```
import pandas as pd
import numpy as np
import operator
import matplotlib.pyplot as plt
```

data = pd.read_csv('https://archive.ics.uci.edu/ml/machine-learning-databases/ir

print(data)

	sepal length	sepal width	petal length	petal width	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
145	6.7	3.0	5.2	2.3	Iris-virginica
146	6.3	2.5	5.0	1.9	Iris-virginica
147	6.5	3.0	5.2	2.0	Iris-virginica
148	6.2	3.4	5.4	2.3	Iris-virginica
149	5.9	3.0	5.1	1.8	Iris-virginica

[150 rows x 5 columns]

```
indices = np.random.permutation(data.shape[0])
div = int(0.75 * len(indices))
development_id, test_id = indices[:div], indices[div:]
```

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	class
44	5.1	3.8	1.9	0.4	Iris-setosa
37	4.9	3.1	1.5	0.1	Iris-setosa
140	6.7	3.1	5.6	2.4	Iris-virginica
19	5.1	3.8	1.5	0.3	Iris-setosa
28	5.2	3.4	1.4	0.2	Iris-setosa
81	5.5	2.4	3.7	1.0	Iris-versicolor
78	6.0	2.9	4.5	1.5	Iris-versicolor
70	5.9	3.2	4.8	1.8	Iris-versicolor
10	5.4	3.7	1.5	0.2	Iris-setosa
90	5.5	2.6	4.4	1.2	Iris-versicolor

[112 rows x 5 columns]

Test Set:

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	sepal_length	sepal_width	petal_length	petal_width	class
100	6.3	3.3	6.0	2.5	Iris-virginica
74	6.4	2.9	4.3	1.3	Iris-versicolor
15	5.7	4.4	1.5	0.4	Iris-setosa
141	6.9	3.1	5.1	2.3	Iris-virginica

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                                                                   1113 JC COJU
              6.9
                                                         2.1
139
                            3.1
                                           5.4
                                                                Iris-virginica
33
              5.5
                            4.2
                                           1.4
                                                         0.2
                                                                   Iris-setosa
                                           4.2
61
              5.9
                            3.0
                                                         1.5 Iris-versicolor
120
              6.9
                            3.2
                                           5.7
                                                         2.3
                                                                Iris-virginica
40
              5.0
                            3.5
                                           1.3
                                                         0.3
                                                                   Iris-setosa
89
              5.5
                            2.5
                                           4.0
                                                         1.3 Iris-versicolor
113
              5.7
                            2.5
                                           5.0
                                                         2.0
                                                               Iris-virginica
95
              5.7
                            3.0
                                           4.2
                                                         1.2 Iris-versicolor
                                                         1.5
54
              6.5
                            2.8
                                           4.6
                                                              Iris-versicolor
59
              5.2
                            2.7
                                           3.9
                                                         1.4 Iris-versicolor
128
                                           5.6
              6.4
                            2.8
                                                         2.1
                                                               Iris-virginica
94
              5.6
                            2.7
                                           4.2
                                                         1.3 Iris-versicolor
5
              5.4
                            3.9
                                           1.7
                                                         0.4
                                                                   Iris-setosa
17
              5.1
                            3.5
                                           1.4
                                                         0.3
                                                                   Iris-setosa
                                           4.5
              5.6
                            3.0
                                                         1.5
                                                               Iris-versicolor
66
92
              5.8
                            2.6
                                           4.0
                                                         1.2
                                                               Iris-versicolor
34
              4.9
                            3.1
                                           1.5
                                                         0.1
                                                                   Iris-setosa
11
              4.8
                            3.4
                                           1.6
                                                         0.2
                                                                   Iris-setosa
119
                            2.2
                                           5.0
                                                         1.5
              6.0
                                                                Iris-virginica
109
              7.2
                            3.6
                                           6.1
                                                         2.5
                                                                Iris-virginica
              5.8
                            4.0
                                           1.2
                                                         0.2
14
                                                                   Iris-setosa
127
                                           4.9
              6.1
                            3.0
                                                         1.8
                                                                Iris-virginica
87
              6.3
                            2.3
                                           4.4
                                                         1.3 Iris-versicolor
24
                                           1.9
              4.8
                            3.4
                                                         0.2
                                                                   Iris-setosa
55
              5.7
                            2.8
                                           4.5
                                                         1.3 Iris-versicolor
84
              5.4
                            3.0
                                           4.5
                                                         1.5
                                                              Iris-versicolor
107
              7.3
                            2.9
                                           6.3
                                                         1.8
                                                                Iris-virginica
```

```
mean_test_set = test_set.mean()
std_development_set = development_set.std()
std_test_set = test_set.std()

test_class = list(test_set.iloc[:,-1])
dev_class = list(development_set.iloc[:,-1])

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)

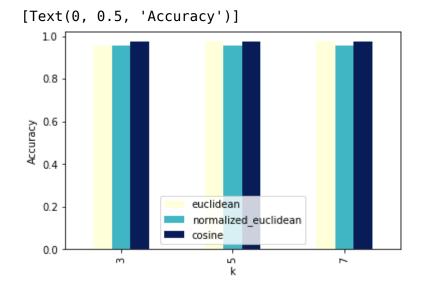
def normalizedEuclideanDistance(data_1, data_2, data_len, data_mean, data_std):
    n_dist = 0
    for i in range(data_len):
        n_dist = n_dist + (np.square(((data_1[i] - data_mean[i])/data_std[i]) - return np.sqrt(n dist)
```

mean_development_set = development_set.mean()

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            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],
            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=Tru
    return(sort counts[0][0])
# Creating a list of list of all columns except 'class' by iterating through the
row list = []
for index, rows in development set.iterrows():
    my list =[rows.sepal length, rows.sepal width, rows.petal length, rows.petal
    row list.append([my list])
# k values for the number of neighbors that need to be considered
k n = [3, 5, 7]
# Distance metrics
distance methods = ['euclidean', 'normalized euclidean', 'cosine']
# Performing kNN on the development set by iterating all of the development set
obs k = \{\}
for dist method in distance methods:
```

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            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)
          euclidean normalized_euclidean
                                              cosine
    0
       3
           0.955357
                                  0.955357 0.973214
      5
    1
           0.973214
                                  0.955357 0.973214
    2
      7
           0.973214
                                  0.955357 0.973214
```

Plotting a Bar Chart for accuracy
draw = df_res.plot(x='k', y=['euclidean', 'normalized_euclidean', 'cosine'], kin
draw.set(ylabel='Accuracy')



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   my_list =[rows.sepal_length, rows.sepal_width, rows.petal_length, rows.petal
    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, be
#print(test_set_obs)
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
```