# K-Nearest-Neighbors

### What type of data is suitable for performing KNN algorithm?

K Nearest Neighbor (KNN) is a machine learning approach that is both basic and versatile. It's utilized in a wide range of applications, including handwriting recognition, picture recognition, and video recognition. When labeled data is too expensive or impossible to gather, KNN comes in handy, because it can solve a wide range of prediction problems with high accuracy.

KNN is a simple algorithm that uses the target function's local minimum to learn an unknown function with the appropriate precision and accuracy. The program also determines the location of an unknown input, as well as its range and distance from it. It works on the notion of "knowledge gain," in which the algorithm determines which method is best for predicting an unknown number.

#### In which situations, can we conduct this algorithm?

Because it is a lazy learning algorithm, it does not require any prior training before providing real-time predictions. This makes the KNN algorithm much faster than other training-based algorithms like SVM, linear regression, and so forth. So, when there is even less training data, we can still use KNN algorithm to get predictions. Even like classifying on common intrest sharing observations data will have better results with KNN.

```
In [1]:
         import matplotlib.pyplot as plt
         import pandas as pd
         import numpy as np
         from sklearn.preprocessing import StandardScaler
         from sklearn.model selection import train test split
         from sklearn.neighbors import KNeighborsClassifier
         from sklearn.metrics import confusion_matrix
          from sklearn import metrics
         import seaborn as sns
         %matplotlib inline
In [2]:
         def map(df):
              ax = sns.heatmap(df, annot=True, cmap='Blues')
              ax.set title('Confusion Matrix\n\n');
              ax.set_xlabel('\nPredicted Values')
              ax.set_ylabel('Actual Values ');
              ax.xaxis.set_ticklabels(['False','True'])
ax.yaxis.set_ticklabels(['False','True'])
```

Dataset we are considering to understand the algorith is pima indians diabetes dataset. source: https://github.com/npradaschnor/Pima-Indians-Diabetes-Dataset/blob/master/diabetes.csv

```
In [3]: data = pd.read_csv('diabetes.csv')
    data
```

3]:		Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	ВМІ	DiabetesPedigreeFunction	Age	Outcome
	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

This dataset classifys whether a particular person has diabetes(outcome as lable) with respect to these attributes/features like glucose, Insulin, BMI, blood pressure, etc., readings. This is a classification problem and it has labels so, this is a supervised learning problem.

• As there are less number of observations, we can select KNN algorithm to classify this data.

• Also, there is high possibility to persons to share common feature values to be in a similar class. This is also considerable to use KNN.

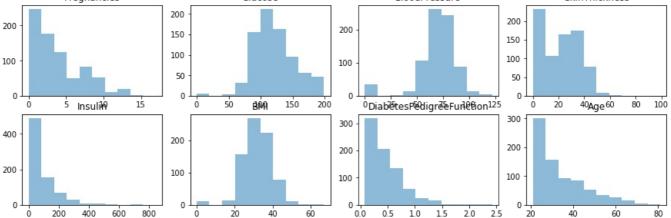
```
In [4]:
         data.info()
        <class 'pandas.core.frame.DataFrame'>
        RangeIndex: 768 entries, 0 to 767
        Data columns (total 9 columns):
         #
              Column
                                         Non-Null Count
                                                          Dtype
         0
             Pregnancies
                                         768 non-null
                                                          int64
         1
              Glucose
                                         768 non-null
                                                          int64
              BloodPressure
                                         768 non-null
                                                          int64
         3
              SkinThickness
                                         768 non-null
                                                          int64
                                         768 non-null
         4
              Insulin
                                                          int64
         5
              BMI
                                         768 non-null
                                                          float64
             DiabetesPedigreeFunction
                                         768 non-null
                                                          float64
                                         768 non-null
                                                          int64
              Age
         8
              Outcome
                                         768 non-null
                                                          int64
        dtypes: float64(2), int64(7)
```

As we see the dataset is already mostly clean and there are no null/NaN values. Let us see statistical data of the dataset.

memory usage: 54.1 KB

```
In [5]:
            data.describe()
Out[5]:
                  Pregnancies
                                  Glucose
                                           BloodPressure
                                                           SkinThickness
                                                                               Insulin
                                                                                               вмі
                                                                                                   DiabetesPedigreeFunction
                                                                                                                                             Outcome
                                                                                                                                     Age
           count
                   768.000000
                               768.000000
                                                768.000000
                                                               768.000000
                                                                           768.000000
                                                                                        768.000000
                                                                                                                  768.000000
                                                                                                                              768.000000
                                                                                                                                           768.000000
                                                                            79.799479
                                                                                         31.992578
           mean
                     3.845052
                               120.894531
                                                69.105469
                                                                20.536458
                                                                                                                    0.471876
                                                                                                                                33.240885
                                                                                                                                             0.348958
                     3 369578
                                31 972618
                                                 19 355807
                                                                15 952218
                                                                           115 244002
                                                                                          7 884160
                                                                                                                    0.331329
                                                                                                                                11 760232
                                                                                                                                             0.476951
             std
            min
                     0.000000
                                  0.000000
                                                 0.000000
                                                                 0.000000
                                                                             0.000000
                                                                                          0.000000
                                                                                                                    0.078000
                                                                                                                                21.000000
                                                                                                                                             0.000000
            25%
                     1.000000
                                99.000000
                                                62.000000
                                                                 0.000000
                                                                             0.000000
                                                                                         27.300000
                                                                                                                    0.243750
                                                                                                                                24.000000
                                                                                                                                             0.000000
                     3.000000
                                                                23.000000
                                                                            30.500000
                                                                                         32.000000
                                                                                                                                29.000000
                                                                                                                                             0.000000
            50%
                               117.000000
                                                72.000000
                                                                                                                    0.372500
            75%
                     6.000000
                               140.250000
                                                80.000000
                                                                32.000000
                                                                           127.250000
                                                                                         36.600000
                                                                                                                    0.626250
                                                                                                                                41.000000
                                                                                                                                             1.000000
                    17.000000 199.000000
                                                122.000000
                                                                99.000000
                                                                           846.000000
                                                                                         67.100000
                                                                                                                    2.420000
                                                                                                                                81.000000
                                                                                                                                              1.000000
            max
```

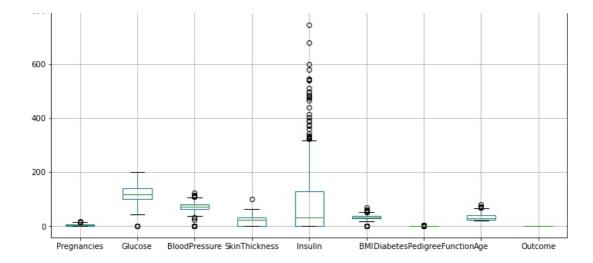
```
In [6]:
          col = list(data.columns)[:-1]
          plt.figure(figsize=(15, 10))
          for x in range(1,len(col)+1):
              plt.subplot(4,4,x)
              plt.hist(data[col[x-1]], alpha = 0.5)
              plt.title(col[x-1])
              plt.plot()
                                                     Glucose
                                                                                 BloodPressure
                                                                                                               SkinThickness
                    Pregnancies
                                        200
                                                                                                     200
         200
                                                                      200
```



```
In [7]:
   plt.figure(figsize=(12, 6))
   data.boxplot()
```

<matplotlib.axes. subplots.AxesSubplot at 0x2dc7ff000b8>

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900					



We can see the data is not sparse and all features have different stats or do not share same range values. There is a scalability issue. As the distance is computed to the K values in the neighborhood, which is a clear influencing factor for KNN algorithms.

```
In [8]:
    data1 = data.copy()
    y = data1['Outcome']
    data1.drop(columns = 'Outcome', inplace = True)
    X = data1
```

Taking 80-20 split for training and testing data.

```
In [9]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20,random_state=4)
```

Because the KNN algorithm is based on Euclidean Distance, it is necessary to scale all variables before running it. KNN is very sensitive to scale from this perspective.

```
In [10]:
            scale = StandardScaler()
            X train = scale.fit transform(X train)
            X_test = scale.transform(X_test)
            X train
          array([[-1.13297401, -1.70544954, 0.3837674 , ..., 1.63727815,
                     -0.83696713, 1.09138367],
                    \hbox{$[-0.83670227,\ -1.29149491,\ -0.6919493\ ,\ \dots,\ -1.55372817,}
                     0.6446041 , -1.0400081 ],
                   \hbox{$[-0.54043053,} \ -0.4954283 \ , \ 0.33254279, \ \dots, \ -1.04219281,
                     0.26310891, 1.68817336],
                   [\ 0.64465642,\ -0.43174297,\ 0.99846265,\ \ldots,\ 0.60202801,
                     0.76505617, -0.18745139],
                    [-0.54043053, -1.45070823, -0.23092786, ..., -0.26271035,
                    -0.54043053, -1.430,002,
-0.30796881, -0.01694005],
-0.54042053 -0.43174297, 0.28131819, ..., 0.21228678,
                   [-0.54043053, -0.43174297,
-0.20577596, -0.86949676]])
```

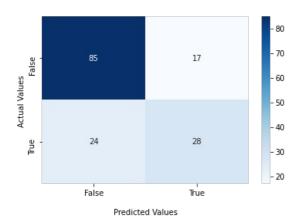
KNN classifier from sklearn library to fit/train the model.

Train set Accuracy: 0.8175895765472313 Test set Accuracy: 0.7337662337662337

```
In [14]: cf_matrix = confusion_matrix(y_test, y_pred)
    print(cf_matrix)
    map(cf_matrix)

[[85 17]
    [24 28]]
```

#### Confusion Matrix



We know, in for KNN algorithm we have to give k value and we do not know exactly which would be perfect k value or which k value will give more accuracy while testing model. So, we will try a certain number of k values and check there accuracies and will proceed with specific k-value which has the best accuracy.

```
In [15]:
          K = 10
          error = []
          mean_accuracy = np.zeros((K-1))
          std_accuracy = np.zeros((K-1))
ConfustionMx = [];
          for n in range(1,K):
               #Train Model and Predict
              model = KNeighborsClassifier(n_neighbors = n).fit(X_train,y_train)
              yhat = model.predict(X_test)
              mean_accuracy[n-1] = metrics.accuracy_score(y_test, yhat)
              std_accuracy[n-1]=np.std(yhat==y_test)/np.sqrt(yhat.shape[0])
               error.append(np.mean(yhat != y_test))
          mean_accuracy
         array([0.68831169, 0.71428571, 0.74675325, 0.74025974, 0.73376623,
Out[15]:
                 0.74025974, 0.75324675, 0.74025974, 0.75974026])
```

we can see here the k-value = 9 has best accuracy so, it is suggested to use k=9 for KNN algorithm inorder classify the new data.

we can see here the k-value = 9 has less error rate.

```
In [17]:
    conf_matrix = confusion_matrix(y_test, yhat) #for k =9
    map(conf_matrix)
```

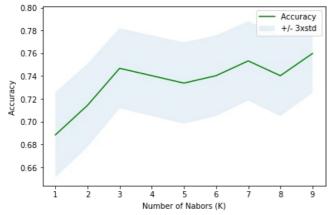
Confusion Matrix





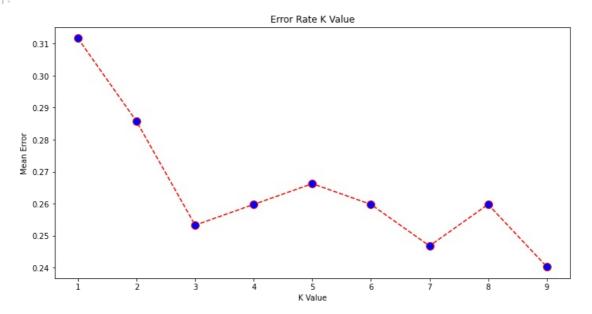
Graphical plot representation of accuracy attained by different k-values.

```
plt.plot(range(1,K),mean_accuracy,'g')
plt.fill_between(range(1,K),mean_accuracy - 1 * std_accuracy,mean_accuracy + 1 * std_accuracy, alpha=0.10)
plt.legend(('Accuracy ', '+/- 3xstd'))
plt.ylabel('Accuracy ')
plt.xlabel('Number of Nabors (K)')
plt.tight_layout()
plt.show()
```



Graphical plot representation of mean-errors attained by different k-values.

Out[19]: Text(0, 0.5, 'Mean Error')



As the k values decrease the error rate also has a downfall in this plot and at k = 9, there is least error value.

## Reference:

- https://neptune.ai/blog/knn-algorithm-explanation-opportunities-limitations#:~:text=KNN%20is%20most%20useful%20when,of%20desired%20precision%20and%20accuracy.
- https://stackabuse.com/k-nearest-neighbors-algorithm-in-python-and-scikit-learn/
- https://uncg.instructure.com/courses/100793/files/9953361?wrap=1
- https://www.stackvidhya.com/plot-confusion-matrix-in-python-and-why/

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