

```
In [1]:
```

```
# KNN Classification https://meet.google.com/hdp-wmjw-bmc
import pandas as pd # data manipulation
import numpy as np # numerical functions
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import confusion_matrix, classification_report, accuracy_score
```

p1

data ----> tarin and test

p2 CV :

data ---> tarin and test

train\_data-> data1,data2,data3,data4,data5

k=1

m1->data1,data2,data3,data4 :::: test-> data5 #91

m2->data1,data2,data3,data5 :::: test-> data4 #89

m3->data1,data2,data4,data5 :::: test-> data3 #80

m4->data1,data3,data4,data5 :::: test-> data2 #82

m5->data2,data3,data4,data5 :::: test-> data1 #87

overall =(91+89+80+82+87)/5

k=3

m1->data1,data2,data3,data4 :::: test-> data5 #91

m2->data1,data2,data3,data5 :::: test-> data4 #89

m3->data1,data2,data4,data5 :::: test-> data3 #80

m4->data1,data3,data4,data5 :::: test-> data2 #82

m5->data2,data3,data4,data5 :::: test-> data1 #87

overall =(91+89+80+82+87)/5

k=5

m1->data1,data2,data3,data4 :::: test-> data5 #91

m2->data1,data2,data3,data5 :::: test-> data4 #89

m3->data1,data2,data4,data5 :::: test-> data3 #80

m4->data1,data3,data4,data5 :::: test-> data2 #82

m5->data2,data3,data4,data5 :::: test-> data1 #87

overall =(91+89+80+82+87)/5

k=7

m1->data1,data2,data3,data4 :::: test-> data5 #91

m2->data1,data2,data3,data5 :::: test-> data4 #89

m3->data1,data2,data4,data5 :::: test-> data3 #80

m4->data1,data3,data4,data5 :::: test-> data2 #82

m5->data2,data3,data4,data5 :::: test-> data1 #87

overall =(91+89+80+82+87)/5

best k value is that one for which we get the best overall score and final model should be created for that value of k using entire training data

```
In [2]: from sklearn.datasets import load_diabetes  
data=load_diabetes()  
print(data.DESCR)  
print(data)
```

```
.. _diabetes_dataset:
```

Diabetes dataset

Ten baseline variables, age, sex, body mass index, average blood pressure, and six blood serum measurements were obtained for each of n = 442 diabetes patients, as well as the response of interest, a quantitative measure of disease progression one year after baseline.

\*\*Data Set Characteristics:\*\*

:Number of Instances: 442

:Number of Attributes: First 10 columns are numeric predictive values

:Target: Column 11 is a quantitative measure of disease progression one year after baseline

:Attribute Information:

- age age in years
- sex
- bmi body mass index
- bp average blood pressure
- s1 tc, total serum cholesterol
- s2 ldl, low-density lipoproteins
- s3 hdl, high-density lipoproteins
- s4 tch, total cholesterol / HDL
- s5 ltg, possibly log of serum triglycerides level
- s6 glu, blood sugar level

Note: Each of these 10 feature variables have been mean centered and scaled by the standard deviation times the square root of `n\_samples` (i.e. the sum of squares of each column totals 1).

Source URL:

<https://www4.stat.ncsu.edu/~boos/var.select/diabetes.html>

For more information see:

Bradley Efron, Trevor Hastie, Iain Johnstone and Robert Tibshirani (2004) "Least Angle Regression," Annals of Statistics (with discussion), 407-499.

([https://web.stanford.edu/~hastie/Papers/LARS/LeastAngle\\_2002.pdf](https://web.stanford.edu/~hastie/Papers/LARS/LeastAngle_2002.pdf))

```
{'data': array([[ 0.03807591,  0.05068012,  0.06169621, ..., -0.00259226,  
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   [-0.00188202, -0.04464164, -0.05147406, ..., -0.03949338,  
    -0.06833155, -0.09220405],  
   [ 0.08529891,  0.05068012,  0.04445121, ..., -0.00259226,  
    0.00286131, -0.02593034],  
   ...,  
   [ 0.04170844,  0.05068012, -0.01590626, ..., -0.01107952,  
    -0.04688253,  0.01549073],  
   [-0.04547248, -0.04464164,  0.03906215, ...,  0.02655962,  
    0.04452873, -0.02593034],  
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    -0.00422151,  0.00306441]]), 'target': array([151.,  75., 141., 206., 135.,  97., 138.,  63., 110., 310.,  
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87., 65., 102., 265., 276., 252., 90., 100., 55., 61., 92.,  
259., 53., 190., 142., 75., 142., 155., 225., 59., 104., 182.,  
128., 52., 37., 170., 170., 61., 144., 52., 128., 71., 163.,  
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200., 252., 113., 143., 51., 52., 210., 65., 141., 55., 134.,  
42., 111., 98., 164., 48., 96., 90., 162., 150., 279., 92.,  
83., 128., 102., 302., 198., 95., 53., 134., 144., 232., 81.,  
104., 59., 246., 297., 258., 229., 275., 281., 179., 200., 200.,  
173., 180., 84., 121., 161., 99., 109., 115., 268., 274., 158.,  
107., 83., 103., 272., 85., 280., 336., 281., 118., 317., 235.,  
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197., 186., 25., 84., 96., 195., 53., 217., 172., 131., 214.,  
59., 70., 220., 268., 152., 47., 74., 295., 101., 151., 127.,  
237., 225., 81., 151., 107., 64., 138., 185., 265., 101., 137.,  
143., 141., 79., 292., 178., 91., 116., 86., 122., 72., 129.,  
142., 90., 158., 39., 196., 222., 277., 99., 196., 202., 155.,  
77., 191., 70., 73., 49., 65., 263., 248., 296., 214., 185.,  
78., 93., 252., 150., 77., 208., 77., 108., 160., 53., 220.,  
154., 259., 90., 246., 124., 67., 72., 257., 262., 275., 177.,  
71., 47., 187., 125., 78., 51., 258., 215., 303., 243., 91.,  
150., 310., 153., 346., 63., 89., 50., 39., 103., 308., 116.,
```

```

145., 74., 45., 115., 264., 87., 202., 127., 182., 241., 66.,
94., 283., 64., 102., 200., 265., 94., 230., 181., 156., 233.,
60., 219., 80., 68., 332., 248., 84., 200., 55., 85., 89.,
31., 129., 83., 275., 65., 198., 236., 253., 124., 44., 172.,
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191., 122., 230., 242., 248., 249., 192., 131., 237., 78., 135.,
244., 199., 270., 164., 72., 96., 306., 91., 214., 95., 216.,
263., 178., 113., 200., 139., 139., 88., 148., 88., 243., 71.,
77., 109., 272., 60., 54., 221., 90., 311., 281., 182., 321.,
58., 262., 206., 233., 242., 123., 167., 63., 197., 71., 168.,
140., 217., 121., 235., 245., 40., 52., 104., 132., 88., 69.,
219., 72., 201., 110., 51., 277., 63., 118., 69., 273., 258.,
43., 198., 242., 232., 175., 93., 168., 275., 293., 281., 72.,
140., 189., 181., 209., 136., 261., 113., 131., 174., 257., 55.,
84., 42., 146., 212., 233., 91., 111., 152., 120., 67., 310.,
94., 183., 66., 173., 72., 49., 64., 48., 178., 104., 132.,
220., 57.]), 'frame': None, 'DESCR': '... _diabetes_dataset:\n\nDiabetes dataset\n-----\nTen baseline variables, age, sex, body mass index, average blood pressure, and six blood serum measurements were obtained for each of n = 308 diabetes patients, as well as the response of interest, a quantitative measure of disease progression one year after baseline.\n**Data Set Characteristics:**\nNumber of Instances: 308\nNumber of Attributes: First 10 columns are numeric predictive values\nTarget: Column 11 is a quantitative measure of disease progression one year after baseline\nAttribute Information:\n - age age in years\n - sex\n - bmi body mass index\n - bp average blood pressure\n - s1 tc, total serum cholesterol\n - s2 ldl, low-density lipoproteins\n - s3 hdl, high-density lipoproteins\n - s4 tc\n - s5 ltg, possibly log of serum triglycerides level\n - s6 glu, blood sugar level\nNote: Each of these 10 feature variables have been mean centered and scaled by the standard deviation times the square root of `n_samples` (i.e. the sum of squares of each column totals 1).\nSource URL:\nhttps://www4.stat.ncsu.edu/~boos/var.select/diabetes.html\nFor more information see:\nBradley Efron, Trevor Hastie, Iain Johnstone and Robert Tibshirani (2004) "Least Angle Regression," Annals of Statistics (with discussion), 32(2), 407-499.\n(nhttps://web.stanford.edu/~hastie/Papers/LARS/LeastAngle_2002.pdf)\n', 'feature_names': ['age', 'sex', 'bmi', 'bp', 's1', 's2', 's3', 's4', 's5', 's6'], 'data_filename': 'diabetes_data_raw.csv.gz', 'target_file_name': 'diabetes_target.csv.gz', 'data_module': 'sklearn.datasets.data'}}

```

In [3]: `ls`

```

Volume in drive C is Windows-SSD
Volume Serial Number is 08B4-FA6D

```

```
Directory of C:\Users\Agnel Sharon Jerald\Machine learning
```

```

03-12-2025 09:43    <DIR>      .
24-11-2025 16:52    <DIR>      ..
03-12-2025 09:26    <DIR>      .ipynb_checkpoints
01-12-2025 09:16          29,822 claimants.csv
01-12-2025 10:02          128,594 Claimants_classification.ipynb
23-10-2025 10:52          252,200 Data Visualisations.ipynb
03-12-2025 09:25          10,523 KNN_updated.ipynb
24-11-2025 16:56          95,226 Linear_Regression.ipynb
18-11-2025 09:21          57,420 Machine Learning basics.ipynb
22-10-2025 17:51          26,046 Numpy.ipynb
03-12-2025 09:43          23,279 pima-indians-diabetes.csv
23-10-2025 16:20          54,750 Practice libraries.ipynb
               9 File(s)   677,860 bytes
               3 Dir(s)  113,203,838,976 bytes free

```

In [4]: `filename = 'pima-indians-diabetes.csv'`  
`names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass', 'pedi', 'age', 'class']`  
`dataframe = pd.read_csv(filename, names=names)`  
`dataframe`

	preg	plas	pres	skin	test	mass	pedi	age	class
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1
...	...	...	...	...	...	...	...	...	...
763	10	101	76	48	180	32.9	0.171	63	0
764	2	122	70	27	0	36.8	0.340	27	0
765	5	121	72	23	112	26.2	0.245	30	0
766	1	126	60	0	0	30.1	0.349	47	1
767	1	93	70	31	0	30.4	0.315	23	0

768 rows × 9 columns

In [5]: `X = dataframe.iloc[:, 0:-1]`

```
Y = dataframe.iloc[:, -1]
```

```
In [6]: dataframe["class"].value_counts()
```

```
Out[6]: class
0    500
1    268
Name: count, dtype: int64
```

```
In [7]: X=(X-X.min(axis=0))/(X.max(axis=0)-X.min(axis=0))
```

```
In [8]: X.round(2)
```

```
Out[8]:   preg  plas  pres  skin  test  mass  pedi  age
0     0.35  0.74  0.59  0.35  0.00  0.50  0.23  0.48
1     0.06  0.43  0.54  0.29  0.00  0.40  0.12  0.17
2     0.47  0.92  0.52  0.00  0.00  0.35  0.25  0.18
3     0.06  0.45  0.54  0.23  0.11  0.42  0.04  0.00
4     0.00  0.69  0.33  0.35  0.20  0.64  0.94  0.20
...
763   0.59  0.51  0.62  0.48  0.21  0.49  0.04  0.70
764   0.12  0.61  0.57  0.27  0.00  0.55  0.11  0.10
765   0.29  0.61  0.59  0.23  0.13  0.39  0.07  0.15
766   0.06  0.63  0.49  0.00  0.00  0.45  0.12  0.43
767   0.06  0.47  0.57  0.31  0.00  0.45  0.10  0.03
```

768 rows × 8 columns

```
In [9]: x_train,x_test,y_train,y_test=train_test_split(X,Y,test_size=0.3,random_state=19)
```

```
In [10]: print(x_train.shape,x_test.shape,y_train.shape,y_test.shape)
```

(537, 8) (231, 8) (537,) (231,)

```
In [11]: # model of train data
model = KNeighborsClassifier(n_neighbors=5)
model.fit(x_train,y_train)
pred=model.predict(x_train)
print(classification_report(y_train,pred))
```

	precision	recall	f1-score	support
0	0.83	0.90	0.87	346
1	0.80	0.67	0.73	191
accuracy			0.82	537
macro avg	0.81	0.79	0.80	537
weighted avg	0.82	0.82	0.82	537

```
In [12]: # model of test data
model = KNeighborsClassifier(n_neighbors=5)
model.fit(x_train,y_train)
pred=model.predict(x_test)
print(classification_report(y_test,pred))
```

	precision	recall	f1-score	support
0	0.80	0.88	0.84	154
1	0.69	0.56	0.62	77
accuracy			0.77	231
macro avg	0.75	0.72	0.73	231
weighted avg	0.76	0.77	0.76	231

## model of test data

```
model = KNeighborsClassifier(n_neighbors=15)
model.fit(x_train,y_train)
pred=model.predict(x_test)
accuracy_score(y_test,pred)
print(classification_report(y_test,pred))
```

```
In [13]: n_neighbors=[2*i+1 for i in range(0,27)]
for i in n_neighbors:
```

```

print(f'i value = {i}')
model = KNeighborsClassifier(n_neighbors=i)
model.fit(x_train,y_train)
pred=model.predict(x_test)
acc = accuracy_score(y_test,pred)
print("acc=",acc)
print(classification_report(y_test,pred))

```

i value = 1  
acc= 0.7229437229437229

	precision	recall	f1-score	support
0	0.78	0.82	0.80	154
1	0.59	0.53	0.56	77
accuracy			0.72	231
macro avg	0.69	0.68	0.68	231
weighted avg	0.72	0.72	0.72	231

i value = 3  
acc= 0.7272727272727273

	precision	recall	f1-score	support
0	0.78	0.83	0.80	154
1	0.61	0.52	0.56	77
accuracy			0.73	231
macro avg	0.69	0.68	0.68	231
weighted avg	0.72	0.73	0.72	231

i value = 5  
acc= 0.7705627705627706

	precision	recall	f1-score	support
0	0.80	0.88	0.84	154
1	0.69	0.56	0.62	77
accuracy			0.77	231
macro avg	0.75	0.72	0.73	231
weighted avg	0.76	0.77	0.76	231

i value = 7  
acc= 0.7272727272727273

	precision	recall	f1-score	support
0	0.77	0.84	0.80	154
1	0.61	0.49	0.55	77
accuracy			0.73	231
macro avg	0.69	0.67	0.68	231
weighted avg	0.72	0.73	0.72	231

i value = 9  
acc= 0.7532467532467533

	precision	recall	f1-score	support
0	0.79	0.86	0.82	154
1	0.66	0.53	0.59	77
accuracy			0.75	231
macro avg	0.72	0.70	0.71	231
weighted avg	0.75	0.75	0.75	231

i value = 11  
acc= 0.7792207792207793

	precision	recall	f1-score	support
0	0.79	0.90	0.84	154
1	0.73	0.53	0.62	77
accuracy			0.78	231
macro avg	0.76	0.72	0.73	231
weighted avg	0.77	0.78	0.77	231

i value = 13  
acc= 0.7705627705627706

	precision	recall	f1-score	support
0	0.80	0.88	0.84	154
1	0.70	0.55	0.61	77
accuracy			0.77	231
macro avg	0.75	0.71	0.73	231
weighted avg	0.76	0.77	0.76	231

i value = 15  
acc= 0.7748917748917749

	precision	recall	f1-score	support
0	0.80	0.89	0.84	154
1	0.71	0.55	0.62	77
accuracy			0.77	231
macro avg	0.75	0.72	0.73	231
weighted avg	0.77	0.77	0.77	231

i value = 17  
acc= 0.7748917748917749

	precision	recall	f1-score	support
0	0.79	0.90	0.84	154
1	0.73	0.52	0.61	77
accuracy			0.77	231
macro avg	0.76	0.71	0.72	231
weighted avg	0.77	0.77	0.76	231

i value = 19  
acc= 0.7532467532467533

	precision	recall	f1-score	support
0	0.76	0.92	0.83	154
1	0.72	0.43	0.54	77
accuracy			0.75	231
macro avg	0.74	0.67	0.68	231
weighted avg	0.75	0.75	0.73	231

i value = 21  
acc= 0.7662337662337663

	precision	recall	f1-score	support
0	0.77	0.93	0.84	154
1	0.76	0.44	0.56	77
accuracy			0.77	231
macro avg	0.76	0.69	0.70	231
weighted avg	0.76	0.77	0.75	231

i value = 23  
acc= 0.7575757575757576

	precision	recall	f1-score	support
0	0.76	0.92	0.84	154
1	0.73	0.43	0.54	77
accuracy			0.76	231
macro avg	0.75	0.68	0.69	231
weighted avg	0.75	0.76	0.74	231

i value = 25  
acc= 0.7705627705627706

	precision	recall	f1-score	support
0	0.76	0.95	0.85	154
1	0.80	0.42	0.55	77
accuracy			0.77	231
macro avg	0.78	0.68	0.70	231
weighted avg	0.78	0.77	0.75	231

i value = 27  
acc= 0.7619047619047619

	precision	recall	f1-score	support
0	0.76	0.94	0.84	154
1	0.76	0.42	0.54	77
accuracy			0.76	231
macro avg	0.76	0.68	0.69	231
weighted avg	0.76	0.76	0.74	231

i value = 29  
acc= 0.7575757575757576

	precision	recall	f1-score	support
0	0.76	0.93	0.84	154

1	0.74	0.42	0.53	77
accuracy			0.76	231
macro avg	0.75	0.67	0.68	231
weighted avg	0.76	0.76	0.74	231

i value = 31  
acc= 0.7575757575757576

	precision	recall	f1-score	support
0	0.75	0.95	0.84	154
1	0.78	0.38	0.51	77
accuracy			0.76	231
macro avg	0.77	0.66	0.67	231
weighted avg	0.76	0.76	0.73	231

i value = 33  
acc= 0.7402597402597403

	precision	recall	f1-score	support
0	0.74	0.94	0.83	154
1	0.73	0.35	0.47	77
accuracy			0.74	231
macro avg	0.74	0.64	0.65	231
weighted avg	0.74	0.74	0.71	231

i value = 35  
acc= 0.7619047619047619

	precision	recall	f1-score	support
0	0.75	0.95	0.84	154
1	0.81	0.38	0.51	77
accuracy			0.76	231
macro avg	0.78	0.67	0.68	231
weighted avg	0.77	0.76	0.73	231

i value = 37  
acc= 0.7575757575757576

	precision	recall	f1-score	support
0	0.75	0.95	0.84	154
1	0.78	0.38	0.51	77
accuracy			0.76	231
macro avg	0.77	0.66	0.67	231
weighted avg	0.76	0.76	0.73	231

i value = 39  
acc= 0.7575757575757576

	precision	recall	f1-score	support
0	0.75	0.95	0.84	154
1	0.78	0.38	0.51	77
accuracy			0.76	231
macro avg	0.77	0.66	0.67	231
weighted avg	0.76	0.76	0.73	231

i value = 41  
acc= 0.7575757575757576

	precision	recall	f1-score	support
0	0.75	0.95	0.84	154
1	0.78	0.38	0.51	77
accuracy			0.76	231
macro avg	0.77	0.66	0.67	231
weighted avg	0.76	0.76	0.73	231

i value = 43  
acc= 0.7489177489177489

	precision	recall	f1-score	support
0	0.75	0.94	0.83	154
1	0.74	0.38	0.50	77
accuracy			0.75	231
macro avg	0.75	0.66	0.67	231
weighted avg	0.75	0.75	0.72	231

```
i value = 45
acc= 0.7575757575757576
      precision    recall  f1-score   support
      0       0.75      0.95     0.84     154
      1       0.78      0.38     0.51      77

accuracy                           0.76     231
macro avg                         0.77     0.66     0.67     231
weighted avg                      0.76     0.76     0.73     231

i value = 47
acc= 0.7619047619047619
      precision    recall  f1-score   support
      0       0.76      0.95     0.84     154
      1       0.79      0.39     0.52      77

accuracy                           0.76     231
macro avg                         0.77     0.67     0.68     231
weighted avg                      0.77     0.76     0.73     231

i value = 49
acc= 0.7575757575757576
      precision    recall  f1-score   support
      0       0.76      0.94     0.84     154
      1       0.77      0.39     0.52      77

accuracy                           0.76     231
macro avg                         0.76     0.67     0.68     231
weighted avg                      0.76     0.76     0.73     231

i value = 51
acc= 0.7619047619047619
      precision    recall  f1-score   support
      0       0.76      0.95     0.84     154
      1       0.79      0.39     0.52      77

accuracy                           0.76     231
macro avg                         0.77     0.67     0.68     231
weighted avg                      0.77     0.76     0.73     231

i value = 53
acc= 0.7575757575757576
      precision    recall  f1-score   support
      0       0.75      0.95     0.84     154
      1       0.78      0.38     0.51      77

accuracy                           0.76     231
macro avg                         0.77     0.66     0.67     231
weighted avg                      0.76     0.76     0.73     231
```

In [14]: `(2*(0.76*0.94))/(0.76+0.94)`

Out[14]: 0.8404705882352941

In [15]: `n_neighbors=[2*i+1 for i in range(0,27)]`  
`n_neighbors`

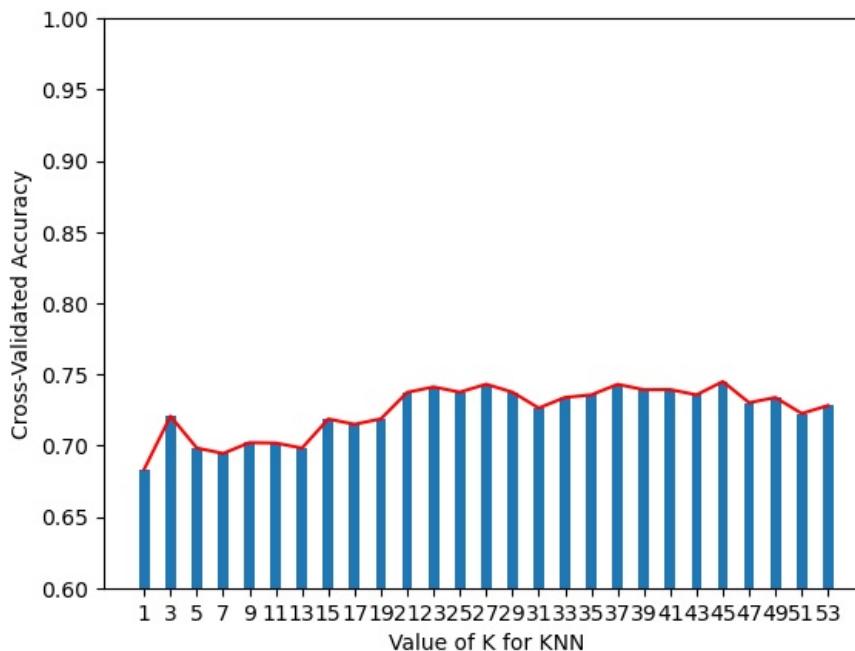
```
Out[15]: [1,
 3,
 5,
 7,
 9,
 11,
 13,
 15,
 17,
 19,
 21,
 23,
 25,
 27,
 29,
 31,
 33,
 35,
 37,
 39,
 41,
 43,
 45,
 47,
 49,
 51,
 53]
```

```
In [ ]: # print(grid.best_score_)
# print(grid.best_params_)
```

## Visualizing the CV results

```
In [16]: import matplotlib.pyplot as plt
%matplotlib inline
# choose k between 1 to 55
k_range = [2*i+1 for i in range(0,27)]
k_scores = []
# use iteration to calculate different k in models, then return the average accuracy based on the cross validation
for k in k_range:
    knn = KNeighborsClassifier(n_neighbors=k)
    scores = cross_val_score(knn,x_train , y_train, cv=10)
    k_scores.append(scores.mean())
# plot to see clearly
plt.bar(k_range, k_scores)
plt.plot(k_range, k_scores,color="red")

plt.xlabel('Value of K for KNN')
plt.ylabel('Cross-Validated Accuracy')
plt.xticks(k_range)
plt.ylim(0.6,1)
plt.show()
```



```
In [17]: np.argmax(k_scores)
```

```
Out[17]: np.int64(22)
```

```
In [18]: k_range[22]
```

```
Out[18]: 45
```

```
In [19]: knn = KNeighborsClassifier(n_neighbors=45)
scores = cross_val_score(knn,x_train , y_train, cv=10)
scores.mean()
```

```
Out[19]: np.float64(0.7449336128581412)
```

```
In [20]: from sklearn.linear_model import LogisticRegression
lrm = LogisticRegression()
lrm.fit(x_train,y_train)
pred = lrm.predict(x_test)
print(classification_report(y_test,pred))
```

	precision	recall	f1-score	support
0	0.78	0.90	0.83	154
1	0.71	0.48	0.57	77
accuracy			0.76	231
macro avg	0.74	0.69	0.70	231
weighted avg	0.75	0.76	0.75	231

```
In [21]: k_scores
```

```
Out[21]: [np.float64(0.6833682739343117),
np.float64(0.7206149545772187),
np.float64(0.698252969951083),
np.float64(0.6944095038434661),
np.float64(0.7019916142557652),
np.float64(0.7017470300489168),
np.float64(0.6981830887491264),
np.float64(0.7186233403214536),
np.float64(0.7148846960167715),
np.float64(0.7187281621243885),
np.float64(0.7373165618448637),
np.float64(0.7411250873515024),
np.float64(0.737456324248777),
np.float64(0.7430468204053109),
np.float64(0.7374563242487772),
np.float64(0.7263102725366877),
np.float64(0.7337526205450733),
np.float64(0.735569531795947),
np.float64(0.7429769392033542),
np.float64(0.7391684136967156),
np.float64(0.7392732354996505),
np.float64(0.735569531795947),
np.float64(0.7449336128581412),
np.float64(0.7300489168413697),
np.float64(0.733717679944095),
np.float64(0.7224668064290706),
np.float64(0.7280573025856045)]
```