### Sumedh Kumar Prasad Heart logistic Regression

### Problem Statement: Finding out the different factors causing Atherosclerotic Heart Disease (AHD)

# importing libraries

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

# importing dataset

In [2]:
```
data=pd.read_csv('Heart.csv',index_col=0)
```

In [3]:
```
data.head(5)
```

Out[3]:

| | Age | Sex | ChestPain | RestBP | Chol | Fbs | RestECG | MaxHR | ExAng | Oldpeak | Slope |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 63 | 1 | typical | 145 | 233 | 1 | 2 | 150 | 0 | 2.3 | 3 |
| **2** | 67 | 1 | asymptomatic | 160 | 286 | 0 | 2 | 108 | 1 | 1.5 | 2 |
| **3** | 67 | 1 | asymptomatic | 120 | 229 | 0 | 2 | 129 | 1 | 2.6 | 2 |
| **4** | 37 | 1 | nonanginal | 130 | 250 | 0 | 0 | 187 | 0 | 3.5 | 3 |
| **5** | 41 | 0 | nontypical | 130 | 204 | 0 | 2 | 172 | 0 | 1.4 | 1 |

In [4]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 303 entries, 1 to 303
Data columns (total 14 columns):
Age          303 non-null int64
Sex          303 non-null int64
ChestPain    303 non-null object
RestBP       303 non-null int64
Chol         303 non-null int64
Fbs          303 non-null int64
RestECG      303 non-null int64
MaxHR        303 non-null int64
ExAng        303 non-null int64
Oldpeak      303 non-null float64
Slope        303 non-null int64
Ca           299 non-null float64
Thal         301 non-null object
AHD          303 non-null object
dtypes: float64(2), int64(9), object(3)
memory usage: 35.5+ KB
```

In [5]:
```
data.describe()
```

Out[5]:

| | Age | Sex | RestBP | Chol | Fbs | RestECG | Max |
|---|---|---|---|---|---|---|---|
| **count** | 303.000000 | 303.000000 | 303.000000 | 303.000000 | 303.000000 | 303.000000 | 303.000( |
| **mean** | 54.438944 | 0.679868 | 131.689769 | 246.693069 | 0.148515 | 0.990099 | 149.6072 |
| **std** | 9.038662 | 0.467299 | 17.599748 | 51.776918 | 0.356198 | 0.994971 | 22.8750( |
| **min** | 29.000000 | 0.000000 | 94.000000 | 126.000000 | 0.000000 | 0.000000 | 71.0000( |
| **25%** | 48.000000 | 0.000000 | 120.000000 | 211.000000 | 0.000000 | 0.000000 | 133.500( |
| **50%** | 56.000000 | 1.000000 | 130.000000 | 241.000000 | 0.000000 | 1.000000 | 153.000( |
| **75%** | 61.000000 | 1.000000 | 140.000000 | 275.000000 | 0.000000 | 2.000000 | 166.000( |
| **max** | 77.000000 | 1.000000 | 200.000000 | 564.000000 | 1.000000 | 2.000000 | 202.000( |

# Dropping the all the NA values from the dataset

In [6]:
```
data.dropna(axis=0,inplace=True)
```

In [7]:
```
data.isnull().any()
```

Out[7]:
```
Age          False
Sex          False
ChestPain    False
RestBP       False
Chol         False
Fbs          False
RestECG      False
MaxHR        False
ExAng        False
Oldpeak      False
Slope        False
Ca           False
Thal         False
AHD          False
dtype: bool
```

In [8]:
```
data.head()
```

Out[8]:

| | Age | Sex | ChestPain | RestBP | Chol | Fbs | RestECG | MaxHR | ExAng | Oldpeak | Slope |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 63 | 1 | typical | 145 | 233 | 1 | 2 | 150 | 0 | 2.3 | 3 |
| **2** | 67 | 1 | asymptomatic | 160 | 286 | 0 | 2 | 108 | 1 | 1.5 | 2 |
| **3** | 67 | 1 | asymptomatic | 120 | 229 | 0 | 2 | 129 | 1 | 2.6 | 2 |
| **4** | 37 | 1 | nonanginal | 130 | 250 | 0 | 0 | 187 | 0 | 3.5 | 3 |
| **5** | 41 | 0 | nontypical | 130 | 204 | 0 | 2 | 172 | 0 | 1.4 | 1 |

## Finding the correlation between all the numerical variables

In [9]:
```
data.corr()
```

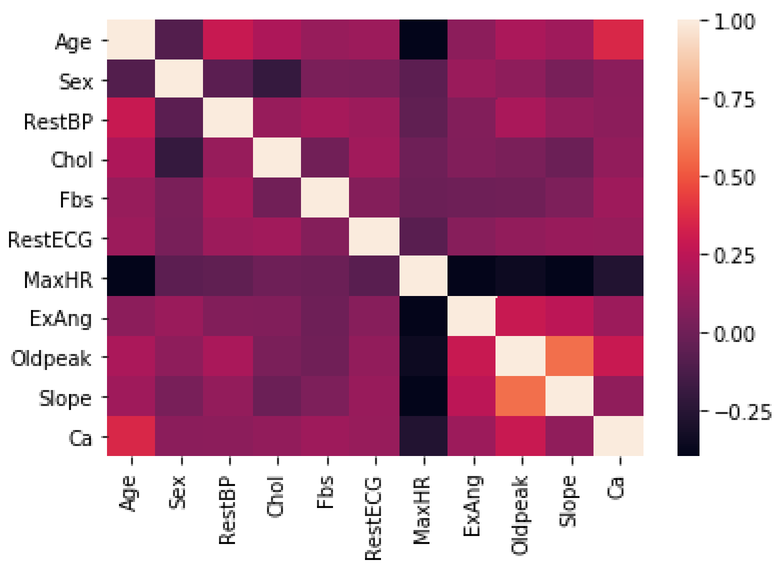
Out[9]:

| | Age | Sex | RestBP | Chol | Fbs | RestECG | MaxHR | |
|---|---|---|---|---|---|---|---|---|
| **Age** | 1.000000 | -0.092399 | 0.290476 | 0.202644 | 0.132062 | 0.149917 | -0.394563 | 0.0 |
| **Sex** | -0.092399 | 1.000000 | -0.066340 | -0.198089 | 0.038850 | 0.033897 | -0.060496 | 0.1 |
| **RestBP** | 0.290476 | -0.066340 | 1.000000 | 0.131536 | 0.180860 | 0.149242 | -0.049108 | 0.0 |
| **Chol** | 0.202644 | -0.198089 | 0.131536 | 1.000000 | 0.012708 | 0.165046 | -0.000075 | 0.0 |
| **Fbs** | 0.132062 | 0.038850 | 0.180860 | 0.012708 | 1.000000 | 0.068831 | -0.007842 | -0. |
| **RestECG** | 0.149917 | 0.033897 | 0.149242 | 0.165046 | 0.068831 | 1.000000 | -0.072290 | 0.0 |
| **MaxHR** | -0.394563 | -0.060496 | -0.049108 | -0.000075 | -0.007842 | -0.072290 | 1.000000 | -0. |
| **ExAng** | 0.096489 | 0.143581 | 0.066691 | 0.059339 | -0.000893 | 0.081874 | -0.384368 | 1.0 |
| **Oldpeak** | 0.197123 | 0.106567 | 0.191243 | 0.038596 | 0.008311 | 0.113726 | -0.347640 | 0.2 |
| **Slope** | 0.159405 | 0.033345 | 0.121172 | -0.009215 | 0.047819 | 0.135141 | -0.389307 | 0.2 |
| **Ca** | 0.362210 | 0.091925 | 0.097954 | 0.115945 | 0.152086 | 0.129021 | -0.268727 | 0.1 |

## Heatmap of correlation variables

In [11]:
```
sns.heatmap(data.corr(),linecolor="yellow")
```

Out[11]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x26b1e4f89b0>
```

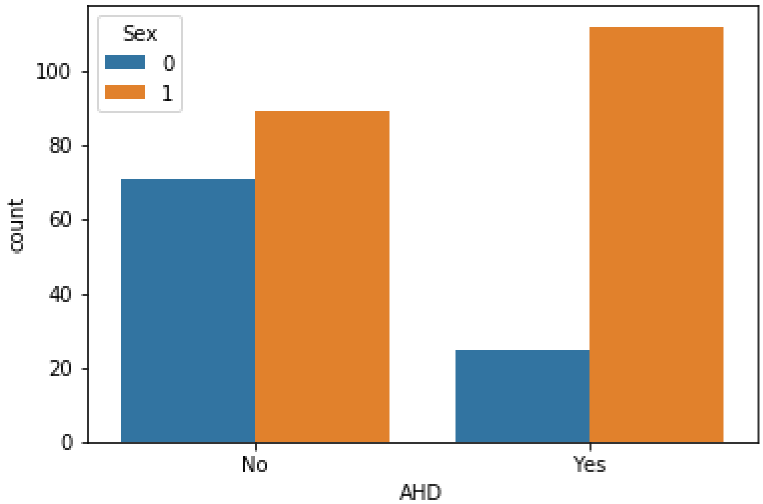


### Conclusion from the Heatmap is :

### From the corelation we conclude that none of variables are related to each other(No interaction is there between the variables) so we can include all the variables in our dataset for the analysis.

In [12]:
```
sns.countplot(x='AHD',hue='Sex', data=data)
```

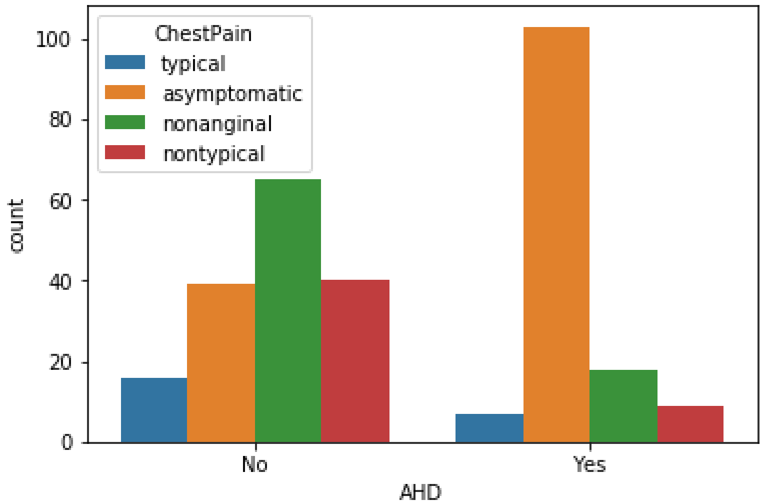
Out[12]: <matplotlib.axes._subplots.AxesSubplot at 0x26b1f7f46d8>




### conclusion : Male has heigher alveolar hydatid disease(AHD) than Female counterpart.

In [13]:
```
sns.countplot(x='AHD',hue='ChestPain', data=data)
```

Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0x26b1f77c0b8>

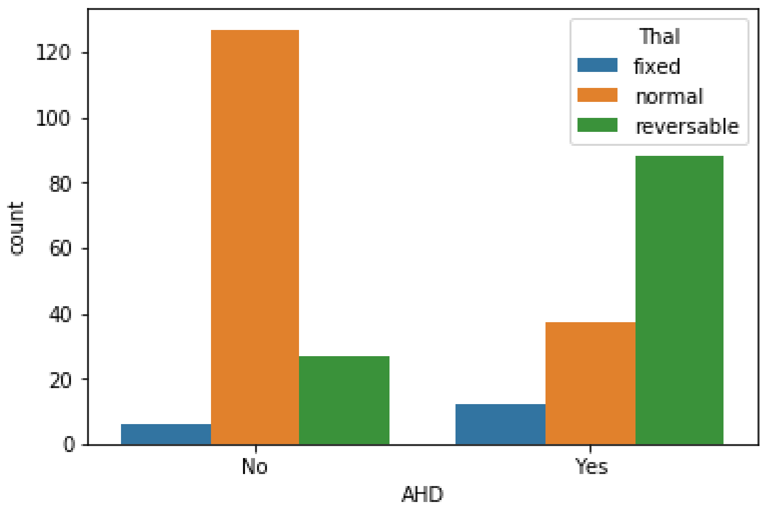


# From the graph it is clear that asymptomatic chest pain causing the Maximum number of AHD attack .

In [13]:
```
sns.countplot(x='AHD',hue='Thal', data=data)
```

```
/Users/sanaam/anaconda3/lib/python3.6/site-packages/seaborn/categorical.py:15
08: FutureWarning: remove_na is deprecated and is a private function. Do not
use.
  stat_data = remove_na(group_data[hue_mask])
```

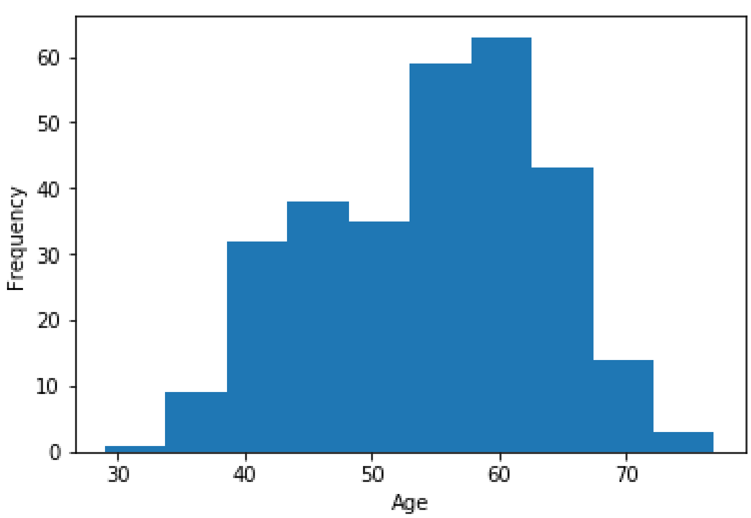
Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0x11a616a20>




# From the graph it is clear that Thal having normal not causing the AHD attack most.

In [14]:
```
data['Age'].plot.hist()
plt.xlabel('Age')
```

Out[14]: Text(0.5,0,'Age')



# From the above graph it is clear that Age is approx normally distributed.

## Categorical variables (creating dummy variables)

In [14]:
```
data.columns
```

Out[14]:
```
Index(['Age', 'Sex', 'ChestPain', 'RestBP', 'Chol', 'Fbs', 'RestECG', 'MaxH
R',
       'ExAng', 'Oldpeak', 'Slope', 'Ca', 'Thal', 'AHD'],
      dtype='object')
```

In [15]:
```
data.head(2)
```

Out[15]:

| | Age | Sex | ChestPain | RestBP | Chol | Fbs | RestECG | MaxHR | ExAng | Oldpeak | Slope |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 63 | 1 | typical | 145 | 233 | 1 | 2 | 150 | 0 | 2.3 | 3 |
| **2** | 67 | 1 | asymptomatic | 160 | 286 | 0 | 2 | 108 | 1 | 1.5 | 2 |

In [16]:
```
data1=data.drop(['ChestPain','Thal'],axis=1)
```

In [17]:
```
data1.head(2)
```

Out[17]:

| | Age | Sex | RestBP | Chol | Fbs | RestECG | MaxHR | ExAng | Oldpeak | Slope | Ca | AHD |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 63 | 1 | 145 | 233 | 1 | 2 | 150 | 0 | 2.3 | 3 | 0.0 | No |
| **2** | 67 | 1 | 160 | 286 | 0 | 2 | 108 | 1 | 1.5 | 2 | 3.0 | Yes |

In [20]:
```
data=pd.concat([data1,dummy],axis=1)
```

In [26]:
```
data.head(2)
```

Out[26]:

| | Age | Sex | RestBP | Chol | Fbs | RestECG | MaxHR | ExAng | Oldpeak | Slope | Ca | AHD | Ch |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 63 | 1 | 145 | 233 | 1 | 2 | 150 | 0 | 2.3 | 3 | 0.0 | No | 0 |
| **2** | 67 | 1 | 160 | 286 | 0 | 2 | 108 | 1 | 1.5 | 2 | 3.0 | Yes | 0 |

## Splitting dataset into dependent (X) & independent variables (Y)

In [27]:
```
data.columns
```

Out[27]:
```
Index(['Age', 'Sex', 'RestBP', 'Chol', 'Fbs', 'RestECG', 'MaxHR', 'ExAng',
       'Oldpeak', 'Slope', 'Ca', 'AHD', 'ChestPain_nonanginal',
       'ChestPain_nontypical', 'ChestPain_typical', 'Thal_normal',
       'Thal_reversable'],
      dtype='object')
```

In [28]:
```
x=data[['Age', 'Sex', 'RestBP', 'Chol', 'Fbs', 'RestECG', 'MaxHR', 'ExAng',
       'Oldpeak', 'Slope', 'Ca', 'ChestPain_nonanginal',
       'ChestPain_nontypical', 'ChestPain_typical', 'Thal_normal',
       'Thal_reversable']]

y=data['AHD']

y=pd.get_dummies(data['AHD'],drop_first=True)
```

In [29]:
```
x.head(2)
```

Out[29]:

| | Age | Sex | RestBP | Chol | Fbs | RestECG | MaxHR | ExAng | Oldpeak | Slope | Ca | ChestPa |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 63 | 1 | 145 | 233 | 1 | 2 | 150 | 0 | 2.3 | 3 | 0.0 | 0 |
| **2** | 67 | 1 | 160 | 286 | 0 | 2 | 108 | 1 | 1.5 | 2 | 3.0 | 0 |

In [30]:
```
y.head(2)
```

Out[30]:

| | Yes |
|---|---|
| **1** | 0 |
| **2** | 1 |

# Building a Logistic Regression model

Let's start by splitting our data into a training set and test set (there is another test.csv file that you can play around with in case you want to use all this data for training).

# Train Test Split of the existing heart dataset.

In [31]:
```
from sklearn.cross_validation import train_test_split
```

```
/Users/sanaam/anaconda3/lib/python3.6/site-packages/sklearn/cross_validation.
py:41: DeprecationWarning: This module was deprecated in version 0.18 in favo
r of the model_selection module into which all the refactored classes and fun
ctions are moved. Also note that the interface of the new CV iterators are di
fferent from that of this module. This module will be removed in 0.20.
  "This module will be removed in 0.20.", DeprecationWarning)
```

In [32]:
```
x_train, x_test, y_train, y_test = train_test_split( x, y, test_size = 0.3,ran
dom_state=101)
```

In [33]:
```
y_test[0:5]
```

Out[33]:

| | Yes |
|---|---|
| **258** | 0 |
| **275** | 1 |
| **190** | 1 |
| **274** | 0 |
| **136** | 0 |

In [34]:
```
x_test[0:3].T
```

Out[34]:

| | 258 | 275 | 190 |
|---|---|---|---|
| **Age** | 76.0 | 59.0 | 69.0 |
| **Sex** | 0.0 | 1.0 | 1.0 |
| **RestBP** | 140.0 | 134.0 | 140.0 |
| **Chol** | 197.0 | 204.0 | 254.0 |
| **Fbs** | 0.0 | 0.0 | 0.0 |
| **RestECG** | 1.0 | 0.0 | 2.0 |
| **MaxHR** | 116.0 | 162.0 | 146.0 |
| **ExAng** | 0.0 | 0.0 | 0.0 |
| **Oldpeak** | 1.1 | 0.8 | 2.0 |
| **Slope** | 2.0 | 1.0 | 2.0 |
| **Ca** | 0.0 | 2.0 | 3.0 |
| **ChestPain_nonanginal** | 1.0 | 0.0 | 1.0 |
| **ChestPain_nontypical** | 0.0 | 0.0 | 0.0 |
| **ChestPain_typical** | 0.0 | 1.0 | 0.0 |
| **Thal_normal** | 1.0 | 1.0 | 0.0 |
| **Thal_reversable** | 0.0 | 0.0 | 1.0 |

# Training and Predicting

In [36]:
```
from sklearn.linear_model import LogisticRegression

logmodel = LogisticRegression()
logmodel.fit(x_train,y_train)
```

```
/Users/sanaam/anaconda3/lib/python3.6/site-packages/sklearn/utils/validation.
py:578: DataConversionWarning: A column-vector y was passed when a 1d array w
as expected. Please change the shape of y to (n_samples, ), for example using
ravel().
  y = column_or_1d(y, warn=True)
```

Out[36]:
```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)
```

In [53]:
```
y_predictions = logmodel.predict(x_test)
```

# Finding significant variables

In [100]:
```
import statsmodels.api as sm
```

In [93]:
```
logit = sm.Logit( y_train, sm.add_constant( x_train ) )
```

In [105]:
```
lg = logit.fit()
```

```
Optimization terminated successfully.
         Current function value: inf
         Iterations 8

/Users/sanaam/anaconda3/lib/python3.6/site-packages/statsmodels/discrete/disc
rete_model.py:1214: RuntimeWarning: overflow encountered in exp
  return 1/(1+np.exp(-X))
/Users/sanaam/anaconda3/lib/python3.6/site-packages/statsmodels/discrete/disc
rete_model.py:1264: RuntimeWarning: divide by zero encountered in log
  return np.sum(np.log(self.cdf(q*np.dot(X,params))))
```

In [107]:
```
lg.summary()
```

Out[107]:

Logit Regression Results

| | | | |
|---|---|---|---|
| **Dep. Variable:** | Yes | **No. Observations:** | 207 |
| **Model:** | Logit | **Df Residuals:** | 190 |
| **Method:** | MLE | **Df Model:** | 16 |
| **Date:** | Sun, 10 Jun 2018 | **Pseudo R-squ.:** | -inf |
| **Time:** | 15:36:30 | **Log-Likelihood:** | -inf |
| **converged:** | True | **LL-Null:** | -1918.8 |
| | | **LLR p-value:** | 1.000 |

| | coef | std err | z | P>\|z\| | [0.025 | 0.975] |
|---|---|---|---|---|---|---|
| **const** | -1.3550 | 3.603 | -0.376 | 0.707 | -8.417 | 5.707 |
| **Age** | -0.0198 | 0.033 | -0.603 | 0.547 | -0.084 | 0.044 |
| **Sex** | 0.9558 | 0.631 | 1.514 | 0.130 | -0.282 | 2.193 |
| **RestBP** | 0.0279 | 0.014 | 1.981 | 0.048 | 0.000 | 0.055 |
| **Chol** | 0.0034 | 0.005 | 0.710 | 0.478 | -0.006 | 0.013 |
| **Fbs** | -0.8584 | 0.795 | -1.079 | 0.281 | -2.418 | 0.701 |
| **RestECG** | 0.3986 | 0.250 | 1.594 | 0.111 | -0.092 | 0.889 |
| **MaxHR** | -0.0351 | 0.015 | -2.398 | 0.016 | -0.064 | -0.006 |
| **ExAng** | 0.1698 | 0.571 | 0.297 | 0.766 | -0.950 | 1.290 |
| **Oldpeak** | 0.4138 | 0.295 | 1.402 | 0.161 | -0.165 | 0.992 |
| **Slope** | 0.6533 | 0.479 | 1.364 | 0.173 | -0.286 | 1.592 |
| **Ca** | 1.3000 | 0.349 | 3.725 | 0.000 | 0.616 | 1.984 |
| **ChestPain_nonanginal** | -2.3257 | 0.665 | -3.496 | 0.000 | -3.630 | -1.022 |
| **ChestPain_nontypical** | -1.0752 | 0.675 | -1.592 | 0.111 | -2.399 | 0.249 |
| **ChestPain_typical** | -2.5429 | 0.862 | -2.952 | 0.003 | -4.232 | -0.854 |
| **Thal_normal** | 0.3314 | 1.121 | 0.296 | 0.767 | -1.865 | 2.528 |
| **Thal_reversable** | 2.1623 | 1.108 | 1.952 | 0.051 | -0.009 | 4.334 |

In [96]:
```
def get_significant_vars( lm ):
    var_p_vals_df = pd.DataFrame( lm.pvalues )
    var_p_vals_df['vars'] = var_p_vals_df.index
    var_p_vals_df.columns = ['pvals', 'vars']
    return list( var_p_vals_df[var_p_vals_df.pvals <= 0.05]['vars'] )
```

In [97]:
```
significant_vars = get_significant_vars( lg )
```

In [98]:
```
significant_vars
```

Out[98]:
```
['RestBP', 'MaxHR', 'Ca', 'ChestPain_nonanginal', 'ChestPain_typical']
```

# Evalutation of the model

We can check Accuracy,precision and recall, using classification report!

# Confusion Matrix

In [44]:
```
from sklearn.metrics import confusion_matrix
```

In [49]:
```
cm=confusion_matrix(y_test,predictions)
```

In [50]:
```
cm
```

Out[50]:
```
array([[47,  6],
       [ 8, 29]])
```

# Graphical representation in terms of confusion matrix

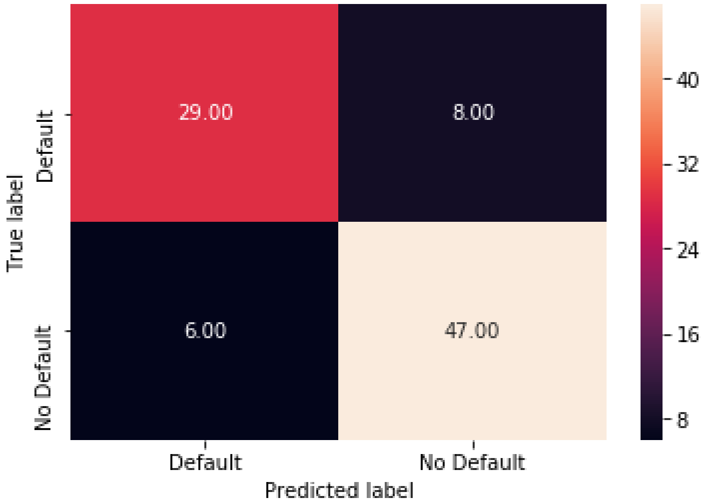
In [71]:
```
import seaborn as sn
def draw_cm( actual, predicted ):
    cm = metrics.confusion_matrix( actual, predicted, [1,0] )
    sn.heatmap(cm, annot=True,  fmt='.2f', xticklabels = ["Default", "No Defau
lt"] , yticklabels = ["Default", "No Default"] )
    plt.ylabel('True label')
    plt.xlabel('Predicted label')
    plt.show()
```

In [72]:
```
from sklearn import metrics
```

In [66]:
```
metrics.confusion_matrix(y_test,y_predictions)
```

Out[66]:
```
array([[47,  6],
       [ 8, 29]])
```

In [73]:
```
draw_cm( y_test, y_predictions )
```




Note: the model could only predict very few default classes.

# Drawing the ROC plot for the Model

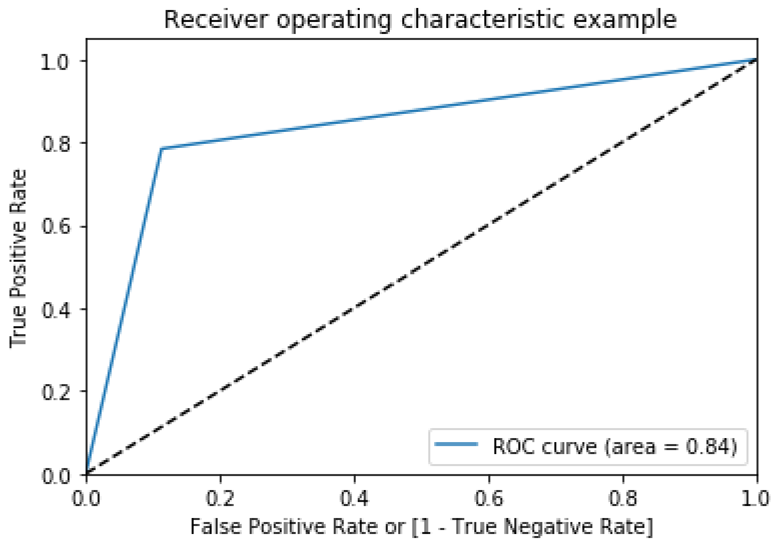
In [75]:
```
auc_score = metrics.roc_auc_score( y_test, y_predictions  )
round( float( auc_score ), 2 )
```

Out[75]: 0.84

In [76]:
```
def draw_roc( actual, probs ):
    fpr, tpr, thresholds = metrics.roc_curve( actual, probs,
                                              drop_intermediate = False )
    auc_score = metrics.roc_auc_score( actual, probs )
    plt.figure(figsize=(6, 4))
    plt.plot( fpr, tpr, label='ROC curve (area = %0.2f)' % auc_score )
    plt.plot([0, 1], [0, 1], 'k--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate or [1 - True Negative Rate]')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver operating characteristic example')
    plt.legend(loc="lower right")
    plt.show()

    return fpr, tpr, thresholds
```

In [78]:
```
fpr, tpr, thresholds = draw_roc( y_test, y_predictions )
## if blue line is below 45 degree it means model is not doing good.
```




In [79]:
```
from sklearn.metrics import classification_report
```

In [80]:
```
print(classification_report(y_test,predictions))
```

```
             precision    recall  f1-score   support

          0       0.85      0.89      0.87        53
          1       0.83      0.78      0.81        37

avg / total       0.84      0.84      0.84        90
```

In [81]:
```
print( 'Total Accuracy : ',np.round( metrics.accuracy_score( y_test, y_predict
ions), 2 ) )
print( 'Precision : ',np.round( metrics.precision_score( y_test, y_predictions
 ), 2 ) )
print( 'Recall : ',np.round( metrics.recall_score( y_test, y_predictions ), 2
) )

cm1 = metrics.confusion_matrix( y_test, y_predictions, [1,0] )

sensitivity = cm1[0,0]/(cm1[0,0]+cm1[0,1])
print('Sensitivity : ', round( sensitivity, 2) )

specificity = cm1[1,1]/(cm1[1,0]+cm1[1,1])
print('Specificity : ', round( specificity, 2 ) )
```

```
Total Accuracy :  0.84
Precision :  0.83
Recall :  0.78
Sensitivity :  0.78
Specificity :  0.89
```

## Total accuracy of my model is 84% .

# Conclusion:

Our model predicted with the accuracy of 84% that (AHD) Atheroselerotic Heart Disease is caused by the above given independent variables like( ChestPain RestBP Cholestrol ,Fbs & so on.) because there is no correlation between the any variable. Precision is 83% and Recall is 78% so there is not much difference between both, as both values close to each other and it is greater than 70%. Area under the Curve is the 84% which is above the 45 degree line which shows that Model is good.

### Target variable for this Model is Atherosclerotic Heart Disease (AHD)

### It is a type of Classification problem within that "Logistics Regression".