FruitClassifier

September 17, 2024

1 Fruit Classifier

1.0.1 Import required modules and load data file

[ ]:
```
import numpy as np
import matplotlib.pyplot as plt
from matplotlib import cm
import pandas as pd
import seaborn as sns
from sklearn.model_selection import train_test_split
```

[ ]:
```
# #Map drive to access train_building_weather_9-2.csv
# from google.colab import drive
# import os
# drive.mount('/content/drive/')
# os.chdir('/content/drive/My Drive/CP-DSAI/')
```

[ ]:
```
fruits = pd.read_csv('fruit_data_with_colors.txt', sep = '\t')
```

[ ]:
```
# let's see what's inside
fruits.head()
```

[ ]:

	fruit_label	fruit_name	fruit_subtype	mass	width	height	color_score
0	1	apple	granny_smith	192	8.4	7.3	0.55
1	1	apple	granny_smith	180	8.0	6.8	0.59
2	1	apple	granny_smith	176	7.4	7.2	0.60
3	2	mandarin	mandarin	86	6.2	4.7	0.80
4	2	mandarin	mandarin	84	6.0	4.6	0.79

[ ]:
```
# create a mapping from fruit label value to fruit name to make results easier␣
↪to interpret
lookup_fruit_name = {1:'apple',2:'mandarin',3:'orange',4:'lemon'}
lookup_fruit_name
```

[ ]:
```
{1: 'apple', 2: 'mandarin', 3: 'orange', 4: 'lemon'}
```

The file contains the mass, height, and width of a selection of oranges, lemons and apples. The heights were measured along the core of the fruit. The widths were the widest width perpendicular to the height.

```
[ ]: fruits.describe()
```

```
[ ]:        fruit_label        mass      width     height  color_score
     count    59.000000   59.000000  59.000000  59.000000    59.000000
     mean      2.542373  163.118644   7.105085   7.693220     0.762881
     std       1.208048   55.018832   0.816938   1.361017     0.076857
     min       1.000000   76.000000   5.800000   4.000000     0.550000
     25%       1.000000  140.000000   6.600000   7.200000     0.720000
     50%       3.000000  158.000000   7.200000   7.600000     0.750000
     75%       4.000000  177.000000   7.500000   8.200000     0.810000
     max       4.000000  362.000000   9.600000  10.500000     0.930000
```

```
[ ]: fruits.info()
```

```
     <class 'pandas.core.frame.DataFrame'>
     RangeIndex: 59 entries, 0 to 58
     Data columns (total 7 columns):
      #   Column         Non-Null Count  Dtype
     ---  ------         --------------  -----
      0   fruit_label    59 non-null     int64
      1   fruit_name     59 non-null     object
      2   fruit_subtype  59 non-null     object
      3   mass           59 non-null     int64
      4   width          59 non-null     float64
      5   height         59 non-null     float64
      6   color_score    59 non-null     float64
     dtypes: float64(3), int64(2), object(2)
     memory usage: 3.4+ KB
```

```
[ ]: fruits.isnull().any()
```

```
[ ]: fruit_label      False
     fruit_name       False
     fruit_subtype    False
     mass             False
     width            False
     height           False
     color_score      False
     dtype: bool
```

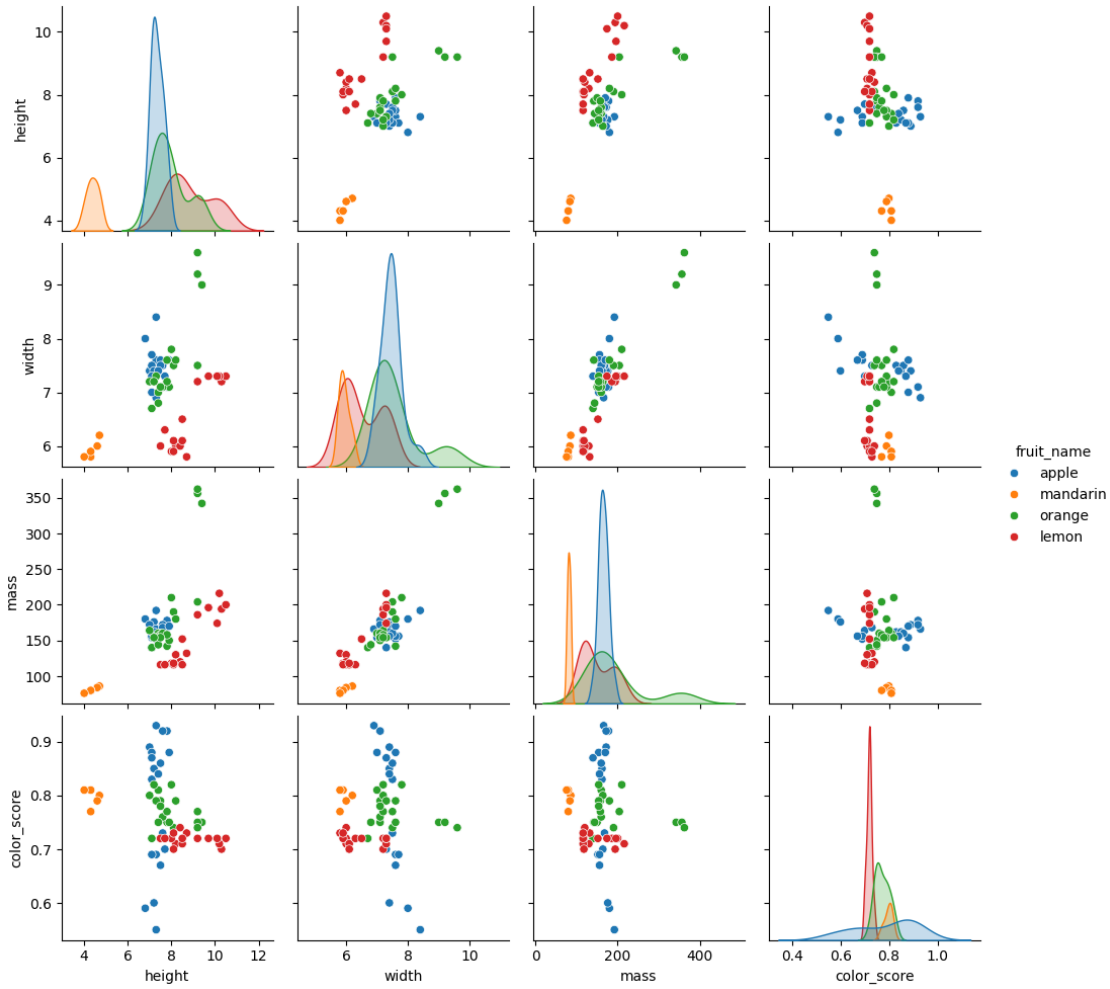
```
[ ]: fruits.corr(numeric_only=True)
```

```
[ ]:              fruit_label      mass     width    height  color_score
     fruit_label     1.000000  0.032738 -0.298090  0.508766    -0.310521
     mass            0.032738  1.000000  0.877687  0.609571    -0.079794
     width          -0.298090  0.877687  1.000000  0.396848    -0.076576
     height          0.508766  0.609571  0.396848  1.000000    -0.247047
     color_score    -0.310521 -0.079794 -0.076576 -0.247047     1.000000
```

1.0.2 Examining the data

[ ]:
```
# plotting a scatter matrix

X = fruits[['height', 'width', 'mass', 'color_score']]
y = fruits['fruit_label']
sns.pairplot(fruits[['height', 'width', 'mass', 'color_score', 'fruit_name']],␣
 ↪hue = "fruit_name")
```

[ ]:
```
<seaborn.axisgrid.PairGrid at 0x1f3f5e20a00>
```



1.0.3 Create train-test split

[ ]:
```
# For this example, we use the mass, width, and height features of each fruit␣
 ↪instance
#Write your code here
```

```
X = fruits[['height', 'width', 'mass']]
y = fruits['fruit_label']
#--------------------------------------


#Write your code to split data into train and test datasets
# default is 75% / 25% train-test split, test_size, random_state

X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.75,␣
 ↪test_size=0.25, random_state=52)
```

[ ]:
```
#What's the size of train and test datasets
#Write your code here

X_train.shape, X_test.shape
```

[ ]:
```
((44, 3), (15, 3))
```

1.0.4 Create classifier object

[ ]:
```
from sklearn.neighbors import KNeighborsClassifier
#Write your code to create an instance called knn from KNN classifier class

knn = KNeighborsClassifier(n_neighbors=1)
```

1.0.5 Train the classifier (fit the estimator) using the training data

[ ]:
```
#Write code to train the model
knn.fit(X_train, y_train)
```

[ ]:
```
KNeighborsClassifier(n_neighbors=1)
```

1.0.6 Estimate the accuracy of the classifier on future data, using the test data. (Evaluate the model's performance to generalize)

[ ]:
```
knn.score(X_test,y_test)
```

[ ]:
```
0.9333333333333333
```

1.0.7 Use the trained k-NN classifier model to classify new, previously unseen objects

[ ]:
```
# first example: a small fruit with mass 20g, width 4.3 cm, height 5.5 cm
#Write code to use the estimator to classify fruit type based on the above␣
 ↪information
#------------------------
small_fruit = pd.DataFrame({"height": [5.5], "width": [4.3], "mass": [20]}) #␣
 ↪'height', 'width', 'mass'
```

```
print("PREDICTION IS:", lookup_fruit_name[knn.predict(small_fruit).item()])
```

```
PREDICTION IS: mandarin
```

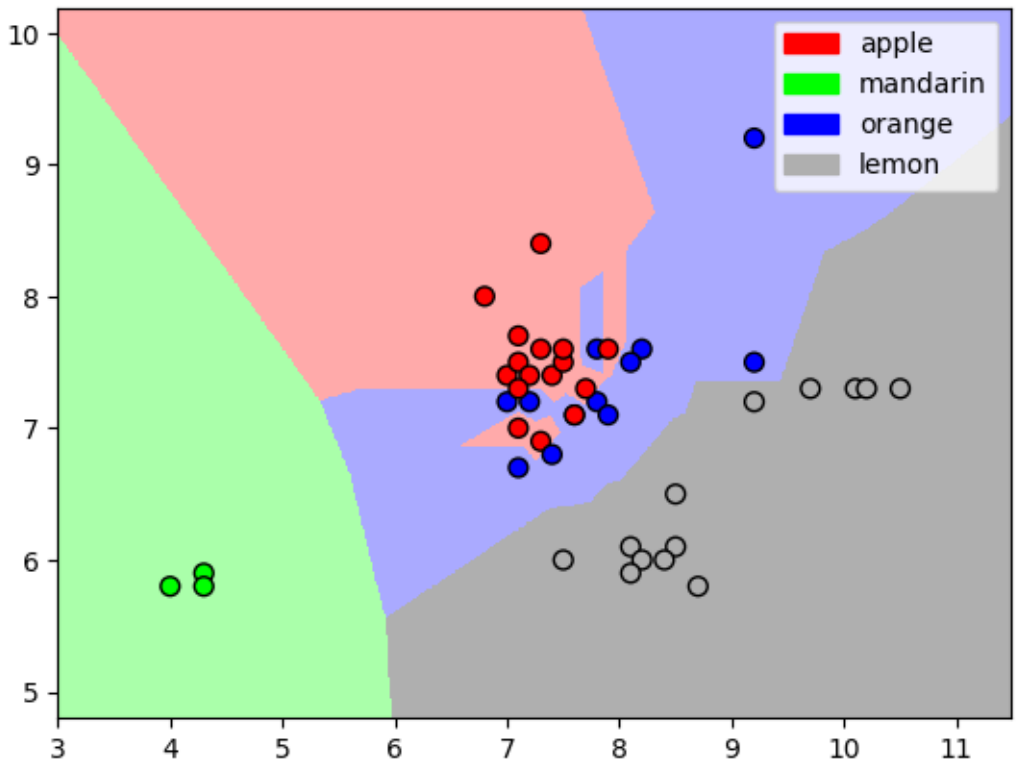
[ ]:
```
# second example: a larger, elongated fruit with mass 100g, width 6.3 cm,␣
 ↪height 8.5 cm
#Write code to use the estimator to classify fruit type based on the above␣
 ↪information
#-----------------------

large_fruit = pd.DataFrame({"height": [8.5], "width": [6.3], "mass": [100]}) #␣
 ↪'height', 'width', 'mass'
print("PREDICTION IS:", lookup_fruit_name[knn.predict(large_fruit).item()])
```

```
PREDICTION IS: lemon
```

1.0.8 Plot the decision boundaries of the k-NN classifier

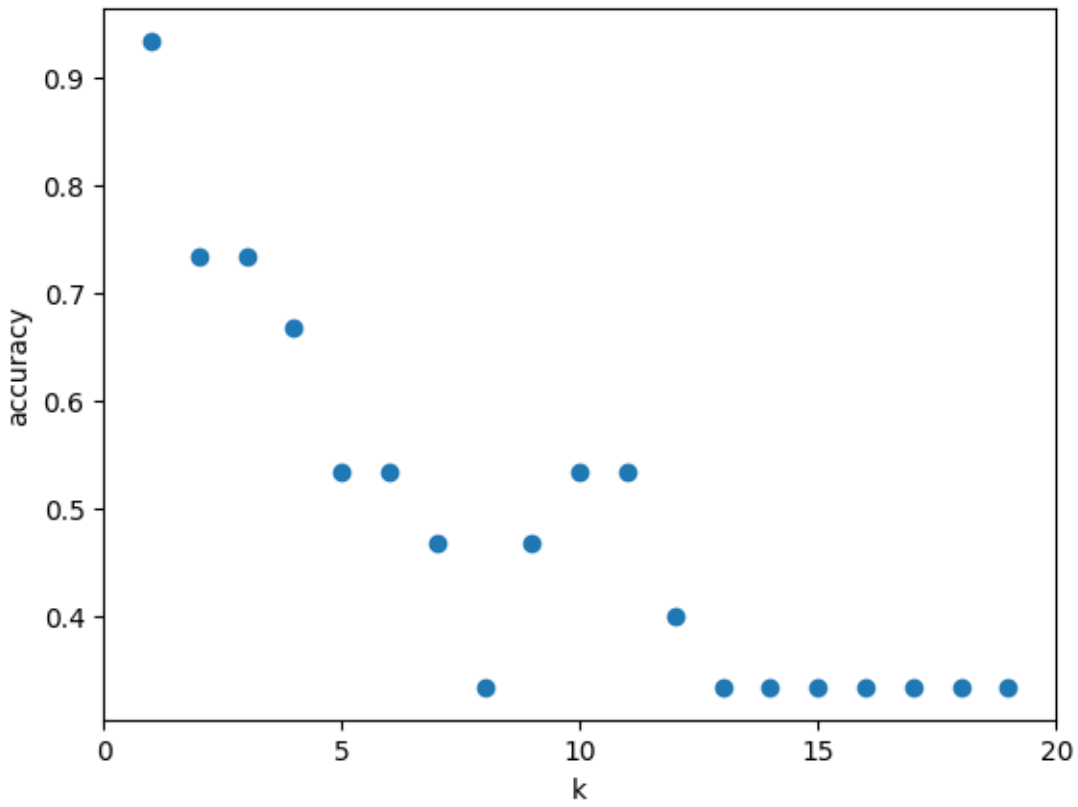
[ ]:
```
import numpy as np
#Need to upload adspy_shared_utilities
from adspy_shared_utilities import plot_fruit_knn

plot_fruit_knn(X_train, y_train, 1, 'uniform')   # we choose 5 nearest neighbors
```

```
d:\DataScience\Anaconda3\envs\dl4cv\lib\site-packages\IPython\core\events.py:82:
UserWarning: Creating legend with loc="best" can be slow with large amounts of
data.
  func(*args, **kwargs)
```



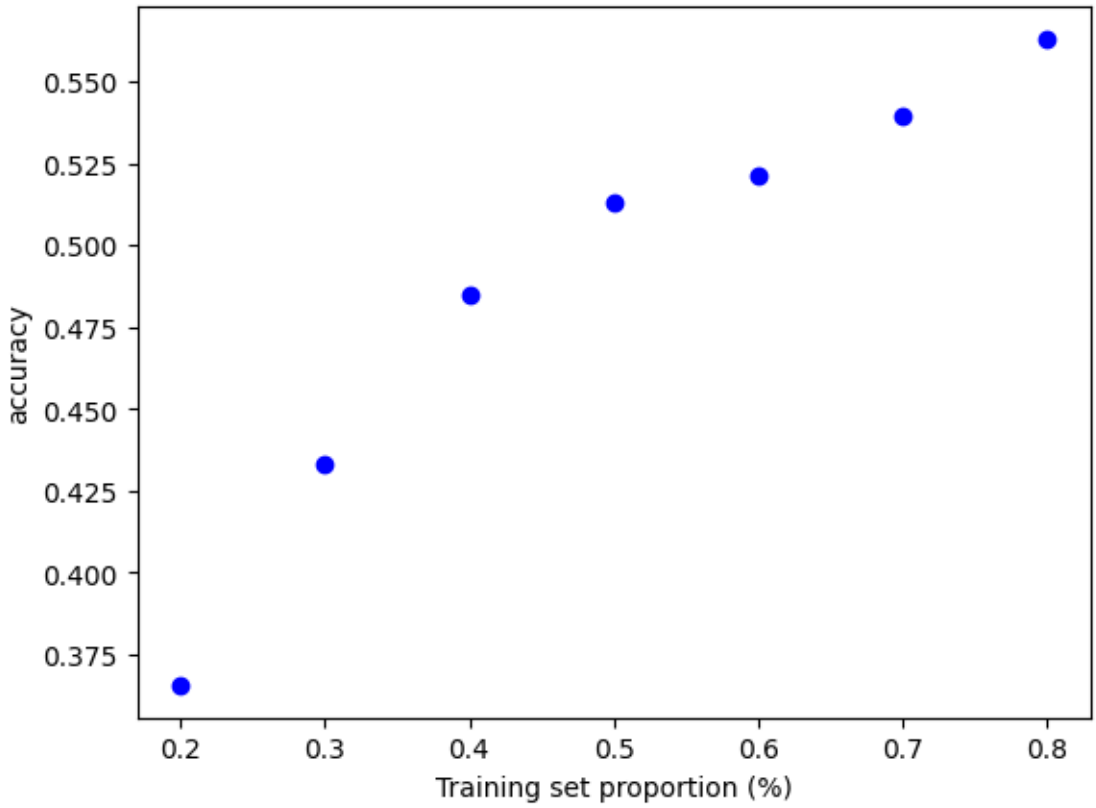
1.0.9 How sensitive is k-NN classification accuracy to the choice of the 'k' parameter?

[ ]:
```
k_range = range(1,20)
scores = []

for k in k_range:
    knn = KNeighborsClassifier(n_neighbors = k)
    knn.fit(X_train, y_train)
    scores.append(knn.score(X_test, y_test))

plt.figure()
plt.xlabel('k')
plt.ylabel('accuracy')
plt.scatter(k_range, scores)
plt.xticks([0,5,10,15,20]);
```



1.0.10 How sensitive is k-NN classification accuracy to the train/test split proportion?

[ ]:
```
t = [0.8, 0.7, 0.6, 0.5, 0.4, 0.3, 0.2]

knn = KNeighborsClassifier(n_neighbors = 5)

plt.figure()

for s in t:

    scores = []
    for i in range(1,1000):
        X_train, X_test, y_train, y_test = train_test_split(X, y, test_size =␣
 ↪1-s)
        knn.fit(X_train, y_train)
        scores.append(knn.score(X_test, y_test))
    plt.plot(s, np.mean(scores), 'bo')

plt.xlabel('Training set proportion (%)')
plt.ylabel('accuracy');
```


0.550
0.525
0.500
0.475
0.450
0.425
0.400
0.375
accuracy
0.2
0.3
0.4
0.5
0.6
0.7
0.8
Training set proportion (%)