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## **Group B: Assignments based on Data Analytics using Python**

**Perform the following operations using Python on the Air quality and Heart Diseases data sets**

- a. Data cleaning
- b. Data integration
- c. Data transformation
- d. Error correcting
- e. Data model building

## **INTRODUCTION**

We have a data which classified if patients have heart disease or not according to features in it. We will try to use this data to create a model which tries predict if a patient has this disease or not. We will use logistic regression (classification) algorithm.

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split

# Input data files are available in the "../input/" directory.
# For example, running this (by clicking run or pressing Shift+Enter) will list the files in the input directory

import os
print(os.listdir("../input"))

# Any results you write to the current directory are saved as output.
```

```
['heart.csv']
```

## **Read Data**

In [2]:

```
# We are reading our data
df = pd.read_csv("../input/heart.csv")
```

In [3]:

```
# First 5 rows of our data  
df.head()
```

Out[3]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
0	63	1	3	145	233	1	0	150	0	2.3	0	0	1	1
1	37	1	2	130	250	0	1	187	0	3.5	0	0	2	1
2	41	0	1	130	204	0	0	172	0	1.4	2	0	2	1
3	56	1	1	120	236	0	1	178	0	0.8	2	0	2	1
4	57	0	0	120	354	0	1	163	1	0.6	2	0	2	1

Data contains;

- age - age in years
- sex - (1 = male; 0 = female)
- cp - chest pain type
- trestbps - resting blood pressure (in mm Hg on admission to the hospital)
- chol - serum cholesterol in mg/dl
- fbs - (fasting blood sugar > 120 mg/dl) (1 = true; 0 = false)
- restecg - resting electrocardiographic results
- thalach - maximum heart rate achieved
- exang - exercise induced angina (1 = yes; 0 = no)
- oldpeak - ST depression induced by exercise relative to rest
- slope - the slope of the peak exercise ST segment
- ca - number of major vessels (0-3) colored by flourosopy
- thal - 3 = normal; 6 = fixed defect; 7 = reversable defect
- target - have disease or not (1=yes, 0=no)

## Data Exploration

In [4]:

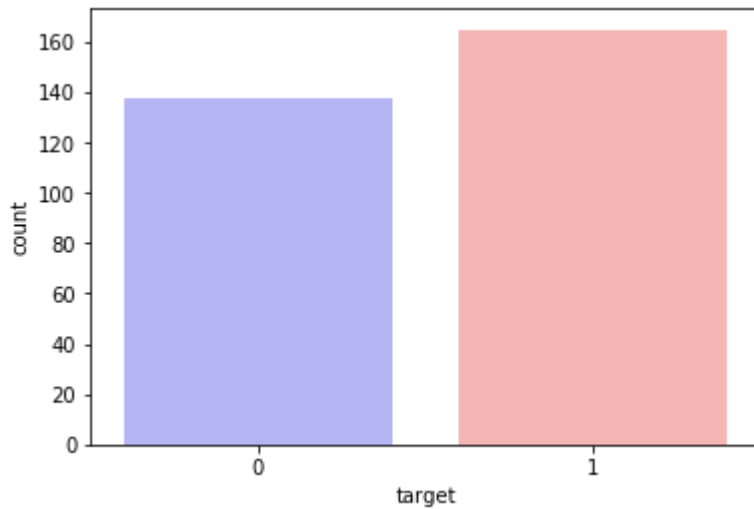
```
df.target.value_counts()
```

Out[4]:

```
1    165  
0    138  
Name: target, dtype: int64
```

In [5]:

```
sns.countplot(x="target", data=df, palette="bwr")  
plt.show()
```



In [6]:

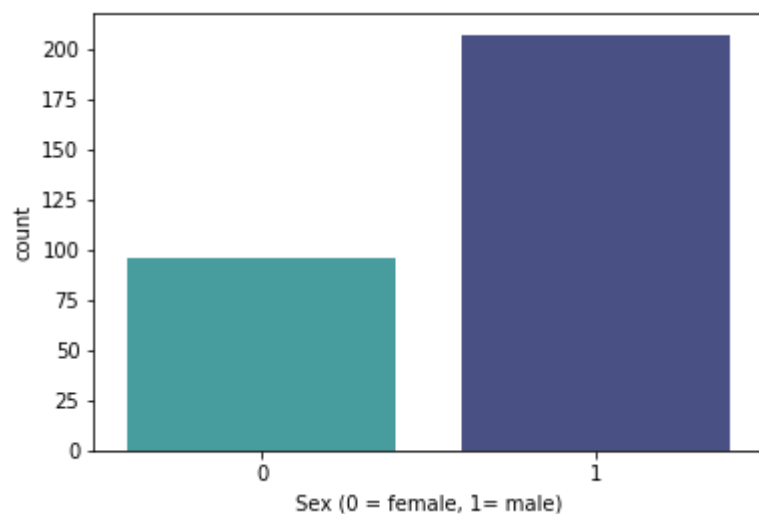
```
countNoDisease = len(df[df.target == 0])  
countHaveDisease = len(df[df.target == 1])  
print("Percentage of Patients Haven't Heart Disease: {:.2f}%".format((countNoDisease / (len(df))))  
print("Percentage of Patients Have Heart Disease: {:.2f}%".format((countHaveDisease / (len(df))))
```

Percentage of Patients Haven't Heart Disease: 45.54%

Percentage of Patients Have Heart Disease: 54.46%

In [7]:

```
sns.countplot(x='sex', data=df, palette="mako_r")
plt.xlabel("Sex (0 = female, 1= male)")
plt.show()
```



In [8]:

```
countFemale = len(df[df.sex == 0])
countMale = len(df[df.sex == 1])
print("Percentage of Female Patients: {:.2f}%".format((countFemale / (len(df.sex))*100)))
print("Percentage of Male Patients: {:.2f}%".format((countMale / (len(df.sex))*100)))
```

Percentage of Female Patients: 31.68%

Percentage of Male Patients: 68.32%

In [9]:

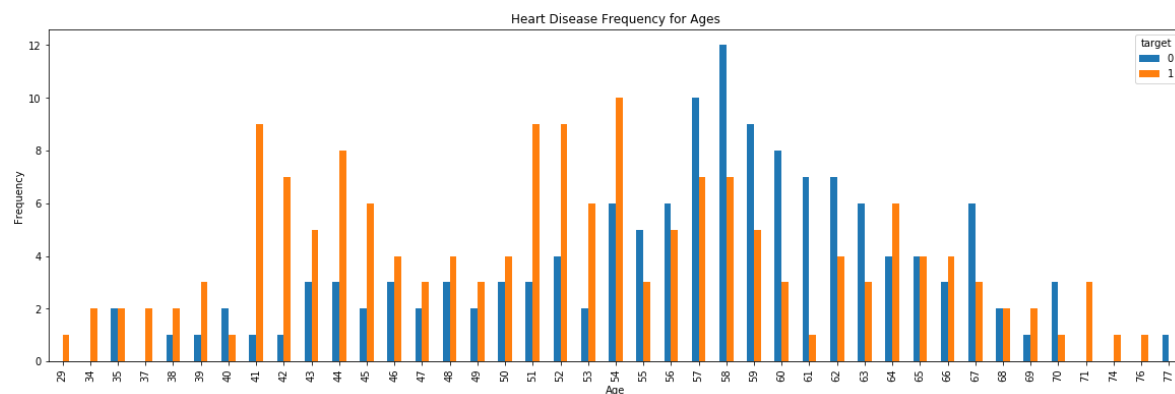
```
df.groupby('target').mean()
```

Out[9]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach
target								
0	56.601449	0.826087	0.478261	134.398551	251.086957	0.159420	0.449275	139.101449
1	52.496970	0.563636	1.375758	129.303030	242.230303	0.139394	0.593939	158.466667

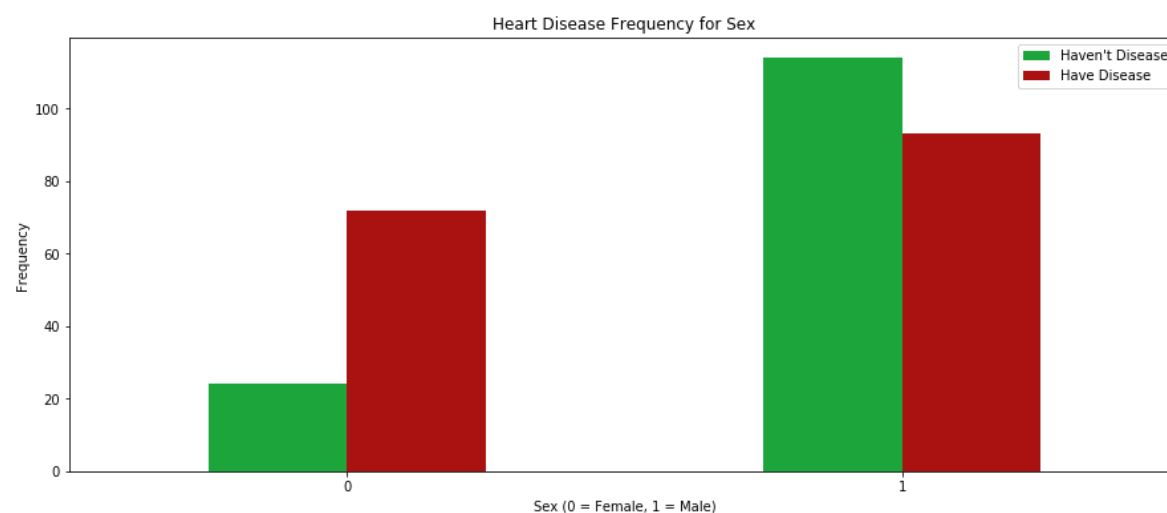
In [10]:

```
pd.crosstab(df.age,df.target).plot(kind="bar",figsize=(20,6))
plt.title('Heart Disease Frequency for Ages')
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.savefig('heartDiseaseAndAges.png')
plt.show()
```



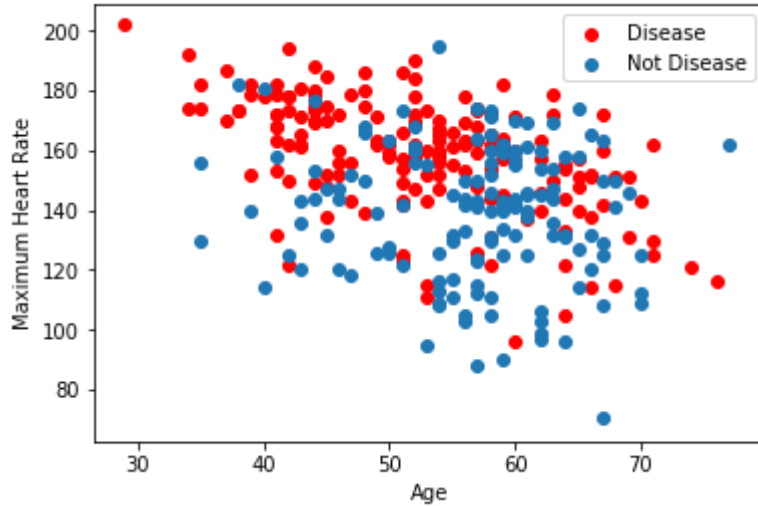
In [11]:

```
pd.crosstab(df.sex,df.target).plot(kind="bar",figsize=(15,6),color=[ '#1CA53B', '#AA1111' ])
plt.title('Heart Disease Frequency for Sex')
plt.xlabel('Sex (0 = Female, 1 = Male)')
plt.xticks(rotation=0)
plt.legend(["Haven't Disease", "Have Disease"])
plt.ylabel('Frequency')
plt.show()
```



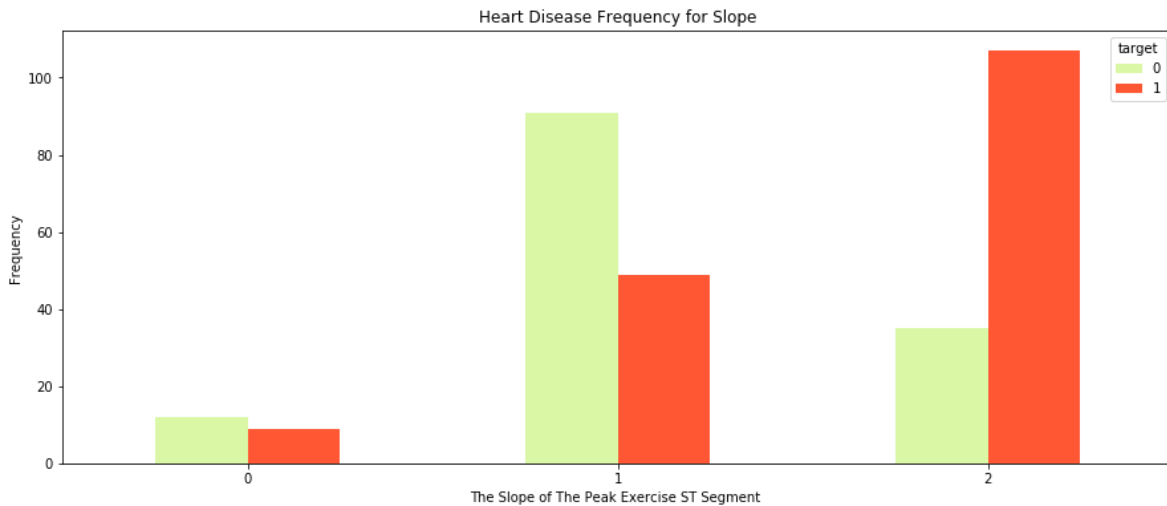
In [12]:

```
plt.scatter(x=df.age[df.target==1], y=df.thalach[(df.target==1)], c="red")
plt.scatter(x=df.age[df.target==0], y=df.thalach[(df.target==0)])
plt.legend(["Disease", "Not Disease"])
plt.xlabel("Age")
plt.ylabel("Maximum Heart Rate")
plt.show()
```



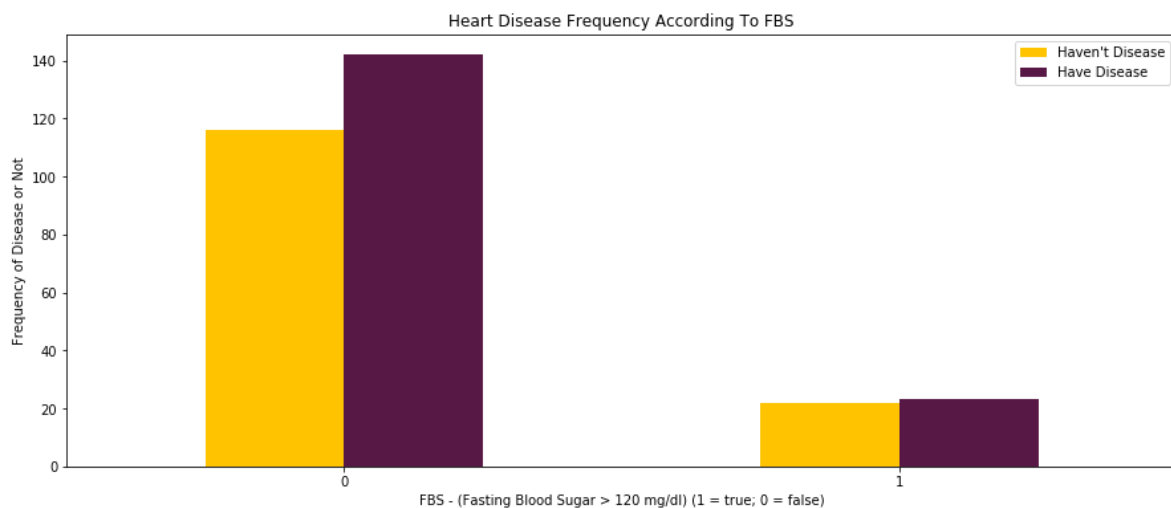
In [13]:

```
pd.crosstab(df.slope,df.target).plot(kind="bar",figsize=(15,6),color=[ '#DAF7A6', '#FF5733' ] )
plt.title('Heart Disease Frequency for Slope')
plt.xlabel('The Slope of The Peak Exercise ST Segment ')
plt.xticks(rotation = 0)
plt.ylabel('Frequency')
plt.show()
```



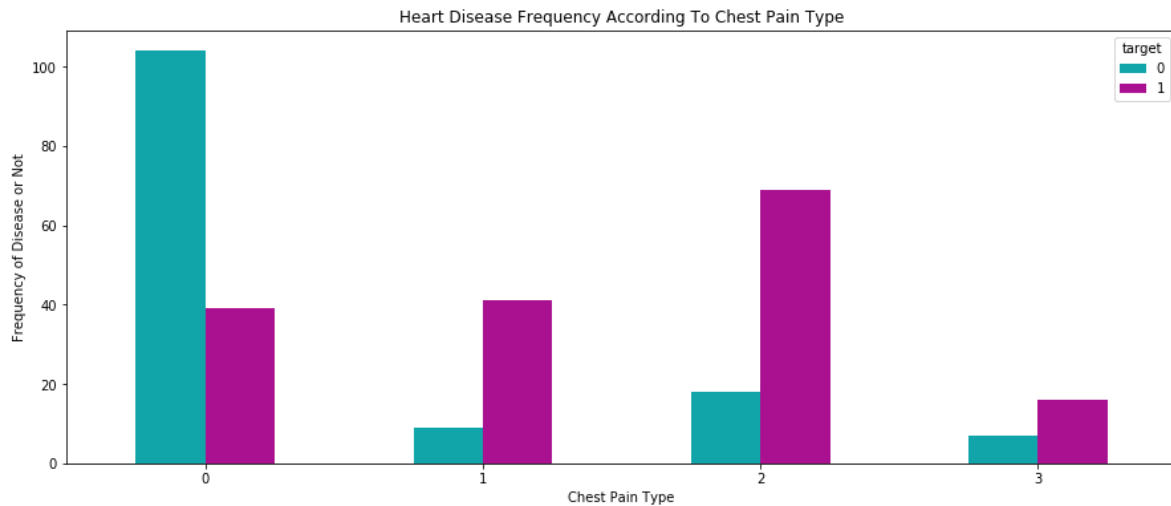
In [14]:

```
pd.crosstab(df.fbs,df.target).plot(kind="bar",figsize=(15,6),color=[ '#FFC300', '#581845' ] )
plt.title('Heart Disease Frequency According To FBS')
plt.xlabel('FBS - (Fasting Blood Sugar > 120 mg/dl) (1 = true; 0 = false)')
plt.xticks(rotation = 0)
plt.legend(["Haven't Disease", "Have Disease"])
plt.ylabel('Frequency of Disease or Not')
plt.show()
```



In [15]:

```
pd.crosstab(df.cp,df.target).plot(kind="bar",figsize=(15,6),color=[ '#11A5AA', '#AA1190' ])
plt.title('Heart Disease Frequency According To Chest Pain Type')
plt.xlabel('Chest Pain Type')
plt.xticks(rotation = 0)
plt.ylabel('Frequency of Disease or Not')
plt.show()
```



## Creating Dummy Variables

Since 'cp', 'thal' and 'slope' are categorical variables we'll turn them into dummy variables.

In [16]:

```
a = pd.get_dummies(df['cp'], prefix = "cp")
b = pd.get_dummies(df['thal'], prefix = "thal")
c = pd.get_dummies(df['slope'], prefix = "slope")
```



In [17]:

```
frames = [df, a, b, c]
df = pd.concat(frames, axis = 1)
df.head()
```

Out[17]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	...	cp_1	cp_2	cp_3
0	63	1	3	145	233	1	0	150	0	2.3	...	0	0	1
1	37	1	2	130	250	0	1	187	0	3.5	...	0	1	0
2	41	0	1	130	204	0	0	172	0	1.4	...	1	0	0
3	56	1	1	120	236	0	1	178	0	0.8	...	1	0	0
4	57	0	0	120	354	0	1	163	1	0.6	...	0	0	0

5 rows × 25 columns

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In [18]:

```
df = df.drop(columns = ['cp', 'thal', 'slope'])
df.head()
```

Out[18]:

	age	sex	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	ca	...	cp_1	cp_2	cp_3
0	63	1	145	233	1	0	150	0	2.3	0	...	0	0	1
1	37	1	130	250	0	1	187	0	3.5	0	...	0	1	0
2	41	0	130	204	0	0	172	0	1.4	0	...	1	0	0
3	56	1	120	236	0	1	178	0	0.8	0	...	1	0	0
4	57	0	120	354	0	1	163	1	0.6	0	...	0	0	0

5 rows × 22 columns

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## Creating Model for Logistic Regression

We can use sklearn library or we can write functions ourselves. Let's them both. Firstly we will write our functions after that we'll use sklearn library to calculate score.

In [19]:

```
y = df.target.values
x_data = df.drop(['target'], axis = 1)
```

## Normalize Data

$$X_{changed} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

In [20]:

```
# Normalize
x = (x_data - np.min(x_data)) / (np.max(x_data) - np.min(x_data)).values
```

We will split our data. 80% of our data will be train data and 20% of it will be test data.

In [21]:

```
x_train, x_test, y_train, y_test = train_test_split(x,y,test_size = 0.2,random_state=0)
```

In [22]:

```
#transpose matrices
x_train = x_train.T
y_train = y_train.T
x_test = x_test.T
y_test = y_test.T
```

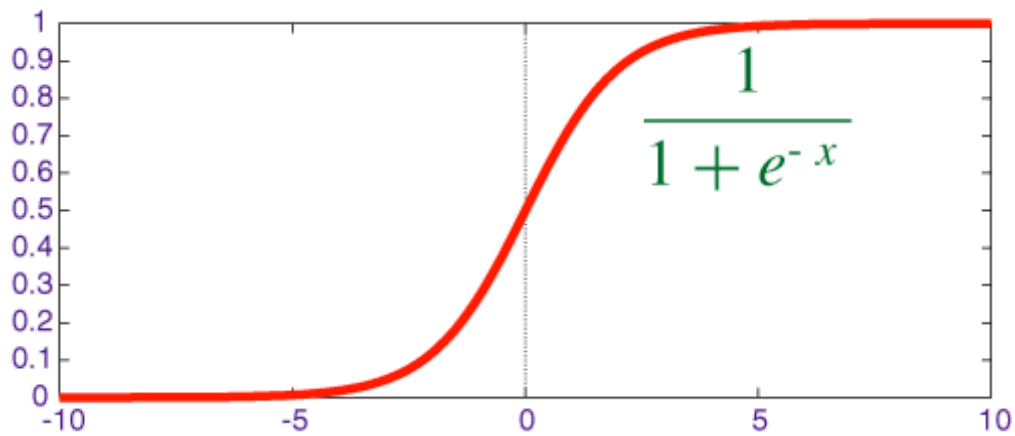
Let's say weight = 0.01 and bias = 0.0

In [23]:

```
#initialize
def initialize(dimension):

    weight = np.full((dimension,1),0.01)
    bias = 0.0
    return weight,bias
```

## Sigmoid Function

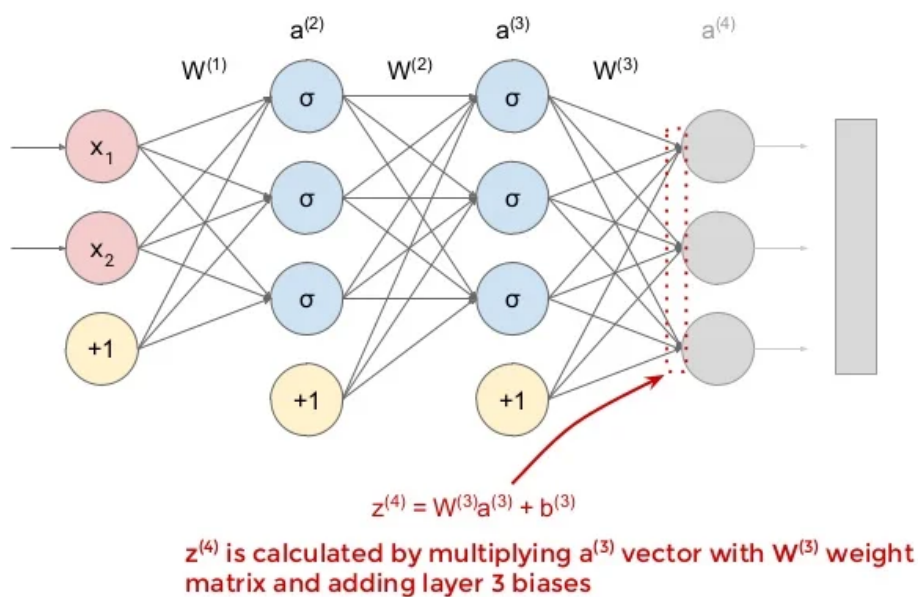


In [24]:

```
def sigmoid(z):
    y_head = 1/(1+ np.exp(-z))
    return y_head
```

## Forward and Backward Propagation

### Forward Propagation



## Cost Function

$$J(\theta) = -\frac{1}{m} \sum_{i=1}^m [y^{(i)} \log(h_{\theta}(x^{(i)})) + (1 - y^{(i)}) \log(1 - h_{\theta}(x^{(i)}))]$$

## Gradient Descent

### Gradient Descent

Remember that the general form of gradient descent is:

$$\begin{aligned} & \textit{Repeat} \{ \\ & \quad \theta_j := \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta) \\ & \} \end{aligned}$$

We can work out the derivative part using calculus to get:

$$\begin{aligned} & \textit{Repeat} \{ \\ & \quad \theta_j := \theta_j - \frac{\alpha}{m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)}) x_j^{(i)} \\ & \} \end{aligned}$$

By the way in formulas;

- $h_0(x^i) = y_{\text{head}}$
- $y^i = y_{\text{train}}$
- $x^i = x_{\text{train}}$

In [25]:

```
def forwardBackward(weight,bias,x_train,y_train):
    # Forward

    y_head = sigmoid(np.dot(weight.T,x_train) + bias)
    loss = -(y_train*np.log(y_head) + (1-y_train)*np.log(1-y_head))
    cost = np.sum(loss) / x_train.shape[1]

    # Backward
    derivative_weight = np.dot(x_train,((y_head-y_train).T))/x_train.shape[1]
    derivative_bias = np.sum(y_head-y_train)/x_train.shape[1]
    gradients = {"Derivative Weight" : derivative_weight, "Derivative Bias" : derivative_bi

    return cost,gradients
```

In [26]:

```
def update(weight,bias,x_train,y_train,learningRate,iteration) :
    costList = []
    index = []

    #for each iteration, update weight and bias values
    for i in range(iteration):
        cost,gradients = forwardBackward(weight,bias,x_train,y_train)
        weight = weight - learningRate * gradients["Derivative Weight"]
        bias = bias - learningRate * gradients["Derivative Bias"]

        costList.append(cost)
        index.append(i)

    parameters = {"weight": weight,"bias": bias}

    print("iteration:",iteration)
    print("cost:",cost)

    plt.plot(index,costList)
    plt.xlabel("Number of Iteration")
    plt.ylabel("Cost")
    plt.show()

    return parameters, gradients
```

In [27]:

```
def predict(weight,bias,x_test):
    z = np.dot(weight.T,x_test) + bias
    y_head = sigmoid(z)

    y_prediction = np.zeros((1,x_test.shape[1]))

    for i in range(y_head.shape[1]):
        if y_head[0,i] <= 0.5:
            y_prediction[0,i] = 0
        else:
            y_prediction[0,i] = 1
    return y_prediction
```

In [28]:

```
def logistic_regression(x_train,y_train,x_test,y_test,learningRate,iteration):
    dimension = x_train.shape[0]
    weight,bias = initialize(dimension)

    parameters, gradients = update(weight,bias,x_train,y_train,learningRate,iteration)

    y_prediction = predict(parameters["weight"],parameters["bias"],x_test)

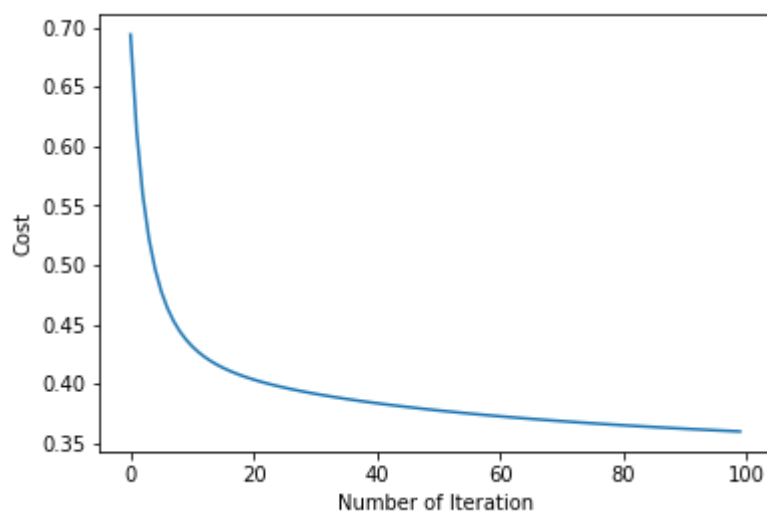
    print("Manuel Test Accuracy: {:.2f}%".format((100 - np.mean(np.abs(y_prediction - y_test)) * 100)))
```

In [29]:

```
logistic_regression(x_train,y_train,x_test,y_test,1,100)
```

iteration: 100

cost: 0.3597736123664534



Manuel Test Accuracy: 86.89%

**Manuel Test Accuracy is 86.89%**

Let's find out sklearn's score.

## Sklearn Logistic Regression

In [30]:

```
accuracies = {}  
  
lr = LogisticRegression()  
lr.fit(x_train.T,y_train.T)  
acc = lr.score(x_test.T,y_test.T)*100  
  
accuracies['Logistic Regression'] = acc  
print("Test Accuracy {:.2f}%".format(acc))
```

Test Accuracy 86.89%

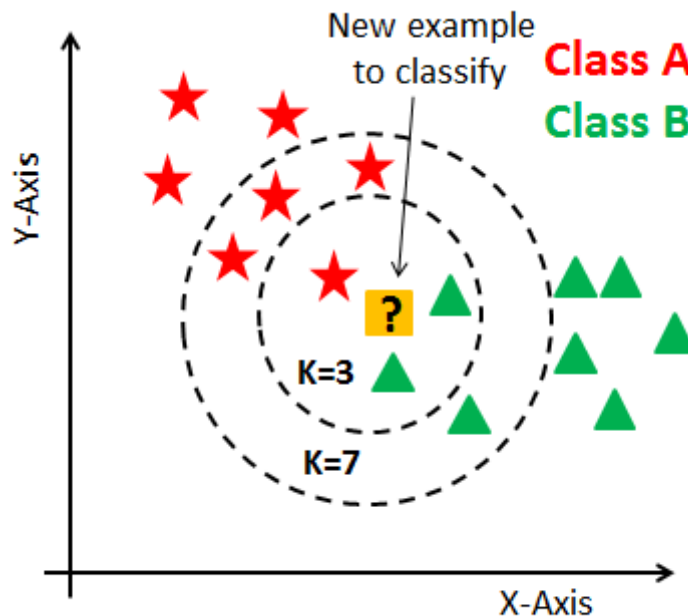
```
/opt/conda/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:432:  
FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specify a  
solver to silence this warning.  
FutureWarning)
```

## 1. Our model works with 86.89% accuracy.

# K-Nearest Neighbour (KNN) Classification

Let's see what will be score if we use KNN algorithm.

## KNN Algorithm



In [31]:

```
# KNN Model
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors = 2) # n_neighbors means k
knn.fit(x_train.T, y_train.T)
prediction = knn.predict(x_test.T)

print("{} NN Score: {:.2f}%".format(2, knn.score(x_test.T, y_test.T)*100))
```

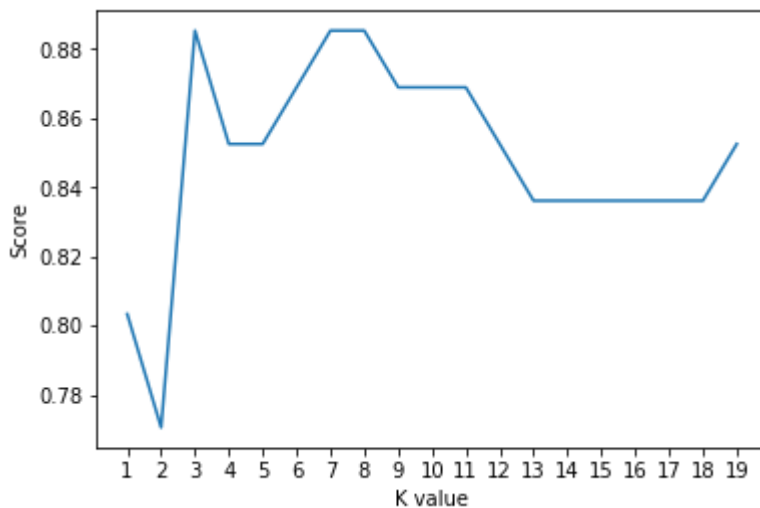
2 NN Score: 77.05%

In [32]:

```
# try to find best k value
scoreList = []
for i in range(1,20):
    knn2 = KNeighborsClassifier(n_neighbors = i) # n_neighbors means k
    knn2.fit(x_train.T, y_train.T)
    scoreList.append(knn2.score(x_test.T, y_test.T))

plt.plot(range(1,20), scoreList)
plt.xticks(np.arange(1,20,1))
plt.xlabel("K value")
plt.ylabel("Score")
plt.show()

acc = max(scoreList)*100
accuracies['KNN'] = acc
print("Maximum KNN Score is {:.2f}%".format(acc))
```



Maximum KNN Score is 88.52%

As you can see above if we define k as 3-7-8 we will reach maximum score.

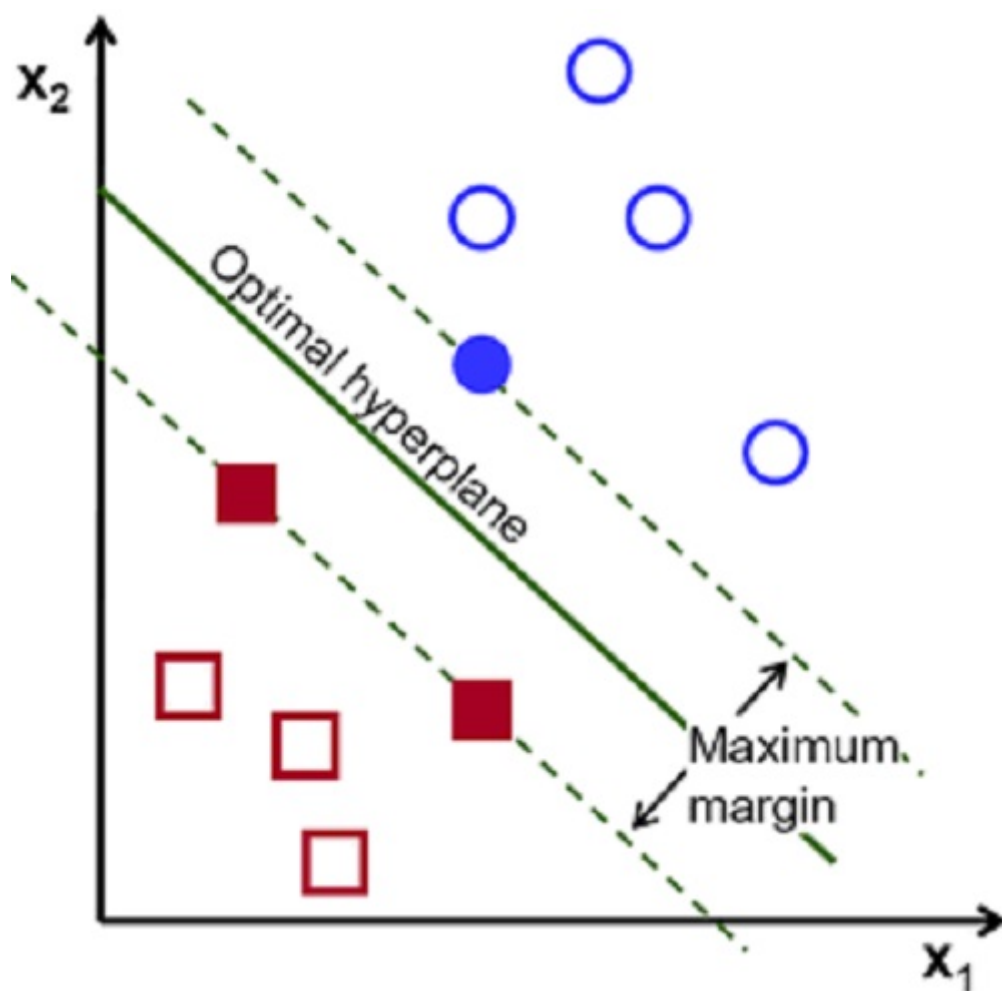
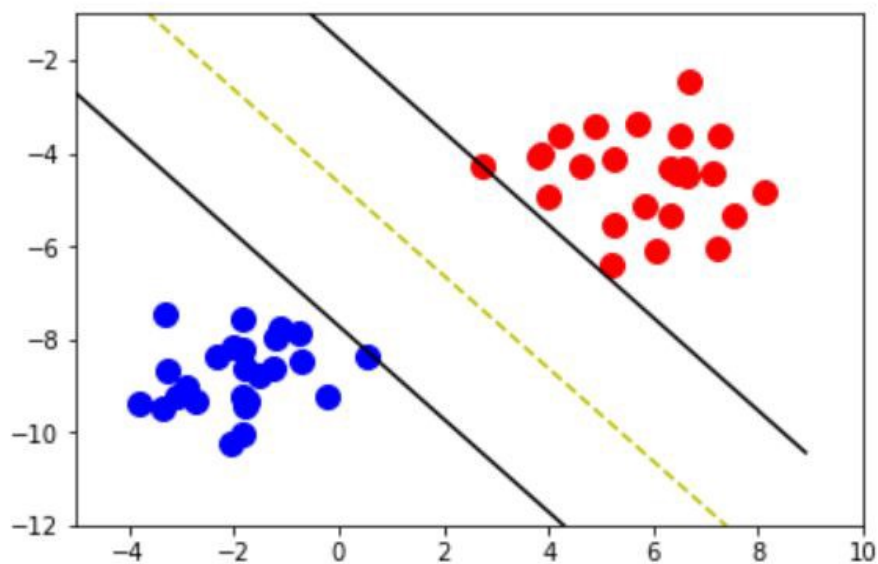
**KNN Model's Accuracy is 88.52%**

## Support Vector Machine (SVM) Algorithm

Now we will use SVM algorithm.

### Support Vector Machine Algorithm





In [33]:

```
from sklearn.svm import SVC
```

In [34]:

```
svm = SVC(random_state = 1)
svm.fit(x_train.T, y_train.T)

acc = svm.score(x_test.T, y_test.T) * 100
accuracies['SVM'] = acc
print("Test Accuracy of SVM Algorithm: {:.2f}%".format(acc))
```

Test Accuracy of SVM Algorithm: 86.89%

/opt/conda/lib/python3.6/site-packages/sklearn/svm/base.py:193: FutureWarning: The default value of gamma will change from 'auto' to 'scale' in version 0.22 to account better for unscaled features. Set gamma explicitly to 'auto' or 'scale' to avoid this warning.  
 "avoid this warning.", FutureWarning)

**Test Accuracy of SVM Algorithm is 86.89%**

## Naive Bayes Algorithm

### Naive Bayes Algorithm

The diagram shows the Naive Bayes formula:  $P(c | x) = \frac{P(x | c)P(c)}{P(x)}$ . Arrows point from the terms to their labels:  $P(c | x)$  is labeled 'Posterior Probability',  $P(x | c)$  is labeled 'Likelihood',  $P(c)$  is labeled 'Class Prior Probability', and  $P(x)$  is labeled 'Predictor Prior Probability'.

$$P(c | X) = P(x_1 | c) \times P(x_2 | c) \times \dots \times P(x_n | c) \times P(c)$$

In [35]:

```
from sklearn.naive_bayes import GaussianNB
nb = GaussianNB()
nb.fit(x_train.T, y_train.T)

acc = nb.score(x_test.T, y_test.T) * 100
accuracies['Naive Bayes'] = acc
print("Accuracy of Naive Bayes: {:.2f}%".format(acc))
```

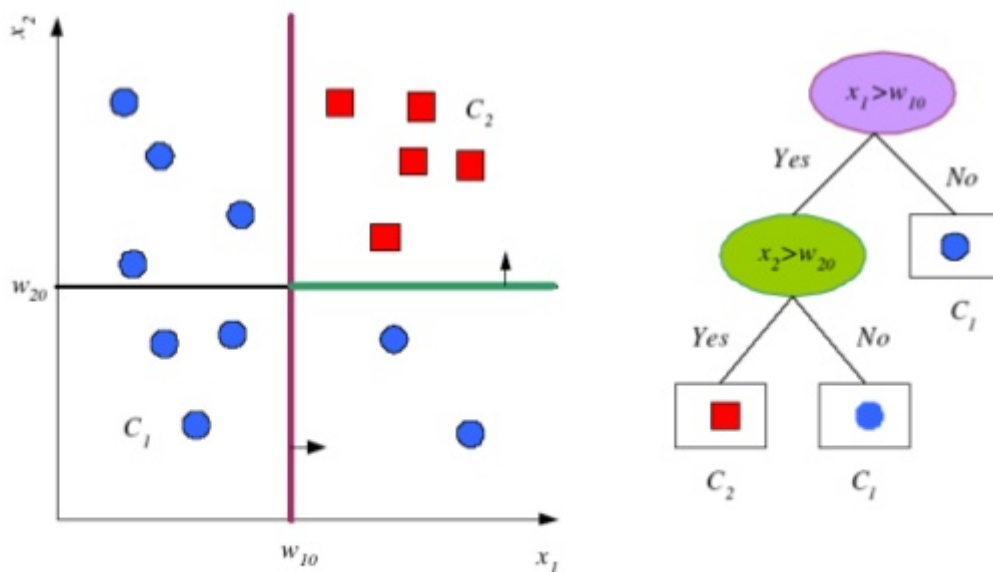
Accuracy of Naive Bayes: 86.89%

**Accuracy of Naive Bayes: 86.89%**

# Decision Tree Algorithm

## Decision Tree Algorithm

### Decision Tree



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Lec 2: Decision Trees - Nearest Neighbors

In [36]:

```
from sklearn.tree import DecisionTreeClassifier
dtc = DecisionTreeClassifier()
dtc.fit(x_train.T, y_train.T)

acc = dtc.score(x_test.T, y_test.T)*100
accuracies['Decision Tree'] = acc
print("Decision Tree Test Accuracy {:.2f}%".format(acc))
```

Decision Tree Test Accuracy 80.33%

**Test Accuracy of Decision Tree Algorithm: 78.69%**

## Random Forest Classification

In [37]:

```
# Random Forest Classification
from sklearn.ensemble import RandomForestClassifier
rf = RandomForestClassifier(n_estimators = 1000, random_state = 1)
rf.fit(x_train.T, y_train.T)

acc = rf.score(x_test.T, y_test.T)*100
accuracies['Random Forest'] = acc
print("Random Forest Algorithm Accuracy Score : {:.2f}%".format(acc))
```

Random Forest Algorithm Accuracy Score : 88.52%

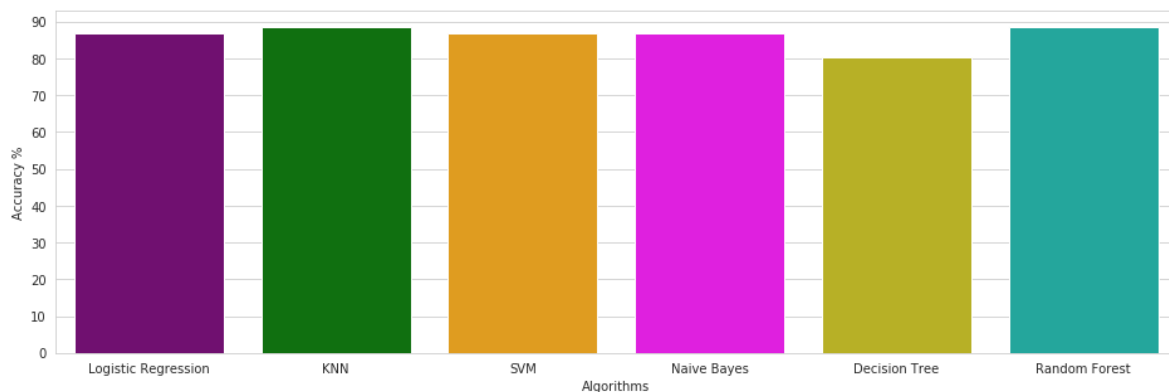
**Test Accuracy of Random Forest: 88.52%**

## Comparing Models

In [38]:

```
colors = ["purple", "green", "orange", "magenta", "#CFC60E", "#0FBBAE"]

sns.set_style("whitegrid")
plt.figure(figsize=(16,5))
plt.yticks(np.arange(0,100,10))
plt.ylabel("Accuracy %")
plt.xlabel("Algorithms")
sns.barplot(x=list(accuracies.keys()), y=list(accuracies.values()), palette=colors)
plt.show()
```



Our models work fine but best of them are KNN and Random Forest with 88.52% of accuracy. Let's look their confusion matrixes.

## Confusion Matrix

In [39]:

```
# Predicted values
y_head_lr = lr.predict(x_test.T)
knn3 = KNeighborsClassifier(n_neighbors = 3)
knn3.fit(x_train.T, y_train.T)
y_head_knn = knn3.predict(x_test.T)
y_head_svm = svm.predict(x_test.T)
y_head_nb = nb.predict(x_test.T)
y_head_dtc = dtc.predict(x_test.T)
y_head_rf = rf.predict(x_test.T)
```

In [40]:

```
from sklearn.metrics import confusion_matrix

cm_lr = confusion_matrix(y_test,y_head_lr)
cm_knn = confusion_matrix(y_test,y_head_knn)
cm_svm = confusion_matrix(y_test,y_head_svm)
cm_nb = confusion_matrix(y_test,y_head_nb)
cm_dtc = confusion_matrix(y_test,y_head_dtc)
cm_rf = confusion_matrix(y_test,y_head_rf)
```

In [41]:

```
plt.figure(figsize=(24,12))

plt.suptitle("Confusion Matrixes",fontsize=24)
plt.subplots_adjust(wspace = 0.4, hspace= 0.4)

plt.subplot(2,3,1)
plt.title("Logistic Regression Confusion Matrix")
sns.heatmap(cm_lr,annot=True,cmap="Blues",fmt="d",cbar=False, annot_kws={"size": 24})

plt.subplot(2,3,2)
plt.title("K Nearest Neighbors Confusion Matrix")
sns.heatmap(cm_knn,annot=True,cmap="Blues",fmt="d",cbar=False, annot_kws={"size": 24})

plt.subplot(2,3,3)
plt.title("Support Vector Machine Confusion Matrix")
sns.heatmap(cm_svm,annot=True,cmap="Blues",fmt="d",cbar=False, annot_kws={"size": 24})

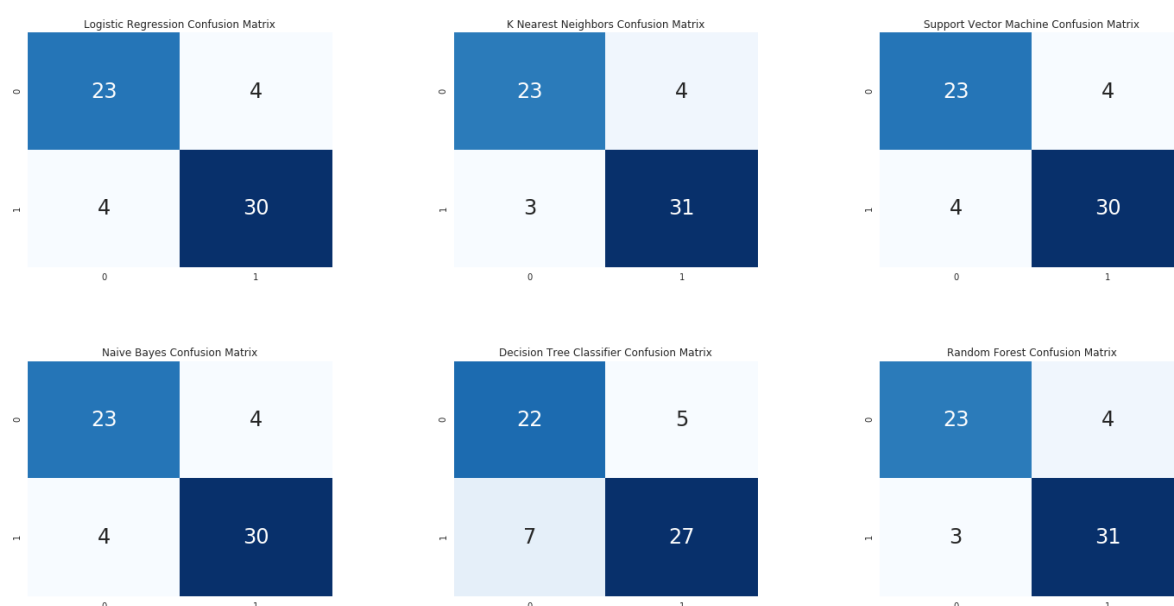
plt.subplot(2,3,4)
plt.title("Naive Bayes Confusion Matrix")
sns.heatmap(cm_nb,annot=True,cmap="Blues",fmt="d",cbar=False, annot_kws={"size": 24})

plt.subplot(2,3,5)
plt.title("Decision Tree Classifier Confusion Matrix")
sns.heatmap(cm_dtc,annot=True,cmap="Blues",fmt="d",cbar=False, annot_kws={"size": 24})

plt.subplot(2,3,6)
plt.title("Random Forest Confusion Matrix")
sns.heatmap(cm_rf,annot=True,cmap="Blues",fmt="d",cbar=False, annot_kws={"size": 24})

plt.show()
```

Confusion Matrixes



Please comment me your feedbacks to help me improve myself. Thanks for your time.

**Mr. Yogesh P Murumkar (Mob. 9657080905)**

[www.youtube.com/yogeshmurumkar](http://www.youtube.com/yogeshmurumkar)  
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