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COURSE TITLE : PRACTICAL MACHINE LEARNING LAB

Lab 09. Employee Hopping Prediction using Random Forests

Step-1

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

In [2]:
```
emp=pan.read_csv("C:\\Users\\user\\Downloads\\dataset_pml\\Employee_hopping.csv")
```

In [3]:
```
emp.head()
```

Out[3]:

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCount	EmployeeNumber	...	R
0	41	Yes	Travel_Rarely	1102	Sales	1	2	Life Sciences	1	1	...	
1	49	No	Travel_Frequently	279	Research & Development	8	1	Life Sciences	1	2	...	
2	37	Yes	Travel_Rarely	1373	Research & Development	2	2	Other	1	4	...	
3	33	No	Travel_Frequently	1392	Research & Development	3	4	Life Sciences	1	5	...	
4	27	No	Travel_Rarely	591	Research & Development	2	1	Medical	1	7	...	

5 rows × 35 columns

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

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

In [5]:
```
emp.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]:
```
emp.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]:
```python
emp.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1470 entries, 0 to 1469
Data columns (total 35 columns):
 #   Column                    Non-Null Count  Dtype 
---  ------                    --------------  ----- 
 0   Age                       1470 non-null   int64 
 1   Attrition                 1470 non-null   object
 2   BusinessTravel            1470 non-null   object
 3   DailyRate                 1470 non-null   int64 
 4   Department                1470 non-null   object
 5   DistanceFromHome          1470 non-null   int64 
 6   Education                 1470 non-null   int64 
 7   EducationField            1470 non-null   object
 8   EmployeeCount             1470 non-null   int64 
 9   EmployeeNumber            1470 non-null   int64 
 10  EnvironmentSatisfaction   1470 non-null   int64 
 11  Gender                    1470 non-null   object
 12  HourlyRate                1470 non-null   int64 
 13  JobInvolvement            1470 non-null   int64 
 14  JobLevel                  1470 non-null   int64 
 15  JobRole                   1470 non-null   object
 16  JobSatisfaction           1470 non-null   int64 
 17  MaritalStatus             1470 non-null   object
 18  MonthlyIncome             1470 non-null   int64 
 19  MonthlyRate               1470 non-null   int64 
 20  NumCompaniesWorked        1470 non-null   int64 
 21  Over18                    1470 non-null   object
 22  OverTime                  1470 non-null   object
 23  PercentSalaryHike         1470 non-null   int64 
 24  PerformanceRating         1470 non-null   int64 
 25  RelationshipSatisfaction  1470 non-null   int64 
 26  StandardHours             1470 non-null   int64 
 27  StockOptionLevel          1470 non-null   int64 
 28  TotalWorkingYears         1470 non-null   int64 
 29  TrainingTimesLastYear     1470 non-null   int64 
 30  WorkLifeBalance           1470 non-null   int64 
 31  YearsAtCompany            1470 non-null   int64 
 32  YearsInCurrentRole        1470 non-null   int64 
 33  YearsSinceLastPromotion   1470 non-null   int64 
 34  YearsWithCurrManager      1470 non-null   int64 
dtypes: int64(26), object(9)
memory usage: 402.1+ KB
```

In [44]:
```
emp["Age"].value_counts()
```

Out[44]:
```
35    78
34    77
36    69
31    69
29    68
32    61
30    60
33    58
38    58
40    57
37    50
27    48
28    48
42    46
39    42
45    41
41    40
26    39
44    33
46    33
43    32
50    30
25    26
24    26
49    24
47    24
55    22
51    19
53    19
48    19
54    18
52    18
22    16
56    14
23    14
58    14
21    13
20    11
59    10
19     9
18     8
60     5
57     4
Name: Age, dtype: int64
```

Step-2 [Extract X and y]

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

In [10]:
```
y=emp["Attrition"].values
```

Step-3. [Feature Engineering]

In [11]:
```
emp.dtypes
```

Out[11]:
```
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 [12]:
```
emp_dum=["BusinessTravel","EducationField","Department","Gender","JobRole","MaritalStatus","Over18","OverTime"]
```

In [13]:
```
dummiesX = pan.get_dummies(X,columns=emp_dum)
```

Step-4

In [14]:
```
X.shape
```
Out[14]:
```
(1470, 34)
```
In [15]:
```
y.shape
```
Out[15]:
```
(1470,)
```

Step-5. [Model Development]

In [16]:
```
from sklearn.model_selection import train_test_split as tts
X_train,X_test,y_train,y_test=tts(dummiesX,y,test_size=.25,random_state=42)
```
In [17]:
```
from sklearn.ensemble import RandomForestClassifier
rf= RandomForestClassifier()
rf.fit(X_train,y_train)
```
Out[17]:
```
RandomForestClassifier()
```
In [18]:
```
y_pred=rf.predict(X_test)
```

Step-6 [Testing]

In [19]:
```
from sklearn.metrics import *
```
In [20]:
```
accuracy_score(y_test, y_pred)
```
Out[20]:
```
0.875
```
In [21]:
```
classification_report(y_test,y_pred)
```
Out[21]:
```
'              precision    recall  f1-score   support\n\n          No       0.88      0.99      0.93       320\n
Yes       0.67      0.08      0.15        48\n\n    accuracy                           0.88       368\n   macro avg
0.77      0.54      0.54       368\nweighted avg       0.85      0.88      0.83       368\n'
```

Step-7 [Feature importance value]

In [22]:
```python
imp=rf.feature_importances_
imp
```

Out[22]:
```
array([0.05294513, 0.04406456, 0.04069169, 0.01695943, 0.        ,
       0.04170964, 0.02478373, 0.03864302, 0.02144051, 0.02292761,
       0.02427507, 0.07498255, 0.04305541, 0.03425137, 0.02740993,
       0.00444482, 0.02104138, 0.        , 0.03156234, 0.04394259,
       0.0243328 , 0.01817268, 0.04125906, 0.02905377, 0.02426619,
       0.03073603, 0.00401763, 0.01021646, 0.00629047, 0.00216476,
       0.00710982, 0.00650052, 0.00710521, 0.00377547, 0.00642365,
       0.0017799 , 0.00623775, 0.00775653, 0.00673764, 0.0061964 ,
       0.00144444, 0.00193078, 0.00962975, 0.00182065, 0.00180486,
       0.0011617 , 0.00631082, 0.00818318, 0.0099643 , 0.00600414,
       0.0072191 , 0.01658899, 0.        , 0.03530234, 0.03337146])
```

In [23]:
```
f_name=pan.DataFrame(imp,index=X_train.columns,columns=["Feature Importance Values"])
f_name
```

Out[23]:

	Feature Importance Values
Age	0.052945
DailyRate	0.044065
DistanceFromHome	0.040692
Education	0.016959
EmployeeCount	0.000000
EmployeeNumber	0.041710
EnvironmentSatisfaction	0.024784
HourlyRate	0.038643
JobInvolvement	0.021441
JobLevel	0.022928
JobSatisfaction	0.024275
MonthlyIncome	0.074983
MonthlyRate	0.043055
NumCompaniesWorked	0.034251
PercentSalaryHike	0.027410
PerformanceRating	0.004445
RelationshipSatisfaction	0.021041
StandardHours	0.000000
StockOptionLevel	0.031562
TotalWorkingYears	0.043943
TrainingTimesLastYear	0.024333
WorkLifeBalance	0.018173
YearsAtCompany	0.041259
YearsInCurrentRole	0.029054
YearsSinceLastPromotion	0.024266
YearsWithCurrManager	0.030736
BusinessTravel_Non-Travel	0.004018
BusinessTravel_Travel_Frequently	0.010216
BusinessTravel_Travel_Rarely	0.006290

	Feature Importance Values
EducationField_Human Resources	0.002165
EducationField_Life Sciences	0.007110
EducationField_Marketing	0.006501
EducationField_Medical	0.007105
EducationField_Other	0.003775
EducationField_Technical Degree	0.006424
Department_Human Resources	0.001780
Department_Research & Development	0.006238
Department_Sales	0.007757
Gender_Female	0.006738
Gender_Male	0.006196
JobRole_Healthcare Representative	0.001444
JobRole_Human Resources	0.001931
JobRole_Laboratory Technician	0.009630
JobRole_Manager	0.001821
JobRole_Manufacturing Director	0.001805
JobRole_Research Director	0.001162
JobRole_Research Scientist	0.006311
JobRole_Sales Executive	0.008183
JobRole_Sales Representative	0.009964
MaritalStatus_Divorced	0.006004
MaritalStatus_Married	0.007219
MaritalStatus_Single	0.016589
Over18_Y	0.000000
OverTime_No	0.035302
OverTime_Yes	0.033371

In [24]:
```
import matplotlib.pyplot as mat
```

In [25]:

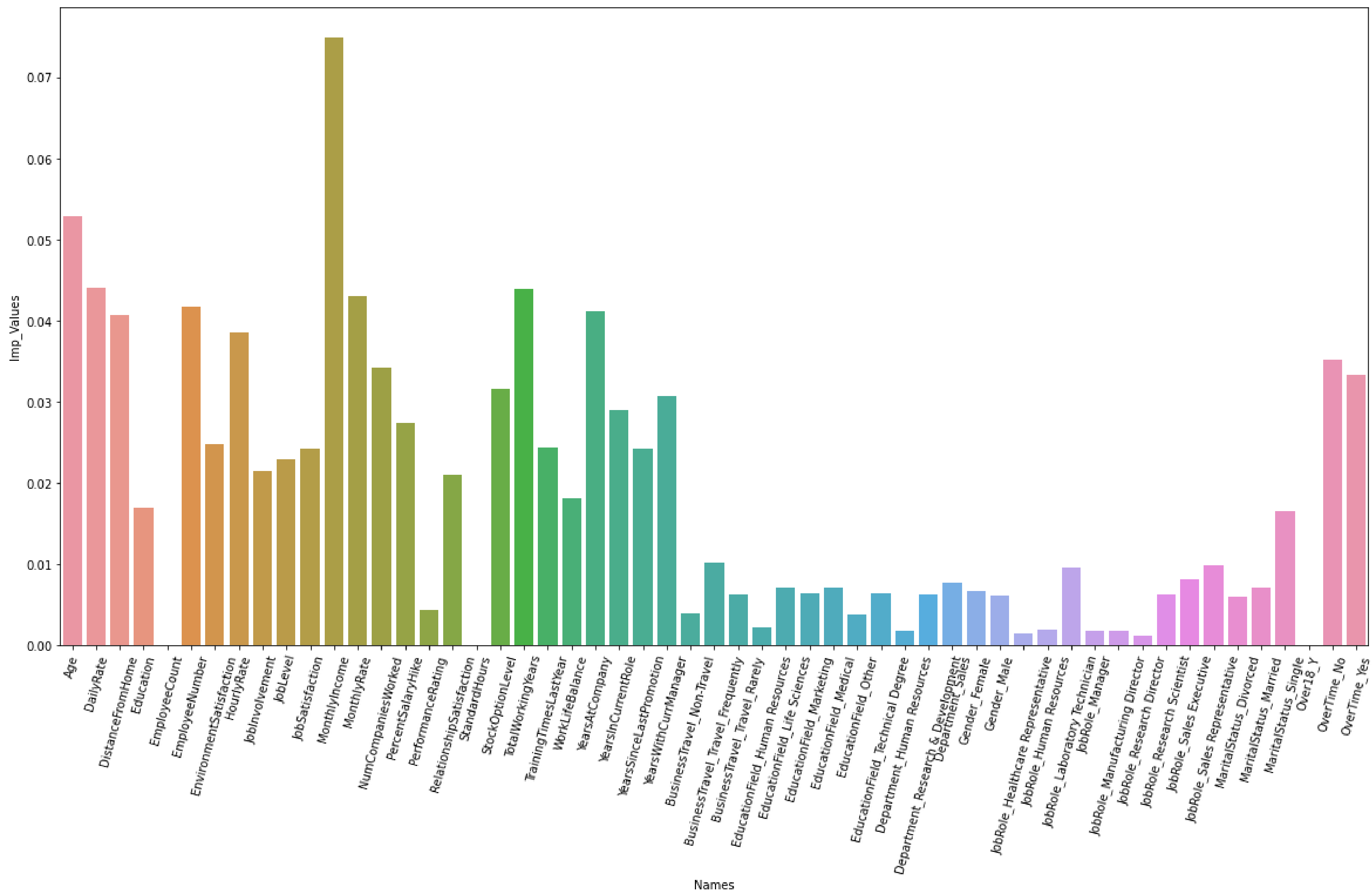
```python
import seaborn as sb
```

In [26]:

```python
mat.figure(figsize=(20,10))
sb.barplot(x=f_name.index,y=f_name["Feature Importance Values"])
mat.xticks(rotation=75)
mat.xlabel("Names")
mat.ylabel("Imp_Values")
```

Out[26]:

```
Text(0, 0.5, 'Imp_Values')
```



Step-8 [Visualize your RF Decision Tree using graphviz]

In [27]:
```
from sklearn import tree
rfc = RandomForestClassifier(n_estimators=10, random_state=42)
rfc.fit(X_train, y_train)
tree = rfc.estimators_[0]
from sklearn.tree import export_graphviz
with open("tree1.dot", "w") as f:
    f= export_graphviz(rfc.estimators_[0], out_file=None,
                           feature_names=X_train.columns,
                           class_names=['No', 'Yes'],
                           filled=True, rounded=True,
                           special_characters=True)
```

In [28]:
```
!type tree1.dot
```

Step-09

In [29]:
```
rf2=RandomForestClassifier(oob_score=True,
                          random_state=42,
                          warm_start=True,
                          n_jobs=-1)
oob_list=list()
```

In [30]:
```
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(pan.Series({'n_trees':n_trees,'oob':oob_error}))



rf_oob_df=pan.concat(oob_list,axis=1).T.set_index('n_trees')

rf_oob_df
```

```
C:\Users\user\anaconda3\lib\site-packages\sklearn\ensemble\_forest.py:560: UserWarning: Some inputs do not have OOB sc
ores. This probably means too few trees were used to compute any reliable OOB estimates.
  warn(
C:\Users\user\anaconda3\lib\site-packages\sklearn\ensemble\_forest.py:560: UserWarning: Some inputs do not have OOB sc
ores. This probably means too few trees were used to compute any reliable OOB estimates.
  warn(
```

Out[30]:

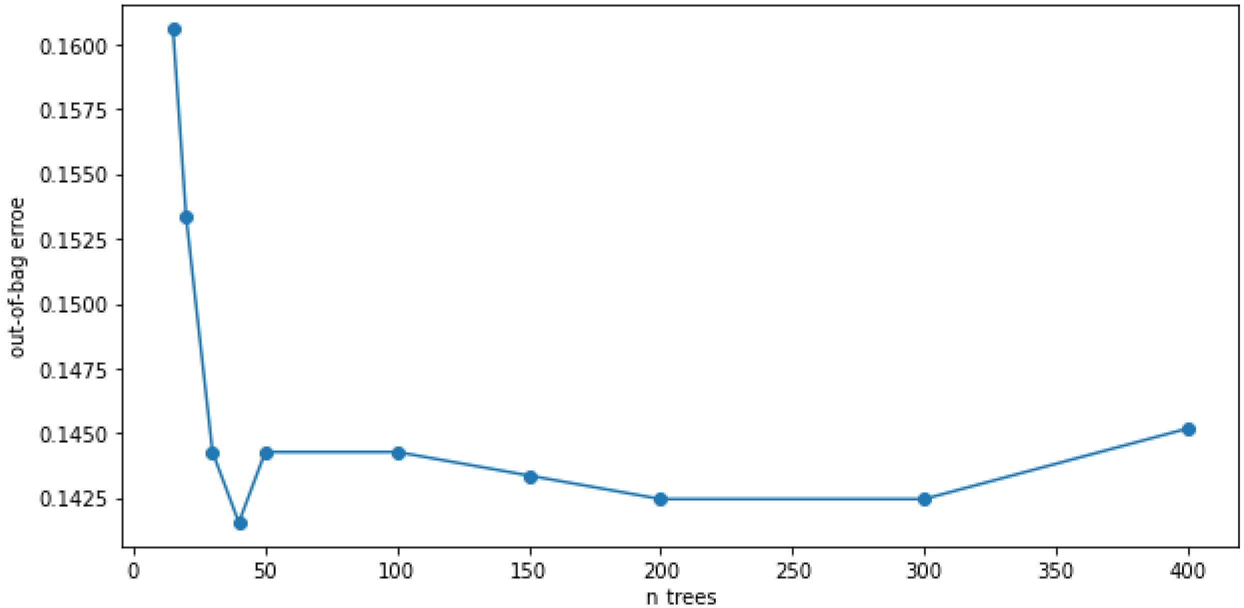
n_trees	oob
15.0	0.160617
20.0	0.153358
30.0	0.144283
40.0	0.141561
50.0	0.144283
100.0	0.144283
150.0	0.143376
200.0	0.142468
300.0	0.142468
400.0	0.145191

In [ ]:

Step-10

In [31]:
```
ax=rf_oob_df.plot(legend=False,marker='o',figsize=(10,5))
ax.set(ylabel='out-of-bag erroe')
```

Out[31]:
```
[Text(0, 0.5, 'out-of-bag erroe')]
```



Step-11 [DecisionTreeClassifier]

In [32]:
```
from sklearn.tree import DecisionTreeClassifier, export_graphviz
from sklearn.metrics import*
```

In [33]:
```
dt = DecisionTreeClassifier(criterion='entropy')
```

In [34]:
```
dt.fit(X_train, y_train)


y_pred = dt.predict(X_test)
```

In [37]:
```python
from sklearn.tree import DecisionTreeClassifier
import sklearn.tree as tree

clf = DecisionTreeClassifier(criterion='entropy')
clf.fit(X_train, y_train)
```

Out[37]:
```
DecisionTreeClassifier(criterion='entropy')
```

In [38]:
```python
with open("tree2.dot", "w") as f:
    f = tree.export_graphviz(clf, out_file=f, max_depth=5, impurity=False,
                             feature_names=X_train.columns.values,
                             class_names=["Yes", "No"], filled=True)
```

In [39]:
```python
!type tree2.dot
```

```
digraph Tree {
node [shape=box, style="filled", color="black", fontname="helvetica"] ;
edge [fontname="helvetica"] ;
0 [label="OverTime_Yes <= 0.5\nsamples = 1102\nvalue = [913, 189]\nclass = Yes", fillcolor="#ea9b62"] ;
1 [label="TotalWorkingYears <= 2.5\nsamples = 780\nvalue = [698, 82]\nclass = Yes", fillcolor="#e89050"] ;
0 -> 1 [labeldistance=2.5, labelangle=45, headlabel="True"] ;
2 [label="JobRole_Research Scientist <= 0.5\nsamples = 71\nvalue = [46, 25]\nclass = Yes", fillcolor="#f3c5a5"] ;
1 -> 2 ;
3 [label="HourlyRate <= 58.5\nsamples = 51\nvalue = [28, 23]\nclass = Yes", fillcolor="#fae8dc"] ;
2 -> 3 ;
4 [label="EnvironmentSatisfaction <= 2.5\nsamples = 18\nvalue = [5, 13]\nclass = No", fillcolor="#85c3ef"] ;
3 -> 4 ;
5 [label="samples = 9\nvalue = [0, 9]\nclass = No", fillcolor="#399de5"] ;
4 -> 5 ;
6 [label="MonthlyIncome <= 2192.5\nsamples = 9\nvalue = [5, 4]\nclass = Yes", fillcolor="#fae6d7"] ;
4 -> 6 ;
7 [label="(...)", fillcolor="#C0C0C0"] ;
6 -> 7 ;
10 [label="(...)", fillcolor="#C0C0C0"] ;
```

In [40]:
```python
print("Accuracy:", accuracy_score(y_test, y_pred))
```

```
Accuracy: 0.7717391304347826
```

```
In [41]: print("Classification Report : ",classification_report(y_test,y_pred))
```

```
Classification Report :                precision    recall  f1-score   support

          No       0.89      0.84      0.87       320
         Yes       0.22      0.29      0.25        48

    accuracy                           0.77       368
   macro avg       0.55      0.57      0.56       368
weighted avg       0.80      0.77      0.79       368
```