Chapter 9: Random Forest Classifier

> (c) 2019 Galit Shmueli, Peter C. Bruce, Peter Gedeck
>
> Code included in
>
> *Data Mining for Business Analytics: Concepts, Techniques, and Applications in Python* (First Edition) Galit Shmueli, Peter C. Bruce, Peter Gedeck, and Nitin R. Patel. 2019.

Import required packages

In [28]:

```
%matplotlib inline

from pathlib import Path

import pandas as pd
from sklearn import preprocessing
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn import metrics
from sklearn.metrics import accuracy_score
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
import matplotlib.pylab as plt
from dmba import classificationSummary, gainsChart, liftChart
```

This is the same dataset as used in Homework #3.

In [29]:

```
hr_df = pd.read_csv('/Users/aminazimi/Downloads/WA_Fn-UseC_-HR-Employee-Attrition.csv')
hr_df.head()
```

Out[29]:

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCount	EmployeeN
0	41	Yes	Travel_Rarely	1102	Sales	1	2	Life Sciences	1	
1	49	No	Travel_Frequently	279	Research & Development	8	1	Life Sciences	1	

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCount	EmployeeN
2	37	Yes	Travel_Rarely	1373	Research & Development	2	2	Other	1	
3	33	No	Travel_Frequently	1392	Research & Development	3	4	Life Sciences	1	
4	27	No	Travel_Rarely	591	Research & Development	2	1	Medical	1	

5 rows × 35 columns

In [30]:

```
hr_df.shape
```

Out[30]:

```
(1470, 35)
```

In [31]:

```
hr_df.dtypes
```

Out[31]:

```
Age                          int64
Attrition                   object
BusinessTravel              object
DailyRate                    int64
Department                  object
DistanceFromHome             int64
Education                    int64
EducationField              object
EmployeeCount                int64
EmployeeNumber               int64
EnvironmentSatisfaction      int64
Gender                      object
HourlyRate                   int64
JobInvolvement               int64
JobLevel                     int64
JobRole                     object
JobSatisfaction              int64
MaritalStatus               object
MonthlyIncome                int64
MonthlyRate                  int64
NumCompaniesWorked           int64
Over18                      object
OverTime                    object
```

```
PercentSalaryHike            int64
PerformanceRating            int64
RelationshipSatisfaction     int64
StandardHours                int64
StockOptionLevel             int64
TotalWorkingYears            int64
TrainingTimesLastYear        int64
WorkLifeBalance              int64
YearsAtCompany               int64
YearsInCurrentRole           int64
YearsSinceLastPromotion      int64
YearsWithCurrManager         int64
dtype: object
```

In [32]:

```
# Create a y response variable and an X collection of predictors
y = hr_df['Attrition']
X = hr_df.drop(columns=['Attrition'])
print(len(X.columns))
```

```
34
```

In [33]:

```
# Dummy code in preparation of logistic regression
X = pd.get_dummies(X, prefix_sep='_', drop_first=True)
print(len(X.columns))
```

```
47
```

In [34]:

```
# Convert the text of Gone to a binary numeric variable (0/1)
y = y.astype('category').cat.codes

# Check for a class imbalance
y.value_counts()
```

Out[34]:

```
0    1233
1     237
dtype: int64
```

Print out a list of attributes by name and sequence number to prepare for ADASYN

In [35]:

```
print(pd.DataFrame(X.columns))
```

```
                                  0
0                               Age
```

```
1                        DailyRate
2                 DistanceFromHome
3                        Education
4                    EmployeeCount
5                   EmployeeNumber
6          EnvironmentSatisfaction
7                       HourlyRate
8                   JobInvolvement
9                         JobLevel
10                 JobSatisfaction
11                   MonthlyIncome
12                     MonthlyRate
13              NumCompaniesWorked
14               PercentSalaryHike
15               PerformanceRating
16        RelationshipSatisfaction
17                   StandardHours
18                StockOptionLevel
19               TotalWorkingYears
20           TrainingTimesLastYear
21                 WorkLifeBalance
22                  YearsAtCompany
23              YearsInCurrentRole
24         YearsSinceLastPromotion
25            YearsWithCurrManager
26  BusinessTravel_Travel_Frequently
27      BusinessTravel_Travel_Rarely
28 Department_Research & Development
29                Department_Sales
30     EducationField_Life Sciences
31        EducationField_Marketing
32          EducationField_Medical
33            EducationField_Other
34  EducationField_Technical Degree
35                     Gender_Male
36         JobRole_Human Resources
37    JobRole_Laboratory Technician
38                 JobRole_Manager
39   JobRole_Manufacturing Director
40       JobRole_Research Director
41      JobRole_Research Scientist
42         JobRole_Sales Executive
43    JobRole_Sales Representative
44           MaritalStatus_Married
```

```
45               MaritalStatus_Single
46                      OverTime_Yes
```

Train/test split with stratification of the response variable

In [36]:

```
# Split the data into training and test sets (holdout approach)
train_X, test_X, train_y, test_y = train_test_split(X, y, test_size=0.2, stratify=y, random_state=2019)
```

Fix the class imbalance issue on the training data.

In [37]:

```
from imblearn.over_sampling import ADASYN

ada = ADASYN()
train_X, train_y = ada.fit_sample(train_X, train_y.ravel())
```

Logistic Regression Baseline

In [38]:

```
# Build a logistic regression model as a baseline
logit_reg = LogisticRegression(penalty="l2", C=1e42, solver='liblinear')
logit_reg.fit(train_X, train_y)
```

Out[38]:

```
LogisticRegression(C=1e+42, solver='liblinear')
```

In [39]:

```
# we are only interested in classification accuracy
classificationSummary(train_y, logit_reg.predict(train_X))
classificationSummary(test_y, logit_reg.predict(test_X))
```

```
Confusion Matrix (Accuracy 0.9142)

       Prediction
Actual   0   1
     0 930  56
     1 110 839
Confusion Matrix (Accuracy 0.8367)

       Prediction
Actual   0   1
     0 226  21
     1  27  20
```

In [40]:
```
classes = logit_reg.predict(test_X)

print(metrics.classification_report(test_y, classes))
```

```
              precision    recall  f1-score   support

           0       0.89      0.91      0.90       247
           1       0.49      0.43      0.45        47

    accuracy                           0.84       294
   macro avg       0.69      0.67      0.68       294
weighted avg       0.83      0.84      0.83       294
```

Use RandomForest

Start by recreating the X and y objects to change one-hot encoding parameter

In [41]:
```
# Create a y response variable and an X collection of predictors
y = hr_df['Attrition']
X = hr_df.drop(columns=['Attrition'])
```

In [42]:
```
# Dummy code in preparation of RandomForest model
X = pd.get_dummies(X, prefix_sep='_', drop_first=False)
print(len(X.columns))
```

```
55
```

In [43]:
```
# Convert the text of Gone to a binary numeric variable (0/1)
y = y.astype('category').cat.codes
y.value_counts()
```

Out[43]:
```
0    1233
1     237
dtype: int64
```

In [44]:
```
# Split the data into training and test sets (holdout approach)
train_X, test_X, train_y, test_y = train_test_split(X, y, test_size=0.2, stratify=y, random_state=1)
```

In [45]:
```
from imblearn.over_sampling import ADASYN
```

```
ada = ADASYN()
train_X, train_y = ada.fit_sample(train_X, train_y)
```

In [46]:

```
# user grid search to find optimized tree
param_grid = {
    'n_estimators': [550, 600, 650],
    'criterion' : ['entropy', 'gini'],
    'oob_score': ['True'],
    'min_impurity_decrease': [0.0001, .0005, 0.001],
    'min_samples_split': [2, 4, 6, 8, 10, 12, 14],
}
```

In [47]:

```
gridSearch = GridSearchCV(RandomForestClassifier(), param_grid, cv=2, n_jobs=-1)

gridSearch.fit(train_X, train_y)

print('Initial parameters: ', gridSearch.best_params_)

rfTree = gridSearch.best_estimator_
```

```
Initial parameters:  {'criterion': 'entropy', 'min_impurity_decrease': 0.0005, 'min_samples_split': 2, 'n_estim
ators': 650, 'oob_score': 'True'}
```

Based on these chosen hyperparameters, reprogram the GridSearchCV for a finer search pattern and run again

In [48]:

```
print(rfTree.oob_score_)
```

```
0.9363683393688567
```

In [49]:

```
# we are only interested in classification accuracy
classificationSummary(train_y, rfTree.predict(train_X))

classificationSummary(test_y, rfTree.predict(test_X))
```

```
Confusion Matrix (Accuracy 1.0000)

       Prediction
Actual   0   1
     0 986   0
     1   0 947
```

```
Confusion Matrix (Accuracy 0.8639)

       Prediction
Actual    0    1
     0 236   11
     1  29   18
```

In [50]:

```
classes = rfTree.predict(test_X)

print(metrics.classification_report(test_y, classes))
```

```
              precision    recall  f1-score   support

           0       0.89      0.96      0.92       247
           1       0.62      0.38      0.47        47

    accuracy                           0.86       294
   macro avg       0.76      0.67      0.70       294
weighted avg       0.85      0.86      0.85       294
```

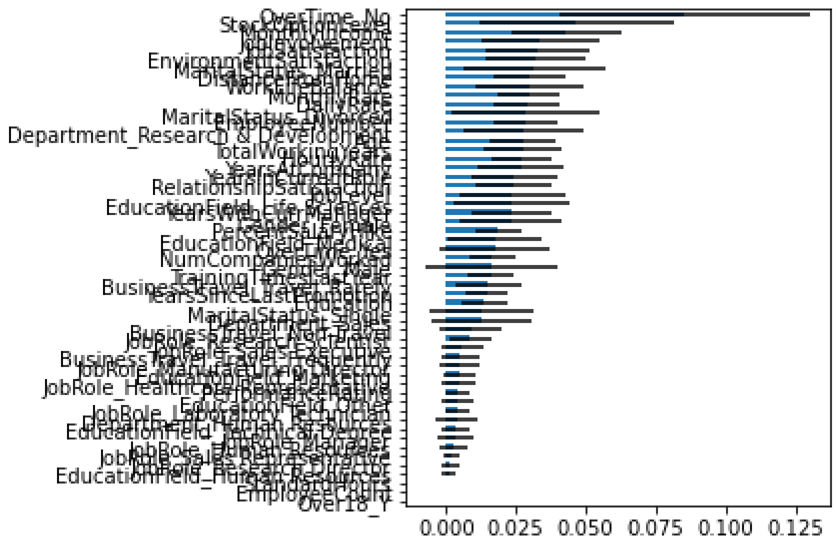
In [51]:

```
%matplotlib inline
import numpy as np

train_X = pd.DataFrame(train_X)

importances = rfTree.feature_importances_
std = np.std([tree.feature_importances_ for tree in rfTree.estimators_], axis=0)

df = pd.DataFrame({'feature': train_X.columns, 'importance': importances, 'std': std})
df = df.sort_values('importance')
print(df)

ax = df.plot(kind='barh', xerr='std', x='feature', legend=False)
ax.set_ylabel('')

plt.tight_layout()
plt.show()
```

```
                             feature  importance       std
52                          Over18_Y    0.000000  0.000000
4                      EmployeeCount    0.000000  0.000000
17                     StandardHours    0.000000  0.000000
32      EducationField_Human Resources    0.001050  0.002481
```

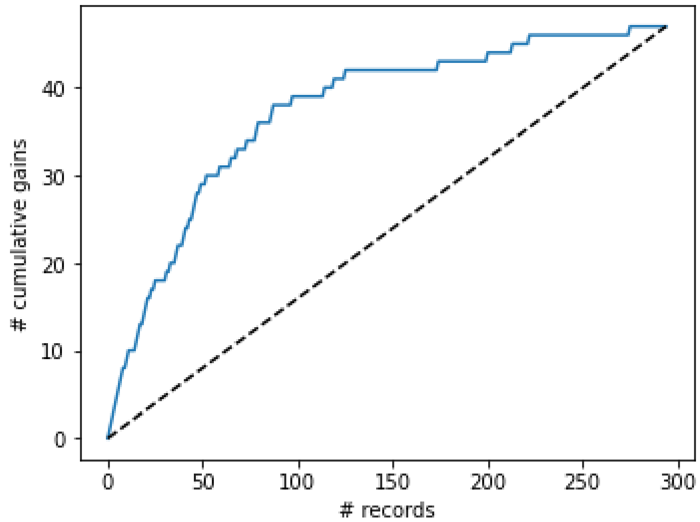
45	JobRole_Research Director	0.001477	0.003329
48	JobRole_Sales Representative	0.001953	0.003030
41	JobRole_Human Resources	0.002479	0.005130
43	JobRole_Manager	0.003424	0.006331
37	EducationField_Technical Degree	0.003461	0.004841
29	Department_Human Resources	0.003739	0.007285
42	JobRole_Laboratory Technician	0.003799	0.004254
36	EducationField_Other	0.003828	0.005746
15	PerformanceRating	0.004056	0.004391
40	JobRole_Healthcare Representative	0.004466	0.006217
34	EducationField_Marketing	0.004548	0.005844
44	JobRole_Manufacturing Director	0.004581	0.007037
27	BusinessTravel_Travel_Frequently	0.005003	0.006703
47	JobRole_Sales Executive	0.005813	0.007366
46	JobRole_Research Scientist	0.008602	0.007331
26	BusinessTravel_Non-Travel	0.008962	0.011186
31	Department_Sales	0.012481	0.017998
51	MaritalStatus_Single	0.012788	0.018689
3	Education	0.013494	0.008160
24	YearsSinceLastPromotion	0.014650	0.007634
28	BusinessTravel_Travel_Rarely	0.015051	0.011942
20	TrainingTimesLastYear	0.015918	0.008534
39	Gender_Male	0.016353	0.023789
13	NumCompaniesWorked	0.016583	0.008010
54	OverTime_Yes	0.017501	0.019800
35	EducationField_Medical	0.017555	0.016783
14	PercentSalaryHike	0.018481	0.008281
38	Gender_Female	0.023157	0.018143
25	YearsWithCurrManager	0.023293	0.014175
33	EducationField_Life Sciences	0.023576	0.020836
9	JobLevel	0.023641	0.018790
16	RelationshipSatisfaction	0.023903	0.013635
23	YearsInCurrentRole	0.024322	0.015407
22	YearsAtCompany	0.026923	0.015451
7	HourlyRate	0.027056	0.010976
19	TotalWorkingYears	0.027402	0.013848
0	Age	0.027570	0.011730
30	Department_Research & Development	0.027627	0.021724
5	EmployeeNumber	0.028345	0.011215
49	MaritalStatus_Divorced	0.028383	0.026416
1	DailyRate	0.029055	0.011895
12	MonthlyRate	0.029524	0.011369
21	WorkLifeBalance	0.029726	0.019256
2	DistanceFromHome	0.029826	0.012640
50	MaritalStatus_Married	0.031528	0.025325

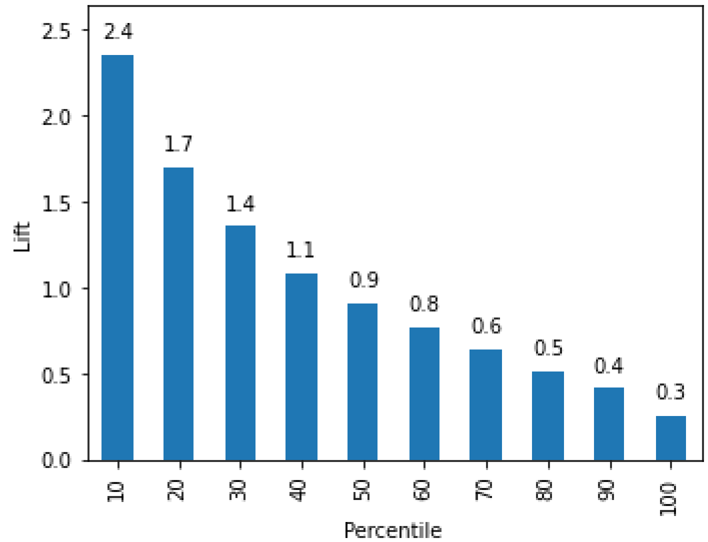
```
6               EnvironmentSatisfaction    0.031860  0.017799
10                      JobSatisfaction    0.032577  0.018582
8                        JobInvolvement    0.033598  0.021211
11                        MonthlyIncome    0.043121  0.019728
18                     StockOptionLevel    0.046621  0.034801
53                          OverTime_No    0.085268  0.044898
```



In [52]:

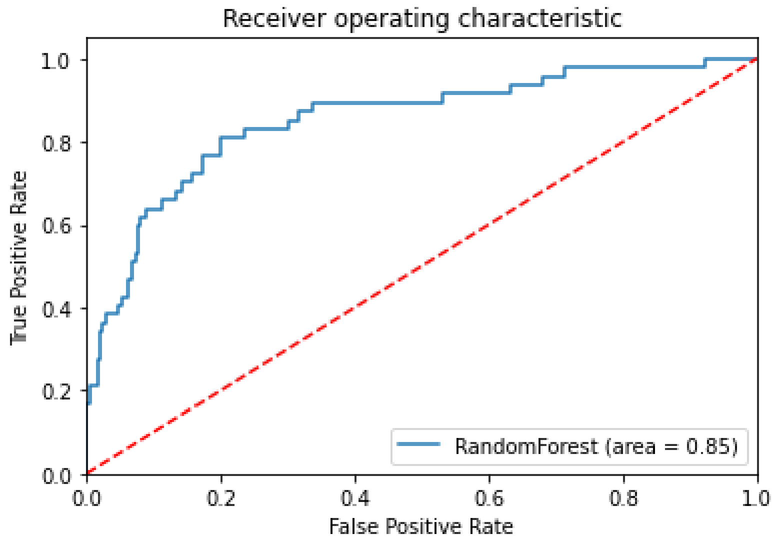
```
rfTree_pred = rfTree.predict(test_X)
rfTree_proba = rfTree.predict_proba(test_X)
rfTree_result = pd.DataFrame({'actual': test_y,
                              'p(0)': [p[0] for p in rfTree_proba],
                              'p(1)': [p[1] for p in rfTree_proba],
                              'predicted': rfTree_pred })

df = rfTree_result.sort_values(by=['p(1)'], ascending=False)
fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(10, 4))

gainsChart(df.actual, ax=axes[0])
liftChart(df['p(1)'], title=False, ax=axes[1])

plt.tight_layout()
plt.show()
```





In [53]:

```
rfTree_pred = rfTree.predict(test_X)
rfTree_proba = rfTree.predict_proba(test_X)

preds = rfTree_proba[:,1]
fpr, tpr, threshold = metrics.roc_curve(test_y, preds)
roc_auc = metrics.auc(fpr, tpr)

plt.figure()
plt.plot(fpr, tpr, label='RandomForest (area = %0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic')
plt.legend(loc="lower right")
plt.savefig('RFTree_ROC')
plt.show()
```


Receiver operating characteristic
True Positive Rate
False Positive Rate
RandomForest (area = 0.85)
0.0
0.2
0.4
0.6
0.8
1.0

In [ ]: