In [1]:
```
import os
import numpy as np
import pandas as pd
from sklearn import model_selection
from sklearn.metrics import roc_curve
from sklearn.metrics import auc,confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.ensemble import AdaBoostClassifier
from sklearn.grid_search import GridSearchCV
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\cross_validation.py:41: De
precationWarning: This module was deprecated in version 0.18 in favor of the
model_selection module into which all the refactored classes and functions ar
e moved. Also note that the interface of the new CV iterators are different f
rom that of this module. This module will be removed in 0.20.
  "This module will be removed in 0.20.", DeprecationWarning)
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\grid_search.py:42: Depreca
tionWarning: This module was deprecated in version 0.18 in favor of the model
_selection module into which all the refactored classes and functions are mov
ed. This module will be removed in 0.20.
  DeprecationWarning)
```

In [2]:
```
os.chdir("D:/Great Lakes PGPDSE/Great Lakes/13 Ensemble Techniques/Mini Projec
t")
```

### Reading the dataset

In [4]:
```
hr = pd.read_csv("HR_Employee_Attrition_Dat.csv")
```

Converting Yes / No values in Attrition column to 1 / 0

In [5]:
```
cleanup_nums = {"Attrition":     {"Yes": 1, "No": 0}}
```

In [6]:
```
hr.replace(cleanup_nums, inplace=True)
```

In [25]:
```
hr.head()
```

Out[25]:

| | Age | Attrition | BusinessTravel | DailyRate | Department | DistanceFromHome | Educati |
|---|---|---|---|---|---|---|---|
| **0** | 41 | 1 | Travel_Rarely | 1102 | Sales | 1 | 2 |
| **1** | 49 | 0 | Travel_Frequently | 279 | Research & Development | 8 | 1 |
| **2** | 37 | 1 | Travel_Rarely | 1373 | Research & Development | 2 | 2 |
| **3** | 33 | 0 | Travel_Frequently | 1392 | Research & Development | 3 | 4 |
| **4** | 27 | 0 | Travel_Rarely | 591 | Research & Development | 2 | 1 |

5 rows × 35 columns

### Splitting to training and testing data

In [26]:
```
from sklearn.cross_validation import train_test_split
import random
```

In [27]:
```
np.random.seed(40)
train,test = train_test_split( hr, test_size = 0.3)
```

### Spliting target variable and independent variables

In [28]:
```
X1 =  train[['Age', 'BusinessTravel', 'DailyRate', 'Department',
       'DistanceFromHome', 'Education', 'EducationField',
       'EnvironmentSatisfaction', 'Gender', 'HourlyRate', 'JobInvolvement',
       'JobLevel', 'JobRole', 'JobSatisfaction', 'MaritalStatus',
       'MonthlyIncome', 'MonthlyRate', 'NumCompaniesWorked', 'OverTime',
       'PercentSalaryHike', 'PerformanceRating', 'RelationshipSatisfaction',
       'StockOptionLevel', 'TotalWorkingYears', 'TrainingTimesLastYear',
       'WorkLifeBalance', 'YearsAtCompany', 'YearsInCurrentRole',
       'YearsSinceLastPromotion', 'YearsWithCurrManager']]
X2 =  test[['Age', 'BusinessTravel', 'DailyRate', 'Department',
       'DistanceFromHome', 'Education', 'EducationField',
       'EnvironmentSatisfaction', 'Gender', 'HourlyRate', 'JobInvolvement',
       'JobLevel', 'JobRole', 'JobSatisfaction', 'MaritalStatus',
       'MonthlyIncome', 'MonthlyRate', 'NumCompaniesWorked', 'OverTime',
       'PercentSalaryHike', 'PerformanceRating', 'RelationshipSatisfaction',
       'StockOptionLevel', 'TotalWorkingYears', 'TrainingTimesLastYear',
       'WorkLifeBalance', 'YearsAtCompany', 'YearsInCurrentRole',
       'YearsSinceLastPromotion', 'YearsWithCurrManager']]
```

In [29]:
```
y_train = train["Attrition"]
y_test = test["Attrition"]
```

### Categorical Variable to Numerical Variables

In [30]:
```
X_train = pd.get_dummies(X1)
X_test = pd.get_dummies(X2)
X_train.columns
```

Out[30]:
```
Index(['Age', 'DailyRate', 'DistanceFromHome', 'Education',
       'EnvironmentSatisfaction', 'HourlyRate', 'JobInvolvement', 'JobLevel',
       'JobSatisfaction', 'MonthlyIncome', 'MonthlyRate', 'NumCompaniesWorke
d',
       'PercentSalaryHike', 'PerformanceRating', 'RelationshipSatisfaction',
       'StockOptionLevel', 'TotalWorkingYears', 'TrainingTimesLastYear',
       'WorkLifeBalance', 'YearsAtCompany', 'YearsInCurrentRole',
       'YearsSinceLastPromotion', 'YearsWithCurrManager',
       'BusinessTravel_Non-Travel', 'BusinessTravel_Travel_Frequently',
       'BusinessTravel_Travel_Rarely', 'Department_Human Resources',
       'Department_Research & Development', 'Department_Sales',
       'EducationField_Human Resources', 'EducationField_Life Sciences',
       'EducationField_Marketing', 'EducationField_Medical',
       'EducationField_Other', 'EducationField_Technical Degree',
       'Gender_Female', 'Gender_Male', 'JobRole_Healthcare Representative',
       'JobRole_Human Resources', 'JobRole_Laboratory Technician',
       'JobRole_Manager', 'JobRole_Manufacturing Director',
       'JobRole_Research Director', 'JobRole_Research Scientist',
       'JobRole_Sales Executive', 'JobRole_Sales Representative',
       'MaritalStatus_Divorced', 'MaritalStatus_Married',
       'MaritalStatus_Single', 'OverTime_No', 'OverTime_Yes'],
      dtype='object')
```

### Fitting AdaBoost model

In [31]:
```
model = AdaBoostClassifier(n_estimators=30)
model.fit(X_train, y_train)
```

Out[31]:
```
AdaBoostClassifier(algorithm='SAMME.R', base_estimator=None,
          learning_rate=1.0, n_estimators=30, random_state=None)
```

In [32]:
```
pred_y_train = model.predict(X_train)
pred_y_train
```

Out[32]:
```
array([0, 0, 0, ..., 0, 0, 1], dtype=int64)
```

### Classification accuracy of the model in train data

In [33]:
```
score = accuracy_score(y_train, pred_y_train)
score
```

Out[33]: 0.8974732750242954

### AUC of the model in train data

In [34]:
```
y_train_prob = model.predict_proba(X_train)
fpr, tpr, thresholds =  roc_curve(y_train, y_train_prob[:,1])
auc(fpr, tpr)
```

Out[34]: 0.9006297150478626

### Classification accuracy of the model in test data

In [35]:
```
pred_y_test = model.predict(X_test)
pred_y_test
```

Out[35]:
```
array([1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0,
       1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1,
       0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0,
       0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0,
       1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0,
       0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0,
       0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0,
       0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0,
       0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0,
       0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0,
       0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       1, 0], dtype=int64)
```

In [36]:
```
score_test = accuracy_score(y_test, pred_y_test)
score_test
```

Out[36]:
```
0.8968253968253969
```

### AUC of the model in train data

In [37]:
```
y_test_prob = model.predict_proba(X_test)
fpr, tpr, thresholds =  roc_curve(y_test, y_test_prob[:,1])
auc(fpr, tpr)
```

Out[37]: 0.8435021178282633

Here the AUC for test data differs alot compared to that of train data. That is the model is overfitting. So we need to do some parameter tuning

#### Cross validatin

In [38]:
```
scores = model_selection.cross_val_score(model, X_train, y_train, cv = 10, sco
ring='roc_auc')
scores.mean()
```

Out[38]: 0.8504723144558511

In [21]:
```
scores.std()
```

Out[21]: 0.04768426938729329

So by cross validation we get the correct AUC of the model, that is 85.04% is the correct AUC with standard deviation of 0.047. For test data it is almost same, but auc for training data is high. so the model is overfitted. Need to tune the model.

#### Checking important variables

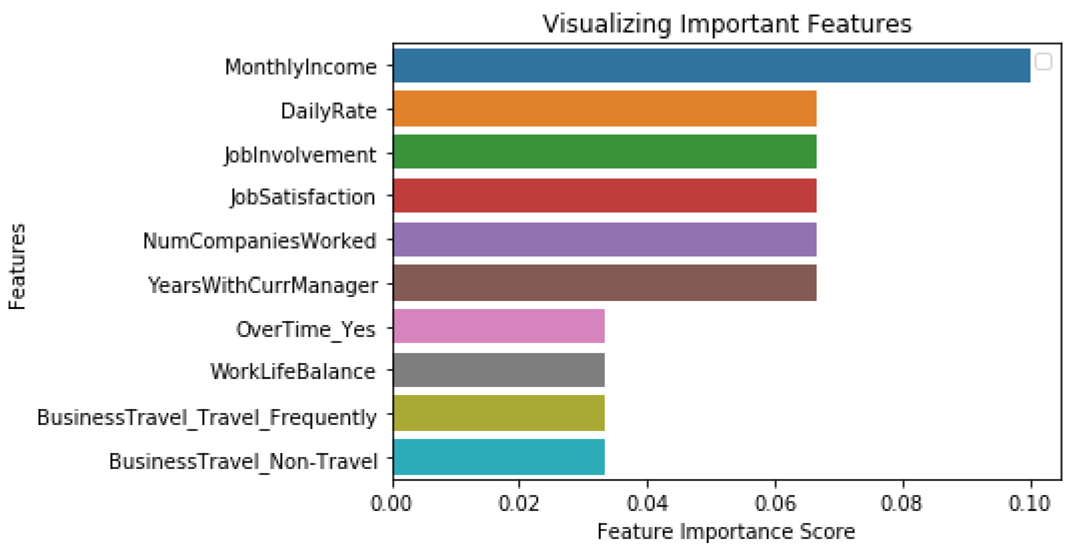
In [39]:
```
import pandas as pd
feature_imp = pd.Series(model.feature_importances_,index=X_train.columns).sort
_values(ascending=False)
feature_imp
```

```
Out[39]: MonthlyIncome                        0.100000
         DailyRate                            0.066667
         JobInvolvement                       0.066667
         JobSatisfaction                      0.066667
         NumCompaniesWorked                   0.066667
         YearsWithCurrManager                 0.066667
         OverTime_Yes                         0.033333
         WorkLifeBalance                      0.033333
         BusinessTravel_Travel_Frequently     0.033333
         BusinessTravel_Non-Travel            0.033333
         YearsSinceLastPromotion              0.033333
         YearsAtCompany                       0.033333
         StockOptionLevel                     0.033333
         TrainingTimesLastYear                0.033333
         TotalWorkingYears                    0.033333
         Department_Research & Development    0.033333
         RelationshipSatisfaction             0.033333
         EnvironmentSatisfaction              0.033333
         DistanceFromHome                     0.033333
         OverTime_No                          0.033333
         Age                                  0.033333
         EducationField_Technical Degree      0.033333
         JobRole_Laboratory Technician        0.033333
         EducationField_Human Resources       0.000000
         PerformanceRating                    0.000000
         MaritalStatus_Single                 0.000000
         MaritalStatus_Married                0.000000
         Education                            0.000000
         MaritalStatus_Divorced               0.000000
         HourlyRate                           0.000000
         JobRole_Sales Representative         0.000000
         JobLevel                             0.000000
         JobRole_Sales Executive              0.000000
         JobRole_Research Scientist           0.000000
         MonthlyRate                          0.000000
         JobRole_Research Director            0.000000
         PercentSalaryHike                    0.000000
         JobRole_Manufacturing Director       0.000000
         Department_Sales                     0.000000
         JobRole_Manager                      0.000000
         JobRole_Human Resources              0.000000
         JobRole_Healthcare Representative    0.000000
         Gender_Male                          0.000000
         YearsInCurrentRole                   0.000000
         Gender_Female                        0.000000
         EducationField_Other                 0.000000
         EducationField_Medical               0.000000
         EducationField_Marketing             0.000000
         Department_Human Resources           0.000000
         EducationField_Life Sciences         0.000000
         BusinessTravel_Travel_Rarely         0.000000
         dtype: float64
```

In [40]:
```
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
# Creating a bar plot
feature_imp=feature_imp[0:10,]

sns.barplot(x=feature_imp, y=feature_imp.index)
# Add labels to your graph
plt.xlabel('Feature Importance Score')
plt.ylabel('Features')
plt.title("Visualizing Important Features")
plt.legend()
plt.show()
```

```
No handles with labels found to put in legend.
```




Here most important variable is monthly income followed by daily rate, jobInvolvement etc

### Parameter Tuning

In [43]:
```
param_dist = {"n_estimators":np.arange(10,20),
               "learning_rate": [0.1,0.2,0.3,0.5,0.6,0.7,0.8,0.9,1],
             }
```

In [44]:
```
tree = AdaBoostClassifier(random_state=None)
tree_cv  = GridSearchCV(tree, cv = 10,
                     param_grid=param_dist,
                     n_jobs = 3)
tree_cv.fit(X_train, y_train)
```

Out[44]:
```
GridSearchCV(cv=10, error_score='raise',
       estimator=AdaBoostClassifier(algorithm='SAMME.R', base_estimator=None,
          learning_rate=1.0, n_estimators=50, random_state=None),
       fit_params={}, iid=True, n_jobs=3,
       param_grid={'n_estimators': array([10, 11, 12, 13, 14, 15, 16, 17, 18,
19]), 'learning_rate': [0.1, 0.2, 0.3, 0.5, 0.6, 0.7, 0.8, 0.9, 1]},
       pre_dispatch='2*n_jobs', refit=True, scoring=None, verbose=0)
```

### Building the model using best combination of parameters

In [45]:
```
print("Tuned Decision Tree parameter : {}".format(tree_cv.best_params_))
classifier = tree_cv.best_estimator_
classifier.fit(X_train,y_train)
```

```
Tuned Decision Tree parameter : {'learning_rate': 0.9, 'n_estimators': 15}
```

Out[45]:
```
AdaBoostClassifier(algorithm='SAMME.R', base_estimator=None,
          learning_rate=0.9, n_estimators=15, random_state=None)
```

### Checking AUC of the tuned model

For train data

In [46]:
```
y_train_prob = classifier.predict_proba(X_train)
fpr, tpr, thresholds = roc_curve(y_train, y_train_prob[:,1])
auc_d = auc(fpr, tpr)
auc_d
```

Out[46]:
```
0.8702762688080915
```

For test data

In [47]:
```
y_test_prob = classifier.predict_proba(X_test)
fpr, tpr, thresholds = roc_curve(y_test, y_test_prob[:,1])
auc_h = auc(fpr, tpr)
auc_h
```

Out[47]:
```
0.8084809395456295
```

### Scoring and Rank ordering

In [48]:
```
Prediction = classifier.predict_proba(X_train)
train["prob_score"] = Prediction[:,1]
```

```
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:2: SettingWi
thCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/st
able/indexing.html#indexing-view-versus-copy
```

decile code

In [49]:
```
def deciles(x):
    decile = pd.Series(index=[0,1,2,3,4,5,6,7,8,9])
    for i in np.arange(0.1,1.1,0.1):
        decile[int(i*10)]=x.quantile(i)
    def z(x):
        if x<decile[1]: return(1)
        elif x<decile[2]: return(2)
        elif x<decile[3]: return(3)
        elif x<decile[4]: return(4)
        elif x<decile[5]: return(5)
        elif x<decile[6]: return(6)
        elif x<decile[7]: return(7)
        elif x<decile[8]: return(8)
        elif x<decile[9]: return(9)
        elif x<=decile[10]: return(10)
        else:return(np.NaN)
    s=x.map(z)
    return(s)
```

In [51]:
```
def Rank_Ordering(X,y,Target):
    X['decile']=deciles(X[y])
    Rank=X.groupby('decile').apply(lambda x: pd.Series([
        np.min(x[y]),
        np.max(x[y]),
        np.mean(x[y]),
        np.size(x[y]),
        np.sum(x[Target]),
        np.size(x[Target][x[Target]==0]),
        ],
        index=(["min_resp","max_resp","avg_resp",
                "cnt","cnt_resp","cnt_non_resp"])
        )).reset_index()
    Rank = Rank.sort_values(by='decile',ascending=False)
    Rank["rrate"] = Rank["cnt_resp"]*100/Rank["cnt"]
    Rank["cum_resp"] = np.cumsum(Rank["cnt_resp"])
    Rank["cum_non_resp"] = np.cumsum(Rank["cnt_non_resp"])
    Rank["cum_resp_pct"] = Rank["cum_resp"]/np.sum(Rank["cnt_resp"])
    Rank["cum_non_resp_pct"]=Rank["cum_non_resp"]/np.sum(Rank["cnt_non_resp"])
    Rank["KS"] = Rank["cum_resp_pct"] - Rank["cum_non_resp_pct"]
    Rank
    return(Rank)
```

### Rank ordering of train data

In [52]:
```
Rank = Rank_Ordering(train,"prob_score","Attrition")
Rank
```

```
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:2: SettingWi
thCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/st
able/indexing.html#indexing-view-versus-copy
```

Out[52]:

| | decile | min_resp | max_resp | avg_resp | cnt | cnt_resp | cnt_non_resp | rrate | cum |
|---|---|---|---|---|---|---|---|---|---|
| **9** | 10 | 0.492985 | 0.552292 | 0.508124 | 207.0 | 149.0 | 58.0 | 71.980676 | 149. |
| **8** | 9 | 0.478632 | 0.492753 | 0.485165 | 205.0 | 73.0 | 132.0 | 35.609756 | 222. |
| **7** | 8 | 0.470529 | 0.478534 | 0.474212 | 206.0 | 50.0 | 156.0 | 24.271845 | 272. |
| **6** | 7 | 0.462778 | 0.470368 | 0.466580 | 209.0 | 16.0 | 193.0 | 7.655502 | 288. |
| **5** | 6 | 0.456808 | 0.462664 | 0.460072 | 203.0 | 12.0 | 191.0 | 5.911330 | 300. |
| **4** | 5 | 0.450552 | 0.456662 | 0.453513 | 213.0 | 11.0 | 202.0 | 5.164319 | 311. |
| **3** | 4 | 0.443132 | 0.450531 | 0.447345 | 200.0 | 11.0 | 189.0 | 5.500000 | 322. |
| **2** | 3 | 0.435527 | 0.443102 | 0.440030 | 200.0 | 5.0 | 195.0 | 2.500000 | 327. |
| **1** | 2 | 0.424101 | 0.435035 | 0.430296 | 212.0 | 5.0 | 207.0 | 2.358491 | 332. |
| **0** | 1 | 0.389532 | 0.423488 | 0.413146 | 203.0 | 2.0 | 201.0 | 0.985222 | 334. |

Here Best KS=0.6136 and response rate in 10th decile = 72.68%

**Rank ordering for test data**

In [53]:
```
Prediction_h = classifier.predict_proba(X_test)
test["prob_score"] = Prediction_h[:,1]

Rank_h = Rank_Ordering(test,"prob_score","Attrition")
Rank_h
```

```
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexing-view-versus-copy
```

Out[53]:

| | decile | min_resp | max_resp | avg_resp | cnt | cnt_resp | cnt_non_resp | rrate | cum_ |
|---|---|---|---|---|---|---|---|---|---|
| **9** | 10 | 0.491897 | 0.552292 | 0.508638 | 89.0 | 57.0 | 32.0 | 64.044944 | 57.0 |
| **8** | 9 | 0.479137 | 0.491757 | 0.484948 | 88.0 | 24.0 | 64.0 | 27.272727 | 81.0 |
| **7** | 8 | 0.471644 | 0.479030 | 0.474969 | 88.0 | 21.0 | 67.0 | 23.863636 | 102.0 |
| **6** | 7 | 0.463812 | 0.471616 | 0.467919 | 90.0 | 8.0 | 82.0 | 8.888889 | 110.0 |
| **5** | 6 | 0.458810 | 0.463751 | 0.461099 | 86.0 | 6.0 | 80.0 | 6.976744 | 116.0 |
| **4** | 5 | 0.451048 | 0.458749 | 0.454577 | 88.0 | 5.0 | 83.0 | 5.681818 | 121.0 |
| **3** | 4 | 0.443638 | 0.451027 | 0.447738 | 88.0 | 7.0 | 81.0 | 7.954545 | 128.0 |
| **2** | 3 | 0.437537 | 0.443423 | 0.440701 | 90.0 | 6.0 | 84.0 | 6.666667 | 134.0 |
| **1** | 2 | 0.428106 | 0.437471 | 0.431890 | 87.0 | 4.0 | 83.0 | 4.597701 | 138.0 |
| **0** | 1 | 0.389532 | 0.427822 | 0.416982 | 88.0 | 2.0 | 86.0 | 2.272727 | 140.0 |

***Here on testing the model on test data we are getting KS value of 0.5088 and response rate of 64.04% in the top decile. This looks very good but compared to the training data this is less. The model looks bit over fitted.***

Here the employees who all comes in the 10th decile are most likely to leave the company. Let's assume that training of new employee costs 1000 dollar and since we know which employee is likely to leave next month, and propose him/her a bonus program worth 500 to keep him for next 6 months, we are 500 dollar to keep him for next 6 months,we are 500 dollar on plus and keep experienced, well-trained employee under the hood, with higher morale. So better to take care of these employees and company should be prepared to find substitution for those.