 Number Lists
# Author: dontloo
# Date: 03.27.2017
# Code version: 1
# Availability: https://stackoverflow.com/questions/18424228/
 ↪cosine-similarity-between-2-number-lists
def cosineSimilarity(data_1, data_2):
    dot = np.dot(data_1, data_2[:-1])
    norm_data_1 = np.linalg.norm(data_1)
    norm_data_2 = np.linalg.norm(data_2[:-1])
    cos = dot / (norm_data_1 * norm_data_2)
    return (1-cos)
```

### 1.1.6 KNN function

[44]:
```
# KNN
def knn(dataset, testInstance, k, dist_method, dataset_mean, dataset_std):
    distances = {}
    length = testInstance.shape[1]
    if dist_method == 'euclidean':
        for x in range(len(dataset)):
            dist_up = euclideanDistance(testInstance, dataset.iloc[x], length)
            distances[x] = dist_up[0]
    elif dist_method == 'normalized_euclidean':
        for x in range(len(dataset)):
            dist_up = normalizedEuclideanDistance(testInstance, dataset.
 ↪iloc[x], length, dataset_mean, dataset_std)
            distances[x] = dist_up[0]
    elif dist_method == 'cosine':
        for x in range(len(dataset)):
            dist_up = cosineSimilarity(testInstance, dataset.iloc[x])
            distances[x] = dist_up[0]
    # Sort values based on distance
    sort_distances = sorted(distances.items(), key=operator.itemgetter(1))
    neighbors = []
    # Extracting nearest k neighbors
```

```
    for x in range(k):
        neighbors.append(sort_distances[x][0])
    # Initializing counts for 'class' labels counts as 0
    counts = {"Iris-setosa" : 0, "Iris-versicolor" : 0, "Iris-virginica" : 0}
    # Computing the most frequent class
    for x in range(len(neighbors)):
        response = dataset.iloc[neighbors[x]][-1]
        if response in counts:
            counts[response] += 1
        else:
            counts[response] = 1
    # Sorting the class in reverse order to get the most frequest class
    sort_counts = sorted(counts.items(), key=operator.itemgetter(1),␣
↪reverse=True)
    return(sort_counts[0][0])
```

### 1.1.7 Iterating the development data with K=[1,3,5,7] for the distance matrics

[45]:
```
# Creating a list of list of all columns except 'class' by iterating through␣
↪the development set
row_list = []
for index, rows in development_set.iterrows():
    my_list =[rows.sepal_length, rows.sepal_width, rows.petal_length, rows.
↪petal_width]
    row_list.append([my_list])
# k values for the number of neighbors that need to be considered
k_n = [1, 3, 5, 7]
# Distance metrics
distance_methods = ['euclidean', 'normalized_euclidean', 'cosine']
# Performing kNN on the development set by iterating all of the development set␣
↪data points and for each k and each distance metric
obs_k = {}
for dist_method in distance_methods:
    development_set_obs_k = {}
    for k in k_n:
        development_set_obs = []
        for i in range(len(row_list)):
            development_set_obs.append(knn(development_set, pd.
↪DataFrame(row_list[i]), k, dist_method, mean_development_set,␣
↪std_development_set))
        development_set_obs_k[k] = development_set_obs
    # Nested Dictionary containing the observed class for each k and each␣
↪distance metric (obs_k of the form obs_k[dist_method][k])
    obs_k[dist_method] = development_set_obs_k
    print(dist_method.upper() + " distance method performed on the dataset for␣
↪all k values!")
```

```
print(obs_k)
```

```
EUCLIDEAN distance method performed on the dataset for all k values!
NORMALIZED_EUCLIDEAN distance method performed on the dataset for all k values!
COSINE distance method performed on the dataset for all k values!
```

### 1.1.8 Calculate the accuracy and plot

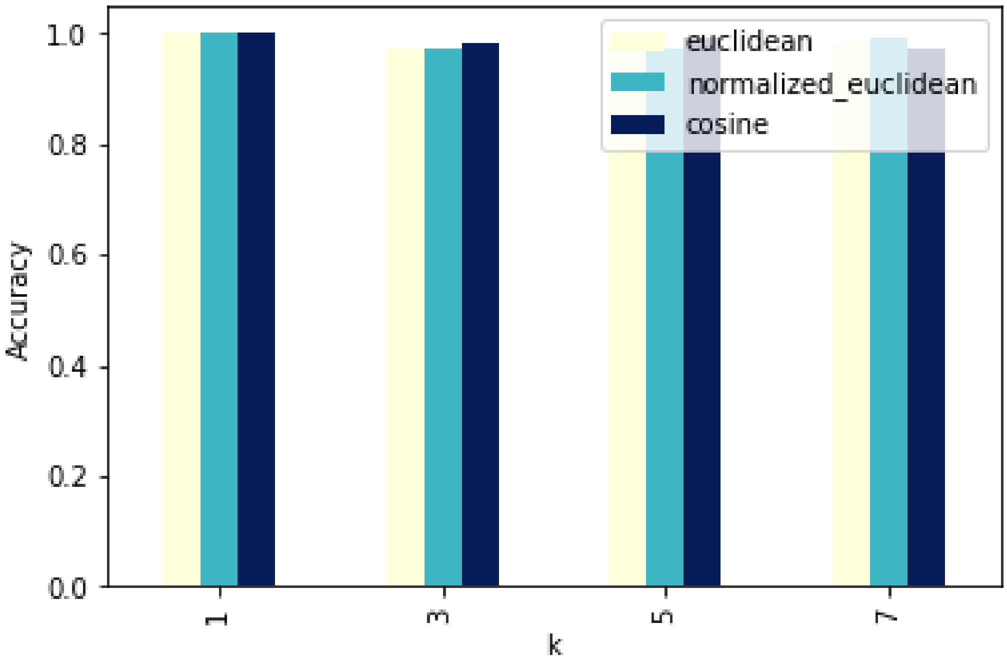
[46]:
```
# Calculating the accuracy of the development set by comparing it with the␣
↪development set 'class' list created earlier
accuracy = {}
for key in obs_k.keys():
    accuracy[key] = {}
    for k_value in obs_k[key].keys():
        #print('k = ', key)
        count = 0
        #for i,j in zip(dev_class, obs_k[key][k_value]):
        for i,j in zip(dev_class, obs_k[key][k_value]):
            if i == j:
                count = count + 1
            else:
                pass
        accuracy[key][k_value] = count/(len(dev_class))

# Storing the accuracy for each k and each distance metric into a dataframe
df_res = pd.DataFrame({'k': k_n})
for key in accuracy.keys():
    value = list(accuracy[key].values())
    df_res[key] = value
print(df_res)

# Plotting a Bar Chart for accuracy
draw = df_res.plot(x='k', y=['euclidean', 'normalized_euclidean', 'cosine'],␣
↪kind="bar", colormap='YlGnBu')
draw.set(ylabel='Accuracy')

# Ignoring k=1 if the value of accuracy for k=1 is 100%, since this mostly␣
↪implies overfitting
df_res.loc[df_res['k'] == 1.0, ['euclidean', 'normalized_euclidean', 'cosine']]␣
↪= np.nan

# Fetching the best k value for using all hyper-parameters
# In case the accuracy is the same for different k and different distance␣
↪metric selecting the first of all the same
column_val = [c for c in df_res.columns if not c.startswith('k')]
#col_max = df_res[column_val].max().idxmax(1)
col_max = df_res[column_val].max().idxmax()
```

```
best_dist_method = col_max
row_max = df_res[col_max].argmax()
best_k = int(df_res.iloc[row_max]['k'])
if df_res.isnull().values.any():
    print('\n\n\nBest k value is\033[1m', best_k, '\033[0mand best distance␣
 ↪metric is\033[1m', best_dist_method, '\033[0m. Ignoring k=1 if the value of␣
 ↪accuracy for k=1 is 100%, since this mostly implies overfitting')
else:
    print('\n\n\nBest k value is\033[1m', best_k, '\033[0mand best distance␣
 ↪metric is\033[1m', best_dist_method, '\033[0m.')
```

```
   k  euclidean  normalized_euclidean    cosine
0  1   1.000000              1.000000  1.000000
1  3   0.973214              0.973214  0.982143
2  5   0.982143              0.973214  0.991071
3  7   0.982143              0.991071  0.973214
```

Best k value is 7 and best distance metric is **normalized_euclidean**

. Ignoring k=1 if the value of accuracy for k=1 is 100%, since this mostly implies overfitting



### 1.1.9 Print the result for the development dataset

[47]:
```
print('\nBest k value is', best_k, 'and best distance metric is',␣
↪best_dist_method)
```

```

Best k value is 7 and best distance metric is normalized_euclidean
```

### 1.1.10 Iterating the test data and the best distance metric to determine the class in test data

[48]:
```
# Creating a list of list of all columns except 'class' by iterating through␣
↪the development set
row_list_test = []
for index, rows in test_set.iterrows():
    my_list =[rows.sepal_length, rows.sepal_width, rows.petal_length, rows.
↪petal_width]
    row_list_test.append([my_list])
test_set_obs = []
for i in range(len(row_list_test)):
    test_set_obs.append(knn(test_set, pd.DataFrame(row_list_test[i]), best_k,␣
↪best_dist_method, mean_test_set, std_test_set))
for x in test_set_obs:
  print(x)
```

```
Versicolor
Virginica
Virginica
Versicolor
Setosa
Setosa
Virginica
Virginica
Virginica
Setosa
Versicolor
Setosa
Virginica
Versicolor
Versicolor
Virginica
Versicolor
Versicolor
Virginica
Setosa
Versicolor
Virginica
Setosa
```

```
Virginica
Setosa
Setosa
Versicolor
Versicolor
Setosa
Virginica
Setosa
Virginica
Versicolor
Versicolor
Versicolor
Versicolor
Versicolor
Virginica
```

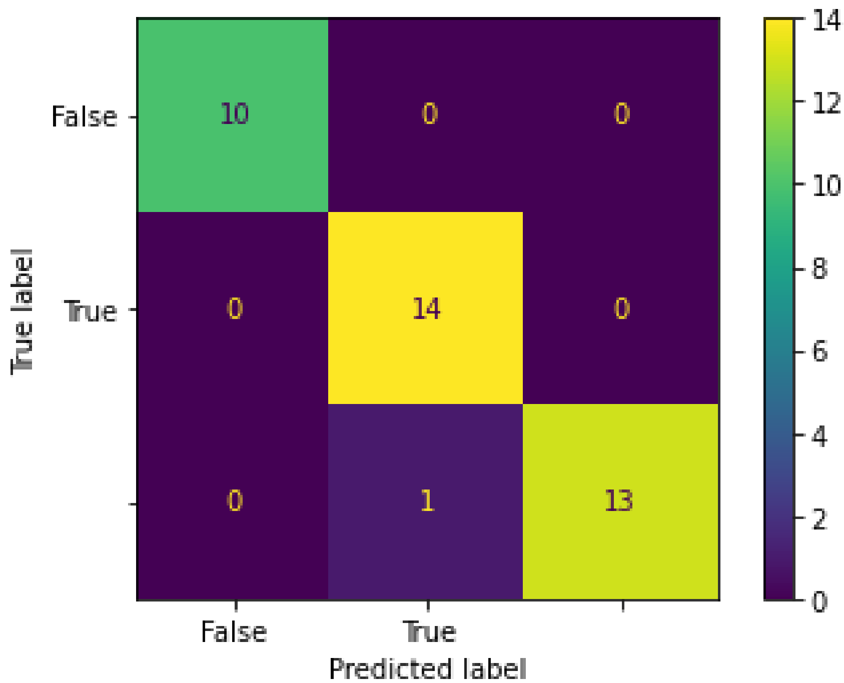
### 1.1.11 Calculate the accuracy for class prediction

[49]:
```python
count = 0
for i,j in zip(test_class, test_set_obs):
    if i == j:
        count = count + 1
    else:
        pass
accuracy_test = count/(len(test_class))
print('Final Accuracy of the Test dataset is ', accuracy_test)
```

```
Final Accuracy of the Test dataset is  0.9736842105263158
```

### 1.1.12 Use python library to show confusion matrix and Accuracy

[53]:
```python
import matplotlib.pyplot as plt
import numpy
from sklearn import metrics

confusion_matrix = metrics.confusion_matrix(test_class, test_set_obs)

cm_display = metrics.ConfusionMatrixDisplay(confusion_matrix =␣
↪confusion_matrix, display_labels = [False, True])

cm_display.plot()
plt.show()
```




[59]:
```
Accuracy = metrics.accuracy_score(test_class, test_set_obs)
#metrics
print("Accuracy",Accuracy)
```

```
Accuracy 0.9736842105263158
```