This project features the implementation of an employee turnover analysis that is built using Python's Scikit-Learn library. In this article, I will use Logistic Regression and Random Forest Machine Learning algorithms. At the end of this article, you would be able to choose the best algorithm for your future projects like Employee Turnover Prediction.

What is Employee Turnover?

Employee Turnover or Employee Turnover ratio is the measurement of the total number of employees who leave an organization in a particular year. Employee Turnover Prediction means to predict whether an employee is going to leave the organization in the coming period.

A Company uses this predictive analysis to measure how many employees they will need if the potential employees will leave their organization. A company also uses this predictive analysis to make the workplace better for employees by understanding the core reasons for the high turnover ratio.

Data Preprocessing

Now let's dive into the data to move further with this project on Employee Turnover Prediction.

```
In [9]:
           import pandas as pd
           hr = pd.read csv(r'C:\Users\Soumitra Sinha\Downloads\datasets 9768 13874 HR comma sep.csv')
           col names = hr.columns.tolist()
           print("Column names:")
           print(col_names)
           print("\nSample data:")
           hr.head(15)
          Column names:
          ['satisfaction level', 'last evaluation', 'number project', 'average montly hours', 'time spend company', 'Work a
          ccident', 'left', 'promotion_last_5years', 'sales', 'salary']
          Sample data:
              satisfaction_level last_evaluation
                                              number_project
                                                              average_montly_hours time_spend_company Work_accident
                                                                                                                         left promotion_last_5years
Out[9]:
           0
                          0.38
                                         0.53
                                                           2
                                                                                157
                                                                                                       3
                                                                                                                      0
                                                                                                                                                 0
                          0.80
                                                           5
                                                                                262
                                                                                                       6
                                                                                                                      0
                                                                                                                                                 0
                                         0.86
           2
                                                           7
                                                                               272
                                                                                                       4
                                                                                                                      0
                                                                                                                                                 0
                         0.11
                                         0.88
                                                           5
           3
                          0.72
                                         0.87
                                                                                223
                                                                                                       5
                                                                                                                      0
                                                                                                                                                 0
                                                           2
                                                                                                       3
                                                                                                                      0
           4
                          0.37
                                         0.52
                                                                                159
                                                                                                                           1
                                                                                                                                                 0
                                                           2
                                                                                                       3
           5
                         0.41
                                         0.50
                                                                                153
                                                                                                                      0
                                                                                                                                                 0
                                                           6
           6
                          0.10
                                         0.77
                                                                                247
                                                                                                       4
                                                                                                                      0
                                                                                                                           1
                                                                                                                                                 0
                                                           5
                          0.92
                                         0.85
                                                                                259
                                                                                                       5
                                                                                                                      0
                                                                                                                                                 0
           8
                         0.89
                                                           5
                                                                                224
                                                                                                       5
                                                                                                                      0
                                                                                                                                                 0
                                         1.00
                                                           2
           9
                          0.42
                                         0.53
                                                                                142
                                                                                                       3
                                                                                                                      0
                                                                                                                                                 0
                                                           2
                                                                                                       3
          10
                          0.45
                                         0.54
                                                                                135
                                                                                                                      0
                                                                                                                                                 0
                                                           6
                                                                                305
                                                                                                                                                 0
                                         0.81
                                                                                                       4
                                                                                                                      0
          11
                         0.11
          12
                          0.84
                                         0.92
                                                           4
                                                                                234
                                                                                                       5
                                                                                                                      n
                                                                                                                           1
                                                                                                                                                 n
                                                           2
                                                                                                       3
          13
                          0.41
                                         0.55
                                                                                148
                                                                                                                      0
                          0.36
                                         0.56
                                                           2
                                                                                137
                                                                                                       3
                                                                                                                      0
          14
```

Renaming column name from "sales" to "department"

```
In [13]:
            hr=hr.rename(columns = {'sales':'department'})
In [14]:
                  satisfaction level last evaluation
                                                    number_project average_montly_hours
                                                                                          time_spend_company
                                                                                                                Work accident
                                                                                                                                left
                                                                                                                                    promotion_last_5yea
Out[14]:
                0
                              0.38
                                              0.53
                                                                 2
                                                                                     157
                                                                                                             3
                                                                                                                             0
                                                                 5
                                                                                                             6
                                                                                                                             0
                              0.80
                                              0.86
                                                                                     262
                2
                              0.11
                                              0.88
                                                                 7
                                                                                     272
                                                                                                                             0
```

4							
7	0.37	0.52	2	159	3	0 1	
14994	0.40	0.57	2	151	3	0 1	
14995	0.37	0.48	2	160	3	0 1	
14996	0.37	0.53	2	143	3	0 1	
14997	0.11	0.96	6	280	4	0 1	
14998	0.37	0.52	2	158	3	0 1	
14999 rows × 1	0 columns						
4							

```
In [15]: hr.shape
Out[15]: (14999, 10)
```

The "left" column is the outcome variable recording one and 0. 1 for employees who left the company and 0 for those who didn't.

The department column of the dataset has many categories, and we need to reduce the categories for better modelling. Let's see all the categories of the department column:

Let's add all the "technical", "support" and "IT" columns into one column to make our analysis easier.

```
import numpy as np
hr['department']=np.where(hr['department'] =='support', 'technical', hr['department'])
hr['department']=np.where(hr['department'] =='IT', 'technical', hr['department'])
```

Creating Variables for Categorical Variables

As there are two categorical variables (department, salary) in the dataset and they need to be converted to dummy variables before they can be used for modelling.

```
cat_vars=['department','salary']
for var in cat_vars:
    cat_list='var'+'_'+var
    cat_list = pd.get_dummies(hr[var], prefix=var)
    hrl=hr.join(cat_list)
    hr=hr1
```

Now the actual variables need to be removed after the dummy variable have been created. Column names after creating dummy variables for categorical variables:

The outcome variable is "left", and all the other variables are predictors.

```
In [21]: hr_vars=hr.columns.values.tolist()
    y=['left']
    X=[i for i in hr_vars if i not in y]
```

Feature Selection for Employee Turnover Prediction

Let's use the feature selection method to decide which variables are the best option that can predict employee turnover with great accuracy. There are a total of 18 columns in X, and now let's see how we can select about 10 from them:

```
In [22]:
          from sklearn.feature selection import RFE
          from sklearn.linear_model import LogisticRegression
          model = LogisticRegression()
          rfe = RFE(model, 10)
          rfe = rfe.fit(hr[X], hr[y])
          print(rfe.support_)
          print(rfe.ranking )
         D:\anaconda\lib\site-packages\sklearn\utils\validation.py:70: FutureWarning: Pass n features to select=10 as keyw
         ord args. From version 1.0 (renaming of 0.25) passing these as positional arguments will result in an error
           warnings.warn(f"Pass {args_msg} as keyword args. From version '
         D:\anaconda\lib\site-packages\sklearn\utils\validation.py:63: DataConversionWarning: A column-vector y was passed
         when a 1d array was expected. Please change the shape of y to (n_samples, ), for example using ravel().
           return f(*args, **kwargs)
         D:\anaconda\lib\site-packages\sklearn\linear model\ logistic.py:763: ConvergenceWarning: lbfgs failed to converge
         (status=1):
         STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
         Increase the number of iterations (max_iter) or scale the data as shown in:
             https://scikit-learn.org/stable/modules/preprocessing.html
         Please also refer to the documentation for alternative solver options:
             https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
           n iter i = check optimize result(
         D:\anaconda\lib\site-packages\sklearn\utils\validation.py:63: DataConversionWarning: A column-vector y was passed
         when a 1d array was expected. Please change the shape of y to (n_samples, ), for example using ravel().
           return f(*args, **kwargs)
         D:\anaconda\lib\site-packages\sklearn\utils\validation.py:63: DataConversionWarning: A column-vector y was passed
         when a 1d array was expected. Please change the shape of y to (n_samples, ), for example using ravel().
           return f(*args, **kwargs)
         D:\anaconda\lib\site-packages\sklearn\utils\validation.py:63: DataConversionWarning: A column-vector y was passed
         when a 1d array was expected. Please change the shape of y to (n samples, ), for example using ravel().
           return f(*args, **kwargs)
         D:\anaconda\lib\site-packages\sklearn\utils\validation.py:63: DataConversionWarning: A column-vector y was passed
         when a 1d array was expected. Please change the shape of y to (n_samples, ), for example using ravel().
           return f(*args, **kwargs)
         D:\anaconda\lib\site-packages\sklearn\utils\validation.py:63: DataConversionWarning: A column-vector y was passed
         when a 1d array was expected. Please change the shape of y to (n samples, ), for example using ravel().
           return f(*args, **kwargs)
         [ True True False False True True True True False True True False False False True True False]
         [1 1 3 9 1 1 1 1 5 1 1 6 8 7 4 1 1 2]
         D:\anaconda\lib\site-packages\sklearn\utils\validation.py:63: DataConversionWarning: A column-vector y was passed
         when a 1d array was expected. Please change the shape of y to (n samples, ), for example using ravel().
           return f(*args, **kwargs)
         D:\anaconda\lib\site-packages\sklearn\utils\validation.py:63: DataConversionWarning: A column-vector y was passed
         when a 1d array was expected. Please change the shape of y to (n_samples, ), for example using ravel().
           return f(*args, **kwargs)
         D:\anaconda\lib\site-packages\sklearn\utils\validation.py:63: DataConversionWarning: A column-vector y was passed
         when a 1d array was expected. Please change the shape of y to (n samples, ), for example using ravel().
         return f(*args, **kwargs)
```

We can see that or feature selection chose the 10 variables for us, which are marked True in the support_array and marked with a choice "1" in the ranking_array. Now lets have a look at these columns:

Logistic Regression Model to Predict Employee Turnover

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=0)
from sklearn.linear_model import LogisticRegression
from sklearn import metrics
logreg = LogisticRegression()
logreg.fit(X_train, y_train)
```

LogisticRegression()

Let's check the accuracy of our logistic regression model.

```
In [32]:
          from sklearn.metrics import accuracy score
          print('Logistic regression accuracy: {:.3f}'.format(accuracy_score(y_test, logreg.predict(X_test))))
```

Logistic regression accuracy: 0.771

Random Forest Classification Model

```
In [33]:
          from sklearn.ensemble import RandomForestClassifier
          rf = RandomForestClassifier()
          rf.fit(X train, y train)
         RandomForestClassifier()
```

Now let's check the accuracy of our Random Forest Classification Model:

```
In [34]:
          print('Random Forest Accuracy: {:.3f}'.format(accuracy_score(y_test, rf.predict(X_test))))
```

Random Forest Accuracy: 0.978

Confusion Matrix for our Machine Learning Models

Now lets construct a confusion matrix to visualize predictions made by our classifier and evaluate the accuracy of our machine learning classification.

Random Forest

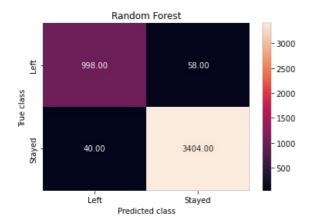
```
In [35]:
          from sklearn.metrics import classification_report
          print(classification_report(y_test, rf.predict(X_test)))
```

	precision	recall	f1-score	support
0 1	0.99 0.95	0.98 0.96	0.99 0.95	3462 1038
accuracy macro avg	0.97	0.97	0.98 0.97	4500 4500
weighted avg	0.98	0.98	0.98	4500

```
In [37]:
          import matplotlib.pyplot as plt
          y_pred = rf.predict(X_test)
          from sklearn.metrics import confusion matrix
          import seaborn as sns
          forest\_cm = metrics.confusion\_matrix(y\_pred, y\_test, [1,0])
          sns.heatmap(forest_cm, annot=True, fmt='.2f',xticklabels = ["Left", "Stayed"] , yticklabels = ["Left", "Stayed"]
          plt.ylabel('True class')
          plt.xlabel('Predicted class')
          plt.title('Random Forest')
```

D:\anaconda\lib\site-packages\sklearn\utils\validation.py:70: FutureWarning: Pass labels=[1, 0] as keyword args. From version 1.0 (renaming of 0.25) passing these as positional arguments will result in an error warnings.warn(f"Pass {args_msg} as keyword args. From version " Text(0.5, 1.0, 'Random Forest')

Out[371:



Logistic Regression

```
In [38]:
          print(classification_report(y_test, logreg.predict(X_test)))
                                      recall f1-score
                        precision
                                                          support
                     0
                             0.81
                                        0.92
                                                  0.86
                                                             3462
                             0.51
                                        0.26
                                                  0.35
                                                             1038
                                                  0.77
                                                             4500
             accuracy
            macro avg
                             0.66
                                        0.59
                                                  0.60
                                                             4500
                             0.74
                                        0.77
                                                  0.74
                                                             4500
         weighted avg
```

```
In [39]:
    logreg_y_pred = logreg.predict(X_test)
    logreg_cm = metrics.confusion_matrix(logreg_y_pred, y_test, [1,0])
    sns.heatmap(logreg_cm, annot=True, fmt='.2f',xticklabels = ["Left", "Stayed"] , yticklabels = ["Left", "Stayed"]
    plt.ylabel('True class')
    plt.xlabel('Predicted class')
    plt.title('Logistic Regression')

D:\anaconda\lib\site-packages\sklearn\utils\validation.py:70: FutureWarning: Pass labels=[1, 0] as keyword args.
From version 1.0 (renaming of 0.25) passing these as positional arguments will result in an error
    warnings.warn(f"Pass {args_msg} as keyword args. From version "
```

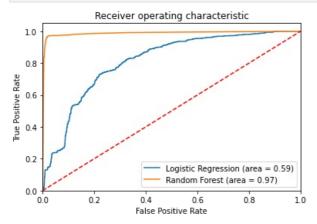
Out[39]: Text(0.5, 1.0, 'Logistic Regression')



Employee Turnover Prediction Curve

```
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve
logit_roc_auc = roc_auc_score(y_test, logreg.predict(X_test))
fpr, tpr, thresholds = roc_curve(y_test, logreg.predict_proba(X_test)[:,1])
```

```
rf_roc_auc = roc_auc_score(y_test, rf.predict(X_test))
rf_fpr, rf_tpr, rf_thresholds = roc_curve(y_test, rf.predict_proba(X_test)[:,1])
plt.figure()
plt.plot(fpr, tpr, label='Logistic Regression (area = %0.2f)' % logit_roc_auc)
plt.plot(rf_fpr, rf_tpr, label='Random Forest (area = %0.2f)' % rf_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.show()
```



The receiver operating characteristic (ROC) curve is a standard tool used with binary classifiers. The red dotted line represents the ROC curve of a purely random classifier; a good classifier stays as far away from that line as possible (toward the top-left corner).

So, as we can see that the Random Forest Model has proven to be more useful in the prediction of employee turnover, now let's have a look at the feature importance of our random forest classification model.

```
feature_labels = np.array(['satisfaction_level', 'last_evaluation', 'time_spend_company', 'Work_accident', 'promotion_last_5years-0.25%
    department_management-0.25%
    promotion_last_5years-0.25%
    department_hr-0.30%
    department_hr-0.30%
    salary_high-0.73%
    salary_low-1.20%
    Work_accident-1.52%
    last_evaluation-18.59%
    time_spend_company-26.49%
    satisfaction_level-50.38%
```

According to our Random Forest classification model, the above aspects show the most important features which will influence whether an employee will leave the company, in ascending order.