Salifort Motors project lab

February 13, 2025

1 Capstone project: Providing data-driven suggestions for HR

1.1 Description and deliverables

This capstone project is an opportunity to analyze a dataset and build predictive models that can provide insights to the Human Resources (HR) department of a large consulting firm.

2 PACE stages

2.1 Pace: Plan

In this stage, consider the following:

2.1.1 Understand the business scenario and problem

The HR department at Salifort Motors wants to take some initiatives to improve employee satisfaction levels at the company. They collected data from employees, but now they don't know what to do with it. They refer to you as a data analytics professional and ask you to provide data-driven suggestions based on your understanding of the data. They have the following question: what's likely to make the employee leave the company?

Your goals in this project are to analyze the data collected by the HR department and to build a model that predicts whether or not an employee will leave the company.

If you can predict employees likely to quit, it might be possible to identify factors that contribute to their leaving. Because it is time-consuming and expensive to find, interview, and hire new employees, increasing employee retention will be beneficial to the company.

2.1.2 Familiarize yourself with the HR dataset

In this dataset, there are 14,999 rows, 10 columns, and these variables:

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

Variable	Description
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
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)

2.2 Step 1. Imports

- Import packages
- Load dataset

2.2.1 Import packages

[1]:

```
# Import packages

# For data manipulation
import numpy as np
import pandas as pd

# For data visualization
import matplotlib.pyplot as plt
import seaborn as sns

# For displaying all of the columns in dataframes
pd.set_option('display.max_columns', None)

# For data modeling
from xgboost import XGBClassifier
from xgboost import XGBRegressor
from xgboost import plot_importance

from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier

# For metrics and helpful functions
from sklearn.model_selection import GridSearchCV, train_test_split
from sklearn.metrics import accuracy_score, precision_score,
 ↪recall_score,f1_score, confusion_matrix, ConfusionMatrixDisplay,
 ↪classification_report
```

```python
from sklearn.metrics import roc_auc_score, roc_curve
from sklearn.tree import plot_tree

# For displaying all of the columns in dataframes
pd.set_option('display.max_columns', None)

# Saving Model
import pickle
```

2.2.2 Load dataset

[2]:
```python
# Load dataset into a dataframe
df0 = pd.read_csv("HR_capstone_dataset.csv")

# Display first few rows of the dataframe
df0.head()
```

[2]:
```
   satisfaction_level  last_evaluation  number_project  average_montly_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

   time_spend_company  Work_accident  left  promotion_last_5years Department  \
0                   3              0     1                      0      sales
1                   6              0     1                      0      sales
2                   4              0     1                      0      sales
3                   5              0     1                      0      sales
4                   3              0     1                      0      sales

   salary
0     low
1  medium
2  medium
3     low
4     low
```

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

2.3.1 Gather basic information about the data

[3]:
```python
# Gather basic information about the data
df0.info()
```

```
<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
```

2.3.2 Gather descriptive statistics about the data

[4]:
```python
# Gather descriptive statistics about the data
df0.describe()
```

[4]:
```
       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
```

2.3.3 Rename columns

As a data cleaning step, we rename the columns as needed. We 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.

[5]:
```
# Display all column names
df0.columns
```

[5]:
```
Index(['satisfaction_level', 'last_evaluation', 'number_project',
       'average_montly_hours', 'time_spend_company', 'Work_accident', 'left',
       'promotion_last_5years', 'Department', 'salary'],
      dtype='object')
```

[6]:
```
# Rename columns as needed
df0 = df0.rename(columns={'Work_accident': 'work_accident',
                          'average_montly_hours': 'average_monthly_hours',
                          'time_spend_company': 'tenure',
                          'Department': 'department'})

# Display all column names after the update
df0.columns
```

[6]:
```
Index(['satisfaction_level', 'last_evaluation', 'number_project',
       'average_monthly_hours', 'tenure', 'work_accident', 'left',
       'promotion_last_5years', 'department', 'salary'],
      dtype='object')
```

2.3.4 Check missing values

We check for any missing values in the data.

[7]:
```
# Check for missing values
df0.isna().sum()
```

[7]:
```
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
```

There are no missing values in the data.

2.3.5 Check duplicates

We check for any duplicate entries in the data.

[8]:
```python
# Check for duplicates
df0.duplicated().sum()
```

[8]:
```
np.int64(3008)
```

3,008 rows contain duplicates. That is 20% of the data.

[9]:
```python
# Inspect some rows containing duplicates as needed
df0[df0.duplicated()].head()
```

[9]:
```
      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
```

The above output shows the first five occurences of rows that are duplicated farther down in the dataframe. With several continuous variables across 10 columns, it seems very unlikely that these observations are legitimate. We can proceed by dropping them.

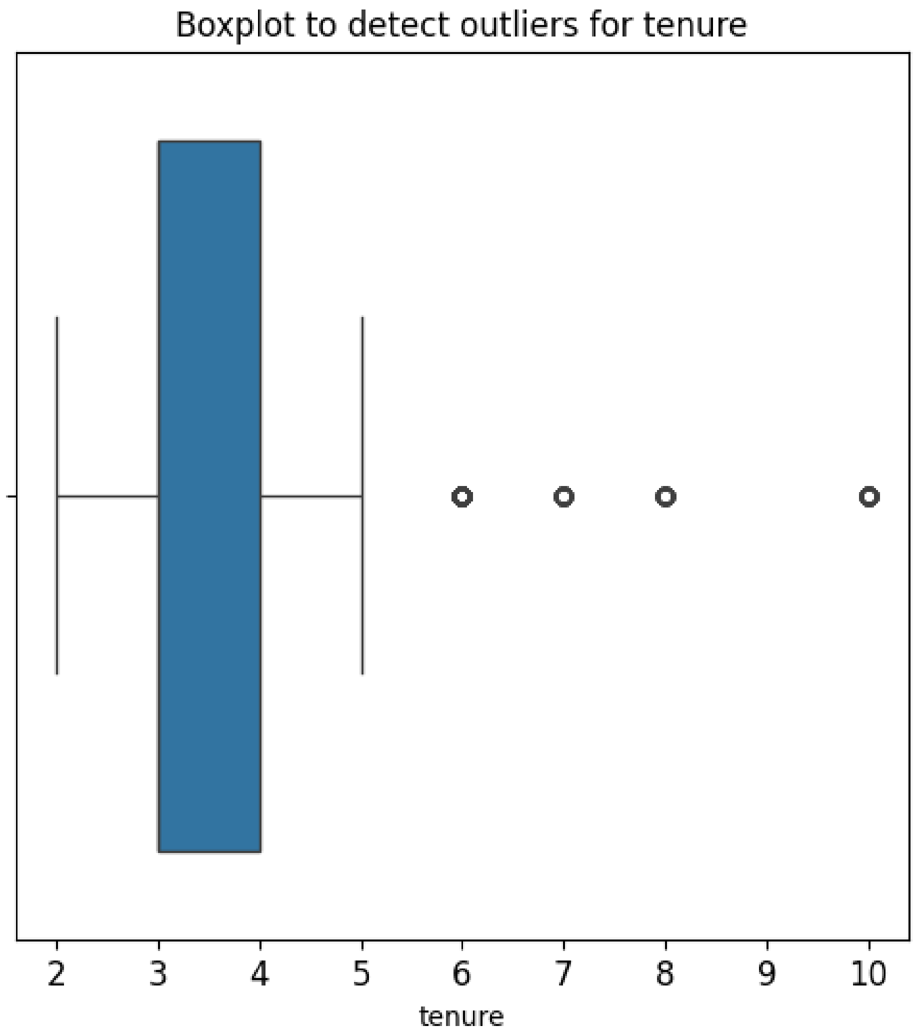
[10]:
```python
# Drop duplicates and save resulting dataframe in a new variable
df1 = df0.drop_duplicates(keep='first')

# Display first few rows of new dataframe
df1.head()
```

[10]:
```
   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
```

2.3.6 Check outliers

Check for outliers in the data.

[11]:
```python
# Create a boxplot to visualize distribution of `tenure` and detect any outliers
plt.figure(figsize=(6,6))
plt.title('Boxplot to detect outliers for tenure', fontsize=12)
plt.xticks(fontsize=12)
plt.yticks(fontsize=12)
sns.boxplot(x=df1['tenure'])
plt.show()
```



The boxplot above shows that there are outliers in the `tenure` variable.

It would be helpful to investigate how many rows in the data contain outliers in the `tenure` column.

[12]:
```
# Determine the number of rows containing outliers

# Compute the 25th percentile value in `tenure`
percentile25 = df1['tenure'].quantile(0.25)

# Compute the 75th percentile value in `tenure`
percentile75 = df1['tenure'].quantile(0.75)

# Compute the interquartile range in `tenure`
iqr = percentile75 - percentile25
```

```
# Define the upper limit and lower limit for non-outlier values in `tenure`
upper_limit = percentile75 + 1.5 * iqr
lower_limit = percentile25 - 1.5 * iqr
print("Lower limit:", lower_limit)
print("Upper limit:", upper_limit)

# Identify subset of data containing outliers in `tenure`
outliers = df1[(df1['tenure'] > upper_limit) | (df1['tenure'] < lower_limit)]

# Count how many rows in the data contain outliers in `tenure`
print("Number of rows in the data containing outliers in `tenure`:",␣
 ↪len(outliers))
```

```
Lower limit: 1.5
Upper limit: 5.5
Number of rows in the data containing outliers in `tenure`: 824
```

Certain types of models are more sensitive to outliers than others. Depending on the models we choose, we may need to consider whether to remove these outliers.

3 pAce: Analyze Stage

- Perform EDA (analyze relationships between variables)

3.1 Step 2. Data Exploration (Continue EDA)

Begin by understanding how many employees left and what percentage of all employees this represents.

[13]:
```
# Get numbers of people who left vs. stayed
print(df1['left'].value_counts())
print()

# Get percentages of people who left vs. stayed
print(df1['left'].value_counts(normalize=True))
```

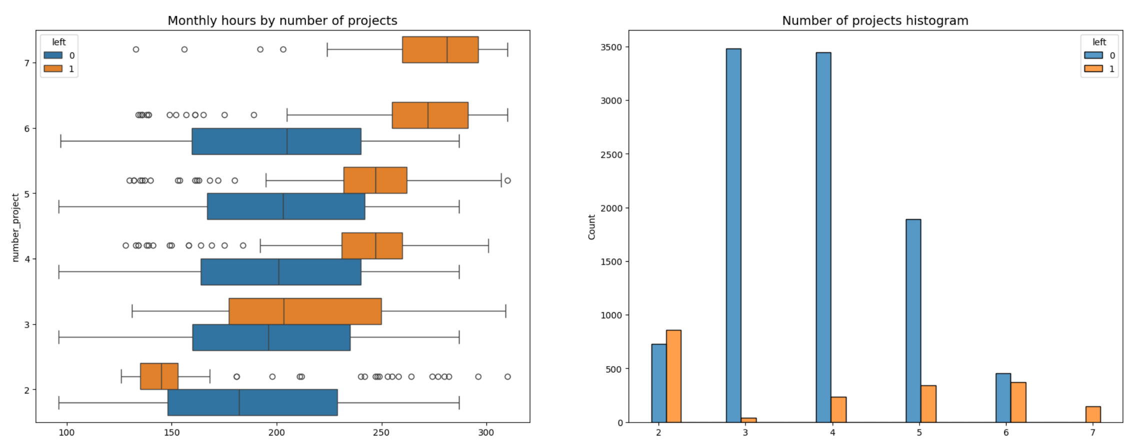
```
left
0    10000
1     1991
Name: count, dtype: int64

left
0    0.833959
1    0.166041
Name: proportion, dtype: float64
```

3.1.1 Data visualizations

Now, we examine variables and create plots to visualize relationships between them.

We can start by creating a stacked boxplot showing `average_monthly_hours` distributions for `number_project`, comparing the distributions of employees who stayed versus those who left.

[14]:
```python
# Create a boxplot and histogram

# Set figure and axes
fig, ax = plt.subplots(1, 2, figsize = (22,8))

# Create boxplot showing `average_monthly_hours` distributions for `number_project`, comparing employees who stayed versus those who left
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('Monthly hours by number of projects', fontsize='14')

# Create histogram showing distribution of `number_project`, comparing employees who stayed versus those who left
#tenure_stay = df1[df1['left']==0]['number_project']
#tenure_left = df1[df1['left']==1]['number_project']
sns.histplot(data=df1, x='number_project', hue='left', multiple='dodge', shrink=2, ax=ax[1])
ax[1].set_title('Number of projects histogram', fontsize='14')

# Display the plots
plt.show()
```



It might be natural that people who work on more projects would also work longer hours. This appears to be the case here, with the mean hours of each group (stayed and left) increasing with number of projects worked. However, a few things stand out from this plot.

1. There are two groups of employees who left the company: (A) those who worked considerably less than their peers with the same number of projects, and (B) those who worked much more. Of those in group A, it's possible that they were fired. It's also possible that this group

includes employees who had already given their notice and were assigned fewer hours because they were already on their way out the door. For those in group B, it's reasonable to infer that they probably quit. The folks in group B likely contributed a lot to the projects they worked in; they might have been the largest contributors to their projects.

2. Everyone with seven projects left the company, and the interquartile ranges of this group and those who left with six projects was ~255–295 hours/month—much more than any other group.

3. The optimal number of projects for employees to work on seems to be 3–4. The ratio of left/stayed is very small for these cohorts.

4. If you assume a work week of 40 hours and two weeks of vacation per year, then the average number of working hours per month of employees working Monday–Friday `= 50 weeks * 40 hours per week / 12 months = 166.67 hours per month`. This means that, aside from the employees who worked on two projects, every group—even those who didn't leave the company—worked considerably more hours than this. It seems that employees here are overworked.

As the next step, we can confirm that all employees with seven projects left.

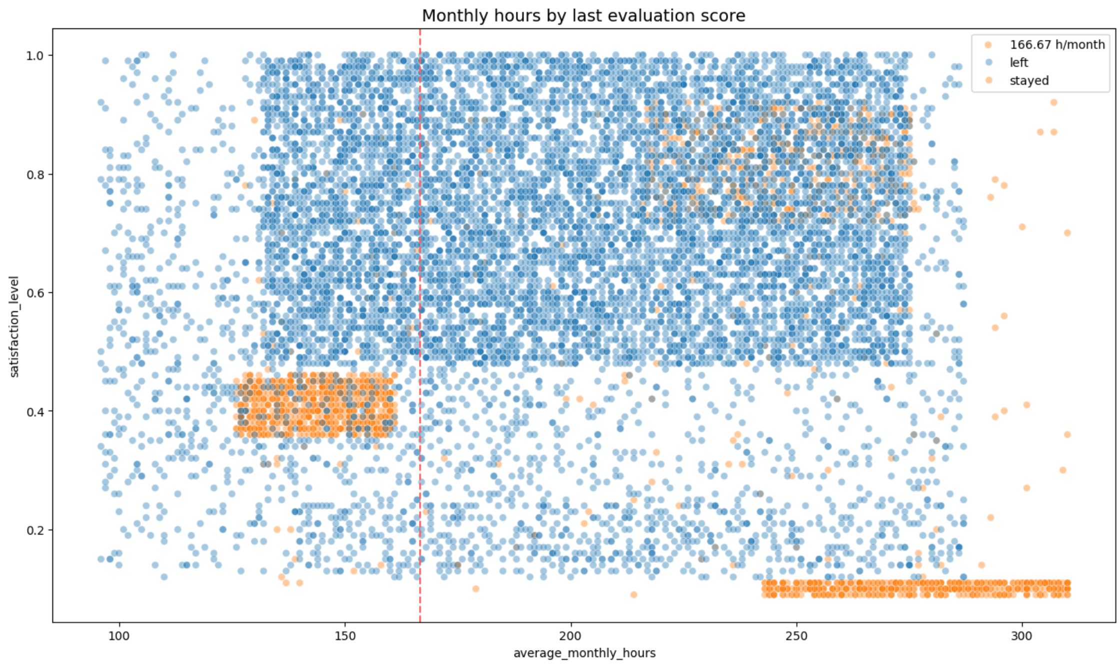
[15]:
```
# Get value counts of stayed/left for employees with 7 projects
df1[df1['number_project']==7]['left'].value_counts()
```

[15]:
```
left
1    145
Name: count, dtype: int64
```

This confirms that all employees with 7 projects did leave, no one stays.

Next, we can examine the average monthly hours versus the satisfaction levels.

[16]:
```
# Create scatterplot of `average_monthly_hours` versus `satisfaction_level`,␣
↪comparing employees who stayed versus those who left
plt.figure(figsize=(16, 9))
sns.scatterplot(data=df1, x='average_monthly_hours', y='satisfaction_level',␣
↪hue='left', alpha=0.4)
plt.axvline(x=166.67, color='#ff6361', label='166.67 h/month', ls='--')
plt.legend(labels=['166.67 h/month', 'left', 'stayed'])
plt.title('Monthly hours by last evaluation score', fontsize='14');
```



The scatterplot above shows that there was a sizeable group of employees who worked ~240–315 hours per month. 315 hours per month is over 75 hours per week for a whole year. It's likely this is related to their satisfaction levels being close to zero.

The plot also shows another group of people who left, those who had more normal working hours. Even so, their satisfaction was only around 0.4. It's difficult to speculate about why they might have left. It's possible they felt pressured to work more, considering so many of their peers worked more. And that pressure could have lowered their satisfaction levels.

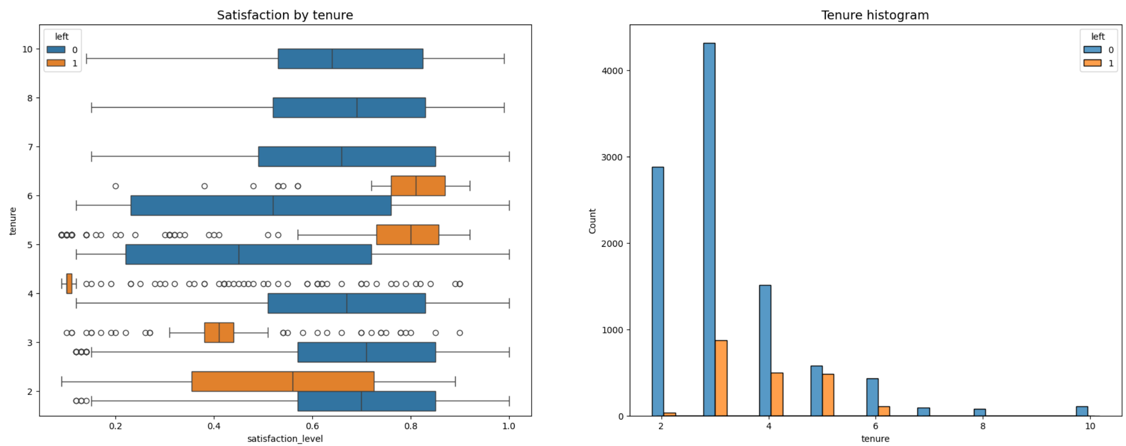
Finally, there is a group who worked ~210–280 hours per month, and they had satisfaction levels ranging ~0.7–0.9.

The strange shape of the plot indicates that the data is not issued from the real world but built for academic purposes probably.

For the next visualization, it might be interesting to visualize satisfaction levels by tenure.

[17]:
```
# Create a boxplot and histogram

# Set figure and axes
fig, ax = plt.subplots(1, 2, figsize = (22,8))

# Create boxplot showing distributions of `satisfaction_level` by tenure,␣
↪comparing employees who stayed versus those who left
sns.boxplot(data=df1, x='satisfaction_level', y='tenure', hue='left',␣
↪orient="h", ax=ax[0])
ax[0].invert_yaxis()
ax[0].set_title('Satisfaction by tenure', fontsize='14')
```

```python
# Create histogram showing distribution of `tenure`, comparing employees who␣
↪stayed versus those who left
#tenure_stay = df1[df1['left']==0]['tenure']
#tenure_left = df1[df1['left']==1]['tenure']
sns.histplot(data=df1, x='tenure', hue='left', multiple='dodge', shrink=5,␣
↪ax=ax[1])
ax[1].set_title('Tenure histogram', fontsize='14')

plt.show();
```



- Employees who left fall into two general categories: dissatisfied employees with shorter tenures and very satisfied employees with medium-length tenures.
- Four-year employees who left seem to have an unusually low satisfaction level. It's worth investigating changes to company policy that might have affected people specifically at the four-year mark.
- The longest-tenured employees didn't leave. Their satisfaction levels aligned with those of newer employees who stayed.
- The histogram shows that there are relatively few longer-tenured employees. It's possible that they're the higher-ranking, higher-paid employees.

As the next step in analyzing the data, we can calculate the mean and median satisfaction scores of employees who left and those who didn't.

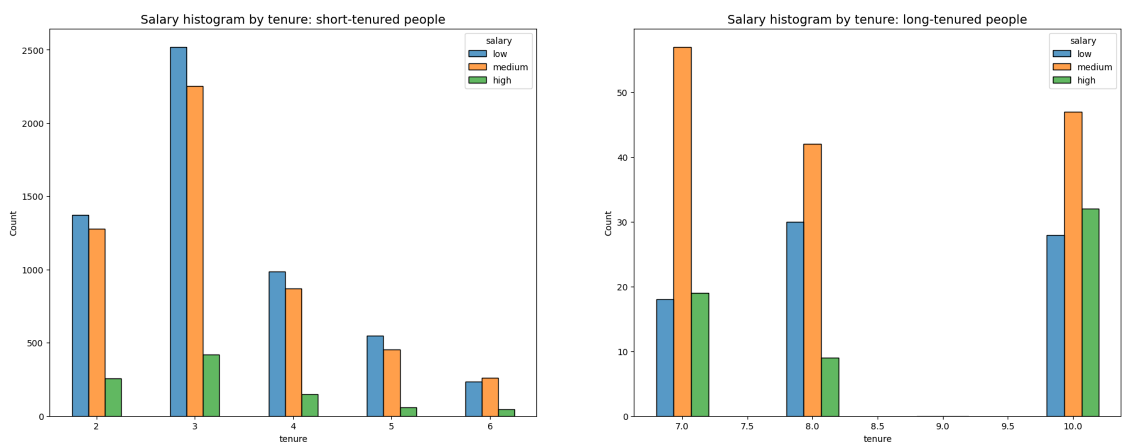
[18]:
```python
# Calculate mean and median satisfaction scores of employees who left and those␣
↪who stayed
df1.groupby(['left'])['satisfaction_level'].agg(["mean","median"])
```

[18]:
```
          mean  median
left
0     0.667365    0.69
1     0.440271    0.41
```

The mean and median satisfaction scores of employees who left are lower than those of employees who stayed.

Next, we can examine salary levels for different tenures.

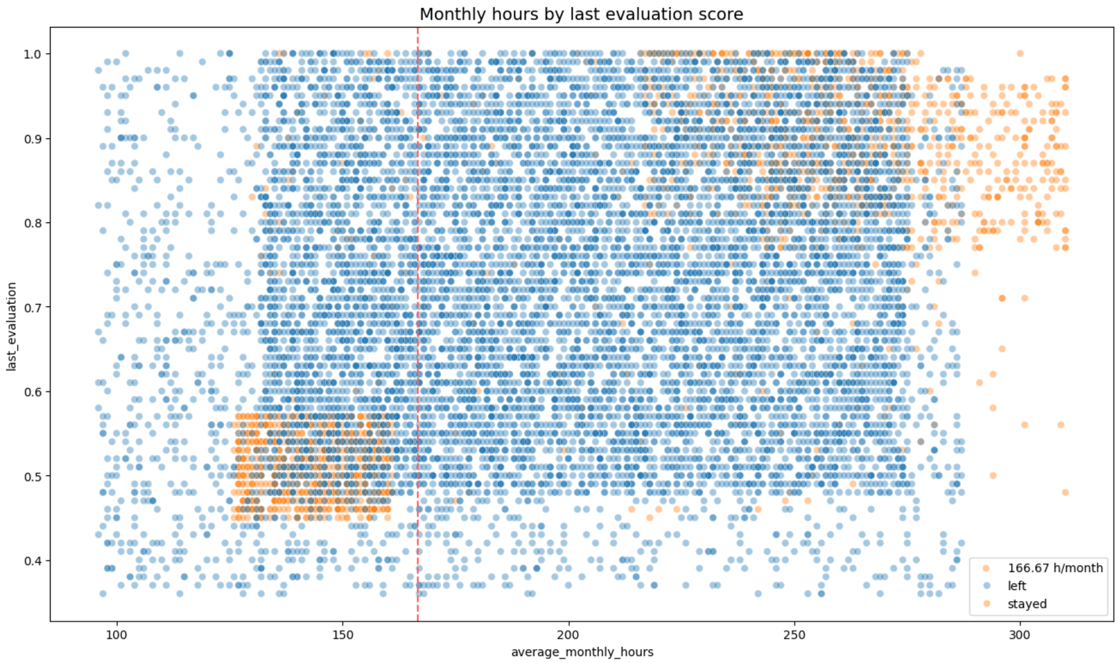
[19]:
```
# Create histograms

# Set figure and axes
fig, ax = plt.subplots(1, 2, figsize = (22,8))

# Consider short-tenured employees as less or equal to 6 years
tenure_short = df1[df1['tenure'] < 7]

# Define long-tenured employees as greater or equal to 7 years
tenure_long = df1[df1['tenure'] > 6]

# Plot short-tenured histogram
sns.histplot(data=tenure_short, x='tenure', hue='salary', discrete=1,
             hue_order=['low', 'medium', 'high'], multiple='dodge', shrink=.5,␣
 ↪ax=ax[0])
ax[0].set_title('Salary histogram by tenure: short-tenured people',␣
 ↪fontsize='14')

# Plot long-tenured histogram
sns.histplot(data=tenure_long, x='tenure', hue='salary', discrete=1,
             hue_order=['low', 'medium', 'high'], multiple='dodge', shrink=.4,␣
 ↪ax=ax[1])
ax[1].set_title('Salary histogram by tenure: long-tenured people',␣
 ↪fontsize='14');
```



The graphs above show that employee salaries have no impact on their tenure.

Next, we can explore whether there's a correlation between working long hours and receiving high evaluation scores. We can create a scatterplot of `average_monthly_hours` versus `last_evaluation`.

[20]:
```
# Create scatterplot of `average_monthly_hours` versus `last_evaluation`
plt.figure(figsize=(16, 9))
sns.scatterplot(data=df1, x='average_monthly_hours', y='last_evaluation',␣
↪hue='left', alpha=0.4)
plt.axvline(x=166.67, color='#ff6361', label='166.67 h/month', ls='--')
plt.legend(labels=['166.67 h/month', 'left', 'stayed'])
plt.title('Monthly hours by last evaluation score', fontsize='14');
```

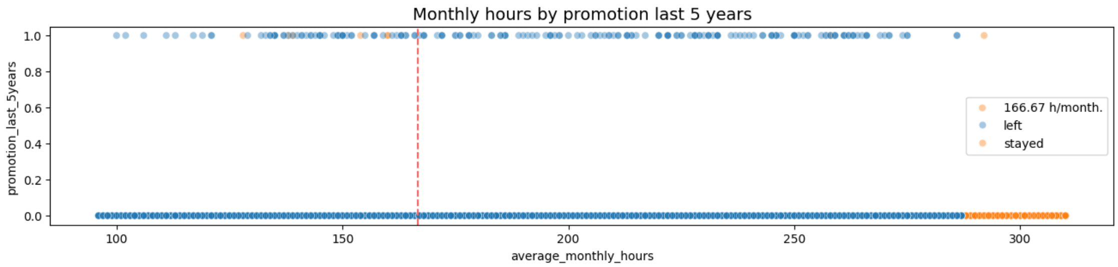


- The scatterplot indicates two groups of employees who left: overworked employees who performed very well and employees who worked slightly under the nominal monthly average of 166.67 hours with lower evaluation scores.
- There seems to be a correlation between hours worked and evaluation score.
- Most of the employees in this company work well over 167 hours per month.

Next, we can examine whether employees who worked very long hours were promoted in the last five years.

[21]:
```
# Create plot to examine relationship between `average_monthly_hours` and␣
↪`promotion_last_5years`
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=166.67, color='#ff6361', ls='--')
```

```
plt.legend(labels=['166.67 h/month.', 'left', 'stayed'])
plt.title('Monthly hours by promotion last 5 years', fontsize='14');
```



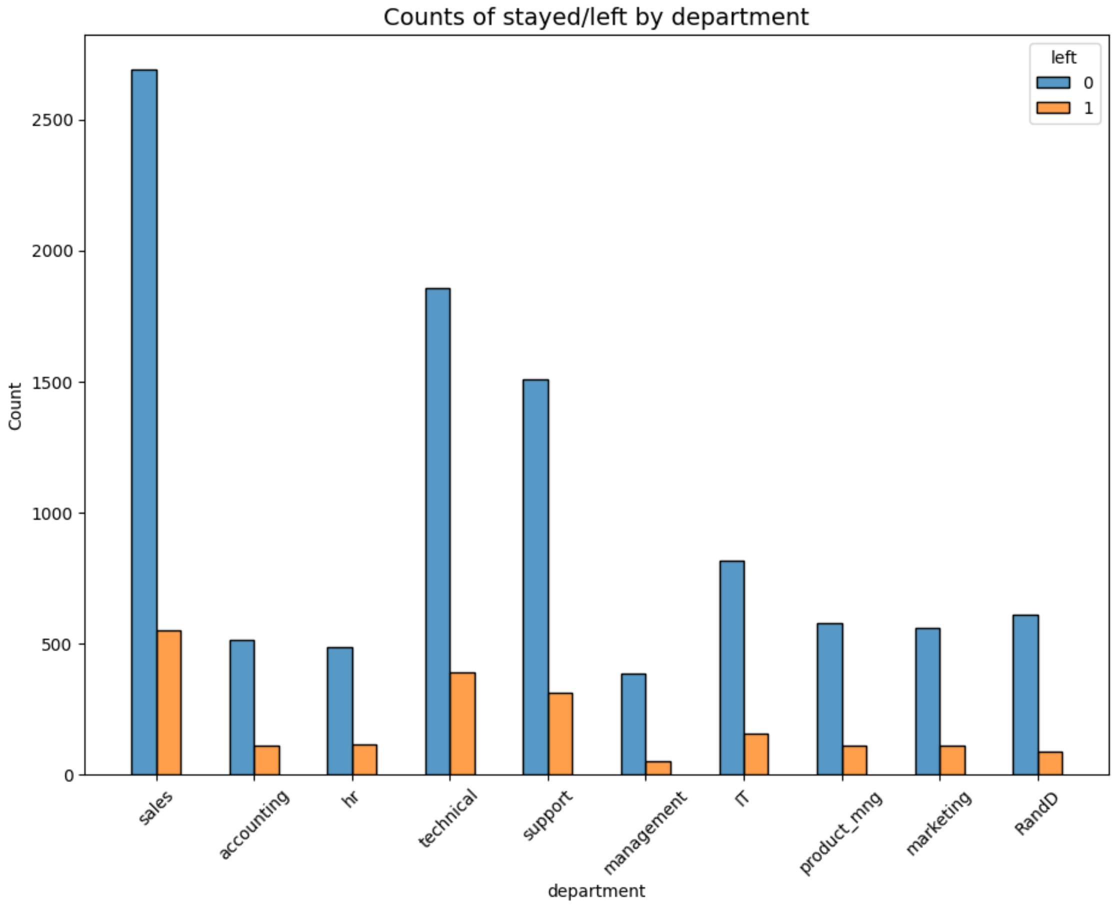
- Very few employees, who were promoted in the last five years, left
- Very few employees who worked the most hours were promoted
- All of the employees who left were working the longest hours

Next, we can inspect how the employees who left are distributed across departments.

[22]:
```
# Display counts for each department
df1["department"].value_counts()
```

[22]:
```
department
sales          3239
technical      2244
support        1821
IT              976
RandD           694
product_mng     686
marketing       673
accounting      621
hr              601
management      436
Name: count, dtype: int64
```

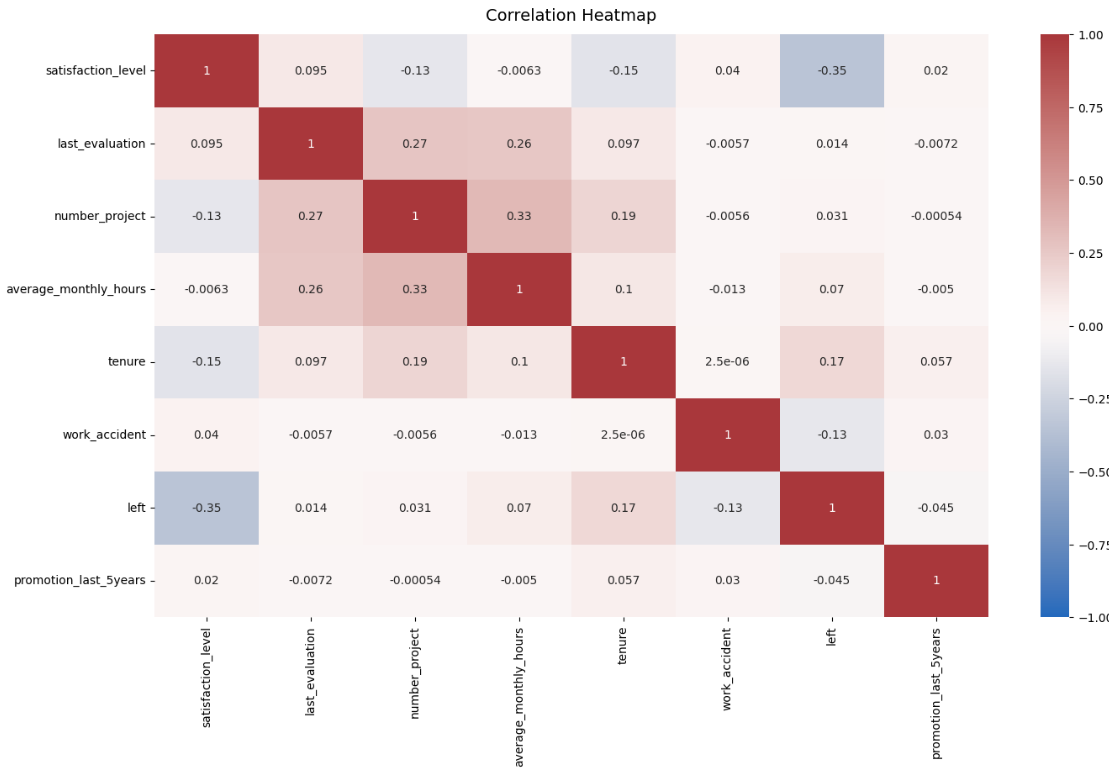
[23]:
```
# Create stacked histogram to compare department distribution of employees who␣
↪left to that of employees who didn't
plt.figure(figsize=(11,8))
sns.histplot(data=df1, x='department', hue='left', discrete=1,
             hue_order=[0, 1], multiple='dodge', shrink=.5)
plt.xticks(rotation=45)
plt.title('Counts of stayed/left by department', fontsize=14);
```



There doesn't seem to be any department that differs significantly in its proportion of employees who left to those who stayed.

Lastly, we can check for strong correlations between variables in the data.

[24]:
```
# Plot a correlation heatmap
plt.figure(figsize=(16, 9))
heatmap = sns.heatmap(df1.corr(numeric_only=True), vmin=-1, vmax=1, annot=True,
 ↪cmap=sns.color_palette("vlag", as_cmap=True))
heatmap.set_title('Correlation Heatmap', fontdict={'fontsize':14}, pad=12);
```



The correlation heatmap confirms that the number of projects, monthly hours, and evaluation scores all have some positive correlation with each other, and whether an employee leaves is negatively correlated with their satisfaction level.

3.1.2 Insights

It appears that employees are leaving the company as a result of poor management. Leaving is tied to longer working hours, many projects, and generally lower satisfaction levels. It can be ungratifying to work long hours and not receive promotions or good evaluation scores. There's a sizeable group of employees at this company who are probably burned out. It also appears that if an employee has spent more than six years at the company, they tend not to leave.

4 paCe: Construct Stage

- Determine which models are most appropriate
- Construct the model
- Confirm model assumptions
- Evaluate model results to determine how well the model fits the data

4.1 Recall model assumptions

Logistic Regression model assumptions - Outcome variable is categorical - Observations are independent of each other - No severe multicollinearity among X variables - No extreme outliers

- Linear relationship between each X variable and the logit of the outcome variable - Sufficiently large sample size

4.2 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

4.2.1 Identify the type of prediction task.

The goal is to predict whether an employee leaves the company, which is a categorical outcome variable. So this task involves classification. More specifically, this involves binary classification, since the outcome variable `left` can be either 1 (indicating employee left) or 0 (indicating employee didn't leave).

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

Since the variable we want to predict (whether an employee leaves the company) is categorical, we could either build a Logistic Regression model, or a Tree-based Machine Learning model.

4.2.3 Modeling Approach A: Logistic Regression Model

This approach covers implementation of Logistic Regression.

Logistic regression Note that binomial logistic regression suits the task because it involves binary classification.

Before splitting the data, we encode the non-numeric variables. There are two: `department` and `salary`.

`department` is a categorical variable, which means you can dummy it for modeling.

`salary` is categorical too, but it's ordinal. There's a hierarchy to the categories, so it's better not to dummy this column, but rather to convert the levels to numbers, 0–2.

[25]:
```
# Copy the dataframe
df_enc = df1.copy()

# Encode the `salary` column as an ordinal numeric category
df_enc['salary'] = (
    df_enc['salary'].astype('category')
    .cat.set_categories(['low', 'medium', 'high'])
    .cat.codes
)

# Dummy encode the `department` column
df_enc = pd.get_dummies(df_enc, drop_first=False)

# Display the new dataframe
```

```
df_enc.head()
```

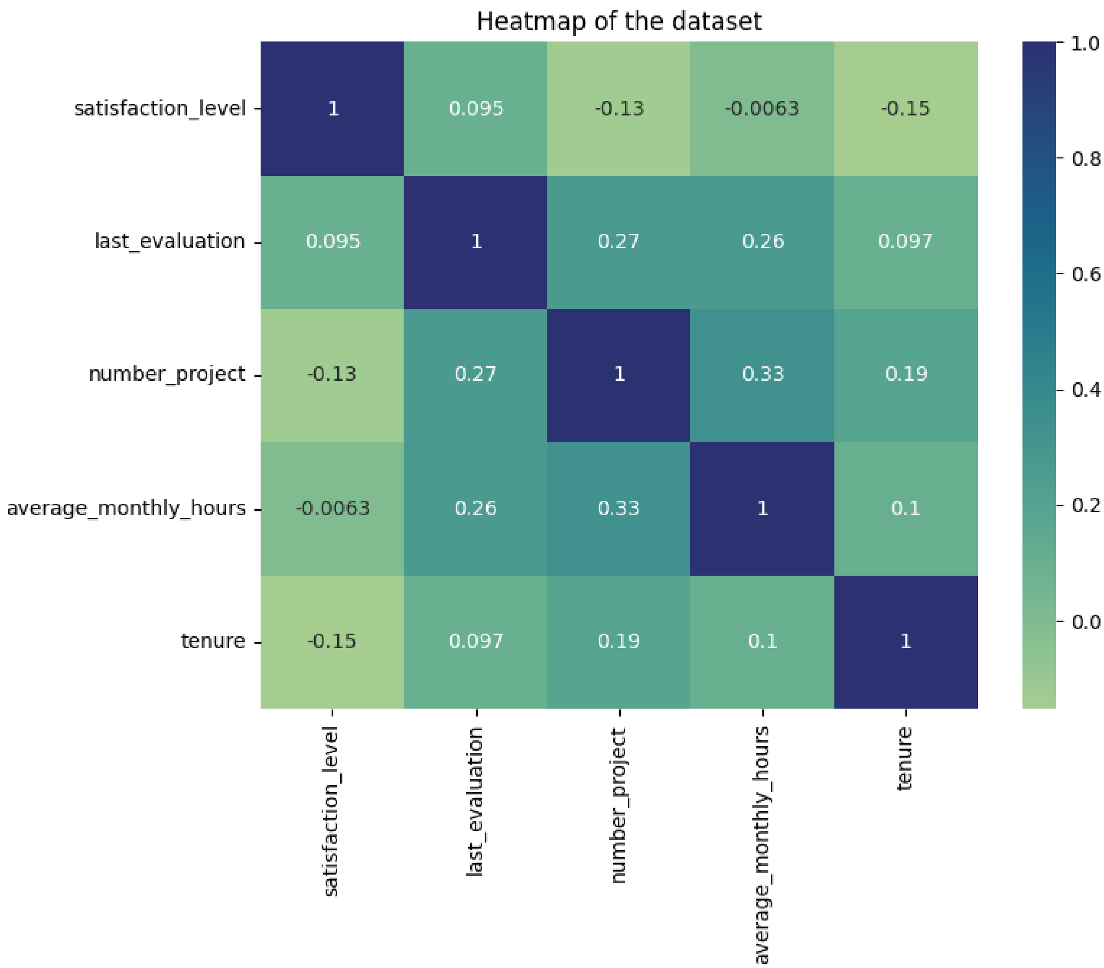
[25]:

```
   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  salary  department_IT  \
0       3              0     1                      0       0          False
1       6              0     1                      0       1          False
2       4              0     1                      0       1          False
3       5              0     1                      0       0          False
4       3              0     1                      0       0          False

   department_RandD  department_accounting  department_hr  \
0             False                  False          False
1             False                  False          False
2             False                  False          False
3             False                  False          False
4             False                  False          False

   department_management  department_marketing  department_product_mng  \
0                  False                 False                   False
1                  False                 False                   False
2                  False                 False                   False
3                  False                 False                   False
4                  False                 False                   False

   department_sales  department_support  department_technical
0              True               False                 False
1              True               False                 False
2              True               False                 False
3              True               False                 False
4              True               False                 False
```

Create a heatmap to visualize how correlated variables are.

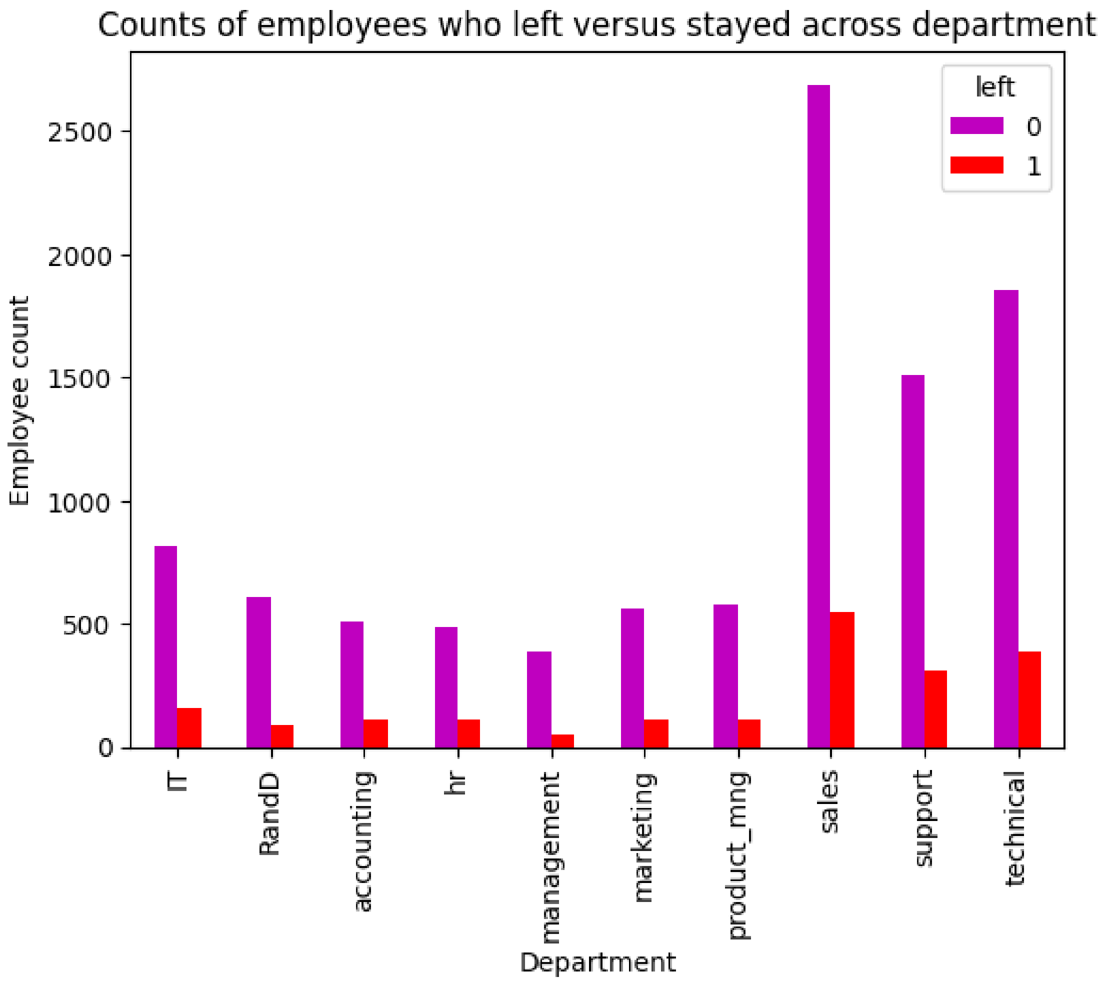
[26]:

```
# Create a heatmap to visualize how correlated variables are
plt.figure(figsize=(8, 6))
sns.heatmap(df_enc[['satisfaction_level', 'last_evaluation', 'number_project',␣
↪'average_monthly_hours', 'tenure']]
            .corr(), annot=True, cmap="crest")
plt.title('Heatmap of the dataset')
plt.show()
```



We create a stacked bart plot to visualize number of employees across department, comparing those who left with those who didn't.

[27]:
```
# In the legend, 0 (purple color) represents employees who did not leave, 1␣
↪(red color) represents employees who left
pd.crosstab(df1['department'], df1['left']).plot(kind ='bar',color='mr')
plt.title('Counts of employees who left versus stayed across department')
plt.ylabel('Employee count')
plt.xlabel('Department')
plt.show()
```



Since logistic regression is quite sensitive to outliers, it would be a good idea at this stage to remove the outliers in the `tenure` column that were identified earlier.

[28]:
```
# Select rows without outliers in `tenure` and save resulting dataframe in a␣
↪new variable
df_logreg = df_enc[(df_enc['tenure'] >= lower_limit) & (df_enc['tenure'] <=␣
↪upper_limit)]

# Display first few rows of new dataframe
df_logreg.head()
```

[28]:
```
   satisfaction_level  last_evaluation  number_project  average_monthly_hours  \
0                0.38             0.53               2                    157
2                0.11             0.88               7                    272
3                0.72             0.87               5                    223
4                0.37             0.52               2                    159
```

```
5                0.41             0.50              2                 153

   tenure  work_accident  left  promotion_last_5years  salary  department_IT  \
0       3              0     1                      0       0          False
2       4              0     1                      0       1          False
3       5              0     1                      0       0          False
4       3              0     1                      0       0          False
5       3              0     1                      0       0          False

   department_RandD  department_accounting  department_hr  \
0             False                  False          False
2             False                  False          False
3             False                  False          False
4             False                  False          False
5             False                  False          False

   department_management  department_marketing  department_product_mng  \
0                  False                 False                   False
2                  False                 False                   False
3                  False                 False                   False
4                  False                 False                   False
5                  False                 False                   False

   department_sales  department_support  department_technical
0              True               False                 False
2              True               False                 False
3              True               False                 False
4              True               False                 False
5              True               False                 False
```

We isolate the outcome variable, which is the variable you want your model to predict.

[29]:
```python
# Isolate the outcome variable
y = df_logreg['left']

# Display first few rows of the outcome variable
y.head()
```

[29]:
```
0    1
2    1
3    1
4    1
5    1
Name: left, dtype: int64
```

We keep the features to use in your model to predict the outcome variable, `left`.

[30]:
```python
# Select the features to use in your model
X = df_logreg.drop('left', axis=1)

# Display the first few rows of the selected features
X.head()
```

[30]:
```
   satisfaction_level  last_evaluation  number_project  average_monthly_hours  \
0                0.38             0.53               2                    157
2                0.11             0.88               7                    272
3                0.72             0.87               5                    223
4                0.37             0.52               2                    159
5                0.41             0.50               2                    153

   tenure  work_accident  promotion_last_5years  salary  department_IT  \
0       3              0                      0       0          False
2       4              0                      0       1          False
3       5              0                      0       0          False
4       3              0                      0       0          False
5       3              0                      0       0          False

   department_RandD  department_accounting  department_hr  \
0             False                  False          False
2             False                  False          False
3             False                  False          False
4             False                  False          False
5             False                  False          False

   department_management  department_marketing  department_product_mng  \
0                  False                 False                   False
2                  False                 False                   False
3                  False                 False                   False
4                  False                 False                   False
5                  False                 False                   False

   department_sales  department_support  department_technical
0              True               False                 False
2              True               False                 False
3              True               False                 False
4              True               False                 False
5              True               False                 False
```

We split the data into training set and testing set: we stratify based on the values in y, since the classes are unbalanced.

[31]:
```python
# Split the data into training set and testing set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,␣
↪stratify=y, random_state=42)
```

We construct a logistic regression model and fit it to the training dataset.

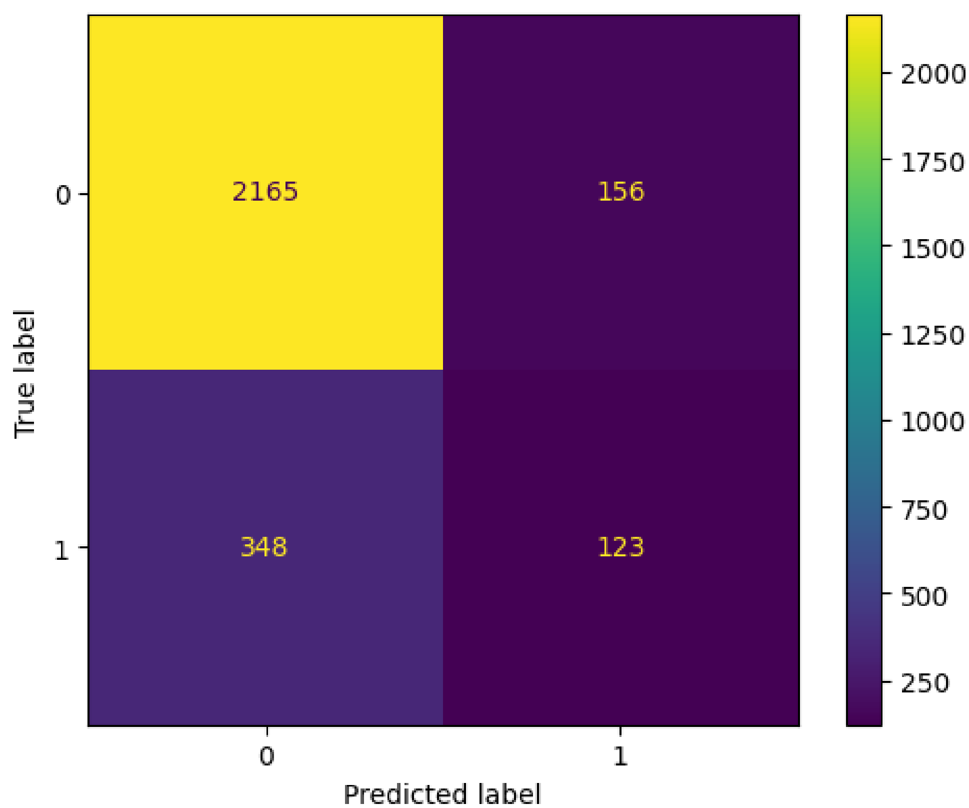
[32]:
```
# Construct a logistic regression model and fit it to the training dataset
log_clf = LogisticRegression(random_state=42, max_iter=500).fit(X_train,␣
 ↪y_train)
```

We test the logistic regression model on the test set.

[33]:
```
# Use the logistic regression model to get predictions on the test set
y_pred = log_clf.predict(X_test)
```

We create the confusion matrix to visualize the results of the logistic regression model.

[34]:
```
# Compute values for the confusion matrix
log_cm = confusion_matrix(y_test, y_pred, labels=log_clf.classes_)

# Create the display of the confusion matrix
log_disp = ConfusionMatrixDisplay(confusion_matrix=log_cm,
                                  display_labels=log_clf.classes_)

# Plot confusion matrix
log_disp.plot(values_format='')

# Display plot
plt.show()
```



The upper-left quadrant displays the number of true negatives.
True negatives: The number of people who did not leave that the model accurately predicted did not leave.

The upper-right quadrant displays the number of false positives.
False positives: The number of people who did not leave the model inaccurately predicted as leaving.

The bottom-left quadrant displays the number of false negatives.
False negatives: The number of people who left that the model inaccurately predicted did not leave.

The bottom-right quadrant displays the number of true positives.
True positives: The number of people who left the model accurately predicted as leaving.

A perfect model would yield all true negatives and true positives, and no false negatives or false positives.

We create a classification report that includes precision, recall, f1-score, and accuracy metrics to evaluate the performance of the logistic regression model.

We check the class balance in the data. In other words, we check the value counts in the `left` column. Since this is a binary classification task, the class balance informs the way we interpret accuracy metrics.

[35]:
```
df_logreg['left'].value_counts(normalize=True)
```

[35]:
```
left
0    0.831468
1    0.168532
Name: proportion, dtype: float64
```

There is an approximately 83%-17% split. So the data is not perfectly balanced, but it is not too imbalanced. If it was more severely imbalanced, we might want to resample the data to make it more balanced. In this case, we can use this data without modifying the class balance and continue evaluating the model.

[36]:
```
# Create classification report for logistic regression model
target_names = ['Predicted would not leave', 'Predicted would leave']
print(classification_report(y_test, y_pred, target_names=target_names))
```

```
                           precision    recall  f1-score   support

Predicted would not leave       0.86      0.93      0.90      2321
    Predicted would leave       0.44      0.26      0.33       471

                 accuracy                           0.82      2792
                macro avg       0.65      0.60      0.61      2792
             weighted avg       0.79      0.82      0.80      2792
```

The classification report above shows that the logistic regression model achieved a precision of 79%, recall of 82%, f1-score of 80% (all weighted averages), and accuracy of 82%. However, if it's most important to predict employees who leave, then the scores are significantly lower.

4.2.4 Modeling Approach B: Tree-based Model

This approach covers implementation of Decision Tree and Random Forest.

We isolate the outcome variable.

[37]:
```python
# Isolate the outcome variable
y = df_enc['left']

# Display the first few rows of `y`
y.head()
```

[37]:
```
0    1
1    1
2    1
3    1
4    1
Name: left, dtype: int64
```

We select the features.

[38]:
```python
# Select the features
X = df_enc.drop('left', axis=1)

# Display the first few rows of `X`
X.head()
```

[38]:
```
   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  promotion_last_5years  salary  department_IT  \
0       3              0                      0       0          False
1       6              0                      0       1          False
2       4              0                      0       1          False
3       5              0                      0       0          False
4       3              0                      0       0          False

   department_RandD  department_accounting  department_hr  \
0             False                  False          False
1             False                  False          False
2             False                  False          False
```

```
3             False                  False          False
4             False                  False          False

   department_management  department_marketing  department_product_mng  \
0                  False                 False                   False
1                  False                 False                   False
2                  False                 False                   False
3                  False                 False                   False
4                  False                 False                   False

   department_sales  department_support  department_technical
0              True               False                 False
1              True               False                 False
2              True               False                 False
3              True               False                 False
4              True               False                 False
```

We split the data into training, validating, and testing sets.

[39]:
```python
# Split the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,␣
 ↪stratify=y, random_state=0)
```

Decision tree - Round 1 We construct a decision tree model and set up cross-validated grid-search to exhaustively search for the best model parameters.

[40]:
```python
# Instantiate model
tree = DecisionTreeClassifier(random_state=0)

# Assign a dictionary of hyperparameters to search over
cv_params = {'max_depth':[4, 6, 8, None],
             'min_samples_leaf': [2, 5, 1],
             'min_samples_split': [2, 4, 6]
             }

# Assign a dictionary of scoring metrics to capture
scoring = ['accuracy', 'precision', 'recall', 'f1', 'roc_auc']

# Instantiate GridSearch
tree1 = GridSearchCV(tree, cv_params, scoring=scoring, cv=4, refit='roc_auc')
```

We fit the decision tree model to the training data.

[41]:
```python
%%time
tree1.fit(X_train, y_train)
```

```
CPU times: total: 8.05 s
Wall time: 8.2 s
```

[41]:
```
GridSearchCV(cv=4, estimator=DecisionTreeClassifier(random_state=0),
             param_grid={'max_depth': [4, 6, 8, None],
                         'min_samples_leaf': [2, 5, 1],
                         'min_samples_split': [2, 4, 6]},
             refit='roc_auc',
             scoring=['accuracy', 'precision', 'recall', 'f1', 'roc_auc'])
```

We identify the optimal values for the decision tree parameters.

[42]:
```
# Check best parameters
tree1.best_params_
```

[42]:
```
{'max_depth': 4, 'min_samples_leaf': 5, 'min_samples_split': 2}
```

We identify the best AUC score achieved by the decision tree model on the training set.

[43]:
```
# Check best AUC score on CV
tree1.best_score_
```

[43]:
```
np.float64(0.969819392792457)
```

This is a strong AUC score, which shows that this model can predict employees who will leave very well.

Next, we write a function that will help to extract all the scores from the grid search.

[44]:
```
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 = pd.DataFrame({'model': [model_name],
                          'precision': [precision],
                          'recall': [recall],
                          'F1': [f1],
                          'accuracy': [accuracy],
                          'auc': [auc]
                        })

    return table
```

We use this function to get all the scores from grid search.

[45]:
```
# Get all CV scores
tree1_cv_results = make_results('decision tree cv', tree1, 'auc')
tree1_cv_results
```

[45]:

	model	precision	recall	F1	accuracy	auc
0	decision tree cv	0.914552	0.916949	0.915707	0.971978	0.969819

All of these scores from the decision tree model are strong indicators of good model performance.

However, decision trees can be vulnerable to overfitting, and random forests avoid overfitting by incorporating multiple trees to make predictions. we can construct a random forest model next.

Random forest - Round 1 We construct a random forest model and set up cross-validated grid-search to exhaustively search for the best model parameters.

[46]:
```
# Instantiate model
rf = RandomForestClassifier(random_state=0)

# Assign a dictionary of hyperparameters to search over
cv_params = {'max_depth': [3,5, None],
             'max_features': [1.0],
             'max_samples': [0.7, 1.0],
```

```
              'min_samples_leaf': [1,2,3],
              'min_samples_split': [2,3,4],
              'n_estimators': [300, 500],
              }

# Assign a dictionary of scoring metrics to capture
scoring = ['accuracy', 'precision', 'recall', 'f1', 'roc_auc']

# Instantiate GridSearch
rf1 = GridSearchCV(rf, cv_params, scoring=scoring, cv=4, refit='roc_auc')
```

We fit the random forest model to the training data.

[47]:
```
%%time
#rf1.fit(X_train, y_train) # --> Wall time: ~30min
```

```
CPU times: total: 0 ns
Wall time: 0 ns
```

The fitting time is long. We save the model to reuse later. In that case we specify path to save it.

[48]:
```
# Define a path to the folder where you want to save the model
path = '' #Same folder as project
```

We define functions to pickle the model and read in the model.

[49]:
```
def write_pickle(path, model_object, save_as:str):
    '''
    In:
        path:         path of folder where you want to save the pickle
        model_object: a model you want to pickle
        save_as:      filename for how you want to save the model

    Out: A call to pickle the model in the folder indicated
    '''

    with open(path + save_as + '.pickle', 'wb') as to_write:
        pickle.dump(model_object, to_write)
```

[50]:
```
def read_pickle(path, saved_model_name:str):
    '''
    In:
        path:             path to folder where you want to read from
        saved_model_name: filename of pickled model you want to read in

    Out:
        model: the pickled model
    '''
    with open(path + saved_model_name + '.pickle', 'rb') as to_read:
```

```
        model = pickle.load(to_read)

    return model
```

We us these functions defined above to save the model in a pickle file and then read it in.

[51]:
```
# Write pickle
#write_pickle(path, rf1, 'hr_rf1')
```

[52]:
```
# Read pickle
rf1 = read_pickle(path, 'hr_rf1')
```

We identify the best AUC score achieved by the random forest model on the training set.

[53]:
```
# Check best AUC score on CV
rf1.best_score_
```

[53]:
```
np.float64(0.9804250949807172)
```

We identify the optimal values for the parameters of the random forest model.

[54]:
```
# Check best params
rf1.best_params_
```

[54]:
```
{'max_depth': 5,
 'max_features': 1.0,
 'max_samples': 0.7,
 'min_samples_leaf': 1,
 'min_samples_split': 4,
 'n_estimators': 500}
```

We collect the evaluation scores on the training set for the decision tree and random forest models.

[55]:
```
# Get all CV scores
rf1_cv_results = make_results('random forest cv', rf1, 'auc')
print(tree1_cv_results)
print(rf1_cv_results)
```

```
              model  precision    recall        F1  accuracy       auc
0  decision tree cv   0.914552  0.916949  0.915707  0.971978  0.969819
              model  precision    recall        F1  accuracy       auc
0  random forest cv   0.950023  0.915614  0.932467  0.977983  0.980425
```

The evaluation scores of the random forest model are better than those of the decision tree model, with the exception of recall (the recall score of the random forest model is approximately 0.001 lower, which is a negligible amount). This indicates that the random forest model mostly outperforms the decision tree model.

Next, we can evaluate the final model on the test set.

We define a function that gets all the scores from a model's predictions.

```
[56]: def get_scores(model_name:str, model, X_test_data, y_test_data):
    '''
    Generate a table of test scores.

    In:
        model_name (string):  How you want your model to be named in the output␣
 ↪table
        model:                A fit GridSearchCV object
        X_test_data:          numpy array of X_test data
        y_test_data:          numpy array of y_test data

    Out: pandas df of precision, recall, f1, accuracy, and AUC scores for your␣
 ↪model
    '''

    preds = model.best_estimator_.predict(X_test_data)

    auc = roc_auc_score(y_test_data, preds)
    accuracy = accuracy_score(y_test_data, preds)
    precision = precision_score(y_test_data, preds)
    recall = recall_score(y_test_data, preds)
    f1 = f1_score(y_test_data, preds)

    table = pd.DataFrame({'model': [model_name],
                          'precision': [precision],
                          'recall': [recall],
                          'f1': [f1],
                          'accuracy': [accuracy],
                          'AUC': [auc]
                         })

    return table
```

Now we use the best performing model to predict on the test set.

```
[86]: # Get predictions on test data
rf1_test_scores = get_scores('random forest1 test', rf1, X_test, y_test)
rf1_test_scores
```

```
[86]:                  model  precision    recall        f1  accuracy       AUC
      0  random forest1 test   0.964211  0.919679  0.941418  0.980987  0.956439
```

The test scores are very similar to the validation scores, which is good. This appears to be a strong model. Since this test set was only used for this model, we can be more confident that the model's performance on this data is representative of how it will perform on new, unseeen data.

Feature Engineering The evaluation scores look too high. There is a chance that there is some data leakage occurring. Data leakage is when we use data to train the model that should not be used during training, either because it appears in the test data or because it's not data that we'd expect to have when the model is actually deployed. Training a model with leaked data can give an unrealistic score that is not replicated in production.

In this case, it's likely that the company won't have satisfaction levels reported for all of its employees. It's also possible that the `average_monthly_hours` column is a source of some data leakage. If employees have already decided upon quitting, or have already been identified by management as people to be fired, they may be working fewer hours.

The first round of decision tree and random forest models included all variables as features. This next round will incorporate feature engineering to build improved models.

We proceed by dropping `satisfaction_level` and creating a new feature that roughly captures whether an employee is overworked. We call this new feature `overworked`. It will be a binary variable.

[57]:
```python
# Drop `satisfaction_level` and save resulting dataframe in new variable
df2 = df_enc.drop('satisfaction_level', axis=1)

# Display first few rows of new dataframe
df2.head()
```

[57]:
```
   last_evaluation  number_project  average_monthly_hours  tenure  \
0             0.53               2                    157       3
1             0.86               5                    262       6
2             0.88               7                    272       4
3             0.87               5                    223       5
4             0.52               2                    159       3

   work_accident  left  promotion_last_5years  salary  department_IT  \
0              0     1                      0       0          False
1              0     1                      0       1          False
2              0     1                      0       1          False
3              0     1                      0       0          False
4              0     1                      0       0          False

   department_RandD  department_accounting  department_hr  \
0             False                  False          False
1             False                  False          False
2             False                  False          False
3             False                  False          False
4             False                  False          False

   department_management  department_marketing  department_product_mng  \
0                  False                 False                   False
1                  False                 False                   False
2                  False                 False                   False
3                  False                 False                   False
4                  False                 False                   False
```

```
   department_sales  department_support  department_technical
0              True               False                 False
1              True               False                 False
2              True               False                 False
3              True               False                 False
4              True               False                 False
```

[58]:
```
# Create `overworked` column. For now, it's identical to average monthly hours.
df2['overworked'] = df2['average_monthly_hours']

# Inspect max and min average monthly hours values
print('Max hours:', df2['overworked'].max())
print('Min hours:', df2['overworked'].min())
```

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

166.67 is approximately the average number of monthly hours for someone who works 50 weeks per year, 5 days per week, 8 hours per day.

We can define being overworked as working more than 175 hours per month on average.

To make the `overworked` column binary, we reassign the column using a boolean mask. - `df3['overworked'] > 175` creates a series of booleans, consisting of `True` for every value > 175 and `False` for every values 175 - `.astype(int)` converts all `True` to `1` and all `False` to `0`

[59]:
```
# Define `overworked` as working > 175 hrs/week
df2['overworked'] = (df2['overworked'] > 175).astype(int)

# Display first few rows of new column
df2['overworked'].head()
```

[59]:
```
0    0
1    1
2    1
3    1
4    0
Name: overworked, dtype: int64
```

We drop the `average_monthly_hours` column.

[60]:
```
# Drop the `average_monthly_hours` column
df2 = df2.drop('average_monthly_hours', axis=1)

# Display first few rows of resulting dataframe
df2.head()
```

[60]:
```
   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  salary  department_IT  department_RandD  \
0                      0       0          False             False
1                      0       1          False             False
2                      0       1          False             False
3                      0       0          False             False
4                      0       0          False             False

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

   department_marketing  department_product_mng  department_sales  \
0                 False                   False              True
1                 False                   False              True
2                 False                   False              True
3                 False                   False              True
4                 False                   False              True

   department_support  department_technical  overworked
0               False                 False           0
1               False                 False           1
2               False                 False           1
3               False                 False           1
4               False                 False           0
```

Again, we isolate the features and target variables

[61]:
```
# Isolate the outcome variable
y = df2['left']

# Select the features
X = df2.drop('left', axis=1)
```

We split the data into training and testing sets.

[62]:
```
# Create test data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,␣
↪stratify=y, random_state=0)
```

Decision tree - Round 2

[63]:
```
# Instantiate model
tree = DecisionTreeClassifier(random_state=0)

# Assign a dictionary of hyperparameters to search over
cv_params = {'max_depth':[4, 6, 8, None],
             'min_samples_leaf': [2, 5, 1],
             'min_samples_split': [2, 4, 6]
             }

# Assign a dictionary of scoring metrics to capture
scoring = ['accuracy', 'precision', 'recall', 'f1', 'roc_auc']

# Instantiate GridSearch
tree2 = GridSearchCV(tree, cv_params, scoring=scoring, cv=4, refit='roc_auc')
```

[64]:
```
%%time
tree2.fit(X_train, y_train)
```

```
CPU times: total: 6.84 s
Wall time: 7.17 s
```

[64]:
```
GridSearchCV(cv=4, estimator=DecisionTreeClassifier(random_state=0),
             param_grid={'max_depth': [4, 6, 8, None],
                         'min_samples_leaf': [2, 5, 1],
                         'min_samples_split': [2, 4, 6]},
             refit='roc_auc',
             scoring=['accuracy', 'precision', 'recall', 'f1', 'roc_auc'])
```

[65]:
```
# Check best params
tree2.best_params_
```

[65]:
```
{'max_depth': 6, 'min_samples_leaf': 2, 'min_samples_split': 6}
```

[66]:
```
# Check best AUC score on CV
tree2.best_score_
```

[66]:
```
np.float64(0.9586752505340426)
```

This model performs very well, even without satisfaction levels and detailed hours worked data.

Next, we check the other scores.

[67]:
```
# Get all CV scores
tree2_cv_results = make_results('decision tree2 cv', tree2, 'auc')
print(tree1_cv_results)
print(tree2_cv_results)
```

```
              model  precision    recall        F1  accuracy       auc
0  decision tree cv   0.914552  0.916949  0.915707  0.971978  0.969819
```

```
                model  precision    recall        F1  accuracy       auc
0  decision tree2 cv   0.856693  0.903553  0.878882  0.958523  0.958675
```

Some of the other scores fell. Still, the scores are very good.

Random forest - Round 2

[68]:
```
# Instantiate model
rf = RandomForestClassifier(random_state=0)

# Assign a dictionary of hyperparameters to search over
cv_params = {'max_depth': [3,5, None],
             'max_features': [1.0],
             'max_samples': [0.7, 1.0],
             'min_samples_leaf': [1,2,3],
             'min_samples_split': [2,3,4],
             'n_estimators': [300, 500],
             }

# Assign a dictionary of scoring metrics to capture
scoring = ['accuracy', 'precision', 'recall', 'f1', 'roc_auc']

# Instantiate GridSearch
rf2 = GridSearchCV(rf, cv_params, scoring=scoring, cv=4, refit='roc_auc')
```

[ ]:
```
%%time
#rf2.fit(X_train, y_train) # --> Wall time: 34min 5s
```

```
CPU times: total: 32min 56s
Wall time: 33min 54s
```

[ ]:
```
GridSearchCV(cv=4, estimator=RandomForestClassifier(random_state=0),
             param_grid={'max_depth': [3, 5, None], 'max_features': [1.0],
                         'max_samples': [0.7, 1.0],
                         'min_samples_leaf': [1, 2, 3],
                         'min_samples_split': [2, 3, 4],
                         'n_estimators': [300, 500]},
             refit='roc_auc',
             scoring=['accuracy', 'precision', 'recall', 'f1', 'roc_auc'])
```

[ ]:
```
# Write pickle
#write_pickle(path, rf2, 'hr_rf2')
```

[71]:
```
# Read in pickle
rf2 = read_pickle(path, 'hr_rf2')
```

[72]:
```
# Check best params
rf2.best_params_
```

[72]:
```
{'max_depth': 5,
 'max_features': 1.0,
 'max_samples': 0.7,
 'min_samples_leaf': 2,
 'min_samples_split': 2,
 'n_estimators': 300}
```

[73]:
```
# Check best AUC score on CV
rf2.best_score_
```

[73]:
```
np.float64(0.9648100662833985)
```

[74]:
```
# Get all CV scores
rf2_cv_results = make_results('random forest2 cv', rf2, 'auc')
print(tree2_cv_results)
print(rf2_cv_results)
```

```
               model  precision    recall        F1  accuracy       auc
0  decision tree2 cv   0.856693  0.903553  0.878882  0.958523  0.958675
               model  precision    recall        F1  accuracy      auc
0  random forest2 cv   0.866758  0.878754  0.872407  0.957411  0.96481
```

The scores dropped slightly again, but the random forest performs better than the decision tree if using AUC as the deciding metric.

We score the champion model on the test set now.

[75]:
```
# Get predictions on test data
rf2_test_scores = get_scores('random forest2 test', rf2, X_test, y_test)
rf2_test_scores
```

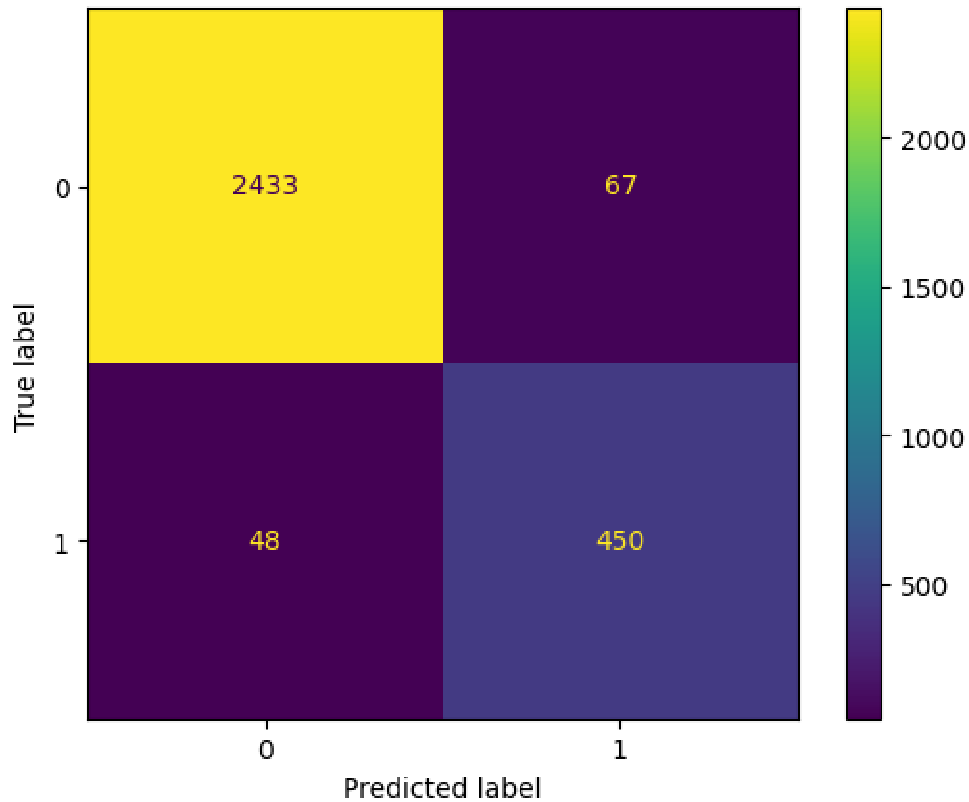
[75]:

	model	precision	recall	f1	accuracy	AUC
0	random forest2 test	0.870406	0.903614	0.8867	0.961641	0.938407

This seems to be a stable, well-performing final model.

We plot a confusion matrix to visualize how well it predicts on the test set.

[76]:
```
# Generate array of values for confusion matrix
preds = rf2.best_estimator_.predict(X_test)
cm = confusion_matrix(y_test, preds, labels=rf2.classes_)

# Plot confusion matrix
disp = ConfusionMatrixDisplay(confusion_matrix=cm,
                              display_labels=rf2.classes_)
disp.plot(values_format='');
```

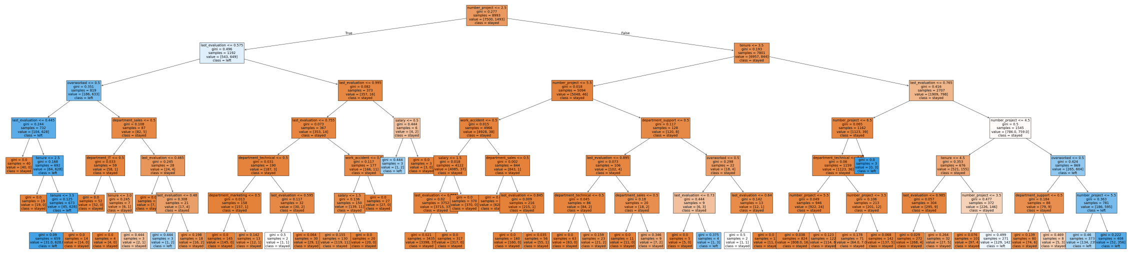


The model predicts more false positives than false negatives, which means that some employees may be identified as at risk of quitting or getting fired, when that's actually not the case. But this is still a strong model.

For exploratory purpose, you inspect the splits of the decision tree model and the most important features in the random forest model.

Decision tree splits

[77]:
```
# Plot the tree
plt.figure(figsize=(85,20))
plot_tree(tree2.best_estimator_, max_depth=6, fontsize=14, feature_names=X.
 ↪columns,
          class_names={0:'stayed', 1:'left'}, filled=True);
plt.show()
```



Decision tree feature importance We can also get the feature importance from decision trees.

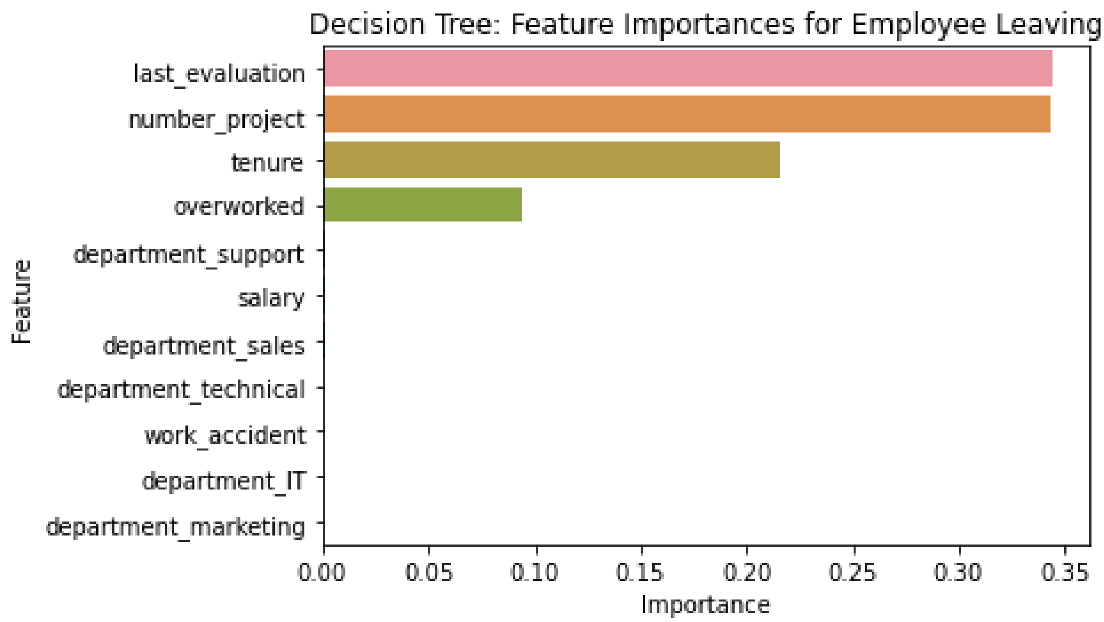
```
[78]: #tree2_importances = pd.DataFrame(tree2.best_estimator_.feature_importances_,␣
       ↪columns=X.columns)
      tree2_importances = pd.DataFrame(tree2.best_estimator_.feature_importances_,
                                       columns=['gini_importance'],
                                       index=X.columns
                                      )
      tree2_importances = tree2_importances.sort_values(by='gini_importance',␣
       ↪ascending=False)

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

[78]:

	gini_importance
last_evaluation	0.343958
number_project	0.343385
tenure	0.215681
overworked	0.093498
department_support	0.001142
salary	0.000910
department_sales	0.000607
department_technical	0.000418
work_accident	0.000183
department_IT	0.000139
department_marketing	0.000078

We can then create a barplot to visualize the decision tree feature importances.

```
[ ]: sns.barplot(data=tree2_importances, x="gini_importance", y=tree2_importances.
      ↪index, orient='h')
     plt.title("Decision Tree: Feature Importances for Employee Leaving",␣
      ↪fontsize=12)
     plt.ylabel("Feature")
     plt.xlabel("Importance")
     plt.show()
```

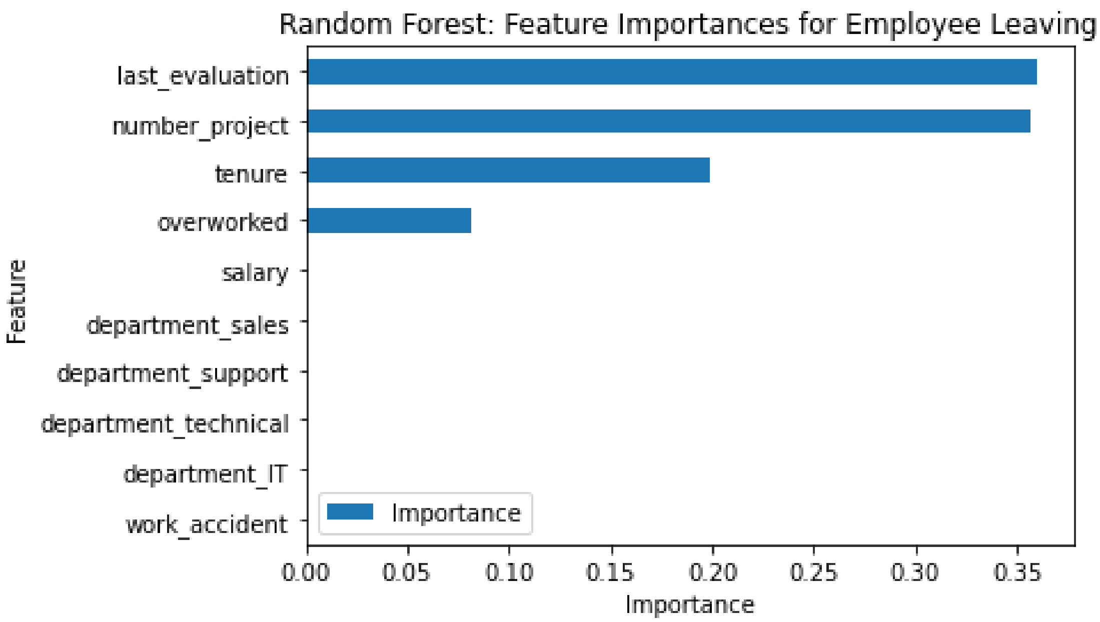


The barplot above shows that in this decision tree model, `last_evaluation`, `number_project`, `tenure`, and `overworked` have the highest importance, in that order. These variables are most helpful in predicting the outcome variable, `left`.

Random forest feature importance Now, we plot the feature importances for the random forest model.

[ ]:
```
# Get feature importances
feat_impt = rf2.best_estimator_.feature_importances_

# Get indices of top 10 features
ind = np.argpartition(rf2.best_estimator_.feature_importances_, -10)[-10:]

# Get column labels of top 10 features
feat = X.columns[ind]

# Filter `feat_impt` to consist of top 10 feature importances
feat_impt = feat_impt[ind]

y_df = pd.DataFrame({"Feature":feat,"Importance":feat_impt})
y_sort_df = y_df.sort_values("Importance")
fig = plt.figure()
ax1 = fig.add_subplot(111)

y_sort_df.plot(kind='barh',ax=ax1,x="Feature",y="Importance")
```

```
ax1.set_title("Random Forest: Feature Importances for Employee Leaving",␣
↪fontsize=12)
ax1.set_ylabel("Feature")
ax1.set_xlabel("Importance")

plt.show()
```



The plot above shows that in this random forest model, `last_evaluation`, `number_project`, `tenure`, and `overworked` have the highest importance, in that order. These variables are most helpful in predicting the outcome variable, `left`, and they are the same as the ones used by the decision tree model.

5 pacE: Execute Stage

5.1 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.

5.2 Step 4. Results and Evaluation

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

5.2.1 Summary of model results

Logistic Regression

The logistic regression model achieved precision of 80%, recall of 83%, f1-score of 80% (all weighted averages), and accuracy of 83%, on the test set.

Tree-based Machine Learning

After conducting feature engineering, the decision tree model achieved AUC of 93.8%, precision of 87.0%, recall of 90.4%, f1-score of 88.7%, and accuracy of 96.2%, on the test set. The random forest modestly outperformed the decision tree model.

5.2.2 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 at least 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.
- Hold company-wide and within-team discussions to understand and address the company work culture, across the board and in specific contexts.
- High evaluation scores should not be reserved for employees who work 200+ hours per month. Consider a proportionate scale for rewarding employees who contribute more/put in more effort.

Next Steps

It may be justified to still have some concern about data leakage. It could be prudent to consider how predictions change when `last_evaluation` is removed from the data. It's possible that evaluations aren't performed very frequently, in which case it would be useful to be able to predict employee retention without this feature. It's also possible that the evaluation score determines whether an employee leaves or stays, in which case it could be useful to pivot and try to predict performance score. The same could be said for satisfaction score.