Wine

April 16, 2020

1 K-Nearest Neighbor Model

using the wine data set

[1]:
```
#pd.options.mode.chained_assignment = None  # default='warn' (DISPLAY PURPOSES)
from IPython.display import display, HTML

# For Parrallel Computing
from dask.distributed import Client, LocalCluster
from dask import compute, delayed
import dask

cluster = LocalCluster()
client = Client(cluster)
client
```

[1]:
```
<Client: 'tcp://127.0.0.1:50777' processes=4 threads=8, memory=34.31 GB>
```

2 Part 1 – Preliminary Tasks (Simple data wrangling)

2.0.1 Load Data

some entries are empty so replacing with averages

[2]:
```
import knn # custom python file

import pandas as pd
data =  pd.read_csv('winequalityN.csv', index_col=False)
data = knn.data_no_nan(data)
data.head()
```

[2]:
```
    type  fixed acidity  volatile acidity  citric acid  residual sugar  \
0  white            7.0              0.27         0.36            20.7
1  white            6.3              0.30         0.34             1.6
2  white            8.1              0.28         0.40             6.9
3  white            7.2              0.23         0.32             8.5
4  white            7.2              0.23         0.32             8.5
```

```
   chlorides  free sulfur dioxide  total sulfur dioxide  density    pH  \
0      0.045                 45.0                 170.0   1.0010  3.00
1      0.049                 14.0                 132.0   0.9940  3.30
2      0.050                 30.0                  97.0   0.9951  3.26
3      0.058                 47.0                 186.0   0.9956  3.19
4      0.058                 47.0                 186.0   0.9956  3.19

   sulphates  alcohol  quality
0       0.45      8.8      6.0
1       0.49      9.5      6.0
2       0.44     10.1      6.0
3       0.40      9.9      6.0
4       0.40      9.9      6.0
```

[3]:
```
data.tail()
```

[3]:
```
      type  fixed acidity  volatile acidity  citric acid  residual sugar  \
6492   red            6.2             0.600         0.08             2.0
6493   red            5.9             0.550         0.10             2.2
6494   red            6.3             0.510         0.13             2.3
6495   red            5.9             0.645         0.12             2.0
6496   red            6.0             0.310         0.47             3.6

      chlorides  free sulfur dioxide  total sulfur dioxide  density    pH  \
6492      0.090                 32.0                  44.0  0.99490  3.45
6493      0.062                 39.0                  51.0  0.99512  3.52
6494      0.076                 29.0                  40.0  0.99574  3.42
6495      0.075                 32.0                  44.0  0.99547  3.57
6496      0.067                 18.0                  42.0  0.99549  3.39

      sulphates  alcohol  quality
6492   0.580000     10.5      5.0
6493   0.658078     11.2      6.0
6494   0.750000     11.0      6.0
6495   0.710000     10.2      5.0
6496   0.660000     11.0      6.0
```

3 Part 2 – Building and training the kNN model

3.0.1 Create Train/Test Data set

[4]:
```
import numpy as np
from sklearn.model_selection import train_test_split
X = data.loc[:,"fixed acidity":"quality"] # data matrix
y = data.loc[:,"type"] # target vector
```

```
#split into train and test
testSize = 0.20
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size = testSize,␣
 ↪stratify=y)

# Reset Index so its all 0 based
X_train.reset_index(drop=True,inplace=True)
X_test.reset_index(drop=True,inplace=True)
y_train.reset_index(drop=True,inplace=True)
y_test.reset_index(drop=True,inplace=True)
```

[5]:
```
print("Train Test Split percentage: " + str(testSize * 100) +  "% test\n")
print("X Training Shape: ", np.shape(X_train))
print("X Test Shape: ", np.shape(X_test))
print("--------------------------------------------------------------------")
print("y Training Shape: ", np.shape(y_train))
print("y Test Shape: ", np.shape(y_test))
```

```
Train Test Split percentage: 20.0% test

X Training Shape:  (5197, 12)
X Test Shape:  (1300, 12)
--------------------------------------------------------------------
y Training Shape:  (5197,)
y Test Shape:  (1300,)
```

3.0.2 Building the kNN Model

[6]:
```
import knn # custom python file
clf = knn.Knn()
clf.fit(X_train,y_train)
```

[6]:
```
Knn(k=3)
```

4 Part 3 – Testing the kNN model

[7]:
```
trainingData = pd.concat([X_train, y_train], axis=1)
print('Data instance: ')
display(HTML(pd.DataFrame(trainingData.loc[20,:]).T.to_html()))
```

```
Data instance:
```

```
<IPython.core.display.HTML object>
```

[8]:
```
X_train.loc[1,"quality"]
```

[8]: 5.0

[9]:
```
instanceData = trainingData.loc[20,"fixed acidity":"quality"]
prediciton = clf.predict(instanceData)
print("True Class: ", trainingData.loc[20,"type"])
print("Predicited Class: ", prediciton)
```

```
True Class:  red
Predicited Class:  red
```

[19]:
```
import knn # custom python file

# search for an optimal value of K for KNN

# list of integers 2 to 25
# integers we want to try
k_range = range(1, 26)

# list of scores from k_range
k_scores = []

# 1. we will loop through reasonable values of k
for kH in k_range:
    # 2. run my custom model with k neighbours
    clf = knn.Knn(k=kH)
    clf.fit(X_train,y_train)
    results = {}
    result = []
    # 3. obtain scores my model with k neighbours
    #for j in range(0,np.shape(X_test)[0]):
    #    delayed_results = delayed(clf.predict)(X_test.loc[j,"fixed acidity":
↪"quality"])
    #    result.append(delayed_results)
    #results[k] = dask.compute(*result)
    score = clf.score(X_test,y_test)
    print("K: ",kH," Score: ", score)
    # 4. append mean of scores for k neighbors to k_scores list
    k_scores.append(score)
```

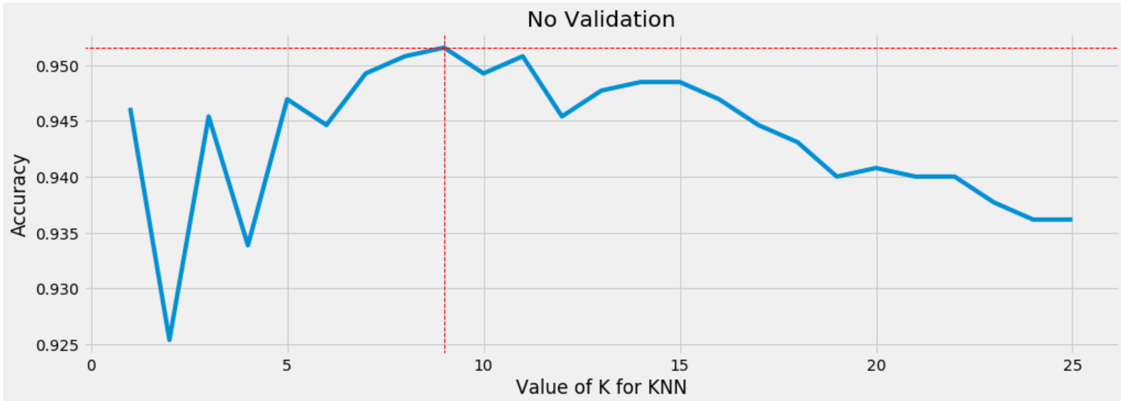
```
K:  1  Score:  0.9461538461538461
K:  2  Score:  0.9253846153846154
K:  3  Score:  0.9453846153846154
K:  4  Score:  0.9338461538461539
K:  5  Score:  0.946923076923077
K:  6  Score:  0.9446153846153846
K:  7  Score:  0.9492307692307692
K:  8  Score:  0.9507692307692308
K:  9  Score:  0.9515384615384616
```

```
K:  10  Score:  0.9492307692307692
K:  11  Score:  0.9507692307692308
K:  12  Score:  0.9453846153846154
K:  13  Score:  0.9476923076923077
K:  14  Score:  0.9484615384615385
K:  15  Score:  0.9484615384615385
K:  16  Score:  0.946923076923077
K:  17  Score:  0.9446153846153846
K:  18  Score:  0.943076923076923
K:  19  Score:  0.94
K:  20  Score:  0.9407692307692308
K:  21  Score:  0.94
K:  22  Score:  0.94
K:  23  Score:  0.9376923076923077
K:  24  Score:  0.9361538461538461
K:  25  Score:  0.9361538461538461
```

[20]:

```
import matplotlib.pyplot as plt
plt.style.use('fivethirtyeight')
plt.figure(figsize=(15,5))

# plot the value of K for KNN (x-axis) versus the cross-validated accuracy␣
↪(y-axis)
plt.plot(k_range, k_scores)
plt.xlabel('Value of K for KNN')
plt.ylabel('Accuracy')
plt.title('No Validation')

max_value = max(k_scores)  # maximum value
max_keys = np.where(k_scores == np.amax(k_scores))[0]+1 # getting all keys␣
↪containing the `maximum`

plt.axhline(max_value, color='r', linestyle='--', linewidth=1);
[plt.axvline(_x, linewidth=1, color='r',linestyle='--') for _x in max_keys];
print("Best Score: %.4f" % max_value)
print("Best K: ", max_keys)
```

```
Best Score: 0.9515
Best K:  [9]
```



5 Part 4 – Cross validation

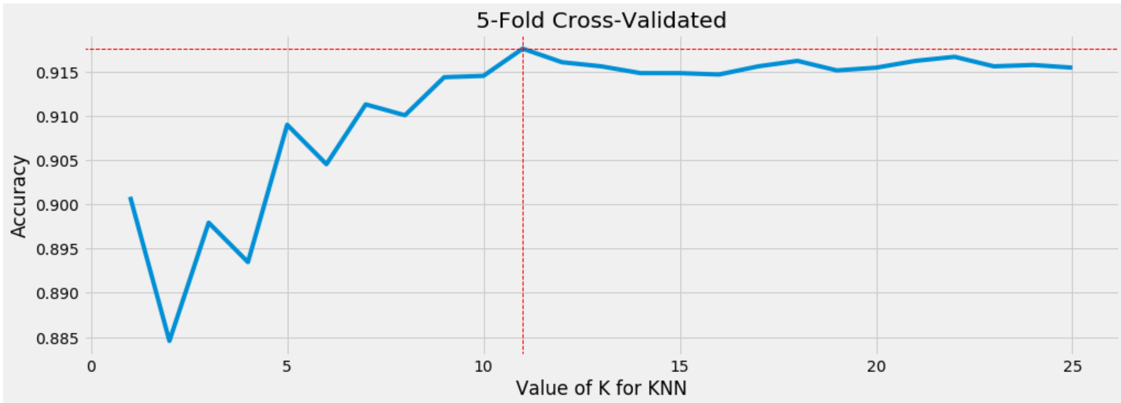
[10]:
```python
from sklearn.model_selection import cross_val_score
import knn # custom python file

# search for an optimal value of K for KNN

# list of integers 1 to 25
# integers we want to try
k_range = range(1, 26)

# list of scores from k_range
k_scores = []

# 1. we will loop through reasonable values of k
for kH in k_range:
    # 2. run my custom model with k neighbours
    clf = knn.Knn(k=kH)
    # 3. obtain cross_val_score my model with k neighbours
    scores = cross_val_score(clf, X, y, cv=5)
    print("K: ",kH," Score: ", scores)
    # 4. append mean of scores for k neighbors to k_scores list
    k_scores.append(scores.mean())
```

```
K:  1  Score:  [0.94230769 0.93       0.94149346 0.91762895 0.77290223]
K:  2  Score:  [0.90307692 0.89153846 0.90300231 0.89992302 0.82525019]
K:  3  Score:  [0.94769231 0.94230769 0.93995381 0.91531948 0.74441878]
K:  4  Score:  [0.92538462 0.92384615 0.91685912 0.91147036 0.78983834]
K:  5  Score:  [0.95846154 0.95692308 0.95765974 0.91839877 0.75365666]
K:  6  Score:  [0.94076923 0.94461538 0.94688222 0.91685912 0.77367206]
K:  7  Score:  [0.95307692 0.96615385 0.95842956 0.91685912 0.76212471]
K:  8  Score:  [0.94461538 0.95846154 0.95150115 0.91839877 0.77752117]
```

```
K:  9  Score:  [0.96153846 0.97076923 0.96150885 0.91762895 0.76058507]
K:  10  Score:  [0.95923077 0.96461538 0.95612009 0.91839877 0.77444188]
K:  11  Score:  [0.96384615 0.97615385 0.96997691 0.91301001 0.765204  ]
K:  12  Score:  [0.95846154 0.97384615 0.96150885 0.91224018 0.77444188]
K:  13  Score:  [0.96307692 0.97692308 0.96535797 0.91454965 0.7582756 ]
K:  14  Score:  [0.95615385 0.97307692 0.9630485  0.91301001 0.76905312]
K:  15  Score:  [0.96538462 0.97692308 0.96766744 0.90993072 0.75442648]
K:  16  Score:  [0.96230769 0.97307692 0.96458814 0.90916089 0.76443418]
K:  17  Score:  [0.96615385 0.97769231 0.96535797 0.90993072 0.75904542]
K:  18  Score:  [0.96       0.97384615 0.9630485  0.90993072 0.77444188]
K:  19  Score:  [0.96153846 0.97461538 0.96535797 0.91070054 0.76366436]
K:  20  Score:  [0.95846154 0.97384615 0.96458814 0.90993072 0.77059276]
K:  21  Score:  [0.96307692 0.97615385 0.96920708 0.91070054 0.76212471]
K:  22  Score:  [0.95538462 0.97538462 0.96920708 0.90993072 0.77367206]
K:  23  Score:  [0.95923077 0.97538462 0.96920708 0.91224018 0.76212471]
K:  24  Score:  [0.95769231 0.97230769 0.96920708 0.91147036 0.76828329]
K:  25  Score:  [0.96       0.97461538 0.96920708 0.91070054 0.76289453]
```

[11]:
```python
import matplotlib.pyplot as plt
plt.style.use('fivethirtyeight')
plt.figure(figsize=(15,5))

# plot the value of K for KNN (x-axis) versus the cross-validated accuracy␣
↪(y-axis)
plt.plot(k_range, k_scores)
plt.xlabel('Value of K for KNN')
plt.ylabel('Accuracy')
plt.title('5-Fold Cross-Validated')

max_value = max(k_scores)  # maximum value
max_keys = np.where(k_scores == np.amax(k_scores))[0]+1 # getting all keys␣
↪containing the `maximum`

plt.axhline(max_value, color='r', linestyle='--', linewidth=1);
[plt.axvline(_x, linewidth=1, color='r',linestyle='--') for _x in max_keys];
print("Best Score: %.4f" % max_value)
print("Best K: ", max_keys)
```

```
Best Score: 0.9176
Best K:  [11]
```



6 Part 5 - Optimizing n-neighbor parameter

[12]:
```
from sklearn.model_selection  import GridSearchCV
```

[13]:
```
param_grid = dict(k=k_range)
print(param_grid)
```

```
{'k': range(1, 26)}
```

[14]:
```
grid = GridSearchCV(clf, param_grid, cv=10)
```

[15]:
```
grid.fit(X,y)
```

[15]:
```
GridSearchCV(cv=10, error_score=nan, estimator=Knn(k=25), iid='deprecated',
             n_jobs=None, param_grid={'k': range(1, 26)},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring=None, verbose=0)
```

[16]:
```
print(grid.best_score_)
print(grid.best_params_)
```

```
0.9306907668602584
{'k': 13}
```

[17]:
```
pd.DataFrame(grid.cv_results_, index=k_range)
```

[17]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_k	\
1	0.012194	0.007137	145.959871	0.661277	1	
2	0.015118	0.008250	146.113404	0.626792	2	
3	0.010698	0.006064	145.629034	0.410074	3	
4	0.007149	0.003001	145.943097	0.571277	4	
5	0.010821	0.005059	145.720607	0.635463	5	

6	0.012394	0.004716	149.432469	4.186962	6
7	0.016793	0.012901	181.038128	18.879334	7
8	0.019090	0.026917	165.405074	21.522480	8
9	0.009695	0.006179	158.215616	9.282849	9
10	0.010697	0.004647	150.221248	0.819576	10
11	0.011497	0.005042	150.310347	0.641916	11
12	0.014696	0.005639	150.192594	0.649189	12
13	0.009298	0.005459	152.113380	3.794160	13
14	0.012596	0.007240	158.166267	4.039523	14
15	0.014097	0.007596	160.675512	0.703552	15
16	0.011499	0.008852	159.322908	5.727702	16
17	0.011596	0.005461	157.121320	3.446851	17
18	0.010897	0.004252	146.206059	0.612426	18
19	0.013896	0.005785	145.981267	0.576557	19
20	0.009698	0.006955	145.958098	0.719079	20
21	0.010091	0.002620	145.948526	0.668996	21
22	0.012495	0.005606	147.498227	0.678451	22
23	0.014399	0.007514	151.032295	6.899717	23
24	0.012383	0.005431	163.020991	1.692016	24
25	0.011197	0.008907	162.399512	1.482105	25

	params	split0_test_score	split1_test_score	split2_test_score	\
1	{'k': 1}	0.963077	0.940000	0.940000	
2	{'k': 2}	0.930769	0.901538	0.923077	
3	{'k': 3}	0.960000	0.949231	0.944615	
4	{'k': 4}	0.938462	0.923077	0.935385	
5	{'k': 5}	0.966154	0.961538	0.964615	
6	{'k': 6}	0.960000	0.944615	0.949231	
7	{'k': 7}	0.975385	0.953846	0.969231	
8	{'k': 8}	0.966154	0.946154	0.966154	
9	{'k': 9}	0.983077	0.960000	0.972308	
10	{'k': 10}	0.975385	0.953846	0.969231	
11	{'k': 11}	0.978462	0.961538	0.975385	
12	{'k': 12}	0.973846	0.958462	0.972308	
13	{'k': 13}	0.978462	0.966154	0.973846	
14	{'k': 14}	0.978462	0.956923	0.972308	
15	{'k': 15}	0.983077	0.963077	0.973846	
16	{'k': 16}	0.978462	0.963077	0.973846	
17	{'k': 17}	0.981538	0.963077	0.975385	
18	{'k': 18}	0.981538	0.963077	0.972308	
19	{'k': 19}	0.984615	0.963077	0.973846	
20	{'k': 20}	0.981538	0.961538	0.972308	
21	{'k': 21}	0.986154	0.961538	0.973846	
22	{'k': 22}	0.975385	0.961538	0.972308	
23	{'k': 23}	0.981538	0.964615	0.972308	
24	{'k': 24}	0.976923	0.961538	0.972308	
25	{'k': 25}	0.981538	0.963077	0.975385	

	split3_test_score	split4_test_score	split5_test_score	\
1	0.952308	0.944615	0.947692	
2	0.912308	0.926154	0.915385	
3	0.958462	0.953846	0.950769	
4	0.943077	0.936923	0.932308	
5	0.969231	0.961538	0.961538	
6	0.960000	0.953846	0.950769	
7	0.973846	0.961538	0.964615	
8	0.966154	0.958462	0.960000	
9	0.981538	0.969231	0.966154	
10	0.973846	0.960000	0.960000	
11	0.980000	0.967692	0.976923	
12	0.978462	0.966154	0.972308	
13	0.986154	0.966154	0.973846	
14	0.981538	0.966154	0.970769	
15	0.981538	0.972308	0.970769	
16	0.980000	0.964615	0.970769	
17	0.984615	0.967692	0.973846	
18	0.981538	0.966154	0.967692	
19	0.981538	0.966154	0.970769	
20	0.981538	0.966154	0.967692	
21	0.981538	0.967692	0.970769	
22	0.980000	0.967692	0.970769	
23	0.983077	0.969231	0.970769	
24	0.980000	0.969231	0.970769	
25	0.983077	0.969231	0.970769	

	split6_test_score	split7_test_score	split8_test_score	\
1	0.952308	0.873652	0.856703	
2	0.906154	0.882897	0.884438	
3	0.966154	0.864407	0.824345	
4	0.946154	0.879815	0.859784	
5	0.973846	0.861325	0.810478	
6	0.961538	0.865948	0.819723	
7	0.972308	0.859784	0.793529	
8	0.964615	0.869029	0.807396	
9	0.970769	0.858243	0.798151	
10	0.970769	0.862866	0.812018	
11	0.973846	0.850539	0.801233	
12	0.969231	0.853621	0.810478	
13	0.972308	0.853621	0.805855	
14	0.969231	0.855162	0.807396	
15	0.972308	0.853621	0.799692	
16	0.967692	0.852080	0.805855	
17	0.967692	0.852080	0.805855	
18	0.967692	0.852080	0.807396	

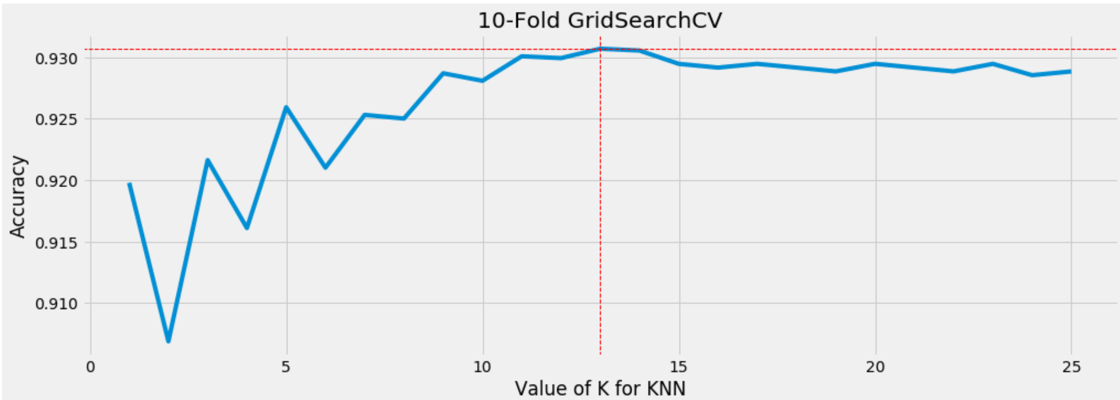
```
19             0.970769           0.850539           0.801233
20             0.969231           0.852080           0.807396
21             0.970769           0.850539           0.804314
22             0.970769           0.850539           0.805855
23             0.973846           0.852080           0.802773
24             0.973846           0.850539           0.802773
25             0.973846           0.845917           0.799692

    split9_test_score  mean_test_score  std_test_score  rank_test_score
1            0.827427         0.919778        0.045651               23
2            0.885978         0.906870        0.016885               25
3            0.844376         0.921620        0.051668               21
4            0.865948         0.916093        0.032018               24
5            0.828968         0.925923        0.061639               18
6            0.844376         0.921005        0.052119               22
7            0.828968         0.925305        0.066041               19
8            0.845917         0.925003        0.057149               20
9            0.827427         0.928690        0.067608               15
10           0.842835         0.928080        0.059615               17
11           0.835131         0.930075        0.067337                3
12           0.844376         0.929924        0.062416                4
13           0.830508         0.930691        0.067000                1
14           0.847458         0.930540        0.062826                2
15           0.824345         0.929458        0.069069                8
16           0.835131         0.929153        0.065286                9
17           0.822804         0.929459        0.068212                6
18           0.832049         0.929153        0.065601               10
19           0.825886         0.928843        0.068563               13
20           0.835131         0.929461        0.065165                5
21           0.824345         0.929151        0.068365               11
22           0.833590         0.928845        0.065648               12
23           0.824345         0.929458        0.068559                7
24           0.827427         0.928535        0.067536               16
25           0.825886         0.928842        0.069733               14
```

[18]:

```python
plt.figure(figsize=(15,5))

grid_mean_scores = grid.cv_results_['mean_test_score']
max_value = max(grid_mean_scores)  # maximum value
max_keys = np.where(grid_mean_scores == np.amax(grid_mean_scores))[0]+1 #␣
↪getting all keys containing the `maximum`

plt.plot(k_range, grid_mean_scores)
plt.xlabel('Value of K for KNN')
plt.ylabel('Accuracy');
plt.title('10-Fold GridSearchCV')
```

```
plt.axhline(max_value, color='r', linestyle='--', linewidth=1);
[plt.axvline(_x, linewidth=1, color='r',linestyle='--') for _x in max_keys];

print("Best Score: %.4f" % max_value)
print("Best K: ", max_keys)
```

```
Best Score: 0.9307
Best K:  [13]
```



7 EXTRA - SCIKIT Learn

7.0.1 1 - Use knn.score() to see the accuracy

[ ]:
```
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
```

[ ]:
```
# split into test and train dataset, and use random_state=48
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=4)
```

[ ]:
```
# build KNN model and choose n_neighbors = 5
knn = KNeighborsClassifier(n_neighbors = 1)
```

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

[ ]:
```
# get the predict value from X_test
y_pred = knn.predict(X_test)
print(y_pred)
```

[ ]:
```
# print the score
print('accuracy: ', knn.score(X_test, y_test))
```

[ ]:
```python
# choose k between 1 to 31
k_range = range(1, 31)

k_scores = []
# use iteration to caclulator different k in models, then return the average␣
↪accuracy based on the cross validation
for k in k_range:
    # build KNN model and choose n_neighbors
    knn = KNeighborsClassifier(n_neighbors=k, algorithm='auto', n_jobs=-1)
    # train the model
    knn.fit(X_train, y_train)
    # Append Scores
    k_scores.append(knn.score(X_test, y_test))
```

[ ]:
```python
import matplotlib.pyplot as plt
plt.style.use('fivethirtyeight')
plt.figure(figsize=(15,5))

plt.bar(k_range, k_scores, 0.5, color='g', edgecolor='k')

#highlight bar that is max
max_value = max(k_scores)
max_keys = [i for i, j in enumerate(k_scores) if j == max_value] # getting all␣
↪keys containing the `maximum`

plt.bar(max_keys, max_value, 0.5, color='b', edgecolor='k');
plt.axhline(max_value, color='b', linestyle='--', linewidth=1)

plt.xticks(np.arange(1, max(k_range)+1, 1));
plt.xlabel('Value of K for KNN')
plt.ylabel('Accuracy');
```

7.0.2 2 - Cross-Validation for Classification

[ ]:
```python
from sklearn.model_selection import cross_val_score

# X,y will automatically devided by 5 folder, the scoring I will still use the␣
↪accuracy
scores = cross_val_score(knn, X, y, cv=5, scoring='accuracy')

# print all 5 times scores
print(scores)

# then I will do the average about these five scores to get more accuracy score.
print(scores.mean())
```

7.0.3 we could choose differenct neighbors to see which K is the best K.

```
[ ]: # choose k between 1 to 31
k_range = range(1, 31)

k_scores = []
# use iteration to caclulator different k in models, then return the average␣
 ↪accuracy based on the cross validation
for k in k_range:
    knn = KNeighborsClassifier(n_neighbors=k, algorithm='auto', n_jobs=-1)
    scores = cross_val_score(knn, X, y, cv=10, scoring='accuracy')
    k_scores.append(scores.mean())
```

```
[ ]: plt.style.use('fivethirtyeight')
plt.figure(figsize=(15,5))

plt.bar(k_range, k_scores, 0.5, color='g', edgecolor='k')

#highlight bar that is max
max_value = max(k_scores)
max_keys = [i for i, j in enumerate(k_scores) if j == max_value] # getting all␣
 ↪keys containing the `maximum`

plt.bar(max_keys, max_value, 0.5, color='b', edgecolor='k');
plt.axhline(max_value, color='b', linestyle='--', linewidth=1)

plt.xticks(np.arange(1, max(k_range)+1, 1));
plt.xlabel('Value of K for KNN')
plt.ylabel('Cross-Validated Accuracy');
```

```
[ ]:
```