Initial Import for Standard Libraries

In [0]:
```
# importing libraries.!!

import pandas as pd
import numpy as np
import os
import seaborn as sns
from matplotlib import pyplot as plt

import warnings
warnings.filterwarnings('ignore')
```

In [0]:
```
#Load the Data

df = pd.read_csv('./heart.csv')
```

In [183]:
```
#Evaluating Non Zero Columns

df.isnull().sum()
```

Out[183]:
```
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
```

There are No Columns that have Non Zero Value

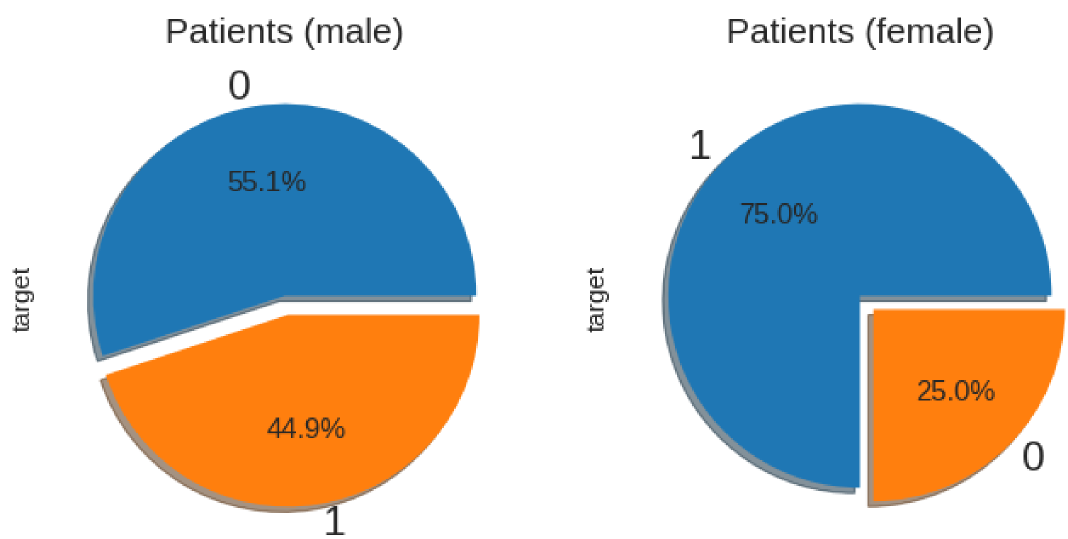
In [184]:
```
df.head()
```

Out[184]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang
0	63	1	3	145	233	1	0	150	0
1	37	1	2	130	250	0	1	187	0
2	41	0	1	130	204	0	0	172	0
3	56	1	1	120	236	0	1	178	0
4	57	0	0	120	354	0	1	163	1

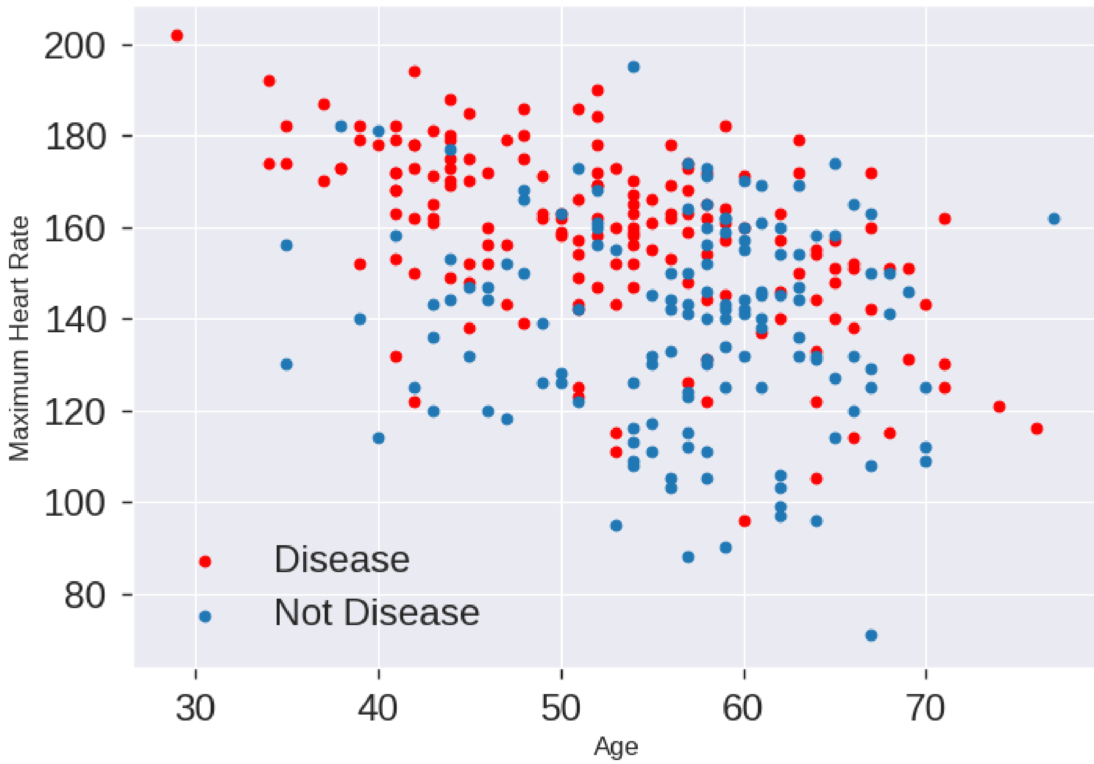
In [185]:

```
f,ax=plt.subplots(1,2,figsize=(8,4))

sns.set_context("paper", font_scale = 2, rc = {"font.size": 12,
"axes.titlesize": 15,"axes.labelsize": 12})

df.loc[df['sex']==1, 'target'].value_counts().plot.pie(explode=[
0,0.10],autopct='%1.1f%%',ax=ax[0],shadow=True)
df.loc[df['sex']==0, 'target'].value_counts().plot.pie(explode=[
0,0.10],autopct='%1.1f%%',ax=ax[1],shadow=True)

ax[0].set_title('Patients (male)')
ax[1].set_title('Patients (female)')

plt.show()
```



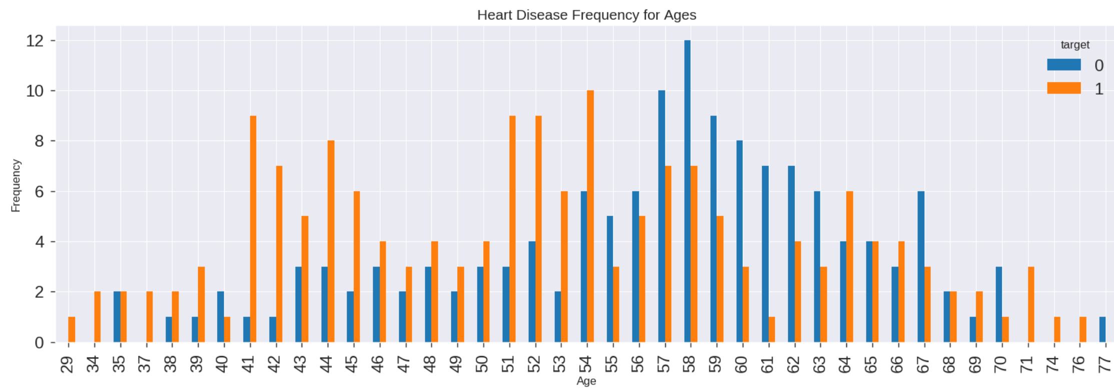
In [186]:

```
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()
```



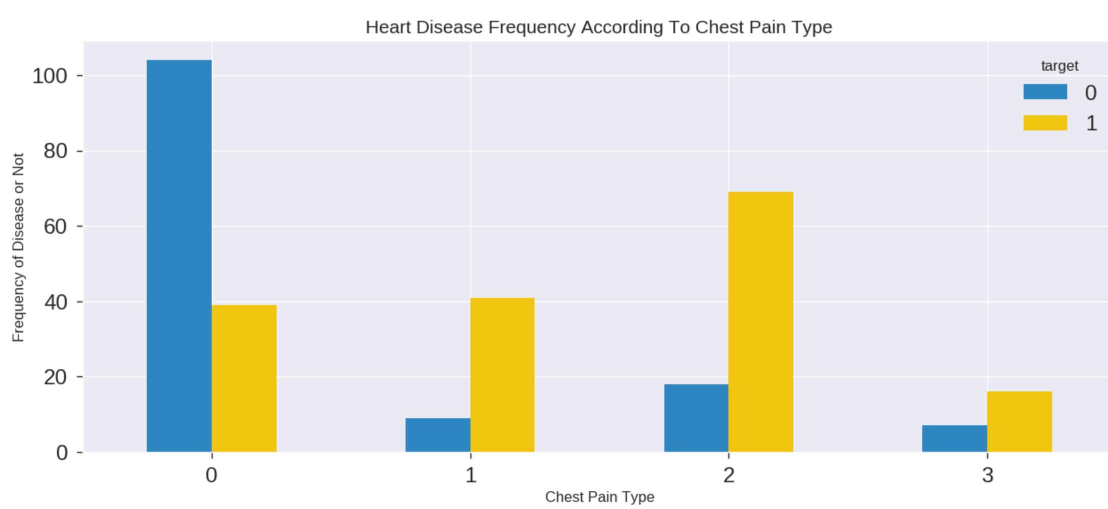
In [187]:

```
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 [188]:

```
pd.crosstab(df.cp,df.target).plot(kind="bar",figsize=(15,6),colo
r=['#2E86C1','#F1C40F' ])
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()
```



Use Pandas Profiling to Improve EDA for data.

In [189]:
```
pip install pandas-profiling
```

```
Requirement already satisfied: pandas-profiling in /usr/loca
l/lib/python3.6/dist-packages (1.4.1)
Requirement already satisfied: pandas>=0.19 in /usr/local/li
b/python3.6/dist-packages (from pandas-profiling) (0.25.3)
Requirement already satisfied: jinja2>=2.8 in /usr/local/lib/
python3.6/dist-packages (from pandas-profiling) (2.10.3)
Requirement already satisfied: matplotlib>=1.4 in /usr/local/
lib/python3.6/dist-packages (from pandas-profiling) (3.1.2)
Requirement already satisfied: six>=1.9 in /usr/local/lib/pyt
hon3.6/dist-packages (from pandas-profiling) (1.12.0)
Requirement already satisfied: python-dateutil>=2.6.1 in /us
r/local/lib/python3.6/dist-packages (from pandas>=0.19->panda
s-profiling) (2.6.1)
Requirement already satisfied: numpy>=1.13.3 in /usr/local/li
b/python3.6/dist-packages (from pandas>=0.19->pandas-profilin
g) (1.17.4)
Requirement already satisfied: pytz>=2017.2 in /usr/local/li
b/python3.6/dist-packages (from pandas>=0.19->pandas-profilin
g) (2018.9)
Requirement already satisfied: MarkupSafe>=0.23 in /usr/loca
l/lib/python3.6/dist-packages (from jinja2>=2.8->pandas-profi
ling) (1.1.1)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.
1.6,>=2.0.1 in /usr/local/lib/python3.6/dist-packages (from m
atplotlib>=1.4->pandas-profiling) (2.4.5)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/loca
l/lib/python3.6/dist-packages (from matplotlib>=1.4->pandas-p
rofiling) (1.1.0)
Requirement already satisfied: cycler>=0.10 in /usr/local/li
b/python3.6/dist-packages (from matplotlib>=1.4->pandas-profi
ling) (0.10.0)
Requirement already satisfied: setuptools in /usr/local/lib/p
ython3.6/dist-packages (from kiwisolver>=1.0.1->matplotlib>=
1.4->pandas-profiling) (42.0.2)
```

In [0]:

```
import pandas_profiling
```

In [191]:

```
pandas_profiling.ProfileReport(df)
```

Out[191]:

Overview

Dataset info

Number of variables	14
Number of observations	303
Total Missing (%)	0.0%
Total size in memory	33.3 KiB
Average record size in memory	112.4 B

Variables types

Numeric	10
Categorical	0
Boolean	4
Date	0
Text (Unique)	0
Rejected	0
Unsupported	0

Warnings

- `cp` has 143 / 47.2% zeros **Zeros**
- `restecg` has 147 / 48.5% zeros **Zeros**
- `oldpeak` has 99 / 32.7% zeros **Zeros**
- `slope` has 21 / 6.9% zeros **Zeros**
- `ca` has 175 / 57.8% zeros **Zeros**
- Dataset has 1 duplicate rows **Warning**

Variables

age
Numeric

Distinct count	41
Unique (%)	13.5%
Missing (%)	0.0%
Missing (n)	0
Infinite (%)	0.0%
Infinite (n)	0

Mean	54.366
Minimum	29
Maximum	77
Zeros (%)	0.0%

Toggle details

sex
Boolean

Distinct count	2
Unique (%)	0.7%
Missing (%)	0.0%
Missing (n)	0

Mean	0.68317

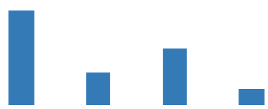
1	207
0	96

Toggle details

cp
Numeric

Distinct count	4
Unique (%)	1.3%
Missing (%)	0.0%
Missing (n)	0
Infinite (%)	0.0%
Infinite (n)	0

Mean	0.967
Minimum	0
Maximum	3
Zeros (%)	47.2%



Toggle details

trestbps
Numeric

Distinct count	49
Unique (%)	16.2%
Missing (%)	0.0%
Missing (n)	0
Infinite (%)	0.0%
Infinite (n)	0

Mean	131.62
Minimum	94
Maximum	200

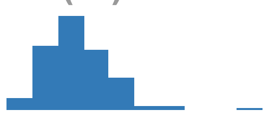
Zeros (%)	0.0%

Toggle details

chol
Numeric

Distinct count	152
Unique (%)	50.2%
Missing (%)	0.0%
Missing (n)	0
Infinite (%)	0.0%
Infinite (n)	0

Mean	246.26
Minimum	126
Maximum	564
Zeros (%)	0.0%



Toggle details

fbs
Boolean

Distinct count	2
Unique (%)	0.7%
Missing (%)	0.0%
Missing (n)	0

Mean	0.14851

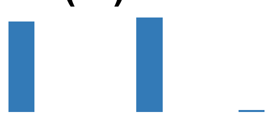
0	258

1 45

Toggle details

restecg
Numeric

Distinct count	3
Unique (%)	1.0%
Missing (%)	0.0%
Missing (n)	0
Infinite (%)	0.0%
Infinite (n)	0
Mean	0.52805
Minimum	0
Maximum	2
Zeros (%)	48.5%

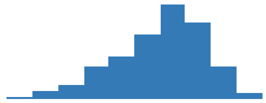


Toggle details

thalach
Numeric

Distinct count	91
Unique (%)	30.0%
Missing (%)	0.0%
Missing (n)	0
Infinite (%)	0.0%
Infinite (n)	0
Mean	149.65

Minimum	71
Maximum	202
Zeros (%)	0.0%



Toggle details

exang
Boolean

Distinct count	2
Unique (%)	0.7%
Missing (%)	0.0%
Missing (n)	0

Mean	0.32673

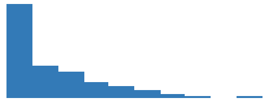
0	204
1	99

Toggle details

oldpeak
Numeric

Distinct count	40
Unique (%)	13.2%
Missing (%)	0.0%
Missing (n)	0
Infinite (%)	0.0%
Infinite (n)	0
Mean	1.0396
Minimum	0

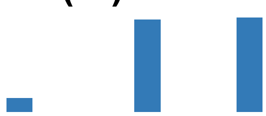
Maximum	6.2
Zeros (%)	32.7%



Toggle details

slope
Numeric

Distinct count	3
Unique (%)	1.0%
Missing (%)	0.0%
Missing (n)	0
Infinite (%)	0.0%
Infinite (n)	0
Mean	1.3993
Minimum	0
Maximum	2
Zeros (%)	6.9%

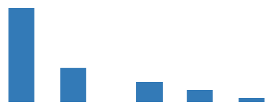


Toggle details

ca
Numeric

Distinct count	5
Unique (%)	1.7%
Missing (%)	0.0%
Missing (n)	0
Infinite (%)	0.0%

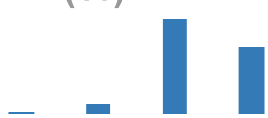
Infinite (n)	0
Mean	0.72937
Minimum	0
Maximum	4
Zeros (%)	57.8%



Toggle details

thal
Numeric

Distinct count	4
Unique (%)	1.3%
Missing (%)	0.0%
Missing (n)	0
Infinite (%)	0.0%
Infinite (n)	0
Mean	2.3135
Minimum	0
Maximum	3
Zeros (%)	0.7%



Toggle details

target
Boolean

Distinct count	2
Unique (%)	0.7%

Missing (%) 0.0%

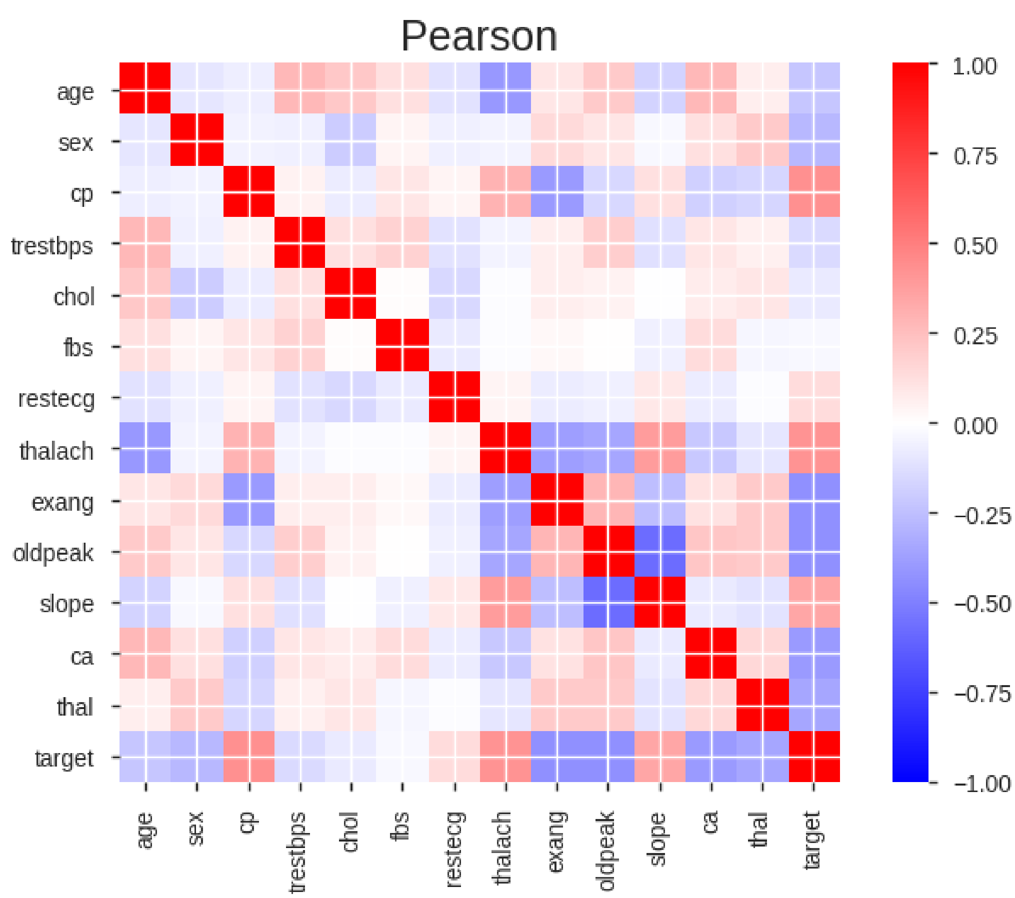
Missing (n) 0

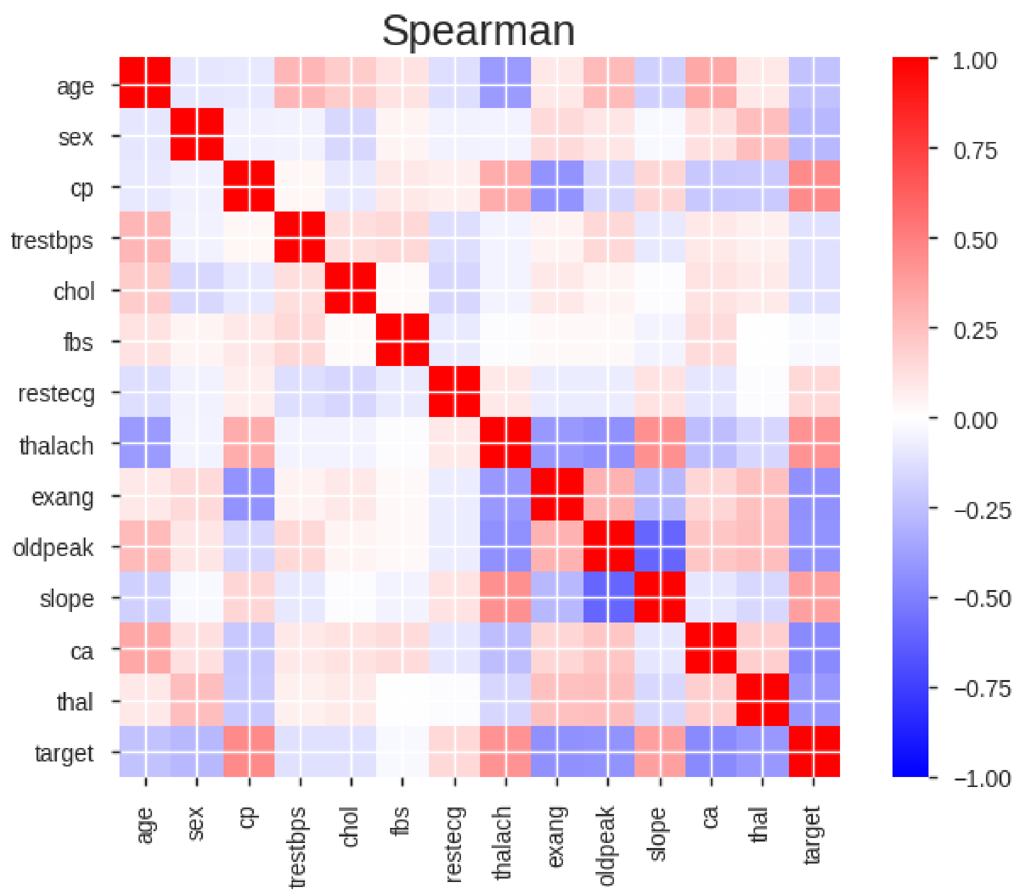
Mean 0.54455

1	165
0	138

Toggle details

Correlations





Sample

	age	sex	cp	trestbps	chol	fbs	reste
0	63	1	3	145	233	1	0
1	37	1	2	130	250	0	1
2	41	0	1	130	204	0	0
3	56	1	1	120	236	0	1
4	57	0	0	120	354	0	1

Plot the Split of Diseases across Male and Female

In [192]:

```
print("{} % of Women Suffer from Heart Diseases".format(100*(df.loc[df.sex == 0].target.sum()/df.loc[df.sex == 0].target.count())))
print("{} % of Men Suffer from Heart Diseases".format(round(100*(df.loc[df.sex == 1].target.sum()/df.loc[df.sex == 1].target.count()))))
```

```
75.0 % of Women Suffer from Heart Diseases
45.0 % of Men Suffer from Heart Diseases
```

Train Test Split

In [0]:

```
X = df.iloc[:, :-1].values
y = df.iloc[:, -1].values
```

In [0]:

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 0)
```

In [195]:
```
X_train
```

Out[195]:
```
array([[43.,  0.,  2., ...,  1.,  0.,  2.],
       [66.,  0.,  2., ...,  1.,  1.,  2.],
       [58.,  1.,  2., ...,  2.,  0.,  2.],
       ...,
       [56.,  1.,  3., ...,  1.,  0.,  3.],
       [47.,  1.,  2., ...,  2.,  0.,  2.],
       [58.,  1.,  1., ...,  1.,  0.,  2.]])
```

Model Evaluation

In [0]:
```
# Importing Models that needs to be evaluated

from sklearn import model_selection
from sklearn.naive_bayes import MultinomialNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn.calibration import CalibratedClassifierCV
from sklearn.ensemble import AdaBoostClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
```

In [0]:
```
# prepare models

model_list = []
```

In [0]:
```
model_list.append(('Multinomial NB', MultinomialNB(alpha=0.1)))
model_list.append(('Decision Tree', DecisionTreeClassifier()))
model_list.append(('SVM',SVC(kernel='linear')))
model_list.append(('ADA Boost With Decision Tree', AdaBoostClass
ifier(DecisionTreeClassifier(max_depth=3),
    n_estimators=200)))
model_list.append(('Logistic Regression',LogisticRegression(solv
er='liblinear')))
model_list.append(('Random Forest',RandomForestClassifier()))
```

In [0]:
```
# Variable to Score Results
results = []
names = []
scoring = 'accuracy'
seed = 5
```

Cross Validation Score

In [200]:
```
# Evaluation of Each Model One by One (Cross Validation Score)

for name, model in model_list:
    kfold = model_selection.KFold(n_splits=10, random_state=seed
)
    cv_results = model_selection.cross_val_score(model, X_train,
y_train, cv=kfold, scoring=scoring)
    results.append(cv_results)
    names.append(name)
    msg = "%s: %f (%f)" % (name, cv_results.mean(), cv_results.s
td())
    print(msg)
```

```
Multinomial NB: 0.740000 (0.086165)
Decision Tree: 0.764833 (0.073088)
SVM: 0.831000 (0.066396)
ADA Boost With Decision Tree: 0.802333 (0.060755)
Logistic Regression: 0.831167 (0.070392)
Random Forest: 0.814667 (0.067814)
```

Preparing a DataFrame to Plot the Scores

In [0]:
```
def insert(df, row):
    insert_loc = df.index.max()
    if np.isnan(insert_loc):
        df.loc[0] = row
    else:
        df.loc[insert_loc + 1] = row
```

In [202]:
```
cv_score = df_ = pd.DataFrame(columns = ['Model_Name','CV_Score'
])
cv_score.head()
```

Out[202]:

	Model_Name	CV_Score

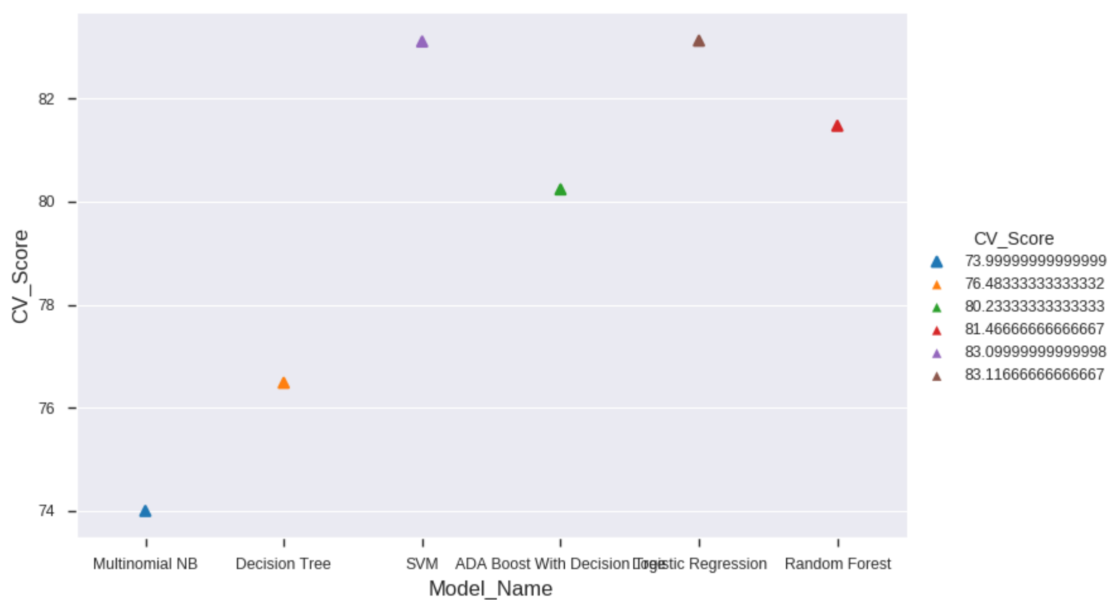
In [0]:
```
for key,value in enumerate(results):
        insert(cv_score,[names[key],value.mean()*100])
```

In [204]:
```
cv_score
```

Out[204]:

	Model_Name	CV_Score
0	Multinomial NB	74.000000
1	Decision Tree	76.483333
2	SVM	83.100000
3	ADA Boost With Decision Tree	80.233333
4	Logistic Regression	83.116667
5	Random Forest	81.466667

In [205]:
```
sns.set_context("paper", font_scale = 1, rc = {"font.size": 12,
"axes.titlesize": 15,"axes.labelsize": 12})
plot = sns.catplot(x="Model_Name", y="CV_Score", hue="CV_Score",
kind="point", data=cv_score,height=5,aspect=1.5,markers="^")
```



Libaries to explain the Models

In [214]:
```
pip install eli5
```

```
Requirement already satisfied: eli5 in /usr/local/lib/python
3.6/dist-packages (0.10.1)
Requirement already satisfied: numpy>=1.9.0 in /usr/local/li
b/python3.6/dist-packages (from eli5) (1.17.4)
Requirement already satisfied: graphviz in /usr/local/lib/pyt
hon3.6/dist-packages (from eli5) (0.10.1)
Requirement already satisfied: scikit-learn>=0.18 in /usr/loc
al/lib/python3.6/dist-packages (from eli5) (0.21.3)
Requirement already satisfied: tabulate>=0.7.7 in /usr/local/
lib/python3.6/dist-packages (from eli5) (0.8.6)
Requirement already satisfied: scipy in /usr/local/lib/python
3.6/dist-packages (from eli5) (1.3.3)
Requirement already satisfied: attrs>16.0.0 in /usr/local/li
b/python3.6/dist-packages (from eli5) (19.3.0)
Requirement already satisfied: six in /usr/local/lib/python3.
6/dist-packages (from eli5) (1.12.0)
Requirement already satisfied: jinja2 in /usr/local/lib/pytho
n3.6/dist-packages (from eli5) (2.10.3)
Requirement already satisfied: joblib>=0.11 in /usr/local/li
b/python3.6/dist-packages (from scikit-learn>=0.18->eli5) (0.
14.0)
Requirement already satisfied: MarkupSafe>=0.23 in /usr/loca
l/lib/python3.6/dist-packages (from jinja2->eli5) (1.1.1)
```

In [0]:
```
#Libraries for Explaning ML Models

import eli5 #for purmutation importance
from eli5.sklearn import PermutationImportance
```

In [0]:
```
df1 = df[df.columns.difference(['target'])]
```

In [0]:
```
perm_list =[]
```

In [0]:

```
# Evaluation of Each Model One by One (Cross Validation Score)

for name, model in model_list:
    model.fit(X_train, y_train)
    perm = PermutationImportance(model, random_state=1).fit(X_te
st, y_test)
    perm_list.append(perm)
```

In [0]:

```
for index,value in enumerate(perm_list):
    eli5.show_weights(perm_list[index], feature_names = df1.colu
mns.tolist())
```

In [220]:

```
# Feature Importance using MultinomialNB
eli5.show_weights(perm_list[0], feature_names = df1.columns.toli
st())
```

Out[220]:

Weight	Feature
0.0230 ± 0.0445	restecg
0.0131 ± 0.0131	ca
0.0098 ± 0.0533	chol
0.0033 ± 0.0382	slope
0 ± 0.0000	trestbps
0 ± 0.0000	thal
0 ± 0.0000	fbs
-0.0033 ± 0.0321	sex
-0.0098 ± 0.0161	oldpeak
-0.0131 ± 0.0131	exang
-0.0131 ± 0.0245	cp
-0.0262 ± 0.0334	age
-0.0393 ± 0.0533	thalach

In [221]:

```
# Feature Importance using DecisionTreeClassifier
eli5.show_weights(perm_list[1], feature_names = df1.columns.tolist())
```

Out[221]:

Weight	Feature
0.0787 ± 0.0564	chol
0.0754 ± 0.0445	restecg
0.0590 ± 0.0161	trestbps
0.0459 ± 0.0435	age
0.0164 ± 0.0415	exang
0.0131 ± 0.0131	thal
0.0131 ± 0.0131	oldpeak
0.0131 ± 0.0435	thalach
0.0066 ± 0.0161	slope
0.0033 ± 0.0245	cp
0 ± 0.0000	sex
0 ± 0.0000	fbs
-0.0131 ± 0.0482	ca

In [222]:

```
# Feature Importance using SVM
eli5.show_weights(perm_list[2], feature_names = df1.columns.tolist())
```

Out[222]:

Weight	Feature
0.0164 ± 0.0293	trestbps
0.0164 ± 0.0464	ca
0.0131 ± 0.0759	slope
0.0131 ± 0.0482	chol
0.0033 ± 0.0525	thalach
0 ± 0.0000	thal
0 ± 0.0000	exang
0 ± 0.0000	age
-0.0033 ± 0.0131	cp
-0.0066 ± 0.0161	oldpeak
-0.0098 ± 0.0161	fbs
-0.0164 ± 0.0207	sex
-0.0197 ± 0.0131	restecg

In [223]:

```
# Feature Importance using AdaBoostClassifier
eli5.show_weights(perm_list[3], feature_names = df1.columns.tolist())
```

Out[223]:

Weight	Feature
0.0787 ± 0.0382	chol
0.0754 ± 0.0675	trestbps
0.0656 ± 0.0549	age
0.0492 ± 0.0359	slope
0.0492 ± 0.0207	ca
0.0328 ± 0.0994	thalach
0.0164 ± 0.0415	restecg
0.0131 ± 0.0435	exang
0.0131 ± 0.0245	fbs
0.0066 ± 0.0262	thal
0.0066 ± 0.0161	sex
0.0033 ± 0.0321	oldpeak
-0.0066 ± 0.0572	cp

In [224]:

```
# Feature Importance using LogisticRegression
eli5.show_weights(perm_list[4], feature_names = df1.columns.toli
st())
```

Out[224]:

Weight	Feature
0.0918 ± 0.0334	chol
0.0492 ± 0.0464	ca
0.0328 ± 0.0207	trestbps
0.0262 ± 0.0334	restecg
0.0197 ± 0.0525	slope
0.0164 ± 0.0549	thalach
0.0164 ± 0.0207	thal
0.0131 ± 0.0131	exang
0.0066 ± 0.0161	cp
0 ± 0.0000	fbs
0 ± 0.0000	age
-0.0033 ± 0.0245	oldpeak
-0.0066 ± 0.0262	sex

In [225]:
```
# Feature Importance using RandomForestClassifier
eli5.show_weights(perm_list[5], feature_names = df1.columns.toli
st())
```

Out[225]:

Weight	Feature
0.1082 ± 0.0894	trestbps
0.0262 ± 0.0572	thalach
0.0066 ± 0.0262	sex
0.0066 ± 0.0262	exang
0.0066 ± 0.0262	ca
0.0033 ± 0.0382	restecg
-0.0066 ± 0.0334	chol
-0.0098 ± 0.0161	oldpeak
-0.0098 ± 0.0161	fbs
-0.0098 ± 0.0262	age
-0.0131 ± 0.0382	thal
-0.0131 ± 0.0321	slope
-0.0492 ± 0.0359	cp

Accuracy & RoC Curve

In [0]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.metrics import roc_curve
from sklearn.metrics import f1_score
from sklearn.metrics import auc

from sklearn.metrics import precision_recall_curve
from sklearn.metrics import average_precision_score
```

In [0]:
```
def plotting(true,pred):
    fig,ax=plt.subplots(1,2,figsize=(10,5))
    precision,recall,threshold = precision_recall_curve(true,pre
d[:,1])
    ax[0].plot(recall,precision,'g--')
    ax[0].set_xlabel('Recall')
    ax[0].set_ylabel('Precision')
    ax[0].set_title("Average Precision Score : {}".format(averag
e_precision_score(true,pred[:,1])))
    fpr,tpr,threshold = roc_curve(true,pred[:,1])
    ax[1].plot(fpr,tpr)
    ax[1].set_title("AUC Score is: {}".format(auc(fpr,tpr)))
    ax[1].plot([0,1],[0,1],'k--')
    ax[1].set_xlabel('False Positive Rate')
    ax[1].set_ylabel('True Positive Rate')
```

In [0]:
```
sns.set_context("paper", font_scale = 1.5, rc = {"font.size": 11
,"axes.titlesize": 14,"axes.labelsize": 11})
```

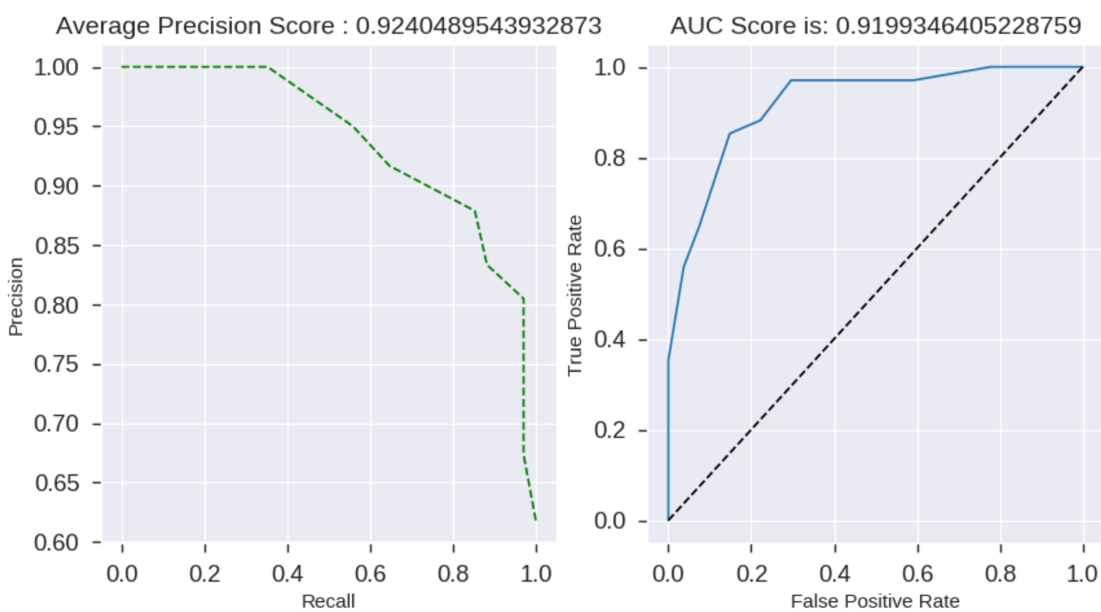
Random Forest

In [229]:
```
RandomForestClassifier = RandomForestClassifier(n_estimators=10,
criterion='entropy',random_state=0)
RandomForestClassifier.fit(X_train,y_train)
```

Out[229]:
```
RandomForestClassifier(bootstrap=True, class_weight=None, cri
terion='entropy',
                       max_depth=None, max_features='auto', m
ax_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurit
y_split=None,
                       min_samples_leaf=1, min_samples_split=
2,
                       min_weight_fraction_leaf=0.0, n_estima
tors=10,
                       n_jobs=None, oob_score=False, random_s
tate=0, verbose=0,
                       warm_start=False)
```

In [230]:
```
plotting(y_test,RandomForestClassifier.predict_proba(X_test))
plt.figure()
```

Out[230]: <Figure size 800x550 with 0 Axes>



<Figure size 800x550 with 0 Axes>

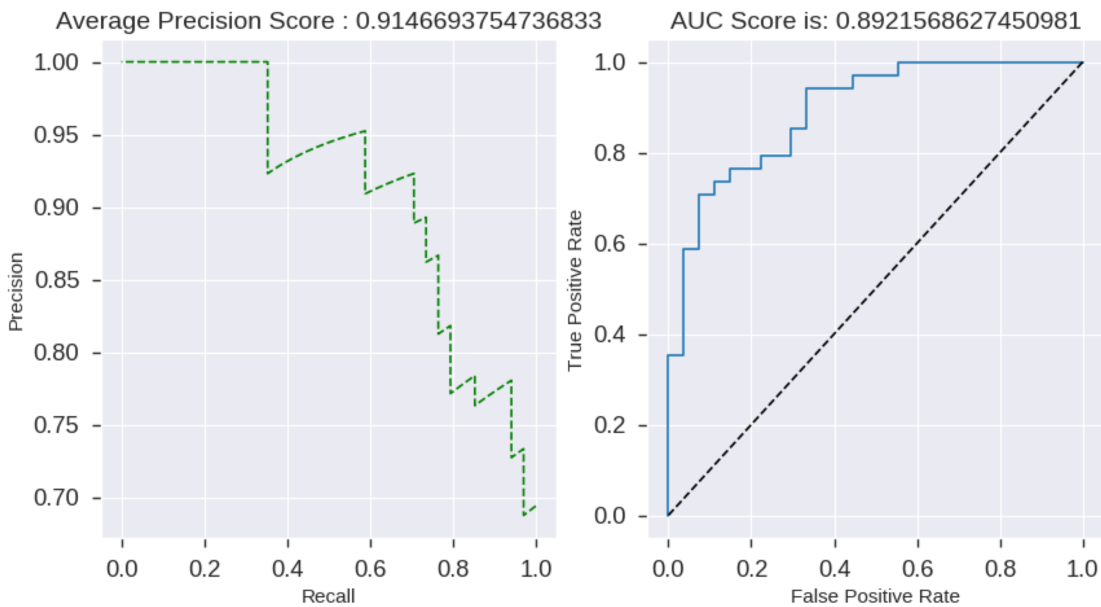
MultinomialNB

In [231]:
```
MultinomialNB = MultinomialNB(alpha=0.1)
MultinomialNB.fit(X_train,y_train)
```

Out[231]: `MultinomialNB(alpha=0.1, class_prior=None, fit_prior=True)`

In [232]:
```
plotting(y_test,MultinomialNB.predict_proba(X_test))
plt.figure()
```

Out[232]: `<Figure size 800x550 with 0 Axes>`



`<Figure size 800x550 with 0 Axes>`

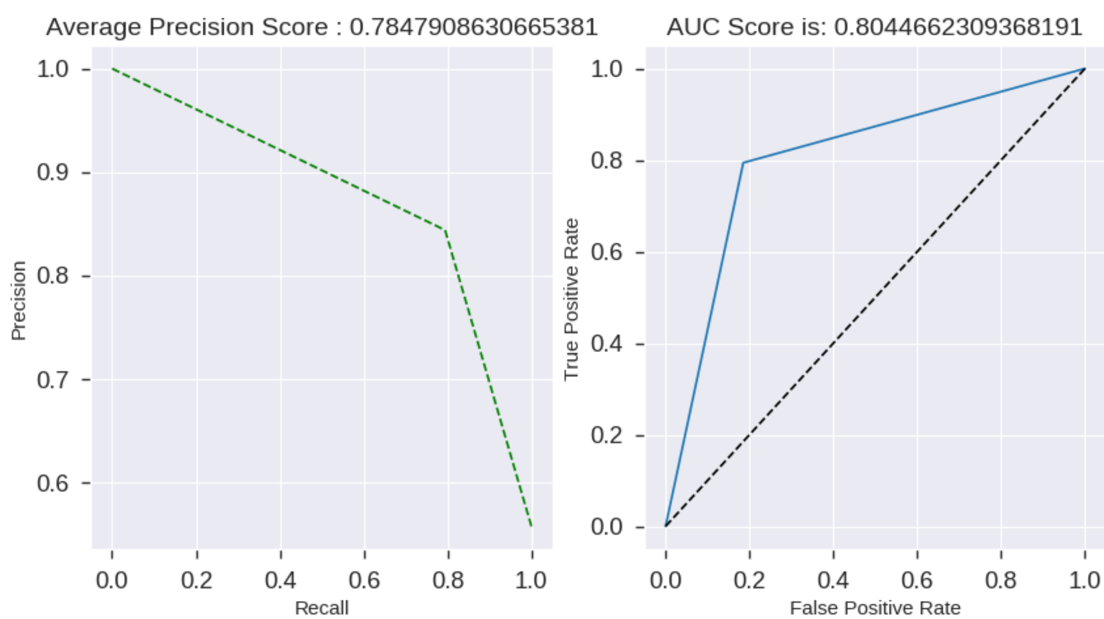
DecisionTreeClassifier

In [233]:
```
DecisionTreeClassifier = DecisionTreeClassifier()
DecisionTreeClassifier.fit(X_train,y_train)
```

Out[233]:
```
DecisionTreeClassifier(class_weight=None, criterion='gini', m
ax_depth=None,
                       max_features=None, max_leaf_nodes=Non
e,
                       min_impurity_decrease=0.0, min_impurit
y_split=None,
                       min_samples_leaf=1, min_samples_split=
2,
                       min_weight_fraction_leaf=0.0, presort=
False,
                       random_state=None, splitter='best')
```

In [234]:
```
plotting(y_test,DecisionTreeClassifier.predict_proba(X_test))
plt.figure()
```

Out[234]: <Figure size 800x550 with 0 Axes>



<Figure size 800x550 with 0 Axes>

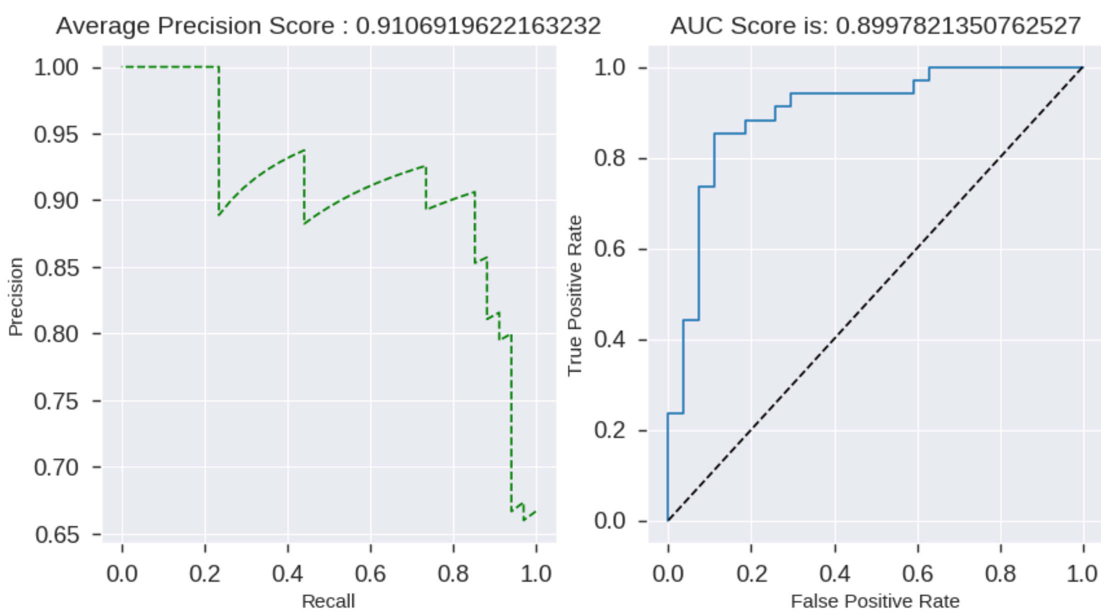
Linear SVC

In [235]:
```
LinearSVC = SVC(kernel='linear',probability=True)
LinearSVC.fit(X_train,y_train)
```

Out[235]:
```
SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0,
    decision_function_shape='ovr', degree=3, gamma='auto_depr
ecated',
    kernel='linear', max_iter=-1, probability=True, random_st
ate=None,
    shrinking=True, tol=0.001, verbose=False)
```

In [236]:
```
plotting(y_test,LinearSVC.predict_proba(X_test))
plt.figure()
```

Out[236]: <Figure size 800x550 with 0 Axes>



<Figure size 800x550 with 0 Axes>

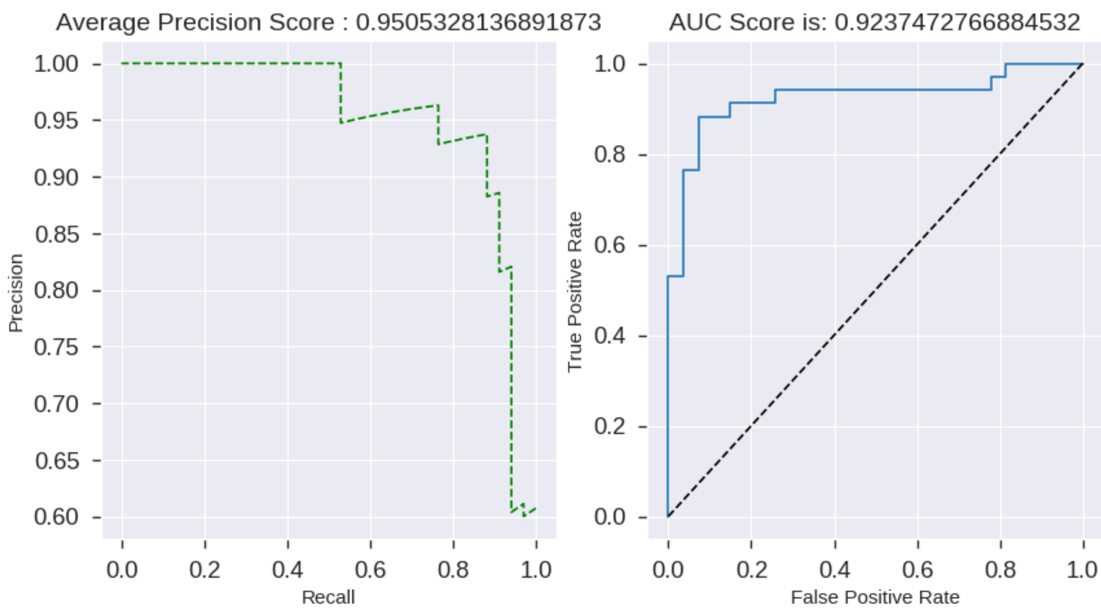
AdaBoostClassifier

In [237]:
```
AdaBoostClassifier = AdaBoostClassifier()
AdaBoostClassifier.fit(X_train,y_train)
```

Out[237]:
```
AdaBoostClassifier(algorithm='SAMME.R', base_estimator=None,
learning_rate=1.0,
                   n_estimators=50, random_state=None)
```

In [238]:
```
plotting(y_test,AdaBoostClassifier.predict_proba(X_test))
plt.figure()
```

Out[238]:
```
<Figure size 800x550 with 0 Axes>
```




```
<Figure size 800x550 with 0 Axes>
```

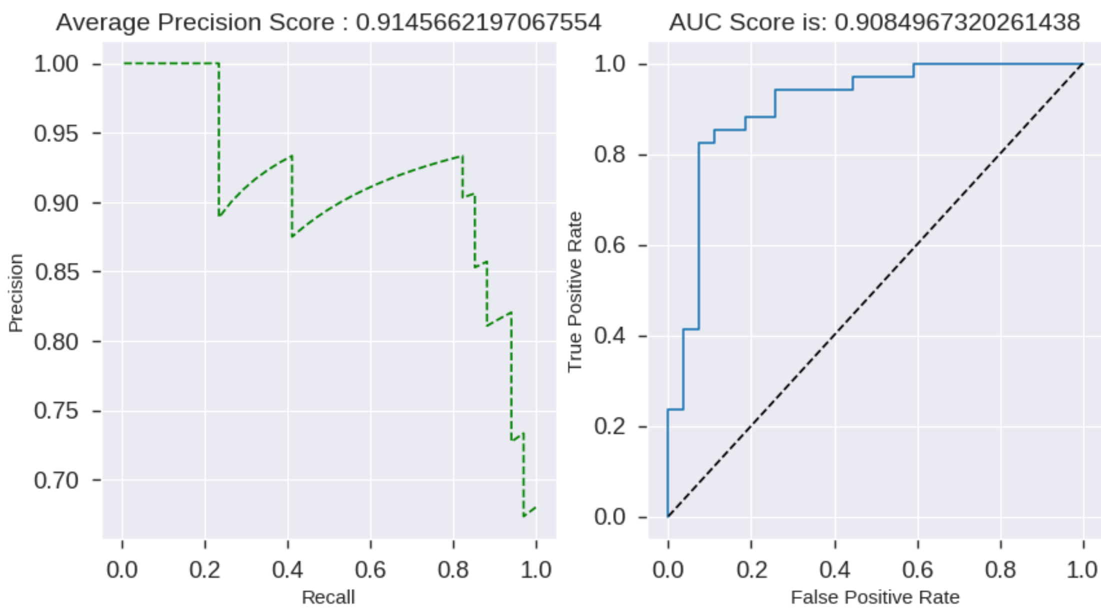
LogisticRegression

In [239]:
```
LogisticRegression = LogisticRegression(solver='liblinear')
LogisticRegression.fit(X_train,y_train)
```

Out[239]:
```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_
intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_it
er=100,
                   multi_class='warn', n_jobs=None, penalty
='l2',
                   random_state=None, solver='liblinear', tol
=0.0001, verbose=0,
                   warm_start=False)
```

In [240]:
```
plotting(y_test,LogisticRegression.predict_proba(X_test))
plt.figure()
```

Out[240]: <Figure size 800x550 with 0 Axes>



<Figure size 800x550 with 0 Axes>