salifort-motors-study-case-lab

July 12, 2024

1 Salifort Motors Study Case: Providing data-driven suggestions for HR

PACE stages

- Plan
- Analyze
- Construct
- Execute

2 Pace: Plan Stage

- Understand data in the problem context
- Consider how data will best address the business need
- Contextualize & understand the data and the problem

2.0.1 HR dataset familiarization

15,000 rows and 10 columns for the variables listed below.

Variable	Description
satisfaction_level	Employee-reported job satisfaction level [0–1]
last_evaluation	Score of employee's last performance review [0–1]
number_project	Number of projects employee contributes to
average_monthly_hours	Average number of hours employee worked per month
time_spend_company	How long the employee has been with the company (years)
Work_accident	Whether or not the employee experienced an accident while at work
left	Whether or not the employee left the company

Variable	Description
promotion_last_5years	Whether or not the employee was promoted in the last 5 years
Department	The employee's department
salary	The employee's salary (U.S. dollars)

2.1 Step 1. Imports

- Import packages
- Load dataset

2.1.1 Import packages

[20]:
```
import numpy as np # This library is used for working with arrays and matrices
import pandas as pd # This library is used for data manipulation and analysis

import matplotlib.pyplot as plt # This library is used for creating␣
↪visualizations
import seaborn as sns # This library is used for creating visualizations

from sklearn.tree import DecisionTreeClassifier # This library is used for␣
↪creating a Decision Tree Classifier
from sklearn.ensemble import RandomForestClassifier # This library is used for␣
↪creating a Random Forest Classifier

from sklearn.model_selection import GridSearchCV, train_test_split # This␣
↪library is used for splitting the data into training and testing sets
from sklearn.metrics import accuracy_score, precision_score, recall_score,\
f1_score, confusion_matrix, ConfusionMatrixDisplay, classification_report #␣
↪This library is used for evaluating the model
from sklearn.metrics import roc_auc_score, roc_curve # This library is used for␣
↪evaluating the model
from sklearn.tree import plot_tree # This library is used for plotting the␣
↪Decision Tree

import pickle # This library is used for saving the model
```

2.1.2 Load dataset

Pandas is used to read a dataset called **HR_capstone_dataset.csv.**

[ ]:
```
df0 = pd.read_csv("HR_capstone_dataset.csv") # Load the dataset


df0.head() # Display the first 5 rows of the dataset
```

2.2 Step 2. Data Exploration (Initial EDA and data cleaning)

- Variables Familiarization
- Cleanning the dataset (missing data, redundant data, outliers)

2.2.1 Gather basic information about the data

[ ]:
```
df0.info() # Display the information about the dataset
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14999 entries, 0 to 14998
Data columns (total 10 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   satisfaction_level     14999 non-null  float64
 1   last_evaluation        14999 non-null  float64
 2   number_project         14999 non-null  int64
 3   average_montly_hours   14999 non-null  int64
 4   time_spend_company     14999 non-null  int64
 5   Work_accident          14999 non-null  int64
 6   left                   14999 non-null  int64
 7   promotion_last_5years  14999 non-null  int64
 8   Department             14999 non-null  object
 9   salary                 14999 non-null  object
dtypes: float64(2), int64(6), object(2)
memory usage: 1.1+ MB
```

2.2.2 Gather descriptive statistics about the data

[ ]:
```
df0.describe() #    Display the summary statistics of the dataset
```

[ ]:
```
       satisfaction_level  last_evaluation  number_project  \
count        14999.000000     14999.000000    14999.000000
mean             0.612834         0.716102        3.803054
std              0.248631         0.171169        1.232592
min              0.090000         0.360000        2.000000
25%              0.440000         0.560000        3.000000
50%              0.640000         0.720000        4.000000
75%              0.820000         0.870000        5.000000
max              1.000000         1.000000        7.000000

       average_montly_hours  time_spend_company  Work_accident          left  \
count          14999.000000        14999.000000   14999.000000  14999.000000
mean             201.050337            3.498233       0.144610      0.238083
std               49.943099            1.460136       0.351719      0.425924
min               96.000000            2.000000       0.000000      0.000000
25%              156.000000            3.000000       0.000000      0.000000
50%              200.000000            3.000000       0.000000      0.000000
```

```
75%           245.000000           4.000000       0.000000       0.000000
max           310.000000          10.000000       1.000000       1.000000

       promotion_last_5years
count           14999.000000
mean                0.021268
std                 0.144281
min                 0.000000
25%                 0.000000
50%                 0.000000
75%                 0.000000
max                 1.000000
```

2.2.3 Rename columns

As a data cleaning step, rename the columns as needed. Standardize the column names so that they are all in `snake_case`, correct any column names that are misspelled, and make column names more concise as needed.

[ ]:
```
# First, let's check the variables from the dataset that are contained as␣
↪columns
df0.columns
```

[ ]:
```
Index(['satisfaction_level', 'last_evaluation', 'number_project',
       'average_montly_hours', 'time_spend_company', 'Work_accident', 'left',
       'promotion_last_5years', 'Department', 'salary'],
      dtype='object')
```

[ ]:
```
# Fix column names
df0 = df0.rename(columns={'Work_accident': 'work_accident',
                          'average_montly_hours': 'average_monthly_hours',
                          'time_spend_company': 'tenure',
                          'Department': 'department'})
df0.columns # Check the column names
```

[ ]:
```
Index(['satisfaction_level', 'last_evaluation', 'number_project',
       'average_monthly_hours', 'tenure', 'work_accident', 'left',
       'promotion_last_5years', 'department', 'salary'],
      dtype='object')
```

2.2.4 Check missing values

Check for any missing values in the data.

[ ]:
```
df0.isna().sum() # no missing values
```

```
[ ]: satisfaction_level       0
     last_evaluation          0
     number_project           0
     average_monthly_hours    0
     tenure                   0
     work_accident            0
     left                     0
     promotion_last_5years    0
     department               0
     salary                   0
     dtype: int64
```

2.2.5 Check duplicates

Check for any duplicate entries in the data.

```
[ ]: df0.duplicated().sum() # no duplicated rows
```

```
[ ]: 3008
```

```
[ ]: df0[df0.duplicated()].head() # Display the duplicated rows
```

```
[ ]:       satisfaction_level  last_evaluation  number_project  \
     396                 0.46             0.57               2
     866                 0.41             0.46               2
     1317                0.37             0.51               2
     1368                0.41             0.52               2
     1461                0.42             0.53               2

           average_monthly_hours  tenure  work_accident  left  \
     396                     139       3              0     1
     866                     128       3              0     1
     1317                    127       3              0     1
     1368                    132       3              0     1
     1461                    142       3              0     1

           promotion_last_5years  department  salary
     396                       0       sales     low
     866                       0  accounting     low
     1317                      0       sales  medium
     1368                      0       RandD     low
     1461                      0       sales     low
```

```
[ ]: df1 = df0.drop_duplicates(keep='first') # Drop the duplicated rows

     df1.head() # Display the first 5 rows of the dataset
```

[ ]:
```
   satisfaction_level  last_evaluation  number_project  average_monthly_hours  \
0                0.38             0.53               2                    157
1                0.80             0.86               5                    262
2                0.11             0.88               7                    272
3                0.72             0.87               5                    223
4                0.37             0.52               2                    159

   tenure  work_accident  left  promotion_last_5years department  salary
0       3              0     1                      0      sales     low
1       6              0     1                      0      sales  medium
2       4              0     1                      0      sales  medium
3       5              0     1                      0      sales     low
4       3              0     1                      0      sales     low
```

pAce: Analyze Stage - Perform EDA (analyze relationships between variables)

Important Insights

- Data Distribution

  The variables are normally distributed. However, there are some outliers that can negatively affect the model's metrics.

- Data transformations and decisions

  I changed the name of the variables, so all of them follow the same structure. Additionally, it was necessary to eliminate null and duplicated values.

- EDA purpose before model construction

  The main purpose is to develop a complete analysis of the data and prepare it for the model by data cleaning.

- Resources

  Analysis functions such as get_dummies() and packages from visualization libraries to clean disfunctional data.

2.3 Step 2. Data Exploration (Continue EDA)

2.3.1 Data visualizations

Now, start examining the variables and create plots to visualize relationships between variables in the data.

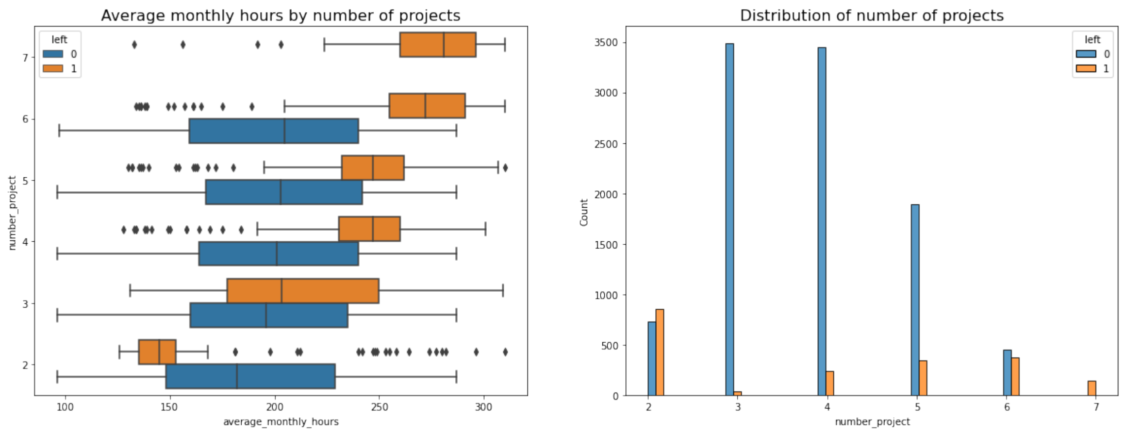
[ ]:
```python
fig, ax = plt.subplots(1,2, figsize = (20,7))

#Boxplot to check distributions of work per number of projects

sns.boxplot(data=df1,x='average_monthly_hours',y='number_project', hue='left',
 ↪orient='h', ax=ax[0])
ax[0].invert_yaxis()
ax[0].set_title('Average monthly hours by number of projects', fontsize=16)
```

```
# Distribution of number of projects among employees who stayed or deserted
stay= df1[df1['left']==0]['number_project']
left= df1[df1['left']==1]['number_project']
sns.histplot(data=df1, x='number_project', hue='left', multiple='dodge', ax=ax[1])
ax[1].set_title('Distribution of number of projects', fontsize=16)

plt.show()
```



The boxplots show the following patterns: 1. Every employee who worked on 7 projects left the company. 2. There is a significant difference between those who stayed or left: When the number of projects increased, those employees who stayed maintained a constant number of hours worked. On the other hand, those who left worked more hours as the number of projects increased. 3. Employees who worked significatively less time than those employees who stayed finally left. 4. The optimal median of worked hours per month is approximately 190-200 hours.

The histogram shows that:

The optimal number of projects per worker are between 3 and 4. While the worsts are 2, 6 and 7.

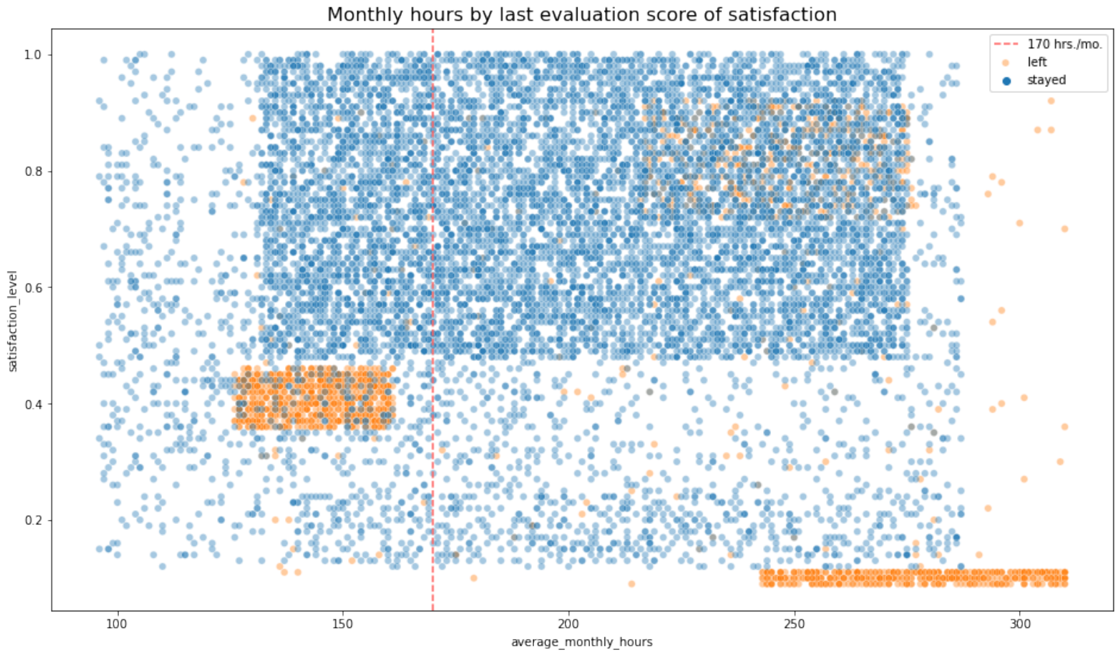
There is a huge difference between the employees who worked on 2 projects compared to those who worked on 3 projects.

[ ]:
```
plt.figure(figsize=(16,9))
sns.scatterplot(data=df1, x='average_monthly_hours', y='satisfaction_level', hue='left', alpha=0.4)

#line to determine the average number of worked hours with an shedule of 8 hours per day
plt.axvline(x=170, color='#ff6361', label='170 hrs./mo.', ls='--')

plt.legend(labels=['170 hrs./mo.', 'left', 'stayed'])
plt.title('Monthly hours by last evaluation score of satisfaction',fontsize=16)
```

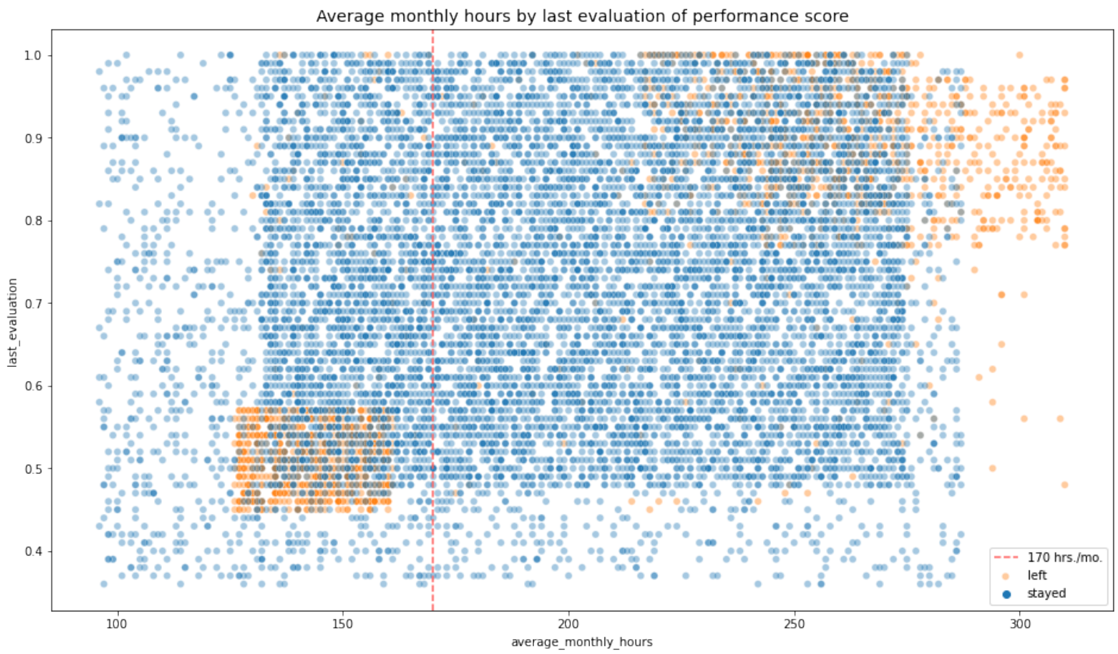
[ ]: Text(0.5, 1.0, 'Monthly hours by last evaluation score of satisfaction')



The plot shows that people who left the company where divided into 3 clusters. 1. People who worked less than the average worked hours and had a satisfaction of 0.4. This satisfaction can be caused by a pressure from directives or maybe lower salaries due to they schedule. 2. People who worked more than 240 hours and showed a minimum satisfaction. This can be due to a overworkload. 3. Satisfied people who worked between 230-270 hours and were satisfied (0.8). This cluster of people is very strange because of their good performance and good satisfaction.

Furthermore, most of the workers who stayed where in a cluster with a satisfaction level of 0.5 or higher and had an average number of hours worked.

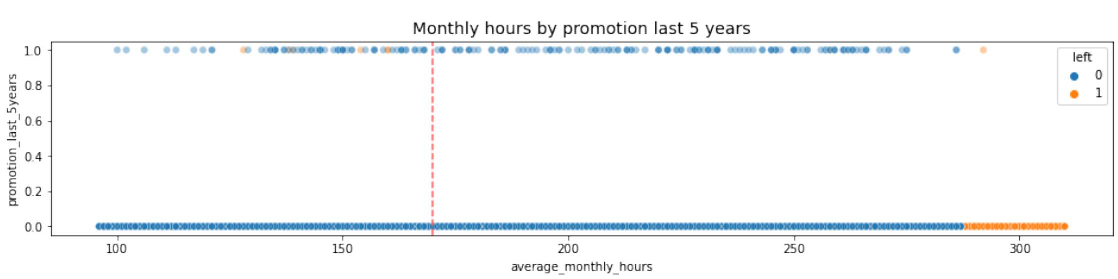
[ ]:
```
plt.figure(figsize=(16, 9))
sns.scatterplot(data=df1, x='average_monthly_hours', y='last_evaluation',␣
  ↪hue='left', alpha=0.4)
plt.axvline(x=170, color='#ff6361', label='170 hrs./mo.', ls='--')
plt.legend(labels=['170 hrs./mo.', 'left', 'stayed'])
plt.title('Average monthly hours by last evaluation of performance score',␣
  ↪fontsize='14');
```



Those who left the company where divided into 2 clusters: 1. Employees who worked less time than the normal and had a bad score (lower than 0.6). This can be due to the fact that they could be fired because of their low performance by level and worked hours. 2. Employees who worked more than 230 hours and scores very well (higher than 0.8). In part this group would be composed of 2 subgroups: those who left the company because overwork (this can be correlated to a lower satisfaction level like the cluster of the last graph), and another group of people who worked more than the normal and had a higher performance (this group can be related to the rare cluster of the last graph, which was characterized also by higher satisfaction levels).

Now it's time to see whether employees who worked more where promoted during the last 5 years.

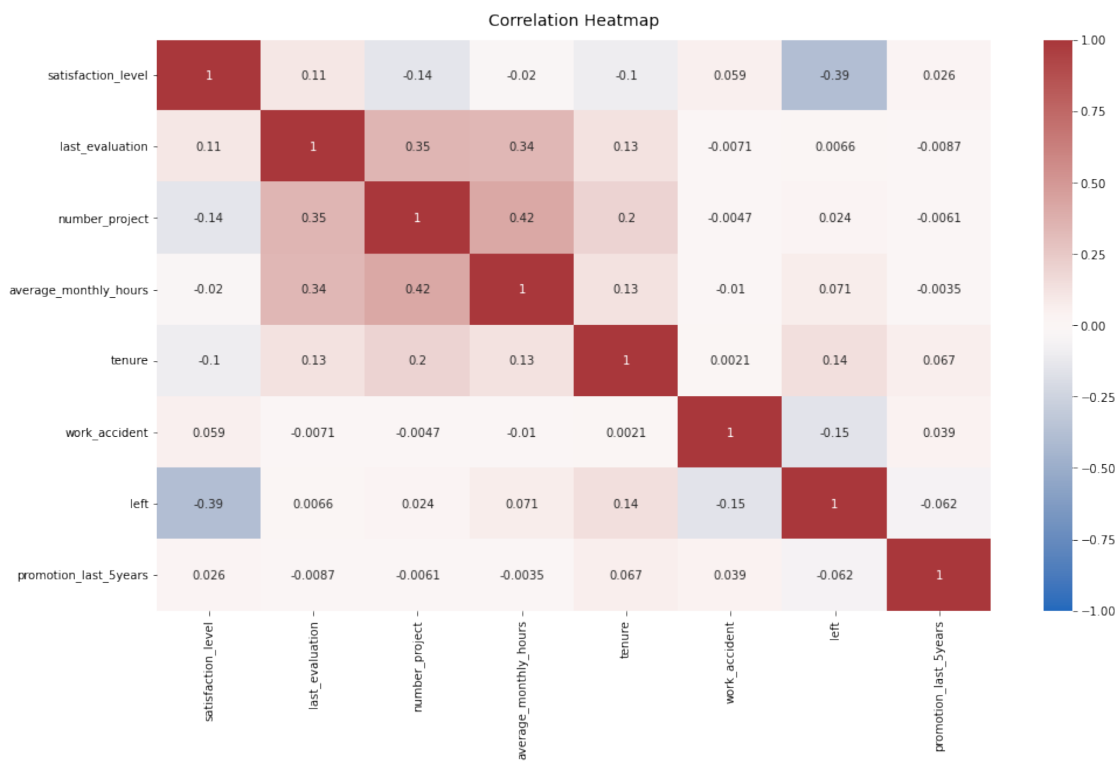
```
[ ]: plt.figure(figsize=(16, 3))
     sns.scatterplot(data=df1, x='average_monthly_hours', y='promotion_last_5years',␣
      ↪hue='left', alpha=0.4)
     plt.axvline(x=170, color='#ff6361', ls='--')
     plt.title('Monthly hours by promotion last 5 years', fontsize='14');
```



Here is an interesting feature. The graph shows that those who worked more than approx. 280 hours per month were not promoted, which is an strong factor that could explan the disatisfaction of the cluster with more hours worked. This is important to evaluate because it is necessary to understand why they were not promoted, and the most important fact, those who worked more showed a higher performance, which means that their overwork does not mean a lack of proactive work. This is very important to evaluate because this can be a key factor.

Next, it is important to evaluate the correlation between variables.

```
[ ]: plt.figure(figsize=(16, 9))
     heatmap = sns.heatmap(df0.corr(), vmin=-1, vmax=1, annot=True, cmap=sns.
      ↪color_palette("vlag", as_cmap=True))
     heatmap.set_title('Correlation Heatmap', fontdict={'fontsize':14}, pad=12);
```



2.3.2 Insights

1. Every employee who worked on 7 projects left the company.
2. There is a significant difference between those who stayed or left: When the number of projects increased, those employees who stayed maintained a constant number of hours worked. On the other hand, those who left worked more hours as the number of projects increased.
3. Employees who worked significatively less time than those who stayed finally left.
4. The optimal median of worked hours per month is approximately 190-200 hours.
5. The optimal number of projects per worker are between 3 and 4. While the worst are 2, 6 and 7.

6. There is a huge difference between the employees who worked on 2 projects compared to those who worked on 3 projects.
7. People who left the company were divided into 3 clusters. People who worked less than the average worked hours and had a satisfaction of 0.4.

This satisfaction can be caused by a pressure from directives or maybe lower salaries due to their schedule.

People who worked more than 240 hours and showed a minimum satisfaction. This can be due to an overworkload.

Satisfied people who worked between 230-270 hours and were satisfied (0.8). This cluster of people is very strange because of their good performance and good satisfaction. 8. Those who left the company where divided into 2 clusters:

Employees who worked less time than the normal and had a bad score (lower than 0.6). This can be due to the fact that they could be fired because of their low performance by level and worked hours.

Employees who worked more than 230 hours and scored very well (higher than 0.8). In part this group would be composed of 2 subgroups: those who left the company because overwork (this can be correlated to a lower satisfaction level like the cluster of the last graph), and another group of people who worked more than the normal and had a higher performance (this group can be related to the rare cluster of the last graph, which was characterized also by higher satisfaction levels). 9. Those who worked more than approx. 280 hours per month were not promoted, which is a strong factor that could explain the low satisfaction of the cluster with more hours worked. This is important to evaluate because it is necessary to understand why they were not promoted, and the most important fact, those who worked more showed a higher performance, which means that their overwork does not mean a lack of proactive work. This is very important to evaluate because this can be a key factor.

paCe: Construct Stage - Model determination - Construct the model - Confirm model assumptions - Evaluate model results to determine how well the model fits the data

Key insights

- Odd findings

There is a group of employees who had good metrics (including satisfaction) and left the company.

- Model independent variables

All variables except satisfaction level because of its huge importance in the model but subjectivity.

- Model Performance

Perfectly, it has pretty good metrics and a significant recall score. However, it might be prone to overfitting.

- Important resources to recall

Principally packages related to decision trees of Sklearn.

- Ethical considerations

It seems that the principal reason for leaving the company is overworking. So the company can be defficient at the moment of showing the basis of their contracts.

2.4 Step 3. Model Building, Step 4. Results and Evaluation

- Fit a model that predicts the outcome variable using two or more independent variables
- Check model assumptions
- Evaluate the model

2.4.1 Identify the type of prediction task.

Predict if an employee will leave the company based on their current position.

2.4.2 Identify the types of models most appropriate for this task.

The best type of model for this case will be a decision tree accompanied by a random forest approach. This is because of the nature of the model, which is categorical and based on the position of the employee. In addition, a decision tree will give better results than a regression model.

2.4.3 Modeling

Add as many cells as you need to conduct the modeling process.

First of all it is important to encode the variables into categorical variables.

[ ]:
```
df2 = pd.get_dummies(df1) # Create dummy variables for the categorical variables
```

Definition of the outcome variable and independent variables.

[ ]:
```
y = df2['left'] # Define the target variable

x = df2.drop('left', axis=1) # Define the features
```

Now, split the data.

[ ]:
```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2,
    stratify=y, random_state=0) # Split the data into training and testing sets

x_tr, x_val, y_tr, y_val = train_test_split(x_train, y_train, test_size=0.25,
    stratify=y_train, random_state=0) # Split the training data into training
    and validation sets
```

First tree to obtain the first tree for the random forest

[ ]:
```
tree = DecisionTreeClassifier(random_state=0) # Create a Decision Tree
    Classifier

cv_params = {'max_depth':[4, 6, 8, None],
             'min_samples_leaf': [2, 5, 1],
             'min_samples_split': [2, 4, 6]
            } # Define the hyperparameters
```

```
scoring = {'accuracy', 'precision', 'recall', 'f1', 'roc_auc'} # Define the␣
↪metrics

tree1 = GridSearchCV(tree, cv_params, scoring=scoring, cv=4, refit='roc_auc') #␣
↪Create a Grid Search
```

[ ]:
```
%%time
tree1.fit(x_tr, y_tr) # Fit the model
```

```
CPU times: user 2.52 s, sys: 0 ns, total: 2.52 s
Wall time: 2.52 s
```

[ ]:
```
GridSearchCV(cv=4, error_score=nan,
             estimator=DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None,
                                              criterion='gini', max_depth=None,
                                              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='deprecated',
                                              random_state=0, splitter='best'),
             iid='deprecated', n_jobs=None,
             param_grid={'max_depth': [4, 6, 8, None],
                         'min_samples_leaf': [2, 5, 1],
                         'min_samples_split': [2, 4, 6]},
             pre_dispatch='2*n_jobs', refit='roc_auc', return_train_score=False,
             scoring={'accuracy', 'roc_auc', 'recall', 'precision', 'f1'},
             verbose=0)
```

[ ]:
```
#Best Parameters
tree1.best_params_ # Display the best hyperparameters
```

[ ]:
```
{'max_depth': 4, 'min_samples_leaf': 1, 'min_samples_split': 2}
```

[ ]:
```
#Best AUC score
tree1.best_score_ # Display the best AUC score
```

[ ]:
```
0.9703634179699269
```

Next, create a table to see the results of the models and have a better visualization.

[ ]:
```
def make_results(model_name:str, model_object, metric:str):
    '''
```

```
    Arguments:
        model_name (string): what you want the model to be called in the output␣
↪table
        model_object: a fit GridSearchCV object
        metric (string): precision, recall, f1, accuracy, or auc

    Returns a pandas df with the F1, recall, precision, accuracy, and auc scores
    for the model with the best mean 'metric' score across all validation folds.
↪
    '''

    # Create dictionary that maps input metric to actual metric name in␣
↪GridSearchCV
    metric_dict = {'auc': 'mean_test_roc_auc',
                   'precision': 'mean_test_precision',
                   'recall': 'mean_test_recall',
                   'f1': 'mean_test_f1',
                   'accuracy': 'mean_test_accuracy',
                   }

    # Get all the results from the CV and put them in a df
    cv_results = pd.DataFrame(model_object.cv_results_)

    # Isolate the row of the df with the max(metric) score
    best_estimator_results = cv_results.iloc[cv_results[metric_dict[metric]].
↪idxmax(), :]

    # Extract Accuracy, precision, recall, and f1 score from that row
    auc = best_estimator_results.mean_test_roc_auc
    f1 = best_estimator_results.mean_test_f1
    recall = best_estimator_results.mean_test_recall
    precision = best_estimator_results.mean_test_precision
    accuracy = best_estimator_results.mean_test_accuracy

    # Create table of results
    table = pd.DataFrame()
    table = table.append({'Model': model_name,
                        'AUC': auc,
                        'Precision': precision,
                        'Recall': recall,
                        'F1': f1,
                        'Accuracy': accuracy,
                        },
                        ignore_index=True
                       )

    return table
```

[ ]:
```
tree1_cv_results = make_results('decision tree cv', tree1, 'auc') # Create a␣
↪table with the results
tree1_cv_results # Display the results
```

[ ]:

	Model	AUC	Precision	Recall	F1	Accuracy
0	decision tree cv	0.970363	0.922167	0.921337	0.921719	0.974007

The model has a magnificient performance by their metrics. Now, let's see the graph of level of importances of the variables in the model.

Feature Engineering

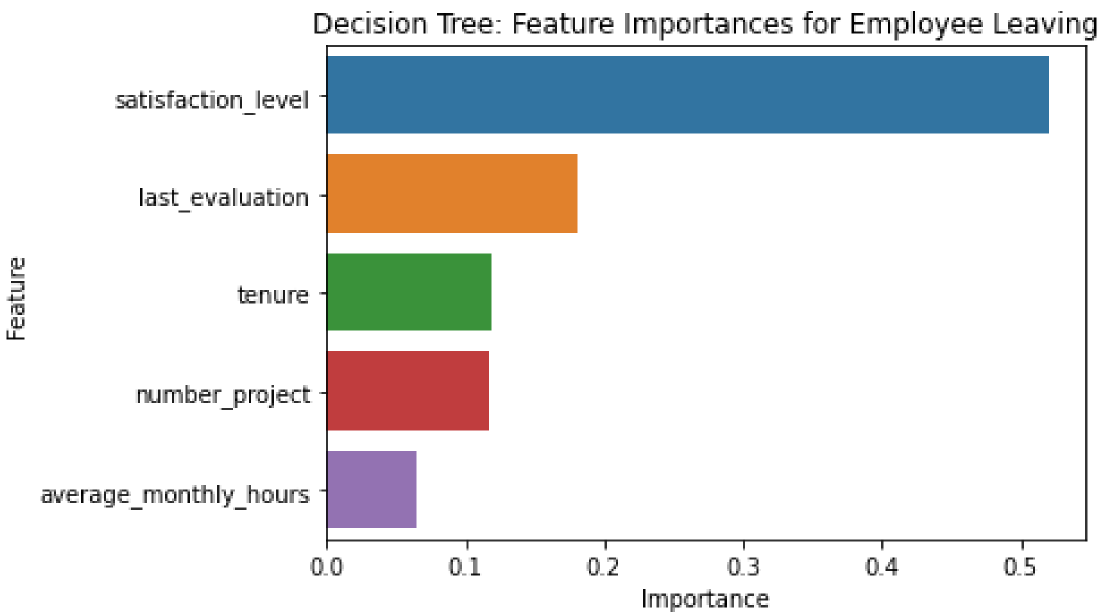
[ ]:
```
tree1_importances = pd.DataFrame(tree1.best_estimator_.feature_importances_,␣
↪columns=['gini_importance'], index=x.columns) # Extract the feature␣
↪importances
tree1_importances = tree1_importances.sort_values(by='gini_importance',␣
↪ascending=False) # Sort the features by importance

# Only extract the features with importances > 0
tree1_importances = tree1_importances[tree1_importances['gini_importance'] != 0]
tree1_importances
```

[ ]:

	gini_importance
satisfaction_level	0.520074
last_evaluation	0.180200
tenure	0.118262
number_project	0.117339
average_monthly_hours	0.064124

[ ]:
```
sns.barplot(data=tree1_importances, x="gini_importance", y=tree1_importances.
↪index, orient='h') # Create a barplot of the feature importances
plt.title("Decision Tree: Feature Importances for Employee Leaving",␣
↪fontsize=12) # Add a title
plt.ylabel("Feature") # Add a y-axis label
plt.xlabel("Importance") # Add an x-axis label
plt.show() # Display the plot
```



After the graph was created it is important to recognize a significant factor for the model. It is mostly based on a subjective feature such as "satisfaction_level", something that is not going to help to adress the current problem of the company. The main factors should be something measurable and more recognizable for the company. So, it would be a good approach decompose that variable in features related to it. As seen in the distribution of people dissatified, one of the most important factors can be that the employee can be overworked, which is directly correlated to the average_monthly_hours (a variable that rarely did not have a high importance in the model). This task would start by dropping satisfaction_level and creating a new feature that roughly captures whether an employee is overworked from the number of hours worked. In this case the variable would be called overworked.

[ ]:
```
df3 = df1.drop('satisfaction_level', axis=1) # Drop the 'satisfaction_level'␣
↪variable
df3['overworked'] = df3['average_monthly_hours'] # Create a new variable␣
↪'overworked' that is equal to 'average_monthly_hours'

#now inspect the range of the variable
print('Max hours:', df3['overworked'].max()) # Display the maximum value
print('Min hours:', df3['overworked'].min()) # Display the minimum value
```

```
Max hours: 310
Min hours: 96
```

As 170 hours was considered as a normal monthly hourly charge, it would be considered that 180 hours a characteristic of overworking, as some studies assert. Finally, to create the variable it would be a boolean where routines higher or equal to 180 hours will be considered true (1).

[ ]:
```
# overworked: employees who work 180 hours per month or more.
df3['overworked'] = (df3['overworked'] >= 180).astype(int) #

df3['overworked'].head() # Display the first 5 rows of the variable
```

[ ]:
```
0    0
1    1
2    1
3    1
4    0
Name: overworked, dtype: int64
```

[ ]:
```
# Now delete the parent variable
df3 = df3.drop('average_monthly_hours', axis=1)
```

Now perform one-hot encoding as needed

[ ]:
```
df4 = pd.get_dummies(df3) # Create dummy variables for the categorical variables
df4.head() # Display the first 5 rows of the dataset
```

[ ]:
```
   last_evaluation  number_project  tenure  work_accident  left  \
0             0.53               2       3              0     1
1             0.86               5       6              0     1
2             0.88               7       4              0     1
3             0.87               5       5              0     1
4             0.52               2       3              0     1

   promotion_last_5years  overworked  department_IT  department_RandD  \
0                      0           0              0                 0
1                      0           1              0                 0
2                      0           1              0                 0
3                      0           1              0                 0
4                      0           0              0                 0

   department_accounting  department_hr  department_management  \
0                      0              0                      0
1                      0              0                      0
2                      0              0                      0
3                      0              0                      0
4                      0              0                      0

   department_marketing  department_product_mng  department_sales  \
0                     0                       0                 1
1                     0                       0                 1
2                     0                       0                 1
3                     0                       0                 1
4                     0                       0                 1
```

```
   department_support  department_technical  salary_high  salary_low  \
0                   0                     0            0           1
1                   0                     0            0           0
2                   0                     0            0           0
3                   0                     0            0           1
4                   0                     0            0           1

   salary_medium
0              0
1              1
2              1
3              0
4              0
```

Next, it is time to define the dependent and independent variables for the model.

```
[ ]: y = df4['left'] # Define the target variable
     x = df4.drop('left', axis=1) # Define the features
```

Split the data into training, validating and testing.

```
[ ]: x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2,␣
      ↪stratify=y, random_state=0) # Split the data into training and testing sets

     x_tr, x_val, y_tr, y_val = train_test_split(x_train, y_train, test_size=0.25,␣
      ↪stratify=y_train, random_state=0) # Split the training data into training␣
      ↪and validation sets
```

Round 2

```
[ ]: tree = DecisionTreeClassifier(random_state=0) # Create a Decision Tree␣
      ↪Classifier

     cv_params = {'max_depth':[4, 6, 8, None],
                  'min_samples_leaf': [2, 5, 1],
                  'min_samples_split': [2, 4, 6]
                  } # Define the hyperparameters

     scoring = {'accuracy', 'precision', 'recall', 'f1', 'roc_auc'} # Define the␣
      ↪metrics

     tree2 = GridSearchCV(tree, cv_params, scoring=scoring, cv=4, refit='roc_auc') #␣
      ↪    Create a Grid Search
```

Fit the model

```
[ ]: %%time
tree2.fit(x_tr, y_tr) # Fit the model
```

```
CPU times: user 2.06 s, sys: 0 ns, total: 2.06 s
Wall time: 2.06 s
```

```
[ ]: GridSearchCV(cv=4, error_score=nan,
                  estimator=DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None,
                                                   criterion='gini', max_depth=None,
                                                   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='deprecated',
                                                   random_state=0, splitter='best'),
                  iid='deprecated', n_jobs=None,
                  param_grid={'max_depth': [4, 6, 8, None],
                              'min_samples_leaf': [2, 5, 1],
                              'min_samples_split': [2, 4, 6]},
                  pre_dispatch='2*n_jobs', refit='roc_auc', return_train_score=False,
                  scoring={'accuracy', 'roc_auc', 'recall', 'precision', 'f1'},
                  verbose=0)
```

Let's check the best parameters:

```
[ ]: tree2.best_params_ # Display the best hyperparameters
```

```
[ ]: {'max_depth': 6, 'min_samples_leaf': 1, 'min_samples_split': 4}
```

And now check the best parameter on CV

```
[ ]: tree2.best_score_ # Display the best AUC score
```

```
[ ]: 0.954227525104376
```

```
[ ]: tree2_cv_results = make_results('decision tree2 cv', tree2, 'recall') # Create␣
     ↪a table with the results
tree2_cv_results # Display the results
```

[ ]:

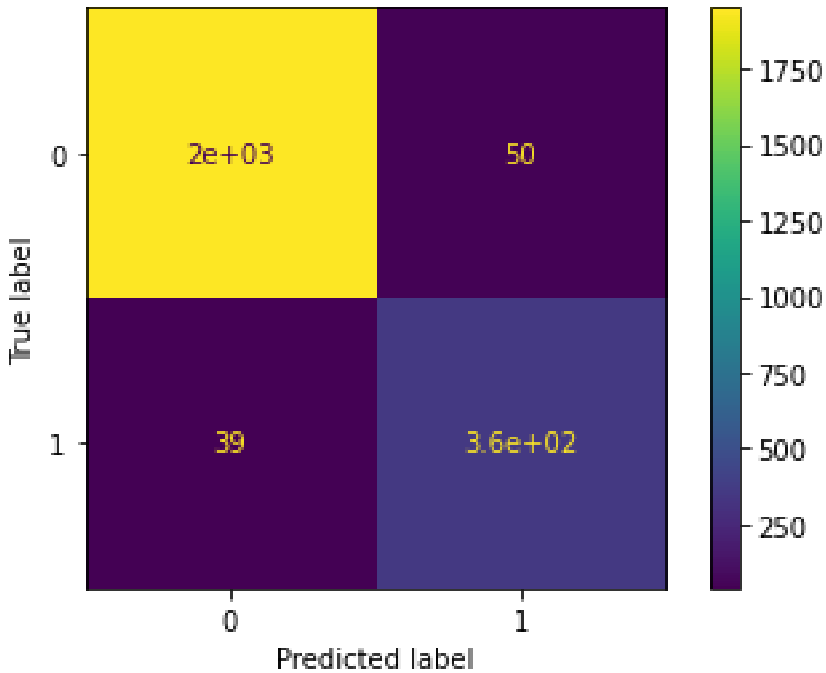
	Model	AUC	Precision	Recall	F1	Accuracy
0	decision tree2 cv	0.952705	0.86824	0.902098	0.884811	0.96094

Now, something expected happened. The scores fell, but that is normal because less features were took into account. However, the metrics are high and the model is understandable.

Next, let's plot a confusion matrix so we can examine the model's performance more visually.

```
[ ]: preds = tree2.best_estimator_.predict(x_test) # Make predictions on the test set
     cm = confusion_matrix(y_test, preds, labels=tree2.classes_) # Create a␣
      ↪confusion matrix

     disp = ConfusionMatrixDisplay(confusion_matrix=cm,
                                   display_labels=tree2.classes_) # Create a␣
      ↪confusion matrix display
     disp.plot() # Display the confusion matrix
```



The model is efficient doing the assigned task, the distribution was pretty good and it is important to recognize that the color of the true possitive values is dark because of the distribution of the model.

Final Feature Importance

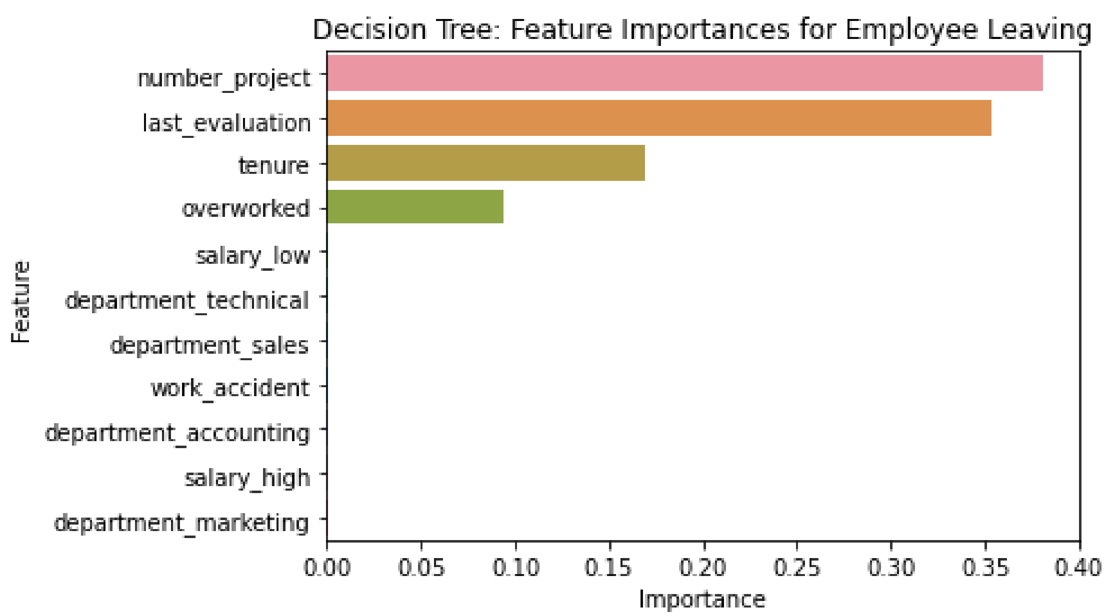
Let's visualize the importance of the variables in the model.

```
[ ]: tree2_importances = pd.DataFrame(tree2.best_estimator_.feature_importances_,␣
      ↪columns=['gini_importance'], index=x.columns) # Extract the feature␣
      ↪importances
     tree2_importances = tree2_importances.sort_values(by='gini_importance',␣
      ↪ascending=False) # Sort the features by importance

     # Only extract the features with importances > 0
     tree2_importances = tree2_importances[tree2_importances['gini_importance'] != 0]
     tree2_importances # Display the feature importances
```

[ ]:
```
                       gini_importance
number_project                0.381322
last_evaluation               0.352896
tenure                        0.169281
overworked                    0.094122
salary_low                    0.000850
department_technical          0.000427
department_sales              0.000363
work_accident                 0.000297
department_accounting         0.000238
salary_high                   0.000119
department_marketing          0.000084
```

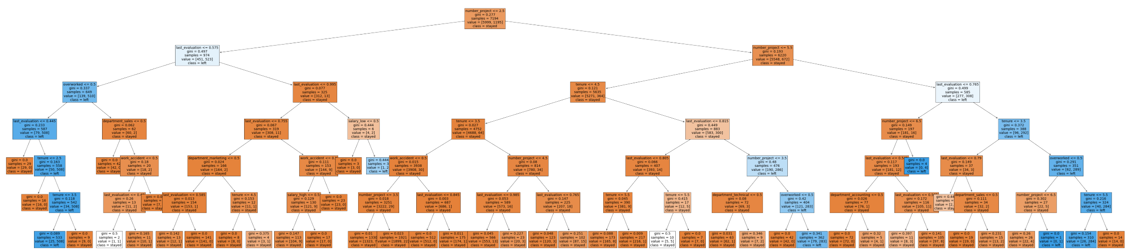
[ ]:
```
sns.barplot(data=tree2_importances, x="gini_importance", y=tree2_importances.
 ↪index, orient='h') # Create a barplot of the feature importances
plt.title("Decision Tree: Feature Importances for Employee Leaving",␣
 ↪fontsize=12) # Add a title
plt.ylabel("Feature") # Add a y-axis label
plt.xlabel("Importance") # Add an x-axis label
plt.show() # Display the plot
```



As seen in the barchart, the most important variables for the model are *number_project*, *last_evaluation*, *tenure*, and *overworked*. This shows that the this variables have a huge impact, so the company can evaluate this aspects as an essential part of the problem-solving. Additionally, it would be important to consider a limitation: the salaries seem to have no impact on the model, something really rare and important to be considered in a future analysis.

Finally, let's see the Decision Tree as our final result, the model itself.

```
[ ]: plt.figure(figsize=(85,20)) # Set the figure size
plot_tree(tree2.best_estimator_, max_depth=6, fontsize=14, feature_names=x.columns,
          class_names={0:'stayed', 1:'left'}, filled=True) # Plot the Decision Tree
plt.show() # Display the plot
```



pacE: Execute Stage - Interpret model performance and results - Share actionable steps with stakeholders

Recall evaluation metrics

- **AUC** is the area under the ROC curve; it's also considered the probability that the model ranks a random positive example more highly than a random negative example.
- **Precision** measures the proportion of data points predicted as True that are actually True, in other words, the proportion of positive predictions that are true positives.
- **Recall** measures the proportion of data points that are predicted as True, out of all the data points that are actually True. In other words, it measures the proportion of positives that are correctly classified.
- **Accuracy** measures the proportion of data points that are correctly classified.
- **F1-score** is an aggregation of precision and recall.

- Key Insights The most important aspects to improve the employees' retention are the satisfaction level (which is subjective, so it is useful only to identify the situation of the employee), number of projects, score in the last evaluation, tenure, and whether the employee is overworked.

- Business Recommendations

It is important to evaluate the workload of the employees. This is because most of the features related to staff exit are related to overworking and number of projects. In the case of being overworked it is seen that surprisingly most of the staff is overworked, working more than 180 hours per month. In the case of the number of projects is essential to consider that to maintain the employees the number of hours worked must be constant when the number of projects increase; also, the number of projects should be closer to 3 or 4, and the number of projects must avoid 7 projects or more (in that case all the employees left the company). In the case of tenure, it is appreciated that there is a crucial error with employees with large ternures. This is because they were not promoted or their salary did not grow despite showing a great performance, something rare considering their loyalty and performance in the company. Finally, the results in the evaluations are important to recognize that in some cases there could be a problem with the capacitation of the staff, it is important to create incentives to make them improve their skills.

- Recommendations for the manager and company's stakeholders

It is important to investigate the cluster of employees who had perfect stats (including satisfaction) and left the company. Also it is important to evaluate why people with more experience in the company have not been promoted despite their loyalty and good performance. Also it is important to evaluate the case of overworking, which is the main cause of the poor staff retention.

- Considerations

Of course, I consider that this model is propense to overfitting due to the nature of decision trees, so a good approach could be the development of a random forest model in rounds. In the case of the present model it was considered that the Recall metric was working pretty well and there is no need to create a model that consumes more time and effort. Furthermore, the model can be also improved by analyzing the nature of the variables more deeply with the help of an expert in the subject. Another thing to consider is that in this case the evaluation score cannot be totally controlled by the managers, so it wouldn't be a good measure for the model, so it can be deleted to create a new round. Finally, a k-means model would be a perfect way to evaluate the case of the clusters of employees who left the company and also had good scores.

2.5 Step 4. Results and Evaluation

- Interpret model
- Evaluate model performance using metrics
- Prepare results, visualizations, and actionable steps to share with stakeholders

2.5.1 Summary of model results

After conducting feature engineering, the decision tree model achieved AUC of 95.3%, precision of 86.8%, recall of 90.2%, f1-score of 88.5%, and accuracy of 96.1%, on the test set.

2.5.2 Conclusion, Recommendations, Next Steps

The models and the feature importances extracted from the models confirm that employees at the company are overworked.

To retain employees, the following recommendations could be presented to the stakeholders:

- Cap the number of projects that employees can work on.
- Consider promoting employees who have been with the company for atleast four years, or conduct further investigation about why four-year tenured employees are so dissatisfied.
- Either reward employees for working longer hours, or don't require them to do so.
- If employees aren't familiar with the company's overtime pay policies, inform them about this. If the expectations around workload and time off aren't explicit, make them clear.
- Help the employees to advance in their professional careers, so they can present a better performance in the evaluations.

Next Steps

This model is propense to overfitting due to the nature of decision trees, so a good approach could be the develop of a random forest model in rounds. In case of the present model it was considered that the Recall metric was working pretty well and there is no need to create a model that consumes more time and effort. Furthermore, the model can be also improved by analyzing the nature of the variables more deeply with the help of an expert in the subject. Another thing to consider is that in this case the evaluation score that cannot be totally controlled by the managers, so it wouldn't be a good measure for the model, so it can be deleted to create a new round. Finally, a k-means model would be a perfect way to evaluate the case of the clusters of employees who left the company and also had good scores.