

Name : Arul Kumar ARK

Roll No. : 225229103

Lab : 9

Employee Hopping Prediction using Random Forests

Step : 1

```
In [1]: import pandas as pd
```

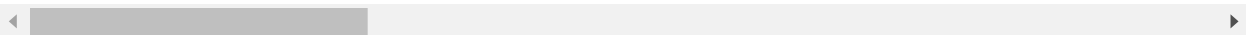
```
In [2]: data = pd.read_csv("Employee_hopping.csv")
```

```
In [3]: data.head(10)
```

Out[3]:

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationalLevel
0	41	Yes	Travel_Rarely	1102	Sales	1	2	Life Science
1	49	No	Travel_Frequently	279	Research & Development	8	1	Life Science
2	37	Yes	Travel_Rarely	1373	Research & Development	2	2	
3	33	No	Travel_Frequently	1392	Research & Development	3	4	Life Science
4	27	No	Travel_Rarely	591	Research & Development	2	1	
5	32	No	Travel_Frequently	1005	Research & Development	2	2	Life Science
6	59	No	Travel_Rarely	1324	Research & Development	3	3	
7	30	No	Travel_Rarely	1358	Research & Development	24	1	Life Science
8	38	No	Travel_Frequently	216	Research & Development	23	3	Life Science
9	36	No	Travel_Rarely	1299	Research & Development	27	3	

10 rows × 9 columns



```
In [4]: data.shape
```

```
Out[4]: (1470, 35)
```

```
In [5]: data.columns
```

```
Out[5]: Index(['Age', 'Attrition', 'BusinessTravel', 'DailyRate', 'Department',  
              'DistanceFromHome', 'Education', 'EducationField', 'EmployeeCount',  
              'EmployeeNumber', 'EnvironmentSatisfaction', 'Gender', 'HourlyRate',  
              'JobInvolvement', 'JobLevel', 'JobRole', 'JobSatisfaction',  
              'MaritalStatus', 'MonthlyIncome', 'MonthlyRate', 'NumCompaniesWorked',  
              'Over18', 'OverTime', 'PercentSalaryHike', 'PerformanceRating',  
              'RelationshipSatisfaction', 'StandardHours', 'StockOptionLevel',  
              'TotalWorkingYears', 'TrainingTimesLastYear', 'WorkLifeBalance',  
              'YearsAtCompany', 'YearsInCurrentRole', 'YearsSinceLastPromotion',  
              'YearsWithCurrManager'],  
             dtype='object')
```

```
In [6]: data.dtypes
```

```
Out[6]: 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 [7]: data.info

1460	29	No	Travel_Rarely	468	Research & Development
1461	50	Yes	Travel_Rarely	410	Sales
1462	39	No	Travel_Rarely	722	Sales
1463	31	No	Non-Travel	325	Research & Development
1464	26	No	Travel_Rarely	1167	Sales
1465	36	No	Travel_Frequently	884	Research & Development
1466	39	No	Travel_Rarely	613	Research & Development
1467	27	No	Travel_Rarely	155	Research & Development
1468	49	No	Travel_Frequently	1023	Sales
1469	34	No	Travel_Rarely	628	Research & Development

	DistanceFromHome	Education	EducationField	EmployeeCount	\
0	1	2	Life Sciences	1	
1	8	1	Life Sciences	1	
2	2	2	Other	1	
3	3	4	Life Sciences	1	
4	2	1	Medical	1	
5	2	2	Life Sciences	1	
6	3	3	Medical	1	
7	24	1	Life Sciences	1	

```
In [8]: data['WorkLifeBalance'].value_counts
```

```
Out[8]: <bound method IndexOpsMixin.value_counts of 0      1
1         3
2         3
3         3
4         3
5         2
6         2
7         3
8         3
9         2
10        3
11        3
12        2
13        3
14        3
15        3
16        2
17        2
18        3
19        3
20        2
21        3
22        3
23        3
24        3
25        2
26        3
27        3
28        3
29        2
..
1440       3
1441       2
1442       4
1443       2
1444       1
1445       3
1446       3
1447       2
1448       3
1449       3
1450       3
1451       3
1452       3
1453       2
1454       3
1455       3
1456       4
1457       3
1458       3
1459       3
1460       1
1461       3
1462       2
1463       3
```

```
1464    3
1465    3
1466    3
1467    3
1468    2
1469    4
```

Name: WorkLifeBalance, Length: 1470, dtype: int64>

Step : 2

```
In [9]: X = data.drop(['Attrition'],axis=1)
```

```
In [10]: y = data['Attrition']
```

```
In [11]: y = y.apply(lambda x:1 if x == 'Yes' else 0)
```

```
In [12]: X.shape
```

```
Out[12]: (1470, 34)
```

```
In [13]: y.shape
```

```
Out[13]: (1470,)
```

Step : 3

```
In [14]: pd.get_dummies(data, columns = ['BusinessTravel','Department','Gender','EducationField'])
```

```
Out[14]:
```

	Age	Attrition	DailyRate	DistanceFromHome	Education	EmployeeCount	EmployeeNumber
1460	29	No	468	28	4	1	2054
1461	50	Yes	410	28	3	1	2055
1462	39	No	722	24	1	1	2056
1463	31	No	325	5	3	1	2057
1464	26	No	1167	5	3	1	2060
1465	36	No	884	23	2	1	2061
1466	39	No	613	6	1	1	2062
1467	27	No	155	4	3	1	2064
1468	49	No	1023	2	3	1	2065
1469	34	No	628	8	3	1	2068

10 rows × 56 columns

Step : 4

```
In [15]: X = data.drop(['Attrition'],axis=1)
```

```
In [16]: X.shape
```

```
Out[16]: (1470, 55)
```

```
In [17]: y=data['Attrition']
```

```
In [18]: y = y.apply(lambda x:1 if x == 'Yes' else 0)
```

```
In [19]: y.shape
```

```
Out[19]: (1470,)
```

Step : 5

```
In [20]: from sklearn.model_selection import train_test_split
```

```
In [21]: X_train, X_test,y_train, y_test = train_test_split(X,y,random_state=42,test_size=
```

```
In [22]: from sklearn.ensemble import RandomForestClassifier  
RFC = RandomForestClassifier(n_estimators=100, max_features=0.3)
```

```
In [23]: RFC.fit(X_train,y_train)
```

```
Out[23]: RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',  
                                max_depth=None, max_features=0.3, max_leaf_nodes=None,  
                                min_impurity_decrease=0.0, min_impurity_split=None,  
                                min_samples_leaf=1, min_samples_split=2,  
                                min_weight_fraction_leaf=0.0, n_estimators=100, n_jobs=1,  
                                oob_score=False, random_state=None, verbose=0,  
                                warm_start=False)
```



```
In [28]: print(RFC.feature_importances_)
```

```
[0.0622317  0.04799897 0.0392698  0.0148707  0.          0.0460996  
0.02389722 0.03670234 0.01809801 0.02075047 0.02381954 0.08537203  
0.04164458 0.03690209 0.02941133 0.0029484  0.01773311 0.  
0.02536605 0.05112048 0.0240187  0.01776033 0.03956104 0.02509407  
0.02245903 0.02704615 0.00281675 0.01158259 0.00418142 0.0012341  
0.00657366 0.00894114 0.00649062 0.00602609 0.00263417 0.00521458  
0.00669461 0.00493512 0.00308905 0.00753628 0.0037791  0.00796889  
0.01847273 0.00172468 0.00206743 0.00667129 0.00097804 0.002338  
0.00072113 0.00539647 0.00687337 0.00716096 0.          0.04148436  
0.0362376 ]
```

```
In [36]: feature_name = pd.DataFrame(RFC.feature_importances_, index=X_train.columns, column_names=feature_name)
```

Out[36]:

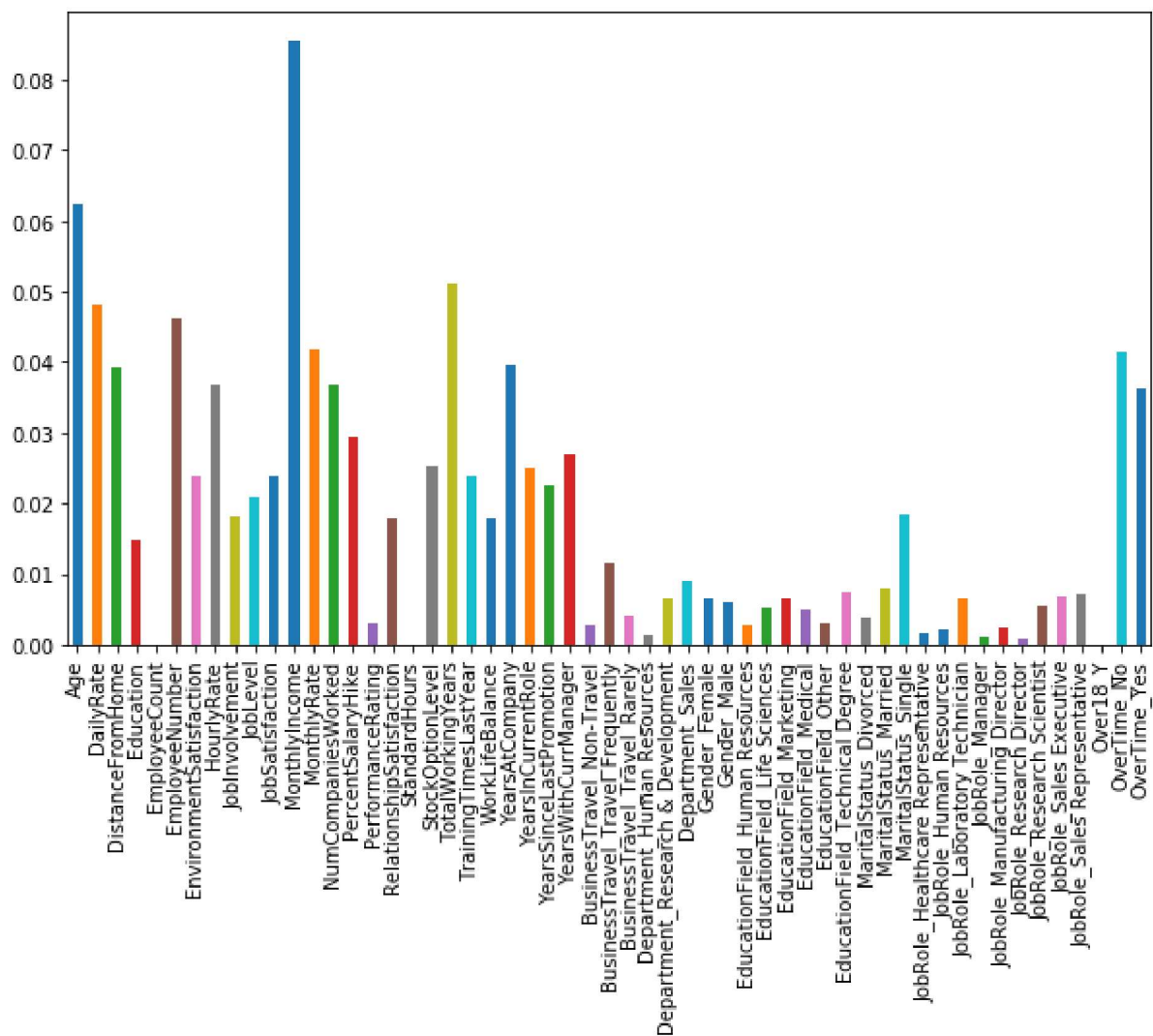
Important Feature	
Age	0.062232
DailyRate	0.047999
DistanceFromHome	0.039270
Education	0.014871
EmployeeCount	0.000000
EmployeeNumber	0.046100
EnvironmentSatisfaction	0.023897
HourlyRate	0.036702
JobInvolvement	0.018098
JobLevel	0.020750
JobSatisfaction	0.023820
MonthlyIncome	0.085372
MonthlyRate	0.041645
NumCompaniesWorked	0.036902
PercentSalaryHike	0.029411
PerformanceRating	0.002948
RelationshipSatisfaction	0.017733
StandardHours	0.000000
StockOptionLevel	0.025366
TotalWorkingYears	0.051120
TrainingTimesLastYear	0.024019
WorkLifeBalance	0.017760
YearsAtCompany	0.039561
YearsInCurrentRole	0.025094
YearsSinceLastPromotion	0.022459
YearsWithCurrManager	0.027046
BusinessTravel_Non-Travel	0.002817
BusinessTravel_Travel_Frequently	0.011583
BusinessTravel_Travel_Rarely	0.004181
Department_Human Resources	0.001234
Department_Research & Development	0.006574
Department_Sales	0.008941
Gender_Female	0.006491

Important Feature	
Gender_Male	0.006026
EducationField_Human Resources	0.002634
EducationField_Life Sciences	0.005215
EducationField_Marketing	0.006695
EducationField_Medical	0.004935
EducationField_Other	0.003089
EducationField_Technical Degree	0.007536
MaritalStatus_Divorced	0.003779
MaritalStatus_Married	0.007969
MaritalStatus_Single	0.018473
JobRole_Healthcare Representative	0.001725
JobRole_Human Resources	0.002067
JobRole_Laboratory Technician	0.006671
JobRole_Manager	0.000978
JobRole_Manufacturing Director	0.002338
JobRole_Research Director	0.000721
JobRole_Research Scientist	0.005396
JobRole_Sales Executive	0.006873
JobRole_Sales Representative	0.007161
Over18_Y	0.000000
OverTime_No	0.041484
OverTime_Yes	0.036238

```
In [37]: import matplotlib.pyplot as plt
import seaborn as sns
```

```
In [45]: fig = plt.figure(figsize = (10, 6))
pd.Series(RFC.feature_importances_, index=X_train.columns).plot.bar()
```

```
Out[45]: <matplotlib.axes._subplots.AxesSubplot at 0x1fc9107f208>
```



Step : 8

```
In [54]: estimator = RFC.estimators_[5]
```

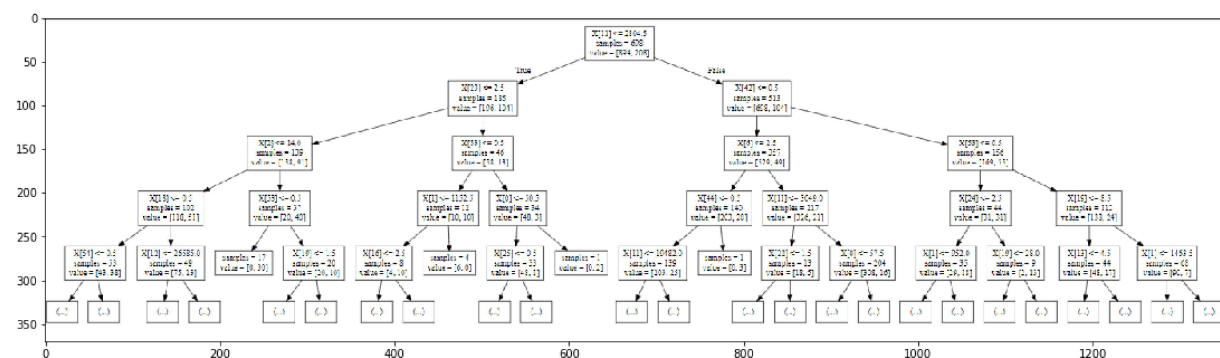
```
In [55]: from sklearn import tree
from sklearn.tree import export_graphviz
with open("RFDT.dot", 'w') as f:
    f = tree.export_graphviz(estimator, out_file=f, max_depth=4, impurity=False)
```

```
In [56]: !dot - Tpng RFDT.dot -o RFDT.png
```

```
'dot' is not recognized as an internal or external command,
operable program or batch file.
```

```
In [59]: import matplotlib.pyplot as plt
image = plt.imread('Screenshot 2023-03-07 104946.png')
plt.figure(figsize=(19,15))
plt.imshow(image)
```

```
Out[59]: <matplotlib.image.AxesImage at 0x1fc91423c88>
```



Step : 9

```
In [62]: rf2 = RandomForestClassifier(oob_score=True, random_state=42, warm_start=True, n_
oob_list = list()
for n_trees in [15, 20, 30, 40, 50, 100, 150, 200, 300, 400]:
    rf2.set_params(n_estimators=n_trees)
    rf2.fit(X_train, y_train)
    oob_error = 1 - rf2.oob_score_
    oob_list.append(pd.Series({'n_trees': n_trees, 'oob': oob_error}))
rf_oob_df = pd.concat(oob_list, axis=1).T.set_index('n_trees')
rf_oob_df
```

C:\Program Files (x86)\Microsoft Visual Studio\Shared\Anaconda3_64\lib\site-packages\sklearn\ensemble\forest.py:453: UserWarning: Some inputs do not have OOB scores. This probably means too few trees were used to compute any reliable oob estimates.

warn("Some inputs do not have OOB scores. "

C:\Program Files (x86)\Microsoft Visual Studio\Shared\Anaconda3_64\lib\site-packages\sklearn\ensemble\forest.py:458: RuntimeWarning: invalid value encountered in true_divide

predictions[k].sum(axis=1)[: , np.newaxis])

C:\Program Files (x86)\Microsoft Visual Studio\Shared\Anaconda3_64\lib\site-packages\sklearn\ensemble\forest.py:453: UserWarning: Some inputs do not have OOB scores. This probably means too few trees were used to compute any reliable oob estimates.

warn("Some inputs do not have OOB scores. "

C:\Program Files (x86)\Microsoft Visual Studio\Shared\Anaconda3_64\lib\site-packages\sklearn\ensemble\forest.py:458: RuntimeWarning: invalid value encountered in true_divide

predictions[k].sum(axis=1)[: , np.newaxis])

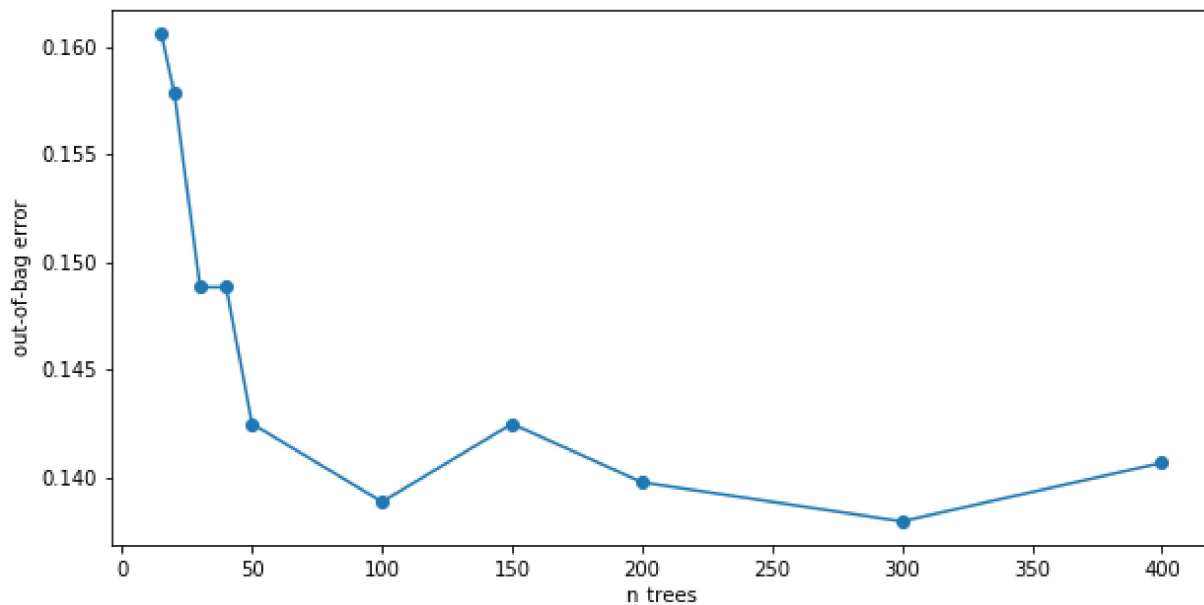
Out[62]:

	oob
n_trees	
15.0	0.160617
20.0	0.157895
30.0	0.148820
40.0	0.148820
50.0	0.142468
100.0	0.138838
150.0	0.142468
200.0	0.139746
300.0	0.137931
400.0	0.140653

Step : 10

```
In [63]: ax = rf_oob_df.plot(legend=False, marker='o', figsize=(10,5))
ax.set(ylabel='out-of-bag error')
```

```
Out[63]: [Text(0,0.5,'out-of-bag error')]
```



```
In [64]: Step : 11
```

```
In [65]: from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, classification_report
clf = DecisionTreeClassifier(max_depth=4, random_state=42)
clf.fit(X_test, y_test)
```

```
Out[65]: DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=4,
max_features=None, max_leaf_nodes=None,
min_impurity_decrease=0.0, min_impurity_split=None,
min_samples_leaf=1, min_samples_split=2,
min_weight_fraction_leaf=0.0, presort=False, random_state=42,
splitter='best')
```



```
In [72]: print(classification_report(y_test,RFC_y_pred))
```

	precision	recall	f1-score	support
0	0.88	0.98	0.93	320
1	0.44	0.08	0.14	48
avg / total	0.82	0.87	0.83	368

```
In [74]: from sklearn.metrics import precision_score, recall_score, accuracy_score, roc_auc
```

```
In [75]: print("RF model :",accuracy_score(y_test,RFC_y_pred))
print("RF Precision:",precision_score(y_test,RFC_y_pred))
print("RF Recall :",recall_score(y_test,RFC_y_pred))
print("RF F1 score :",f1_score(y_test,RFC_y_pred))
print("\n")
print("DT model :",accuracy_score(y_test,y_pred1))
print("DT Precision:",precision_score(y_test,y_pred1))
print("DT Recall :",recall_score(y_test,y_pred1))
print("DT F1 score :",f1_score(y_test,y_pred1))
```

```
RF model : 0.8668478260869565
RF Precision: 0.4444444444444444
RF Recall : 0.08333333333333333
RF F1 score : 0.14035087719298245
```

```
DT model : 0.907608695652174
DT Precision: 0.85
DT Recall : 0.3541666666666667
DT F1 score : 0.5
```

```
In [ ]:
```