This Notebook product generates a predictive model of employee attrition, by applying a random forest algorithm to a human resources dataset

Created by Dee Weinacht (c) 2023

Data Preparation

Initial Setup

First, necessary libraries and functionalities are imported:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline
```

The dataset of human resources employee information is loaded into a pandas data frame:

```
# dataset sourced from kaggle: https://www.kaggle.com/datasets/pavansubhasht/ibm-hr-analytics-attrition-dataset
employee_data = pd.read_csv('HR-Employee-Attrition.csv')
```

Now that the data is loaded, some features of the data can be explored:

```
employee_data.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
```

```
employee_data.isnull().sum()
```

```
Age                         0
Attrition                   0
BusinessTravel              0
DailyRate                   0
```

```
Department                  0
DistanceFromHome            0
Education                   0
EducationField              0
EmployeeCount               0
EmployeeNumber              0
EnvironmentSatisfaction     0
Gender                      0
HourlyRate                  0
JobInvolvement              0
JobLevel                    0
JobRole                     0
JobSatisfaction             0
MaritalStatus               0
MonthlyIncome               0
MonthlyRate                 0
NumCompaniesWorked          0
Over18                      0
OverTime                    0
PercentSalaryHike           0
PerformanceRating           0
RelationshipSatisfaction    0
StandardHours               0
StockOptionLevel            0
TotalWorkingYears           0
TrainingTimesLastYear       0
WorkLifeBalance             0
YearsAtCompany              0
YearsInCurrentRole          0
YearsSinceLastPromotion     0
YearsWithCurrManager        0
dtype: int64
```

The dataset includes **35 columns** of both numeric (26 variables) and categorical data (9 variables). There are **1470 entries** in total, and, significantly, **no null values** in the dataset - this is valuable, as the random forest algorithm cannot process null values and these missing values would need to be addressed.

Data Cleaning

The first step of data cleaning will be to remove personally identifying information, as well as any variables that, if used to make predictions or business decisions, might be considered discriminatory.

In this case 'employee number', 'age', 'gender', and 'marital status' are dropped from the dataset.

```
employee_data.drop(['EmployeeNumber','Age','Gender','MaritalStatus'],axis=1,inplace=True)
```

Each of the remaining variables is examined to determine if any can be removed as having no predictive value.

Each variable is determined to be either numeric or categorical, then either the range of numbers or the categorical values are listed:

```
for attribute in employee_data.columns:
    print(attribute)
    if employee_data[attribute].dtype == object:
        print('Categorical.  Values: {}\n'.format(employee_data[attribute].unique()))
    else:
        print('Numeric.  Range: {} to {}\n'.format(employee_data[attribute].min(),employee_data[attribute].max()))
```

```
Attrition
Categorical.  Values: ['Yes' 'No']

BusinessTravel
Categorical.  Values: ['Travel_Rarely' 'Travel_Frequently' 'Non-Travel']

DailyRate
Numeric.  Range: 102 to 1499

Department
Categorical.  Values: ['Sales' 'Research & Development' 'Human Resources']

DistanceFromHome
Numeric.  Range: 1 to 29

Education
Numeric.  Range: 1 to 5

EducationField
Categorical.  Values: ['Life Sciences' 'Other' 'Medical' 'Marketing' 'Technical Degree'
 'Human Resources']

EmployeeCount
Numeric.  Range: 1 to 1
```

```
EnvironmentSatisfaction
Numeric.  Range: 1 to 4

HourlyRate
Numeric.  Range: 30 to 100

JobInvolvement
Numeric.  Range: 1 to 4

JobLevel
Numeric.  Range: 1 to 5

JobRole
Categorical.  Values: ['Sales Executive' 'Research Scientist' 'Laboratory Technician'
 'Manufacturing Director' 'Healthcare Representative' 'Manager'
 'Sales Representative' 'Research Director' 'Human Resources']

JobSatisfaction
Numeric.  Range: 1 to 4

MonthlyIncome
Numeric.  Range: 1009 to 19999

MonthlyRate
Numeric.  Range: 2094 to 26999

NumCompaniesWorked
Numeric.  Range: 0 to 9

Over18
Categorical.  Values: ['Y']
```

The variables 'employee count', 'over 18', and 'standard hours' have the same value for all employees and thus have no predictive value.

These variables are dropped from the dataset:

```
employee_data.drop(['EmployeeCount','Over18','StandardHours'],axis=1,inplace=True)
```

The top few rows of the reduced data set:

```
employee_data.head()
```

	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	Ed
0	Yes	Travel_Rarely	1102	Sales	1	2	
1	No	Travel_Frequently	279	Research & Development	8	1	
2	Yes	Travel_Rarely	1373	Research & Development	2	2	
3	No	Travel_Frequently	1392	Research & Development	3	4	
4	No	Travel_Rarely	591	Research & Development	2	1	

5 rows × 28 columns

After data cleaning there are 1470 entries, with 28 remaining variables

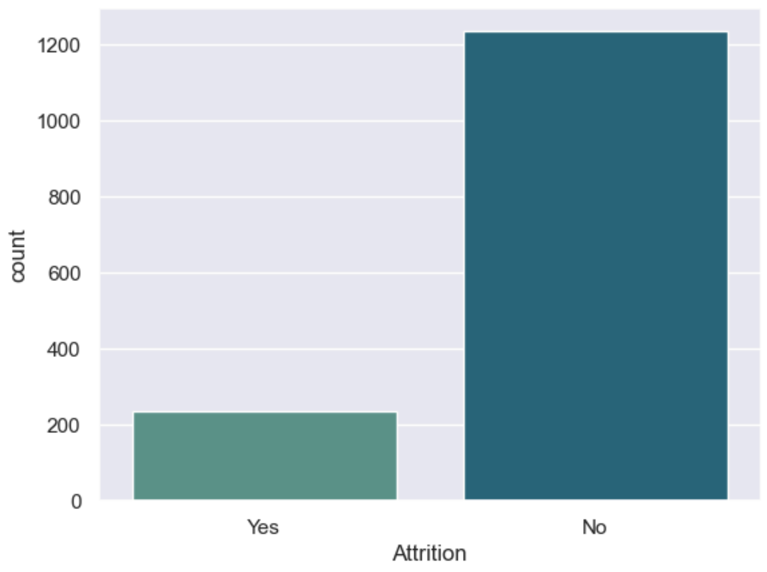
Exploratory Data Analysis

Now some exploratory visualizations of the data can begin, to provide a better understanding of the data and inform any futher data wrangling that should be done before the dataset is ready to be used by a machine learning algorithm.

'Attrition' is the target variable (the variable the model will be created to predict). A simple count plot of this variable:

```
sns.set_theme() #sets the default seaborn theme
sns.countplot(data=employee_data,x='Attrition',palette='crest')
```

```
<AxesSubplot:xlabel='Attrition', ylabel='count'>
```



This graph shows that attrition is a boolean value, with a large disparity between the two predictive outcomes, meaning that this will be an **unbalanced binary classification** task.

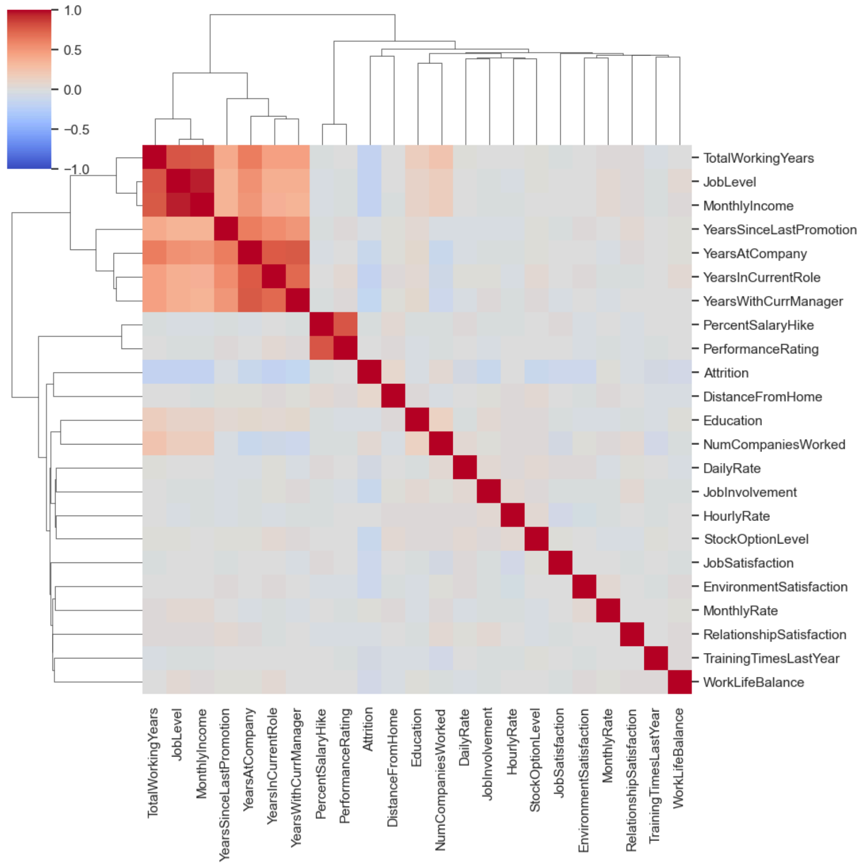
While the other categorical variables will need to be converted to numeric later, it will be useful to convert attrition to a numeric boolean value now:

```
employee_data['Attrition'] = employee_data['Attrition'].apply(lambda val: 1 if val == 'Yes' else 0)
```

A visual inspection of correlations between the numeric variables:

```
employee_data.corr()
sns.clustermap(data=employee_data.corr(),vmin=-1,cmap='coolwarm')
```

```
<seaborn.matrix.ClusterGrid at 0x1de6383b5e0>
```

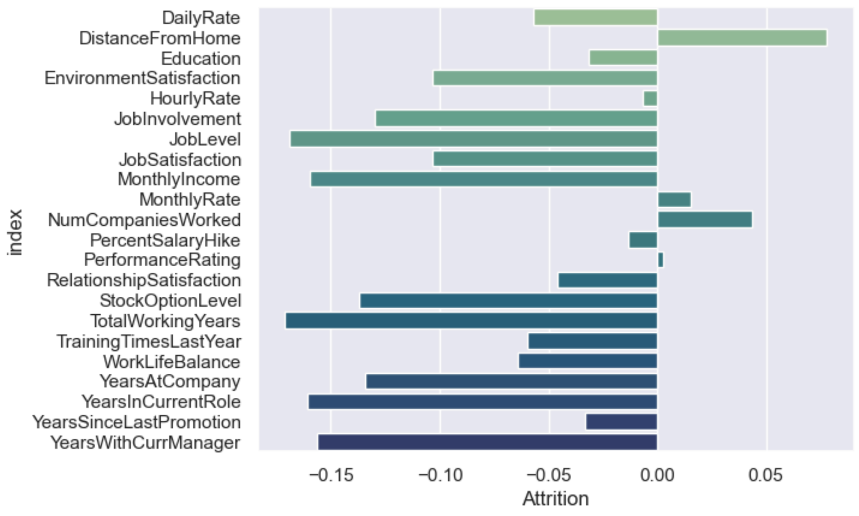


There are several clusters of correlation that become apparent from this graph, however, none of these correlations seem to be indicating that multiple variables are capturing the same information. Even though 'Job level' and 'monthly income' are particularly strongly correlated, there still may be predictive value in maintaining both variables as-is, so neither will be removed.

It is also important to investigate the correlations between these variables and the target variable. A graph of the correlations between the independent variables and the target variable, attrition:

```
sns.barplot(data=employee_data.corr()['Attrition'][1:].reset_index(), x='Attrition',y='index',palette='crest')
```

```
<AxesSubplot:xlabel='Attrition', ylabel='index'>
```



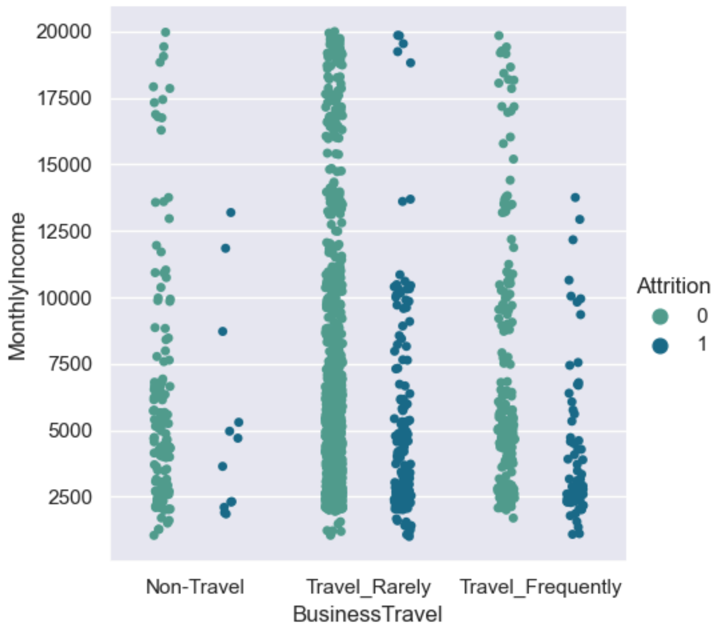
From this graph, a **few very weakly positive correlations** are noted, in particular 'distance from home', which makes intuitive sense to be correlated with employee attrition.

There are also **many variables weakly negatively correlated to attrition**, including most of the cluster noted in the previous graph, other than 'years since last promotion', which, surprisingly, does not appear to be related to attrition likelihood.

There are also some categorical variables that have not been graphically examined yet. Of these, the 'business travel' variable appears to be a good candidate to relate to employee attrition. The following graph examines the 'business travel' variable:

```
sns.catplot(data=employee_data,x='BusinessTravel',y='MonthlyIncome',hue='Attrition',order=['Non-Travel','Travel_Rarely','Travel_Frequent
```

```
<seaborn.axisgrid.FacetGrid at 0x1de63830c70>
```



This graph clearly shows the relationship between employee monthly income and attrition, but it seems like there is **no clear relationship between the amount of travel required of an employee and the attrition rate**.

Data Wrangling

The dataset must be prepared for machine learning by converting the remaining categorical variables into a numeric form for use.

The following is a list of the categorical variables:

```
for attribute in employee_data.columns:
    if employee_data[attribute].dtype == object:
        print('{} : {}\n'.format(attribute,employee_data[attribute].unique()))
```

```
BusinessTravel : ['Travel_Rarely' 'Travel_Frequently' 'Non-Travel']

Department : ['Sales' 'Research & Development' 'Human Resources']

EducationField : ['Life Sciences' 'Other' 'Medical' 'Marketing' 'Technical Degree'
 'Human Resources']

JobRole : ['Sales Executive' 'Research Scientist' 'Laboratory Technician'
 'Manufacturing Director' 'Healthcare Representative' 'Manager'
 'Sales Representative' 'Research Director' 'Human Resources']

OverTime : ['Yes' 'No']
```

Of these categorical variables, we can see that **two are ordinal** - they have a ranking or ordering to the categories.

We can therefore convert these columns, 'BusinessTravel' and 'OverTime', directly to numeric values:

```
employee_data['OverTime'] = employee_data['OverTime'].apply(lambda val: 1 if val == 'Yes' else 0)
```

```
def convert_travel(value):
    if value == 'Non-Travel':
        return 0
    elif value == 'Travel_Rarely':
        return 1
    else:
        return 2
```

```
employee_data['BusinessTravel'] = employee_data['BusinessTravel'].apply(convert_travel)
```

The remaining categorical variables are nominal - there is no ranking or ordering to the categories.

These variables will be **converted to numeric values using dummy variables**:

```
employee_data_final = pd.get_dummies(data=employee_data,columns=['Department','EducationField','JobRole'],drop_first=True)
```

```
employee_data_final.to_csv('Machine-Learning-Employee-Attrition.csv',index=False) #save dataset as csv for future use
employee_data_final.describe()
```

	Attrition	BusinessTravel	DailyRate	DistanceFromHome	Education	Enviro
count	1470.000000	1470.000000	1470.000000	1470.000000	1470.000000	
mean	0.161224	1.086395	802.485714	9.192517	2.912925	
std	0.367863	0.532170	403.509100	8.106864	1.024165	
min	0.000000	0.000000	102.000000	1.000000	1.000000	
25%	0.000000	1.000000	465.000000	2.000000	2.000000	
50%	0.000000	1.000000	802.000000	7.000000	3.000000	
75%	0.000000	1.000000	1157.000000	14.000000	4.000000	
max	1.000000	2.000000	1499.000000	29.000000	5.000000	

8 rows × 40 columns

The dataset, now including 40 features, is ready for use in a machine learning algorithm

Machine Learning

Separate Dataset into Training Data and Testing Data

The first step of machine learning is to separate the dataset into features and target, and then split the data into training and testing categories:

```
from sklearn.model_selection import train_test_split
```

```
X = employee_data_final.drop(columns = 'Attrition')
y = employee_data_final['Attrition']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,random_state=36)
```

Random Forest Model

The training data is used to generate a model with the default random forest algorithm:

```
from sklearn.ensemble import RandomForestClassifier
random_forest = RandomForestClassifier(random_state=36) #default hyper-parameters, other than random state, to ensure consistency
random_forest.fit(X_train, y_train)
```

```
    RandomForestClassifier(random_state=36)
```

The model is then used to generate predictions based on the testing portion of the dataset:

```
random_forest_predict = random_forest.predict(X_test)
```

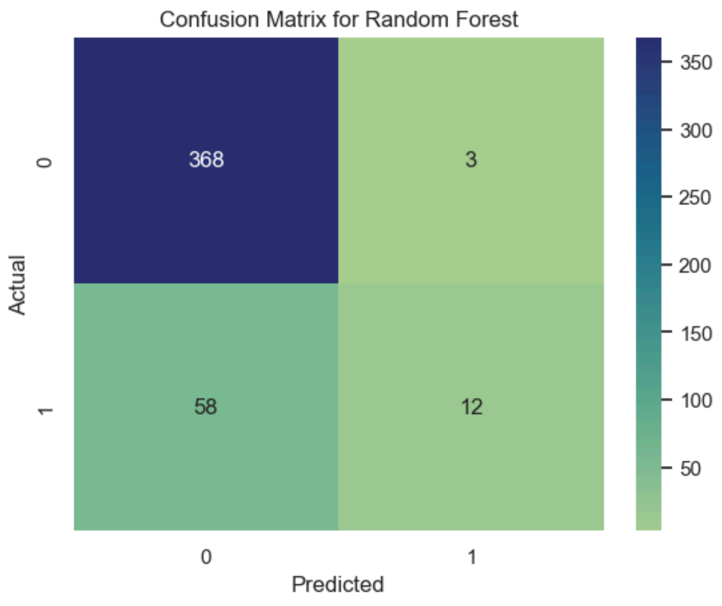
Now the resulting model can be evaluated by comparing the predictions the model makes to the attrition test data.

This will be done in three ways: using a confusion matrix, a classification report, and a AUC-ROC score.

```
from sklearn.metrics import confusion_matrix,classification_report,roc_auc_score
```

```
sns.heatmap(confusion_matrix(y_test, random_forest_predict),annot=True,cmap='crest',fmt='g')
plt.title('Confusion Matrix for Random Forest')
plt.xlabel('Predicted')
plt.ylabel('Actual')
```

```
    Text(47.25, 0.5, 'Actual')
```



```
print(classification_report(y_test,random_forest_predict))
```

```
              precision    recall  f1-score   support

           0       0.86      0.99      0.92       371
           1       0.80      0.17      0.28        70

    accuracy                           0.86       441
   macro avg       0.83      0.58      0.60       441
weighted avg       0.85      0.86      0.82       441
```

```
np.round(roc_auc_score(y_test,random_forest.predict_proba(X_test)[:, 1]),3)
```

```
    0.825
```

From the confusion matrix and the classification report, the model is capturing almost all of the employees who are not in the attrition category (attrition = 0), but failing to capture most of the employees who are (12 out of 70 or 17%).

The area under the curve - receiver operating characteristic (AUC-ROC) is the standard that the model is being measured by, with a **0.825 AUC-ROC** exceeding our model accuracy goal. A 0.5 AUC-ROC is equivalent to random guessing.

The model could be improved by increasing the recall rate of employees who are in the attrition category (attrition = 1).

Balanced Random Forest Model

A random forest model can also be generated with a classification weighting of the two prediction classes to attempt to counteract the class imbalance in the training data, this is called a balanced random forest.

A balanced random forest model is generated and predictions are made:

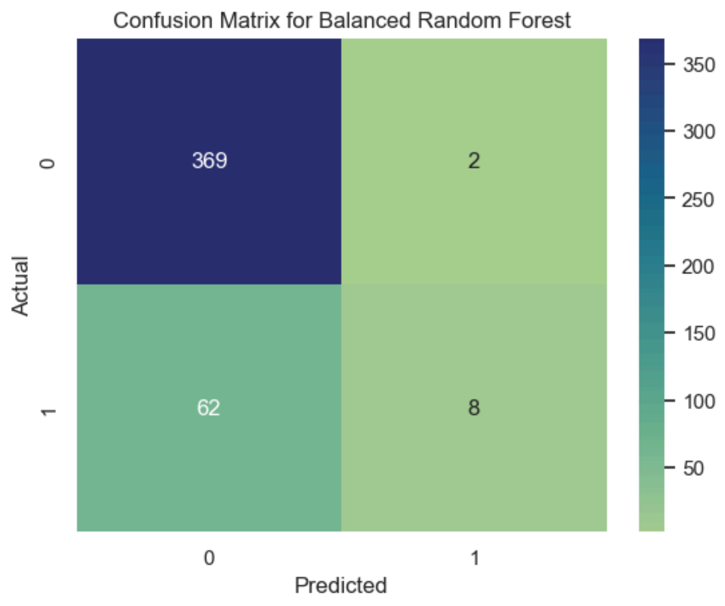
```
balanced_random_forest = RandomForestClassifier(class_weight='balanced',random_state=36)
balanced_random_forest.fit(X_train,y_train)
balanced_predict = balanced_random_forest.predict(X_test)
```

The predictive power of this balanced random forest model can now be evaluated, again using a confusion matrix, classification report, and a AUC-ROC score:

```
sns.heatmap(confusion_matrix(y_test, balanced_predict),annot=True,cmap='crest',fmt='g')
plt.title('Confusion Matrix for Balanced Random Forest')
plt.xlabel('Predicted')

plt.ylabel('Actual')
```

```
    Text(47.25, 0.5, 'Actual')
```



```
print(classification_report(y_test,balanced_predict))
```

```
              precision    recall  f1-score   support

           0       0.86      0.99      0.92       371
           1       0.80      0.11      0.20        70

    accuracy                           0.85       441
   macro avg       0.83      0.55      0.56       441
weighted avg       0.85      0.85      0.81       441
```

```
np.round(roc_auc_score(y_test,balanced_random_forest.predict_proba(X_test)[:, 1]),3)
```

```
    0.79
```

Unfortunately using a balanced random forest lowered the recall of the positive attrition class, which was an unexpected and undesirable result.

The balanced random forest algorithm resulted in a lower **ROC-AUC score of 0.79**, with no improvement to the generated model.

Grid Search for Hyper Parameters

To optimize the hyper parameters of the random forest algorithm, we can run a grid search of multiple input values and compare the results. This evaluates all possible combinations of the possible parameters and then creates a model using the best ones found.

First, the 'grid' of different parameters to be tested is created:

```
from sklearn.model_selection import GridSearchCV
parameter_grid = {'max_features' : ['sqrt','log2',0.3],'n_estimators' : [10,100,1000],'class_weight' : [{0:1,1:1},{0:1,1:10},{0:1,1:100
```

Evaluate all possible combinations of the possible parameters and generate a model with the best parameters:

Note: Executing the grid search may take a substantial amount of time, depending on available processing capacity.

```
grid_search = GridSearchCV(RandomForestClassifier(), parameter_grid, n_jobs=-1, refit=True, verbose=0, scoring='roc_auc',)
grid_search.fit(X_train,y_train)
```

```
    GridSearchCV(estimator=RandomForestClassifier(), n_jobs=-1,
                 param_grid={'class_weight': [{0: 1, 1: 1}, {0: 1, 1: 10},
                                              {0: 1, 1: 100}, {0: 10, 1: 1}],
                             'max_depth': [8, 16, 32, None],
                             'max_features': ['sqrt', 'log2', 0.3],
                             'n_estimators': [10, 100, 1000],
                             'random_state': [36]},
                 scoring='roc_auc')
```

After comparing all 144 candidate models the following hyper parameters are deemed to result in the best AUC-ROC score:

```
print(grid_search.best_params_)
```

```
    {'class_weight': {0: 1, 1: 1}, 'max_depth': 8, 'max_features': 'log2', 'n_estimators': 1000, 'random_state': 36}
```

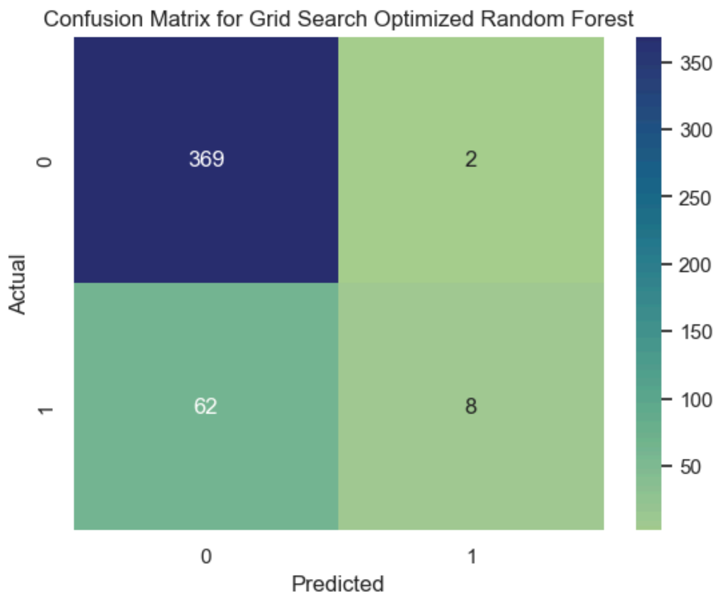
Predictions are made by the model created with these selected parameters.

The results of these predictions are evaluated using a confusion matrix, classification report, and a AUC-ROC score:

```
grid_search_predict = grid_search.predict(X_test)
```

```
sns.heatmap(confusion_matrix(y_test, grid_search_predict),annot=True,cmap='crest',fmt='g')
plt.title('Confusion Matrix for Grid Search Optimized Random Forest')
plt.xlabel('Predicted')
plt.ylabel('Actual')
```

```
    Text(47.25, 0.5, 'Actual')
```



```
print(classification_report(y_test,grid_search_predict))
```

```
              precision    recall  f1-score   support

           0       0.86      0.99      0.92       371
           1       0.80      0.11      0.20        70

    accuracy                           0.85       441
```

```
   macro avg       0.83      0.55      0.56       441
weighted avg       0.85      0.85      0.81       441
```

```
np.round(roc_auc_score(y_test,grid_search.predict_proba(X_test)[:, 1]),3)
```

```
0.817
```

This model has a **ROC-AUC score of 0.817**, meaning no improvement over the default hyperparameters. The grid search could not optimize the default random forest classifier futher. As a result, the default random forest classifier will be used as the predictive model.

Application

Feature Importance

One goal of the project is to identify which variables from the data set offer the most predictive power for employee attrition.

The list below is the top 10 most importance features to the predictive model:

```
feature_importance = pd.DataFrame(np.round(random_forest.feature_importances_,3),employee_data_final.columns[1:],columns=['Importance'])
feature_importance.sort_values('Importance',ascending=False)[:10]
```

	Importance
MonthlyIncome	0.089
MonthlyRate	0.061
DailyRate	0.055
TotalWorkingYears	0.052
DistanceFromHome	0.051
HourlyRate	0.050
OverTime	0.047
YearsAtCompany	0.043
PercentSalaryHike	0.040
StockOptionLevel	0.037

It appears that the employee **monthly income** variable is most significant to employee attrition, but not significantly so. As a result, employee attrition is best explained using a **combination of many factors**.

Predictive Model Interactive Application

An interactive application is provided to allow user input of any combination of values to generate a prediction of employee attrition using the created model.

Imports for the GUI elements:

```
import ipywidgets as widgets
from IPython.display import display
```

A method that accepts input from the GUI, formats it for use in the model, then generates a prediction and displays the result:

```
def predict_attrition(button):
    attribute_list = [travel_widget.value, daily_rate_widget.value, department_widget.value, distance_widget.value, education_widget.val
    input_data = pd.DataFrame(data=[attribute_list],columns=employee_data.drop(columns=['Attrition']).columns)
    input_data = pd.concat([input_data,employee_data.drop(columns=['Attrition'])])
    input_data = pd.get_dummies(data=input_data,columns=['Department','EducationField','JobRole'],drop_first=True)

    if random_forest.predict(input_data[:1])[0] == 0:
        print('This employee is predicted to stay with the company')
    else:
        print('This employee is predicted to leave the company' )
    return
```

Create the interactive elements:

```
travel_widget = widgets.Dropdown(options={'None': 0, 'Rarely': 1, 'Frequently': 2}, description='Travel:', style=dict(description_width='
daily_rate_widget = widgets.IntSlider(min=100, max=1500, description='Daily rate:', style=dict(description_width='initial'), layout=dict(
distance_widget = widgets.IntSlider(min=1, max=30, description='Distance from home:',style=dict(description_width='initial'), layout=dict
education_widget = widgets.IntSlider(min=1, max=5, description='Level of education:', style=dict(description_width='initial'), layout=dic
environment_widget = widgets.IntSlider(min=1, max=4, description='Work environment satisfaction:', style=dict(description_width='initial'
hourly_widget = widgets.IntSlider(min=30, max=100, description='Employee hourly rate:', style=dict(description_width='initial'), layout=d
involvement_widget = widgets.IntSlider(min=1, max=4, description='Job involvement:', style=dict(description_width='initial'), layout=dict
level_widget = widgets.IntSlider(min=1, max=5, description='Job level:', style=dict(description_width='initial'), layout=dict(width='400p
satisfaction_widget = widgets.IntSlider(min=1, max=4, description='Job satisfaction:', style=dict(description_width='initial'), layout=di
income_widget = widgets.IntSlider(min=1000, max=20000, description='Monthly income:', style=dict(description_width='initial'), layout=dic
monthly_widget = widgets.IntSlider(min=2000, max=27000, description='Employee monthly rate:', style=dict(description_width='initial'), la
companies_widget = widgets.IntSlider(min=0, max=10, description='Total companies worked:', style=dict(description_width='initial'), layou
overtime_widget = widgets.Dropdown(options={'No': 0, 'Yes': 1},description='Works overtime:', style=dict(description_width='initial'), la
raise_widget = widgets.IntSlider(min=11, max=25, description='Last raise(percent):', style=dict(description_width='initial'), layout=dict
rating_widget = widgets.IntSlider(min=1, max=4, description='Performance rating:', style=dict(description_width='initial'), layout=dict(w
relationship_widget = widgets.IntSlider(min=1, max=4, description='Relationship satisfaction:', style=dict(description_width='initial'),
stock_widget = widgets.IntSlider(min=0, max=3, description='Stock option level:', style=dict(description_width='initial'), layout=dict(wi
working_widget = widgets.IntSlider(min=0, max=40, description='Total working years:', style=dict(description_width='initial'), layout=dic
training_widget = widgets.IntSlider(min=0, max=6, description='Trainings last year:', style=dict(description_width='initial'), layout=dic
balance_widget = widgets.IntSlider(min=1, max=4, description='Work-life balance:', style=dict(description_width='initial'), layout=dict(w
company_widget = widgets.IntSlider(min=0, max=40, description='Years at company:', style=dict(description_width='initial'), layout=dict(w
role_widget = widgets.IntSlider(min=0, max=18, description='Years in current role:', style=dict(description_width='initial'), layout=dict
promotion_widget = widgets.IntSlider(min=0, max=15, description='Years since promotion:', style=dict(description_width='initial'), layout
manager_widget = widgets.IntSlider(min=0, max=17, description='Years with current manager:', style=dict(description_width='initial'), lay
department_widget = widgets.Dropdown(options=['Sales', 'Research & Development', 'Human Resources'],description='Department:', style=dict
field_widget = widgets.Dropdown(options=['Life Sciences', 'Other', 'Medical', 'Marketing', 'Technical Degree', 'Human Resources'],descrip
title_widget = widgets.Dropdown(options=['Sales Executive', 'Research Scientist', 'Laboratory Technician', 'Manufacturing Director', 'Hea
```