In [28]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as st
from sklearn.model_selection import train_test_split
%matplotlib inline
import statsmodels.api as sm
```

In [2]:
```
df = pd.read_csv('heart.csv')
df.head()
```

Out[2]:

	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

In [3]:
```
df.isna().sum()
```

Out[3]:
```
age         0
sex         0
cp          0
trestbps    0
chol        0
fbs         0
restecg     0
thalach     0
exang       0
oldpeak     0
slope       0
ca          0
thal        0
target      0
dtype: int64
```

In [4]:
```
#determine majority class
y_train = df.target
y_train.value_counts(normalize=True)
```

Out[4]:
```
1    0.544554
0    0.455446
Name: target, dtype: float64
```

In [5]:
```
#Majority class for every prediction

majority_class = y_train.mode()[0]
y_pred = [majority_class] * len(y_train)
print(len(y_pred))
```

```
303
```

In [6]:
```
# Accuracy of majority class baseline =
#frequency of majority class
from sklearn.metrics import accuracy_score
accuracy_score(y_train, y_pred)
```

Out[6]:
```
0.5445544554455446
```

Train/Validat/Test Split

In [7]:
```
X_train = df.drop('target', axis=1)
y_train = df.target

X_train.shape, y_train.shape
```

Out[7]:
```
((303, 13), (303,))
```

In [8]:
```
X_train, X_val, y_train, y_val = train_test_split(X_train, y_train, trai

X_train.shape, X_val.shape, y_train.shape, y_val.shape
```

```
/anaconda3/lib/python3.7/site-packages/sklearn/model_selection/_split.
py:2179: FutureWarning: From version 0.21, test_size will always compl
ement train_size unless both are specified.
  FutureWarning)
```

Out[8]:
```
((242, 13), (61, 13), (242,), (61,))
```

In [9]:
```
y_train.value_counts(normalize=True)
```

Out[9]:
```
1    0.549587
0    0.450413
Name: target, dtype: float64
```

In [10]:
```
y_val.value_counts(normalize=True)
```

Out[10]:
```
1    0.52459
0    0.47541
Name: target, dtype: float64
```

In [11]:
```
#Begin with baseline: fast, first models
X_train_num = X_train.select_dtypes('number')
X_val_num = X_val.select_dtypes('number')
```

In [12]:
```
 X_train_num.isnull().sum()
```

Out[12]:
```
age         0
sex         0
cp          0
trestbps    0
chol        0
fbs         0
restecg     0
thalach     0
exang       0
oldpeak     0
slope       0
ca          0
thal        0
dtype: int64
```

In [13]:
```
# Fit logistic Regression on trai data
from sklearn.linear_model import LogisticRegressionCV

model = LogisticRegressionCV(n_jobs=-1)

model.fit(X_train_num, y_train)
```

```
/anaconda3/lib/python3.7/site-packages/sklearn/model_selection/_split.
py:2053: FutureWarning: You should specify a value for 'cv' instead of
relying on the default value. The default value will change from 3 to
5 in version 0.22.
  warnings.warn(CV_WARNING, FutureWarning)
/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/logistic.p
y:758: ConvergenceWarning: lbfgs failed to converge. Increase the numb
er of iterations.
  "of iterations.", ConvergenceWarning)
```

Out[13]:
```
LogisticRegressionCV(Cs=10, class_weight=None, cv='warn', dual=False,
           fit_intercept=True, intercept_scaling=1.0, max_iter=100,
           multi_class='warn', n_jobs=-1, penalty='l2', random_state=N
one,
           refit=True, scoring=None, solver='lbfgs', tol=0.0001, verbo
se=0)
```

In [14]:
```
y_pred = model.predict(X_val_num)
accuracy_score(y_val, y_pred)
```

Out[14]:
```
0.8688524590163934
```

In [15]:
```
y_pred
```

Out[15]:
```
array([0, 1, 1, 0, 1, 1, 1, 0, 0, 0, 1, 0, 1, 0, 1, 1, 1, 0, 0, 0, 1,
0,
       0, 1, 1, 1, 1, 1, 0, 1, 0, 0, 0, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1,
1,
       1, 0, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0])
```

In [16]:
```
y_pred_prob = model.predict_proba(X_val_num)
y_pred_prob
```

Out[16]:
```
array([[0.91718075, 0.08281925],
       [0.24399618, 0.75600382],
       [0.15474074, 0.84525926],
       [0.94721257, 0.05278743],
       [0.0958871 , 0.9041129 ],
       [0.10145698, 0.89854302],
       [0.44546624, 0.55453376],
       [0.99589874, 0.00410126],
       [0.99068834, 0.00931166],
```

```
[0.50678639, 0.49321361],
[0.31376236, 0.68623764],
[0.87612942, 0.12387058],
[0.10499386, 0.89500614],
[0.96385716, 0.03614284],
[0.02465185, 0.97534815],
[0.06918942, 0.93081058],
[0.02620327, 0.97379673],
[0.92164942, 0.07835058],
[0.98716307, 0.01283693],
[0.97997464, 0.02002536],
[0.27669803, 0.72330197],
[0.98489439, 0.01510561],
[0.89205054, 0.10794946],
[0.19931863, 0.80068137],
[0.10264677, 0.89735323],
[0.30157395, 0.69842605],
[0.16358865, 0.83641135],
[0.35053159, 0.64946841],
[0.98612855, 0.01387145],
[0.11516732, 0.88483268],
[0.94889996, 0.05110004],
[0.94377746, 0.05622254],
[0.98893551, 0.01106449],
[0.89557743, 0.10442257],
[0.3388751 , 0.6611249 ],
[0.89050338, 0.10949662],
[0.34393316, 0.65606684],
[0.13538587, 0.86461413],
[0.16396614, 0.83603386],
[0.17685447, 0.82314553],
[0.42215651, 0.57784349],
[0.21210364, 0.78789636],
[0.24299353, 0.75700647],
[0.31545218, 0.68454782],
[0.1608941 , 0.8391059 ],
[0.98707846, 0.01292154],
[0.32772783, 0.67227217],
[0.06077374, 0.93922626],
[0.89875602, 0.10124398],
[0.95406139, 0.04593861],
[0.8996671 , 0.1003329 ],
[0.97742329, 0.02257671],
[0.24133302, 0.75866698],
[0.03242391, 0.96757609],
[0.6973755 , 0.3026245 ],
[0.99607544, 0.00392456],
[0.91042108, 0.08957892],
[0.05656502, 0.94343498],
[0.96913201, 0.03086799],
```

```
            [0.98972238, 0.01027762],
            [0.94953469, 0.05046531]])
```

In [17]:
```
pd.Series(y_pred).value_counts(normalize=True)
```

Out[17]:
```
1    0.52459
0    0.47541
dtype: float64
```

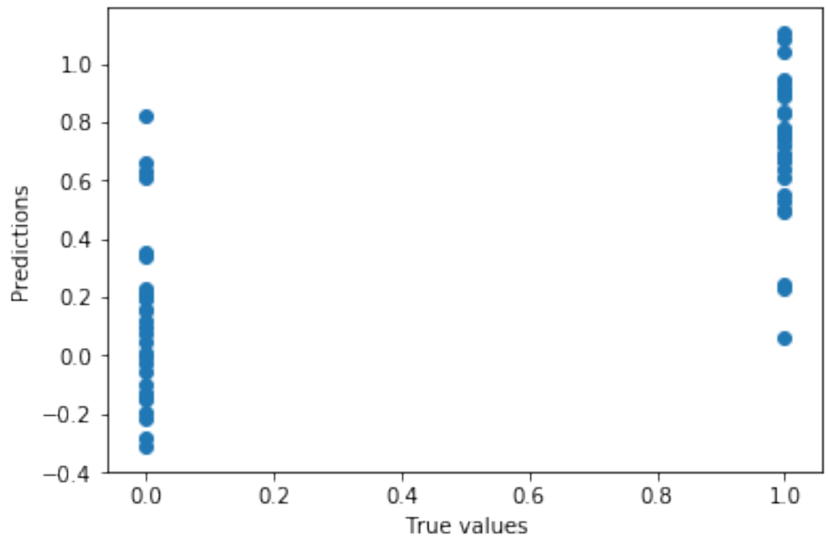
In [18]:
```

X_train.describe(include='number')
```

Out[18]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalac
nt	242.000000	242.000000	242.000000	242.000000	242.000000	242.000000	242.000000	242.00000
an	54.462810	0.657025	0.991736	130.359504	246.842975	0.128099	0.553719	150.11570
td	9.204492	0.475687	1.022533	16.828858	52.795465	0.334893	0.530410	22.35239
in	29.000000	0.000000	0.000000	94.000000	131.000000	0.000000	0.000000	88.00000
%	48.000000	0.000000	0.000000	120.000000	212.000000	0.000000	0.000000	136.00000
%	55.500000	1.000000	1.000000	130.000000	239.500000	0.000000	1.000000	154.00000
%	61.000000	1.000000	2.000000	140.000000	274.750000	0.000000	1.000000	165.75000
ax	77.000000	1.000000	3.000000	192.000000	564.000000	1.000000	2.000000	202.00000

In [19]:

```
from sklearn.linear_model import LinearRegression as lm
model = lm().fit(X_train, y_train)
predictions = model.predict(X_val_num)
plt.xlabel('True values')
plt.ylabel('Predictions')
plt.scatter(y_val, predictions);
plt.show();
```



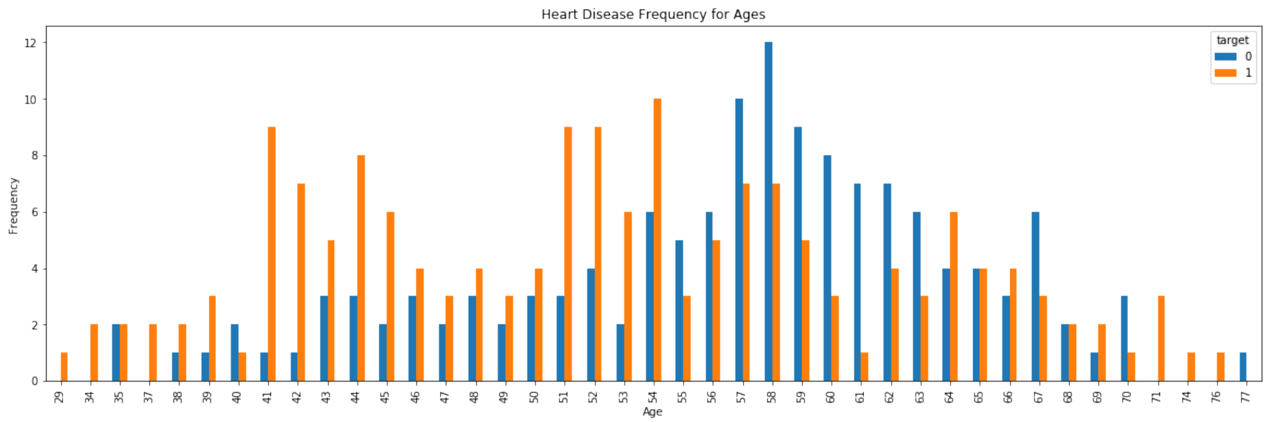
In [20]:

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

Out[20]:

	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	0
1	52.496970	0.563636	1.375758	129.303030	242.230303	0.139394	0.593939	158.466667	0

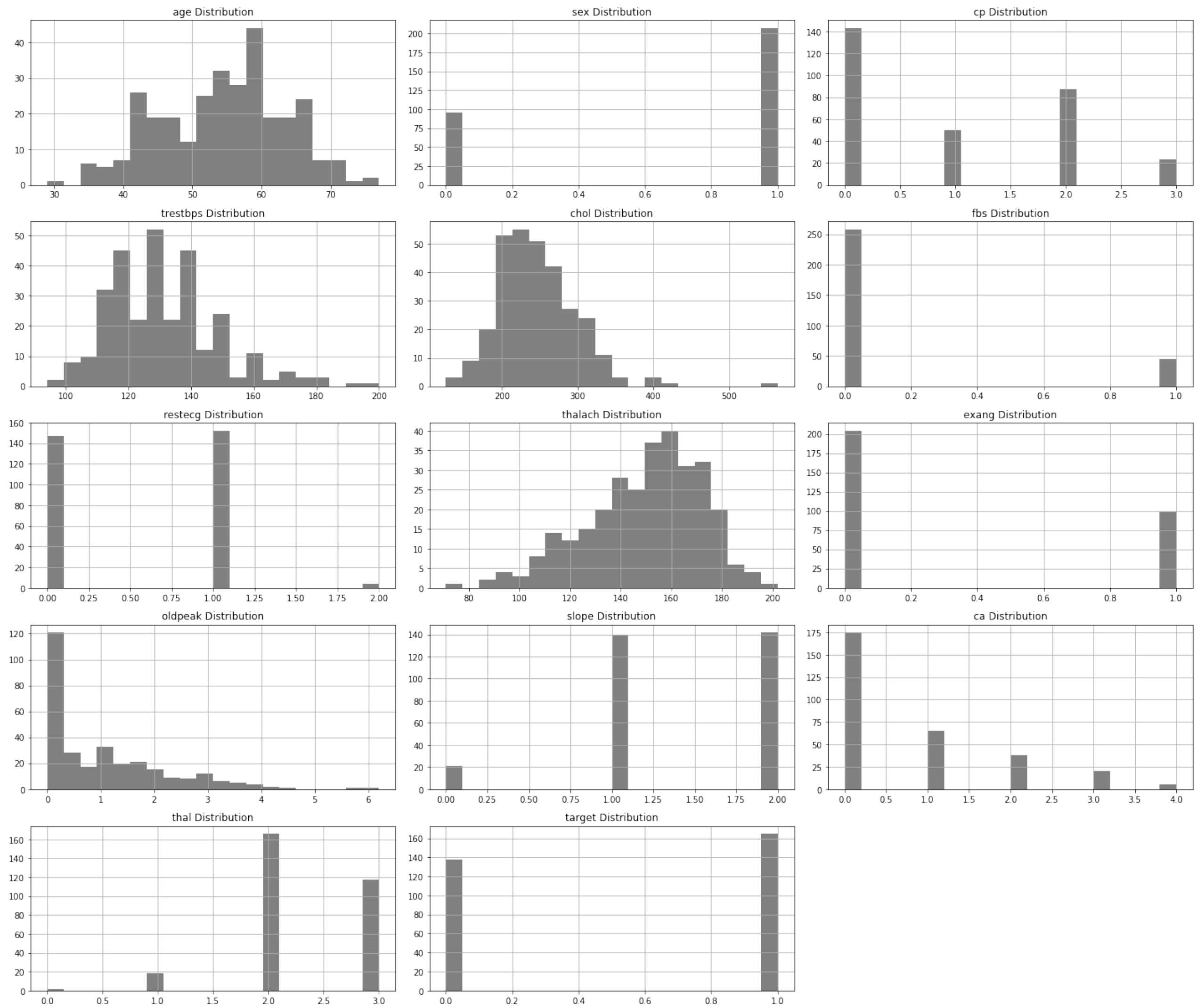
In [21]:
```
pd.crosstab(df.age,df.target).plot.bar( figsize=(20,6))
plt.title('Heart Disease Frequency for Ages')
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.savefig('heartDiseaseAndAges.png')
plt.show()
```



In [22]:
```
X_train_num.isnull().sum()
```

Out[22]:
```
age         0
sex         0
cp          0
trestbps    0
chol        0
fbs         0
restecg     0
thalach     0
exang       0
oldpeak     0
slope       0
ca          0
thal        0
dtype: int64
```

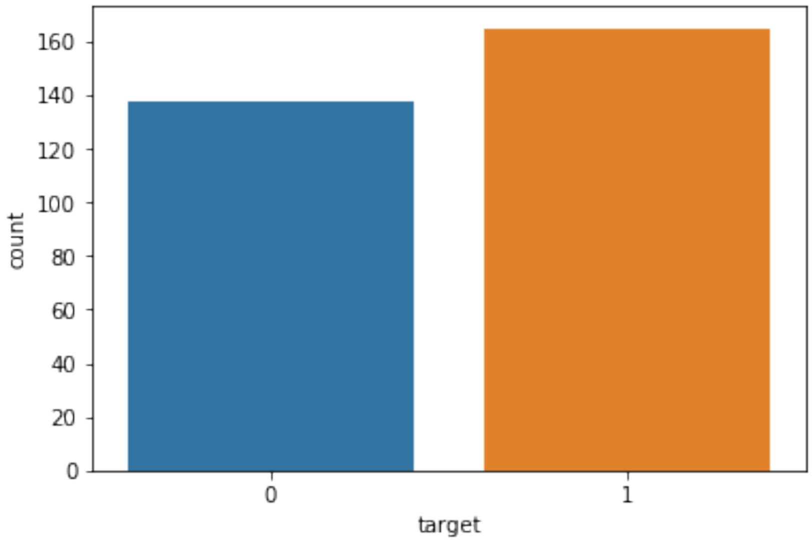
In [23]:
```
def histograms(dataframe, features, rows, cols):
    fig=plt.figure(figsize=(20,20))
    for i, feature in enumerate(features):
        ax=fig.add_subplot(rows,cols,i+1)
        dataframe[feature].hist(bins=20,ax=ax,facecolor='grey')
        ax.set_title(feature+" Distribution",color='black')

    fig.tight_layout()
    plt.show()
histograms(df,df.columns,6,3)
```



In [24]:
```
df.target.value_counts()
```

Out[24]:
```
1    165
0    138
Name: target, dtype: int64
```

In [25]:
```
sns.countplot(x='target', data=df);
```



In [26]:
```
from statsmodels.tools import add_constant as add_constant
target_const = add_constant(df)
target_const.head()
```

Out[26]:

	const	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal
0	1.0	63	1	3	145	233	1	0	150	0	2.3	0	0	1
1	1.0	37	1	2	130	250	0	1	187	0	3.5	0	0	2
2	1.0	41	0	1	130	204	0	0	172	0	1.4	2	0	2
3	1.0	56	1	1	120	236	0	1	178	0	0.8	2	0	2
4	1.0	57	0	0	120	354	0	1	163	1	0.6	2	0	2

In [29]:
```
st.chisqprob = lambda chisq, df: st.chi2.sf(chisq, df)
cols=target_const.columns[:-1]
model=sm.Logit(df.target, target_const[cols])
result=model.fit()
result.summary()
```

```
Optimization terminated successfully.
         Current function value: 0.348904
         Iterations 7
```

Out[29]:

Logit Regression Results

Dep. Variable:	target	**No. Observations:**	303
Model:	Logit	**Df Residuals:**	289
Method:	MLE	**Df Model:**	13
Date:	Fri, 27 Sep 2019	**Pseudo R-squ.:**	0.4937
Time:	09:41:45	**Log-Likelihood:**	-105.72
converged:	True	**LL-Null:**	-208.82
		LLR p-value:	7.262e-37

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
const	3.4505	2.571	1.342	0.180	-1.590	8.490
age	-0.0049	0.023	-0.212	0.832	-0.050	0.041
sex	-1.7582	0.469	-3.751	0.000	-2.677	-0.839
cp	0.8599	0.185	4.638	0.000	0.496	1.223
trestbps	-0.0195	0.010	-1.884	0.060	-0.040	0.001
chol	-0.0046	0.004	-1.224	0.221	-0.012	0.003
fbs	0.0349	0.529	0.066	0.947	-1.003	1.073
restecg	0.4663	0.348	1.339	0.181	-0.216	1.149
thalach	0.0232	0.010	2.219	0.026	0.003	0.044
exang	-0.9800	0.410	-2.391	0.017	-1.783	-0.177
oldpeak	-0.5403	0.214	-2.526	0.012	-0.959	-0.121
slope	0.5793	0.350	1.656	0.098	-0.106	1.265
ca	-0.7733	0.191	-4.051	0.000	-1.147	-0.399
thal	-0.9004	0.290	-3.104	0.002	-1.469	-0.332

In [30]:
```
def feature_sel (data_frame,dep_var,col_list):
        while len(col_list)>0 :
            model=sm.Logit(dep_var,data_frame[col_list])
            result=model.fit(disp=0)
            largest_pvalue=round(result.pvalues,3).nlargest(1)
            if largest_pvalue[0]<(0.05):
                return result
                break
            else:
                col_list=col_list.drop(largest_pvalue.index)

result=feature_sel(target_const, df.target, cols)
```

In [32]:
```
result.summary()
```

Out[32]:

Logit Regression Results

Dep. Variable:	target	**No. Observations:**	303
Model:	Logit	**Df Residuals:**	296
Method:	MLE	**Df Model:**	6
Date:	Fri, 27 Sep 2019	**Pseudo R-squ.:**	0.4651
Time:	09:42:34	**Log-Likelihood:**	-111.71
converged:	True	**LL-Null:**	-208.82
		LLR p-value:	3.209e-39

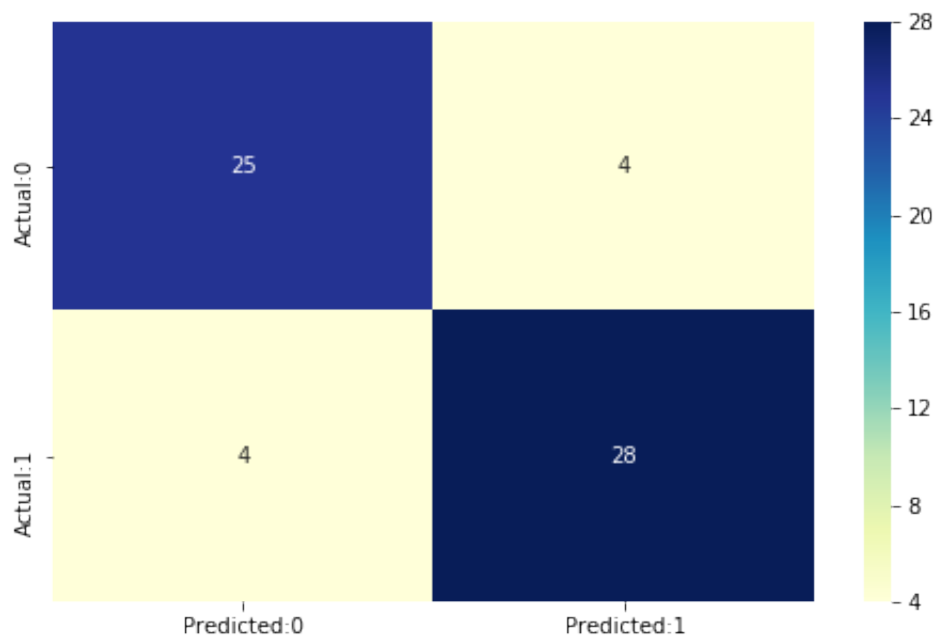
	coef	std err	z	P>|z|	[0.025	0.975]
sex	-1.3898	0.405	-3.431	0.001	-2.184	-0.596
cp	0.7861	0.174	4.509	0.000	0.444	1.128
thalach	0.0261	0.004	5.905	0.000	0.017	0.035
exang	-1.0130	0.376	-2.695	0.007	-1.750	-0.276
oldpeak	-0.7262	0.176	-4.130	0.000	-1.071	-0.382
ca	-0.7053	0.173	-4.087	0.000	-1.043	-0.367
thal	-0.8674	0.259	-3.351	0.001	-1.375	-0.360

In [33]:
```
params = np.exp(result.params)
conf = np.exp(result.conf_int())
conf['OR'] = params
pvalue=round(result.pvalues,3)
conf['pvalue']=pvalue
conf.columns = ['CI 95%(2.5%)', 'CI 95%(97.5%)', 'Odds Ratio','pvalue']
print ((conf))
```

```
         CI 95%(2.5%)  CI 95%(97.5%)  Odds Ratio  pvalue
sex          0.112623       0.551073    0.249126   0.001
cp           1.559575       3.088655    2.194764   0.000
thalach      1.017567       1.035326    1.026408   0.000
exang        0.173839       0.758508    0.363123   0.007
oldpeak      0.342750       0.682775    0.483757   0.000
ca           0.352232       0.692750    0.493973   0.000
thal         0.252918       0.697612    0.420046   0.001
```

In [34]:
```
from sklearn.metrics import confusion_matrix
cm=confusion_matrix(y_val,y_pred)
conf_matrix=pd.DataFrame(data=cm,columns=['Predicted:0','Predicted:1'],i
plt.figure(figsize = (8,5))
sns.heatmap(conf_matrix, annot=True,fmt='d',cmap="YlGnBu")
```

Out[34]: <matplotlib.axes._subplots.AxesSubplot at 0x1a1d99ad30>



In [35]:
```
TN=cm[0,0]
TP=cm[1,1]
FN=cm[1,0]
FP=cm[0,1]
sensitivity=TP/float(TP+FN)
specificity=TN/float(TN+FP)
```

In [36]:
```
print('The acuuracy of the model = TP+TN/(TP+TN+FP+FN) = ',(TP+TN)/float

'The Missclassification = 1-Accuracy = ',1-((TP+TN)/float(TP+TN+FP+FN)),

'Sensitivity or True Positive Rate = TP/(TP+FN) = ',TP/float(TP+FN),'\n'

'Specificity or True Negative Rate = TN/(TN+FP) = ',TN/float(TN+FP),'\n'

'Positive Predictive value = TP/(TP+FP) = ',TP/float(TP+FP),'\n',

'Negative predictive Value = TN/(TN+FN) = ',TN/float(TN+FN),'\n',

'Positive Likelihood Ratio = Sensitivity/(1-Specificity) = ',sensitivity

'Negative likelihood Ratio = (1-Sensitivity)/Specificity = ',(1-sensitiv
```

```
The acuuracy of the model = TP+TN/(TP+TN+FP+FN) =  0.8688524590163934
 The Missclassification = 1-Accuracy =  0.1311475409836066
 Sensitivity or True Positive Rate = TP/(TP+FN) =  0.875
 Specificity or True Negative Rate = TN/(TN+FP) =  0.8620689655172413
 Positive Predictive value = TP/(TP+FP) =  0.875
 Negative predictive Value = TN/(TN+FN) =  0.8620689655172413
 Positive Likelihood Ratio = Sensitivity/(1-Specificity) =  6.34374999
9999997
 Negative likelihood Ratio = (1-Sensitivity)/Specificity =  0.14500000
000000002
```

In [37]:
```
from sklearn.linear_model import LogisticRegression
logr=LogisticRegression()
logr.fit(X_train,y_train)
y_pred=logr.predict(X_val)
```

```
/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/logistic.p
y:433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.2
2. Specify a solver to silence this warning.
  FutureWarning)
```

In [38]:
```
y_pred_prob=logr.predict_proba(X_val_num)[:,:]
y_pred_prob_df=pd.DataFrame(data=y_pred_prob, columns=['Prob of no heart
y_pred_prob_df.head()
```

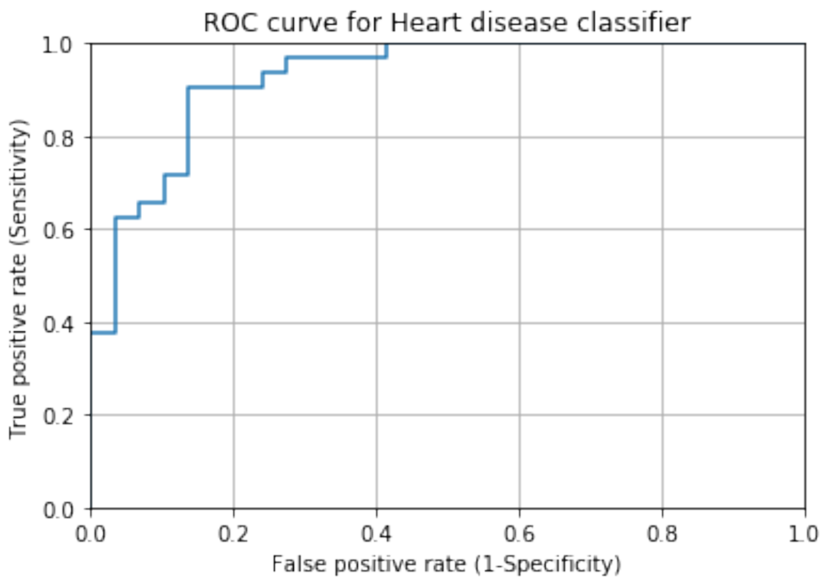
Out[38]:

	Prob of no heart disease (0)	Prob of Heart Disease (1)
0	0.922471	0.077529
1	0.261241	0.738759
2	0.144341	0.855659
3	0.971653	0.028347
4	0.060461	0.939539

In [39]:
```
from sklearn.preprocessing import binarize
for i in range(1,5):
    cm2=0
    y_pred_prob_yes=logr.predict_proba(X_val_num)
    y_pred2=binarize(y_pred_prob_yes,i/10)[:,1]
    cm2=confusion_matrix(y_val,y_pred2)
    print ('With',i/10,'threshold the Confusion Matrix is ','\n',cm2,'\n
            'with',cm2[0,0]+cm2[1,1],'correct predictions and',cm2[1,0],
          'Sensitivity: ',cm2[1,1]/(float(cm2[1,1]+cm2[1,0])),'Specifici
```

```
With 0.1 threshold the Confusion Matrix is
 [[23  6]
 [ 3 29]]
 with 52 correct predictions and 3 Type II errors( False Negatives)

 Sensitivity:  0.90625 Specificity:  0.7931034482758621



With 0.2 threshold the Confusion Matrix is
 [[24  5]
 [ 3 29]]
 with 53 correct predictions and 3 Type II errors( False Negatives)

 Sensitivity:  0.90625 Specificity:  0.8275862068965517



With 0.3 threshold the Confusion Matrix is
 [[25  4]
 [ 3 29]]
 with 54 correct predictions and 3 Type II errors( False Negatives)

 Sensitivity:  0.90625 Specificity:  0.8620689655172413



With 0.4 threshold the Confusion Matrix is
 [[25  4]
 [ 3 29]]
 with 54 correct predictions and 3 Type II errors( False Negatives)

 Sensitivity:  0.90625 Specificity:  0.8620689655172413
```

In [40]:
```
from sklearn.metrics import roc_curve
fpr, tpr, thresholds = roc_curve(y_val, y_pred_prob_yes[:,1])
plt.plot(fpr,tpr)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])
plt.title('ROC curve for Heart disease classifier')
plt.xlabel('False positive rate (1-Specificity)')
plt.ylabel('True positive rate (Sensitivity)')
plt.grid(True)
```



In [41]:
```
import sklearn
```

In [42]:
```
sklearn.metrics.roc_auc_score(y_val,y_pred_prob_yes[:,1])
```

Out[42]: 0.927801724137931

In [ ]:

In [ ]:

In [ ]: