Activity_ Course 7 Salifort Motors project lab

May 29, 2024

1 Capstone project: Providing data-driven suggestions for HR

1.1 Description and deliverables

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

Upon completion, you will have two artifacts that you would be able to present to future employers. One is a brief one-page summary of this project that you would present to external stakeholders as the data professional in Salifort Motors. The other is a complete code notebook provided here. Please consider your prior course work and select one way to achieve this given project question. Either use a regression model or machine learning model to predict whether or not an employee will leave the company. The exemplar following this actiivty shows both approaches, but you only need to do one.

In your deliverables, you will include the model evaluation (and interpretation if applicable), a data visualization(s) of your choice that is directly related to the question you ask, ethical considerations, and the resources you used to troubleshoot and find answers or solutions.

2 PACE stages

2.1 Pace: Plan

Consider the questions in your PACE Strategy Document to reflect on the Plan stage.

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

The dataset that you'll be using in this lab contains 15,000 rows and 10 columns for the variables listed below.

Note: you don't need to download any data to complete this lab. For more information about the data, refer to its source on Kaggle.

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
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)

Reflect on these questions as you complete the plan stage.

- Who are your stakeholders for this project?
- What are you trying to solve or accomplish?
- What are your initial observations when you explore the data?
- What resources do you find yourself using as you complete this stage? (Make sure to include the links.)
- Do you have any ethical considerations in this stage?

[Double-click to enter your responses here.]

2.2 Step 1. Imports

- Import packages

- Load dataset

2.2.1 Import packages

[1]:
```
# Import packages
### YOUR CODE HERE ###
# For data manipulation
import pandas as pd
import numpy as np

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


# 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
from sklearn.metrics import roc_auc_score, roc_curve
from sklearn.tree import plot_tree

# For saving models
import pickle
```

2.2.2 Load dataset

`Pandas` is used to read a dataset called **`HR_capstone_dataset.csv`.** As shown in this cell, the dataset has been automatically loaded in for you. You do not need to download the .csv file, or provide more code, in order to access the dataset and proceed with this lab. Please continue with this activity by completing the following instructions.

[2]:
```
# RUN THIS CELL TO IMPORT YOUR DATA.

# Load dataset into a dataframe
### YOUR CODE HERE ###
df0 = pd.read_csv("HR_capstone_dataset.csv")
```

```
# Display first few rows of the dataframe
### YOUR CODE HERE ###
df0.head(10)
```

[2]:

	satisfaction_level	last_evaluation	number_project	average_montly_hours	time_spend_company	Work_accident	left	promotion_last_5years	Department	salary
0	0.38	0.53	2	157	3	0	1	0	sales	low
1	0.80	0.86	5	262	6	0	1	0	sales	medium
2	0.11	0.88	7	272	4	0	1	0	sales	medium
3	0.72	0.87	5	223	5	0	1	0	sales	low
4	0.37	0.52	2	159	3	0	1	0	sales	low
5	0.41	0.50	2	153	3	0	1	0	sales	low
6	0.10	0.77	6	247	4	0	1	0	sales	low
7	0.92	0.85	5	259	5	0	1	0	sales	low
8	0.89	1.00	5	224	5	0	1	0	sales	low
9	0.42	0.53	2	142	3	0	1	0	sales	low

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

- Understand your variables
- Clean your dataset (missing data, redundant data, outliers)

2.3.1 Gather basic information about the data

[3]:
```
# Gather basic information about the data
### YOUR CODE HERE ###
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]:
```
# Gather descriptive statistics about the data
### YOUR CODE HERE ###
df0.describe(include = "all")
```

[4]:

	satisfaction_level	last_evaluation	number_project	\
count	14999.000000	14999.000000	14999.000000	
unique	NaN	NaN	NaN	
top	NaN	NaN	NaN	
freq	NaN	NaN	NaN	
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	
unique	NaN	NaN	NaN	NaN	

```
top                    NaN                NaN          NaN          NaN
freq                   NaN                NaN          NaN          NaN
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 Department salary
count            14999.000000      14999  14999
unique                    NaN         10      3
top                       NaN      sales    low
freq                      NaN       4140   7316
mean                 0.021268        NaN    NaN
std                  0.144281        NaN    NaN
min                  0.000000        NaN    NaN
25%                  0.000000        NaN    NaN
50%                  0.000000        NaN    NaN
75%                  0.000000        NaN    NaN
max                  1.000000        NaN    NaN
```

2.3.3 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.

[5]:
```
# Display all column names
### YOUR CODE HERE ###
df0.dtypes
```

[5]:
```
satisfaction_level       float64
last_evaluation          float64
number_project             int64
average_montly_hours       int64
time_spend_company         int64
Work_accident              int64
left                       int64
promotion_last_5years      int64
Department                object
salary                    object
dtype: object
```

[6]:
```
# Rename columns as needed
### YOUR CODE HERE ###
df0['last_pro_evaluation']=df0['last_evaluation']
del df0['last_evaluation']

df0['work_accident']=df0['Work_accident']
del df0['Work_accident']

df0['department']=df0['Department']
del df0['Department']

df0['tenure']=df0['time_spend_company']
del df0['time_spend_company']

df0['average_monthly_hours']=df0['average_montly_hours']
del df0['average_montly_hours']


# Display all column names after the update
### YOUR CODE HERE ###
df0.dtypes
```

[6]:
```
satisfaction_level       float64
number_project             int64
left                       int64
promotion_last_5years      int64
salary                    object
last_pro_evaluation      float64
work_accident              int64
department                object
tenure                     int64
average_monthly_hours      int64
dtype: object
```

2.3.4 Check missing values

Check for any missing values in the data.

[7]:
```
# Check for missing values
### YOUR CODE HERE ###
df0.isnull().sum()
```

[7]:
```
satisfaction_level       0
number_project           0
left                     0
promotion_last_5years    0
```

```
salary                   0
last_pro_evaluation      0
work_accident            0
department               0
tenure                   0
average_monthly_hours    0
dtype: int64
```

2.3.5 Check duplicates

Check for any duplicate entries in the data.

[8]:
```
# Check for duplicates
### YOUR CODE HERE ###
df0.duplicated().value_counts()
```

[8]:
```
False    11991
True      3008
dtype: int64
```

[9]:
```
# Inspect some rows containing duplicates as needed
### YOUR CODE HERE ###
duplicate = df0.duplicated()
df_duplicate = df0[duplicate]
df_duplicate.head(10)
```

[9]:

	satisfaction_level	number_project	left	promotion_last_5years	\
396	0.46	2	1	0	
866	0.41	2	1	0	
1317	0.37	2	1	0	
1368	0.41	2	1	0	
1461	0.42	2	1	0	
1516	0.40	2	1	0	
1616	0.37	2	1	0	
1696	0.39	2	1	0	
1833	0.10	6	1	0	
12000	0.38	2	1	0	

	salary	last_pro_evaluation	work_accident	department	tenure	\
396	low	0.57	0	sales	3	
866	low	0.46	0	accounting	3	
1317	medium	0.51	0	sales	3	
1368	low	0.52	0	RandD	3	
1461	low	0.53	0	sales	3	
1516	low	0.50	0	IT	3	
1616	low	0.46	0	sales	3	

```
1696      low                 0.56              0       sales       3
1833      low                 0.85              0       sales       4
12000     low                 0.53              0       sales       3

       average_monthly_hours
396                      139
866                      128
1317                     127
1368                     132
1461                     142
1516                     127
1616                     156
1696                     160
1833                     266
12000                    157
```

[10]:
```
# Drop duplicates and save resulting dataframe in a new variable as needed
### YOUR CODE HERE ###
df = df0.drop_duplicates(subset = None, keep = 'first', inplace = False)

# Display first few rows of new dataframe as needed
### YOUR CODE HERE ###
df.head(10)
df.shape
```

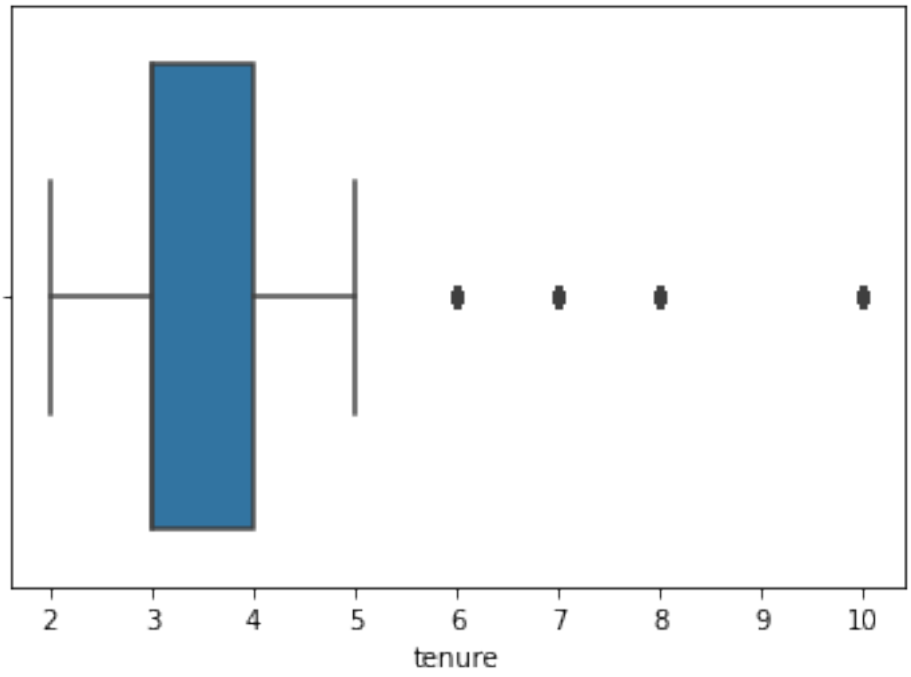
[10]:
```
(11991, 10)
```

2.3.6 Check outliers

Check for outliers in the data.

[11]:
```
# Create a boxplot to visualize distribution of `tenure` and detect any outliers
### YOUR CODE HERE ###

# sns.boxplot(data=df, x= "satisfaction_level") # no outliers

# sns.boxplot(data=df, x= "number_project") # no outliers

# sns.boxplot(data=df, x= "average_montly_hours") # no outliers

sns.boxplot(data=df, x= "tenure") # outliers

# sns.boxplot(data=df, x= "last_pro_evaluation") # no outliers
```

[11]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x70969b841ad0>
```

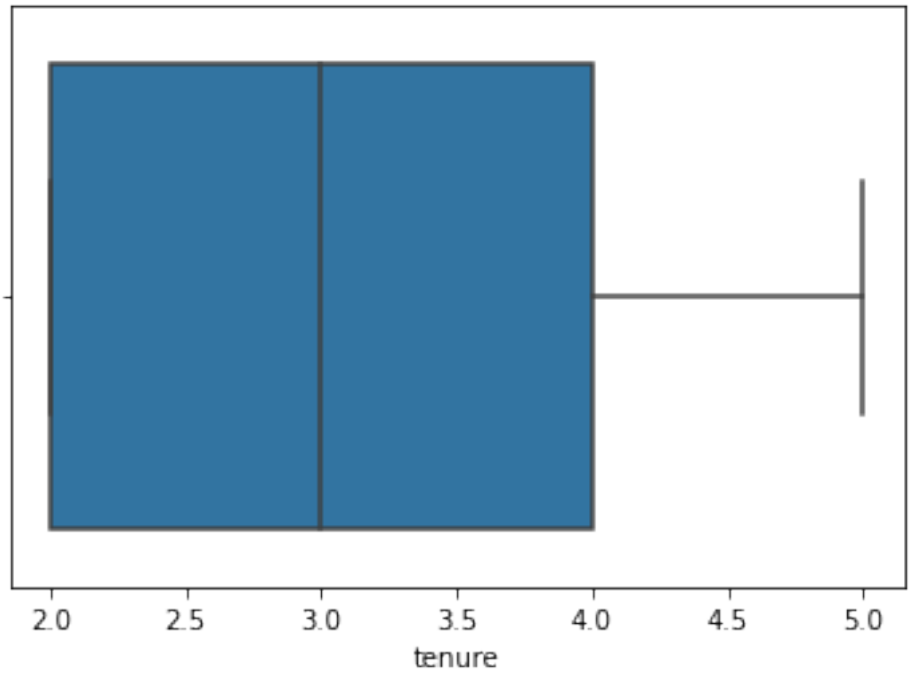


[73]:
```
# Determine the number of rows containing outliers
### YOUR CODE HERE ###

percentile25 = df['tenure'].quantile(0.25)

percentile75 = df['tenure'].quantile(0.75)

iqr = percentile75 - percentile25

upper_limit = percentile75 + 1.5 * iqr

print("upper_limit is: ",upper_limit)
```

```
upper_limit is:  5.5
```

[74]:
```
mask = (df['tenure'] <= upper_limit)

df = df[mask].copy()

sns.boxplot(data=df, x= "tenure")
```

[74]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x71e1256564d0>
```



[75]:
```
# Convert object into int
## Convert department into numbers
df['department'].unique()
department_number = {1:'sales',2:'accounting',3:'hr',4:'technical',5:
 ↪'support',6:'management',7:'IT',8:'product_mng',9:'marketing',10:'RandD'}


## Convert salary into numbers
```

Certain types of models are more sensitive to outliers than others. When you get to the stage of building your model, consider whether to remove outliers, based on the type of model you decide to use.

3 pAce: Analyze Stage

- Perform EDA (analyze relationships between variables)

Reflect on these questions as you complete the analyze stage.

- What did you observe about the relationships between variables?
- What do you observe about the distributions in the data?
- What transformations did you make with your data? Why did you chose to make those decisions?
- What are some purposes of EDA before constructing a predictive model?

- What resources do you find yourself using as you complete this stage? (Make sure to include the links.)
- Do you have any ethical considerations in this stage?

[Double-click to enter your responses here.]

3.1 Step 2. Data Exploration (Continue EDA)

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

[12]:
```
# Get numbers of people who left vs. stayed
### YOUR CODE HERE ###
df.groupby(by="left").count()
# Get percentages of people who left vs. stayed
### YOUR CODE HERE ###
left_percent = 1882 / (1882+9285) *100
stay_percent = 9285 / (1882+9285) *100

print(f"Percentage of leaving employee: {left_percent:.2f}%")
print(f"Percentage of staying employee: {stay_percent:.2f}%")
```

```
Percentage of leaving employee: 16.85%
Percentage of staying employee: 83.15%
```

3.1.1 Data visualizations

Now, examine variables that you're interested in, and create plots to visualize relationships between variables in the data.

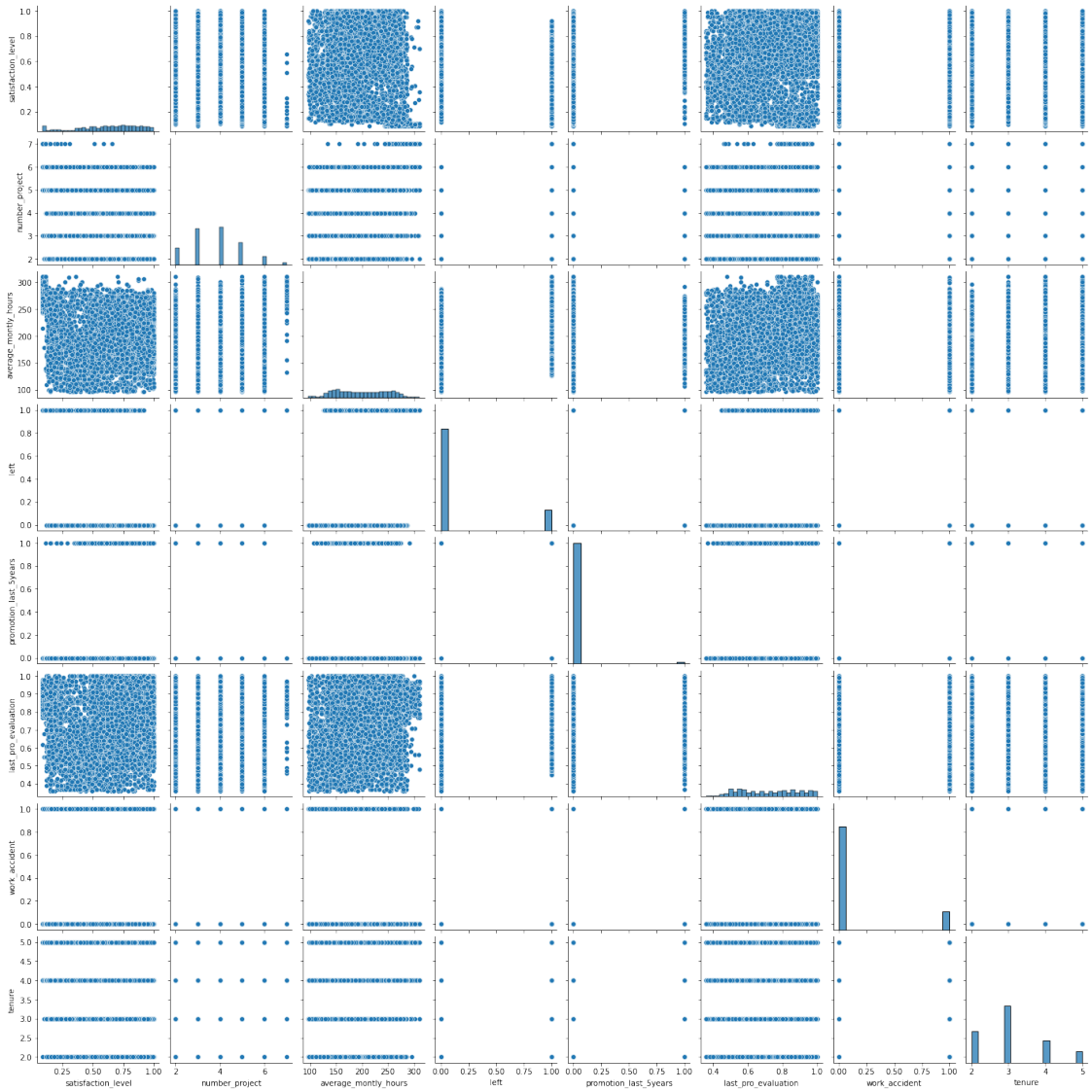
[16]:
```
data_majority = df[df["left"] == "0"]
data_minority = df[df["left"] == "1"]

# Upsample the minority class (which is "verified")
data_minority_upsampled = resample(data_minority,
                                   replace=True,                 # to sample with␣
 ↪replacement
                                   n_samples=len(data_majority), # to match␣
 ↪majority class
                                   random_state=0)               # to create␣
 ↪reproducible results

# Combine majority class with upsampled minority class
data_upsampled = pd.concat([data_majority, data_minority_upsampled]).
 ↪reset_index(drop=True)

# Display new class counts
```

```
data_upsampled["left"].value_counts()
```

```
      ␣
↪---------------------------------------------------------------------------

       NameError                                 Traceback (most recent call␣
↪last)

       <ipython-input-16-56dcc9f3f22d> in <module>
         3
         4 # Upsample the minority class (which is "verified")
    ----> 5 data_minority_upsampled = resample(data_minority,
         6                                     replace=True,                 # to␣
↪sample with replacement
         7                                     n_samples=len(data_majority), # to␣
↪match majority class


       NameError: name 'resample' is not defined
```

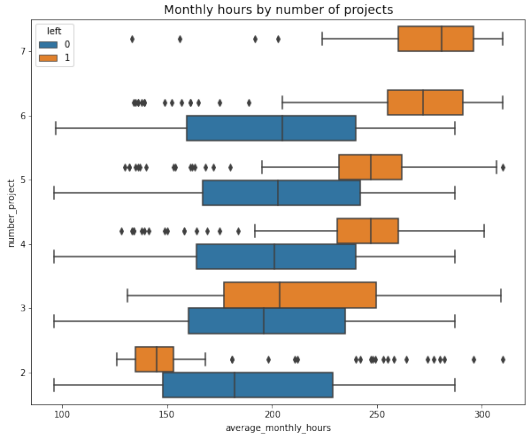
[77]:
```
# Create a plot as needed
### YOUR CODE HERE ###
sns.pairplot(df)
```

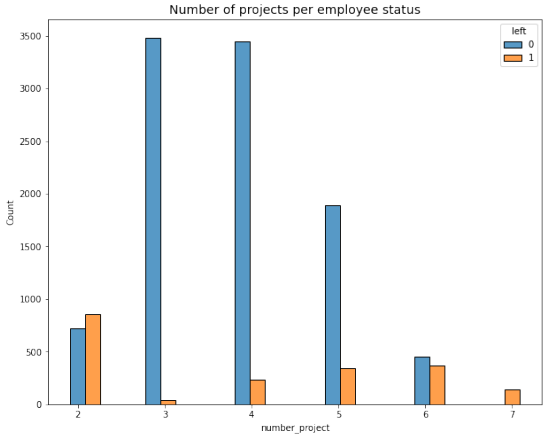
[77]:
```
<seaborn.axisgrid.PairGrid at 0x71e125632c90>
```



[29]:
```
# Create a plot as needed
### YOUR CODE HERE ###
# Create boxplot comparing "average monthly hours" distribution for "number of␣
 ↪project" for staying and left employees
fig, ax = plt.subplots(1,2,figsize = (22,8))
sns.boxplot(data=df, 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 of "numbers of project" per employee who left and stay
tenure_stay = df[df["left"]==0]['number_project']
tenure_left = df[df['left']==1]['number_project']
```

```
sns.histplot(data=df, x="number_project",hue = 'left', multiple = 'dodge',␣
 ↪shrink = 2, ax=ax[1])
ax[1].set_title('Number of projects per employee status', fontsize='14')

plt.show()
```





We can see that lesser project and overproject can possibliy be factor of leaving company. According to the average working hours, the employees work much more than the average French. It seems that 3,4 and 5 project are optimal for employees

[14]:
```
# Create a plot as needed
### YOUR CODE HERE ###
df[df['number_project']==7]['left'].value_counts()
```

[14]:
```
1    145
Name: left, dtype: int64
```

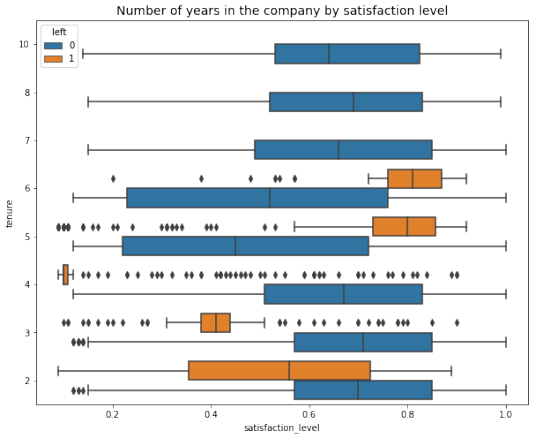
That comfirms that every employee with 7 project left the company

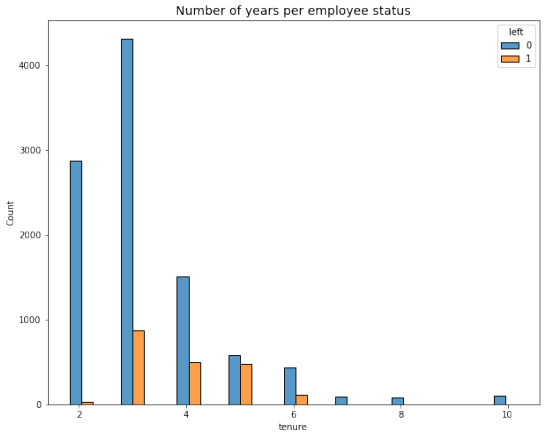
[17]:
```
# Create a plot as needed
### YOUR CODE HERE ###

plt.figure(figsize=(16,9))
sns.scatterplot(data=df, x='average_monthly_hours', y='satisfaction_level',␣
 ↪hue='left', alpha=0.4)
plt.title('Monthly hours by last satisfaction score')
plt.axvline(x=160, color='#ff6361', label='160 hrs./mo.', ls='--')
plt.axvline(x=220, color='#ff6361', label='220 hrs./mo.', ls='--')
```

[17]:
```
<matplotlib.lines.Line2D at 0x7096992c0a10>
```

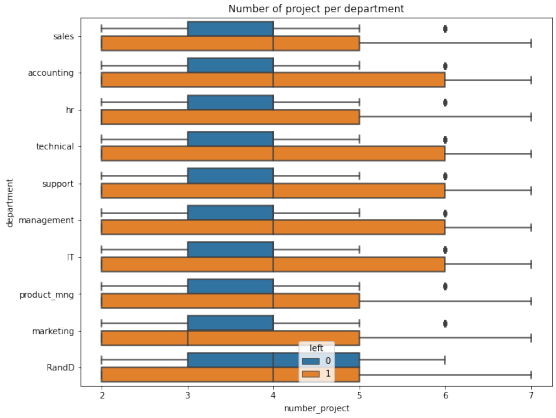
It's interesting to notice that people leaving the company are gather together. There are those who work considerable amount of time who are very less satisfy. Those who work less than the others (and a bit less than the average in France) and some that worked a lot but still are resonnably satisfy. To oppose this to staying employees, they are gather high in the satifsy scale with a lower range of working hours per month

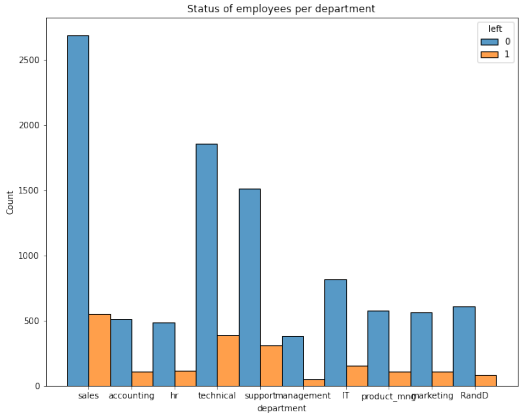
[18]:
```
# Create a plot as needed
### YOUR CODE HERE ###
fig, ax = plt.subplots(1,2,figsize = (22,8))

# Satisfaction level by time spend company
sns.boxplot(data=df, x="satisfaction_level", y="tenure", hue='left',␣
 ↪orient="h", ax=ax[0])
ax[0].invert_yaxis()
ax[0].set_title('Number of years in the company by satisfaction level',␣
 ↪fontsize ='14')

# Create histogram of "numbers of project" per employee who left and stay
tenure_stay = df[df["left"]==0]['tenure']
tenure_left = df[df['left']==1]['tenure']
sns.histplot(data=df, x="tenure",hue = 'left', multiple = 'dodge', shrink = 5,␣
 ↪ax=ax[1])
ax[1].set_title('Number of years per employee status', fontsize='14')

plt.show()
```





[19]:
```
# Create a plot as needed
### YOUR CODE HERE ###

fig, ax = plt.subplots(1,2,figsize=(22,8))

# Number of project by department
sns.boxplot(data=df, x="number_project", y='department', hue='left', orient =␣
↪'h', ax=ax[0])
ax[0].set_title("Number of project per department")

# Left by department
sns.histplot(data=df, x='department', hue = 'left', multiple = 'dodge', shrink␣
↪= 1, ax=ax[1])
ax[1].set_title("Status of employees per department")


plt.show()
```





[20]:
```
df.groupby(by='department').count()
```

[20]:

department	satisfaction_level	number_project	left	promotion_last_5years
IT	976	976	976	976
RandD	694	694	694	694
accounting	621	621	621	621
hr	601	601	601	601
management	436	436	436	436
marketing	673	673	673	673
product_mng	686	686	686	686
sales	3239	3239	3239	3239
support	1821	1821	1821	1821
technical	2244	2244	2244	2244

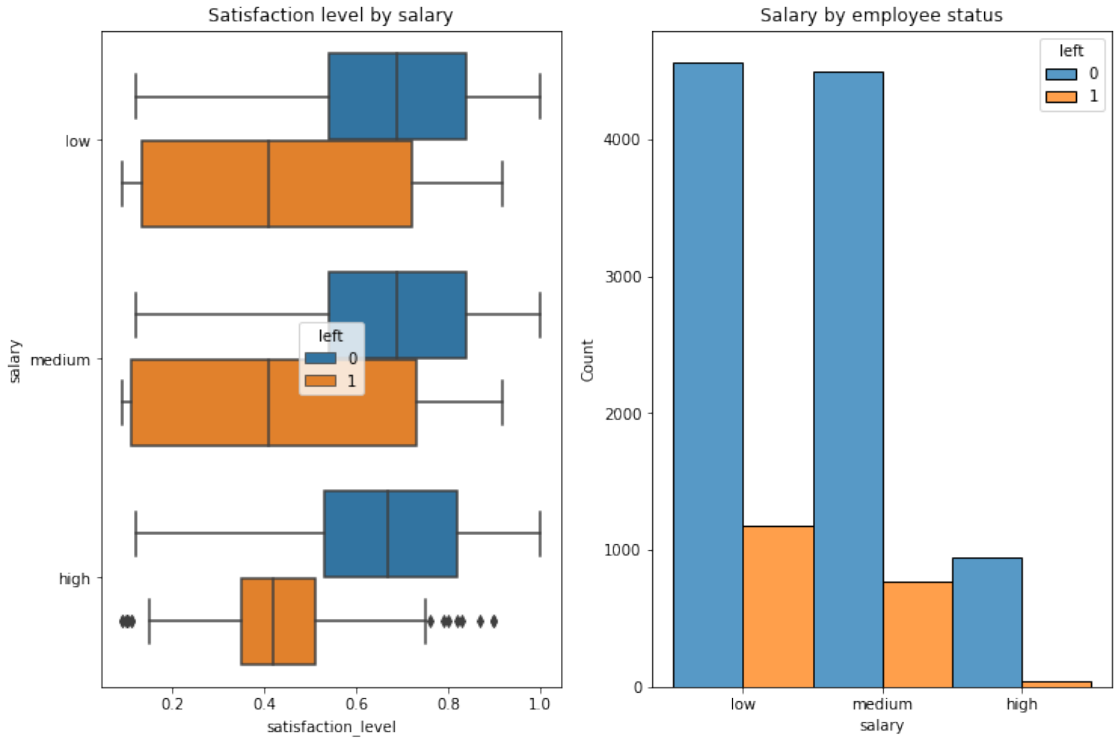
department	salary	last_pro_evaluation	work_accident	tenure
IT	976	976	976	976
RandD	694	694	694	694
accounting	621	621	621	621
hr	601	601	601	601
management	436	436	436	436
marketing	673	673	673	673
product_mng	686	686	686	686
sales	3239	3239	3239	3239
support	1821	1821	1821	1821
technical	2244	2244	2244	2244

department	average_monthly_hours
IT	976
RandD	694
accounting	621
hr	601
management	436
marketing	673
product_mng	686
sales	3239
support	1821
technical	2244

There is more left people in sales, technical and support team to left company. But they are the most representated team in the dataset - not revelant

[21]:
```
# Create a plot as needed
### YOUR CODE HERE ###
fig, ax = plt.subplots(1,2,figsize=(12,8))
```

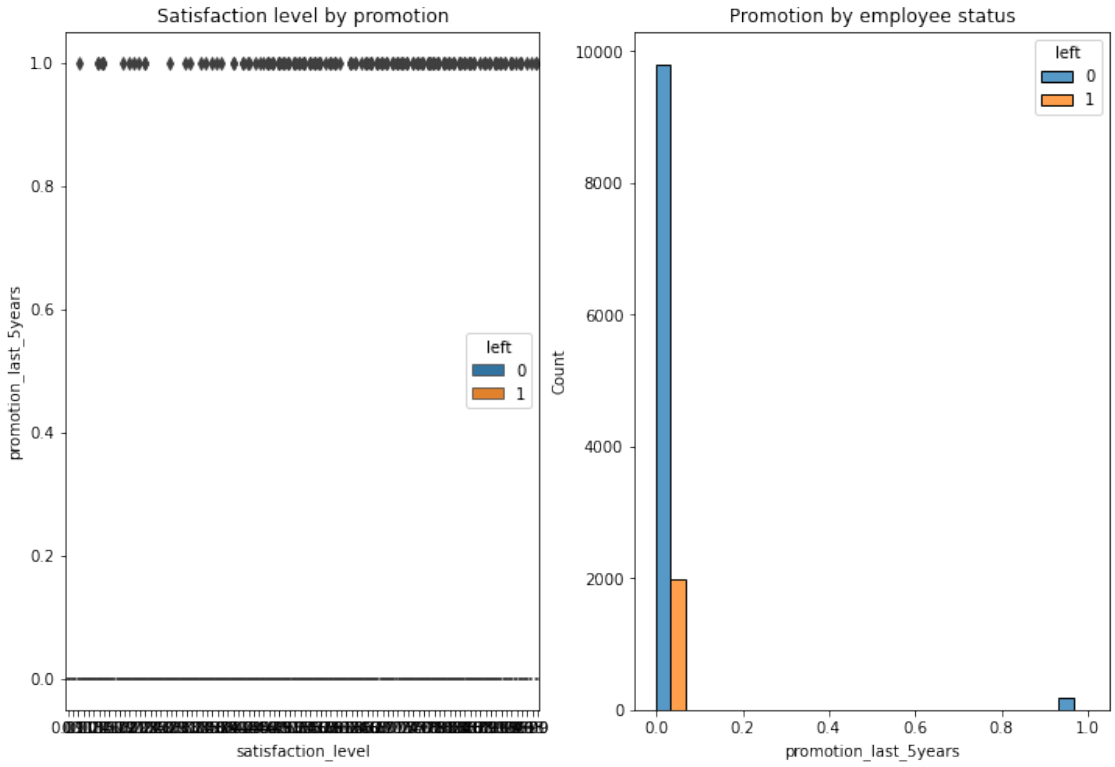
```
# satisfaction by salary
sns.boxplot(data=df, x = 'satisfaction_level', y ='salary', hue='left',␣
 ↪ax=ax[0])
ax[0].set_title('Satisfaction level by salary')

# left by salary
sns.histplot(data=df, x='salary', hue = 'left', multiple = 'dodge', ax=ax[1])
ax[1].set_title('Salary by employee status')

plt.show()
```



Whatever the salary, lefting employees are less satisfy. Which is very present in low and medium salary. High salary, tend to be more satisfy (but less than staying salary)

[22]:
```
# Create a plot as needed
### YOUR CODE HERE ###
fig, ax = plt.subplots(1,2,figsize=(12,8))

# satisfaction by promotion
sns.boxplot(data=df, x = 'satisfaction_level', y ='promotion_last_5years',␣
 ↪hue='left', ax=ax[0])
ax[0].set_title('Satisfaction level by promotion')

# left by promotion
```

```
sns.histplot(data=df, x='promotion_last_5years', hue = 'left', multiple =␣
↪'dodge', ax=ax[1])
ax[1].set_title('Promotion by employee status')

plt.show()
```



[23]:
```
df[df['promotion_last_5years']==1]['left'].value_counts()
```

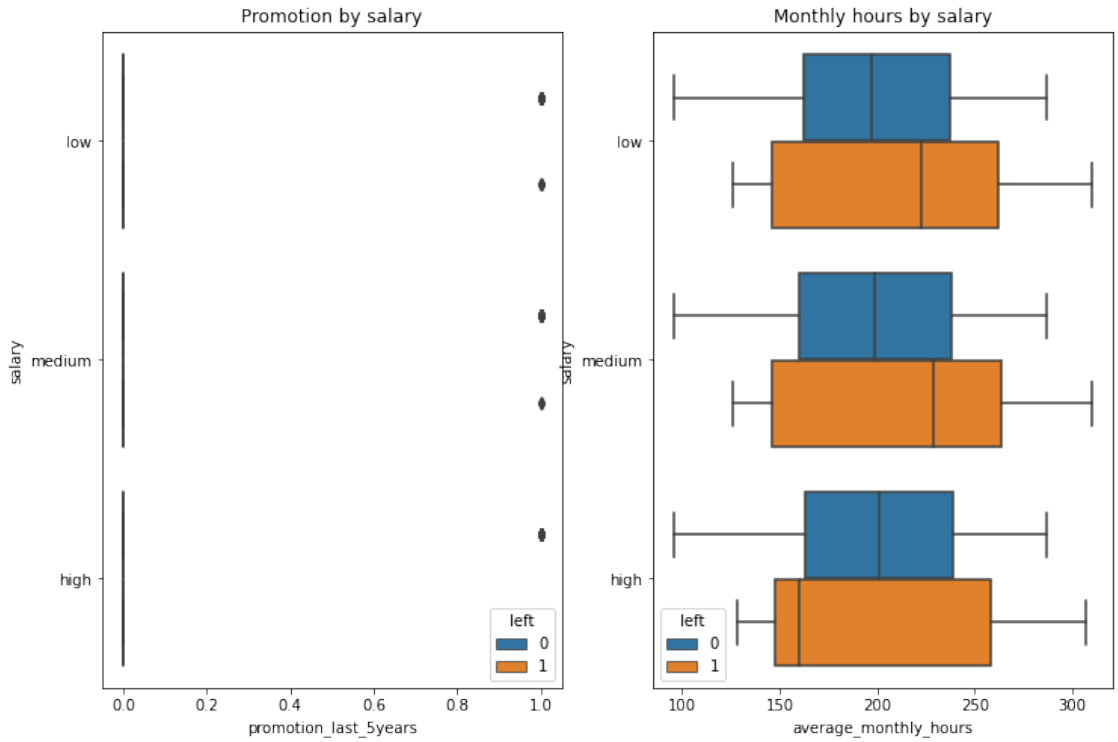
[23]:
```
0    195
1      8
Name: left, dtype: int64
```

[24]:
```
df[(df['promotion_last_5years'] == 1) & (df['left'] == 1)]['salary'].
↪value_counts()
```

[24]:
```
low       5
medium    3
Name: salary, dtype: int64
```

Peole with no promotion in the last 5 years are more eagaly prone to left the company. But it's not a fact, because some people with promotion left also

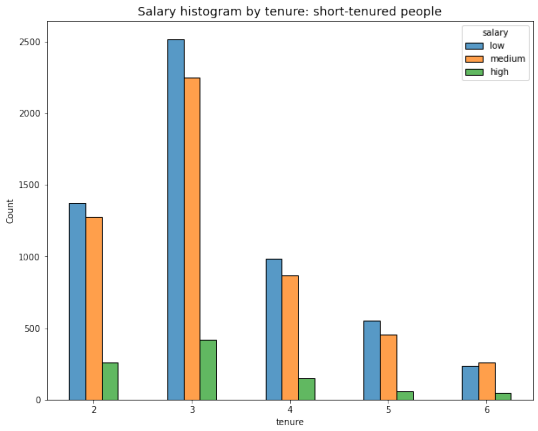
[25]:
```
# Create a plot as needed
### YOUR CODE HERE ###

fig, ax = plt.subplots(1,2,figsize=(12,8))

# promotion by salary
sns.boxplot(data=df, x = 'promotion_last_5years', y ='salary', hue='left',␣
 ↪ax=ax[0])
ax[0].set_title('Promotion by salary')

# Salary by average hours monthly
sns.boxplot(data=df, x = 'average_monthly_hours', y ='salary', hue='left',␣
 ↪ax=ax[1])
ax[1].set_title('Monthly hours by salary')

plt.show()
```

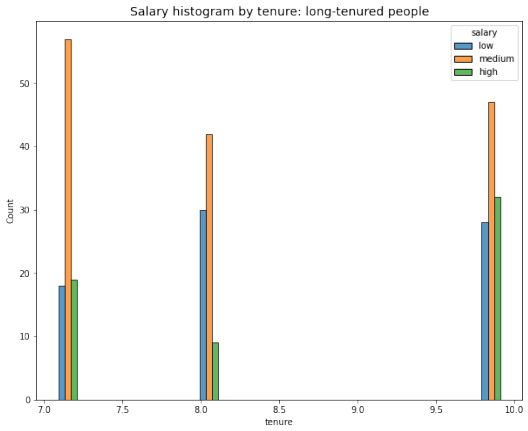


In average people who left work more hours per month thant other employees whatever the salary

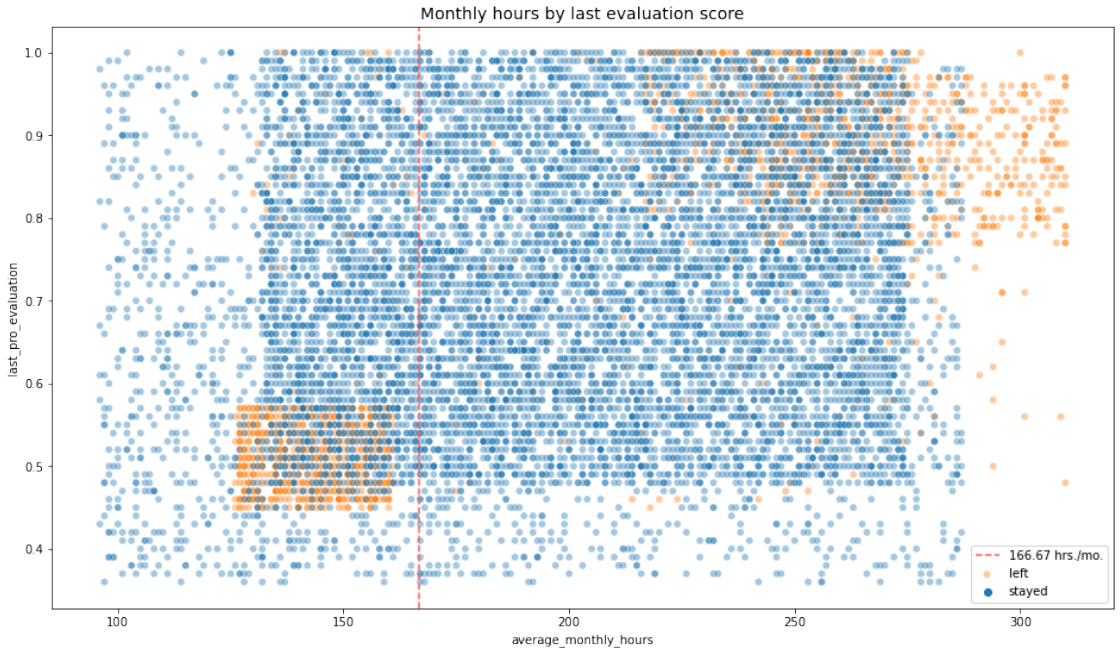
[26]:
```
# Create a plot as needed
### YOUR CODE HERE ###

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

```
# Define short-tenured employees
tenure_short = df[df['tenure'] < 7]

# Define long-tenured employees
tenure_long = df[df['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', 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');
```

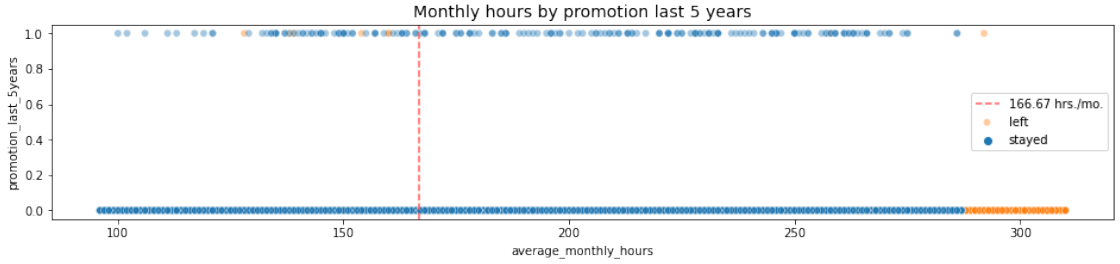




[27]:
```
# Create a plot as needed
### YOUR CODE HERE ###

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

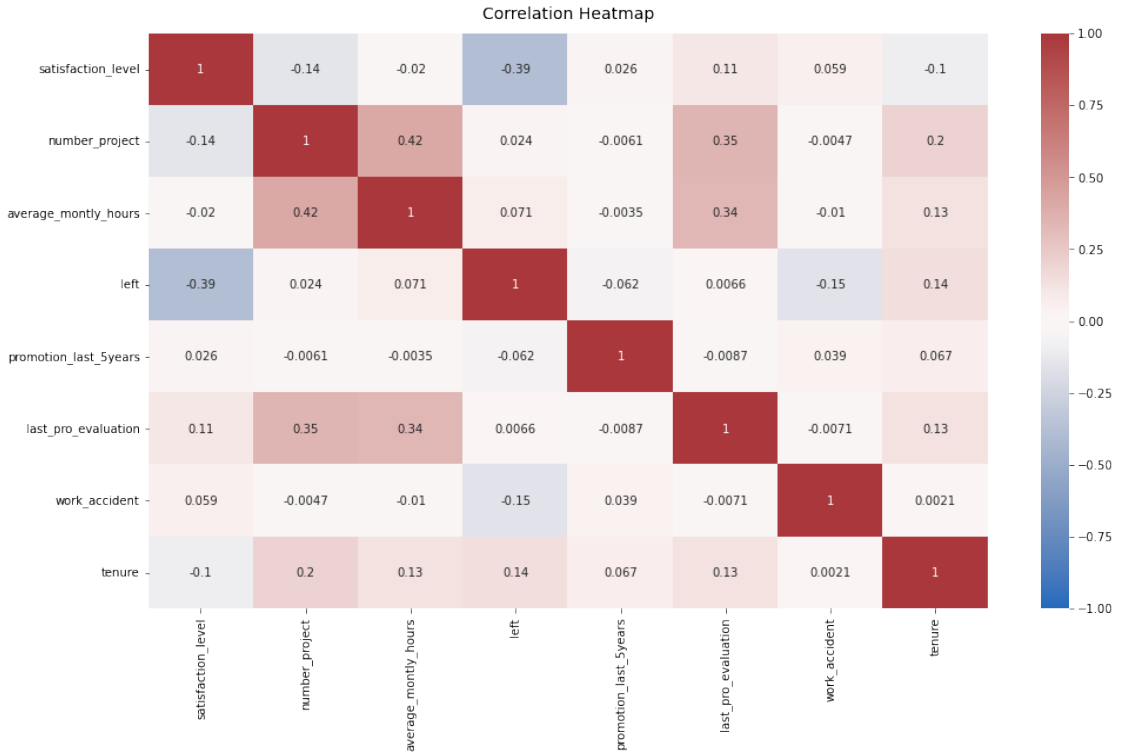


[28]:
```
# Create a plot as needed
### YOUR CODE HERE ###

# Create plot to examine relationship between `average_monthly_hours` and␣
 ↪`promotion_last_5years`
plt.figure(figsize=(16, 3))
sns.scatterplot(data=df, 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 hrs./mo.', 'left', 'stayed'])
plt.title('Monthly hours by promotion last 5 years', fontsize='14');
```



[92]:
```
# Create a plot as needed
### YOUR CODE HERE ###
```

```
# Plot a correlation heatmap
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);
```



3.1.2 Insights

[What insights can you gather from the plots you created to visualize the data? Double-click to enter your responses here.]

4 paCe: Construct Stage

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

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

Reflect on these questions as you complete the constructing stage.

- Do you notice anything odd?
- Which independent variables did you choose for the model and why?
- Are each of the assumptions met?
- How well does your model fit the data?
- Can you improve it? Is there anything you would change about the model?
- What resources do you find yourself using as you complete this stage? (Make sure to include the links.)
- Do you have any ethical considerations in this stage?

[Double-click to enter your responses here.]

4.1 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

4.1.1 Identify the type of prediction task.

[Double-click to enter your responses here.]

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

[Double-click to enter your responses here.]

4.1.3 Modeling

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

5 Modeling Approach A: Logistic Regression Model

[93]:
```
### YOUR CODE HERE ###
## Transform categorical variables into numerical
### Salary

df_enc = df.copy()
df_enc['salary'] = (df_enc['salary'].astype('category').cat.
 ↪set_categories(['low', 'medium', 'high']).cat.codes)

### Department
```

```
df_enc = pd.get_dummies(df_enc, drop_first=False)

df_enc.head(10)
```

[93]:

	satisfaction_level	number_project	average_montly_hours	left
0	0.38	2	157	1
2	0.11	7	272	1
3	0.72	5	223	1
4	0.37	2	159	1
5	0.41	2	153	1
6	0.10	6	247	1
7	0.92	5	259	1
8	0.89	5	224	1
9	0.42	2	142	1
10	0.45	2	135	1

	promotion_last_5years	salary	last_pro_evaluation	work_accident	tenure
0	0	0	0.53	0	3
2	0	1	0.88	0	4
3	0	0	0.87	0	5
4	0	0	0.52	0	3
5	0	0	0.50	0	3
6	0	0	0.77	0	4
7	0	0	0.85	0	5
8	0	0	1.00	0	5
9	0	0	0.53	0	3
10	0	0	0.54	0	3

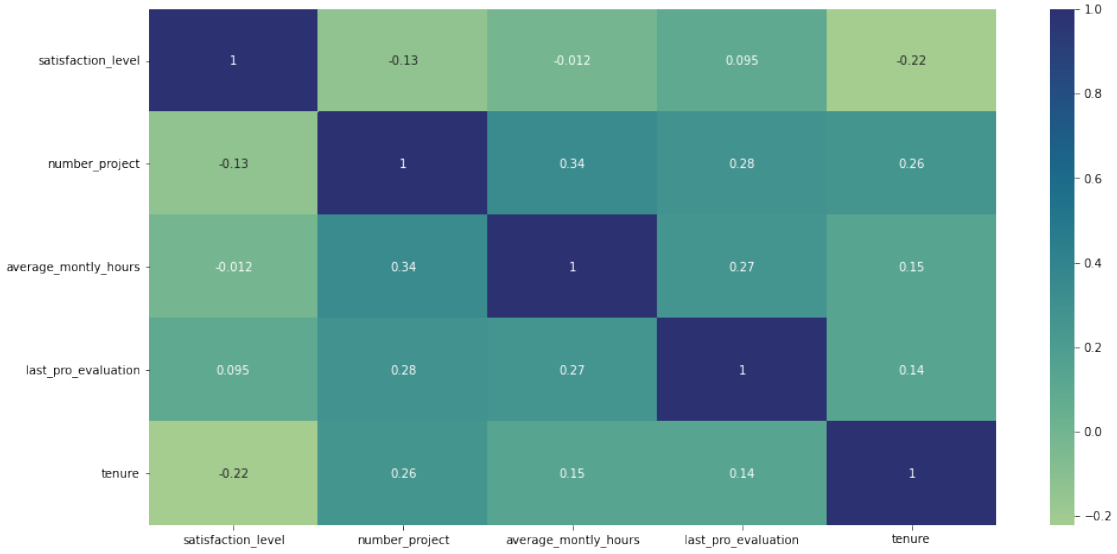
	department_IT	department_RandD	department_accounting	department_hr
0	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0
5	0	0	0	0
6	0	0	0	0
7	0	0	0	0
8	0	0	0	0
9	0	0	0	0
10	0	0	0	0

	department_management	department_marketing	department_product_mng
0	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
5	0	0	0
6	0	0	0

7	0	0	0
8	0	0	0
9	0	0	0
10	0	0	0

	department_sales	department_support	department_technical
0	1	0	0
2	1	0	0
3	1	0	0
4	1	0	0
5	1	0	0
6	1	0	0
7	1	0	0
8	1	0	0
9	1	0	0
10	1	0	0

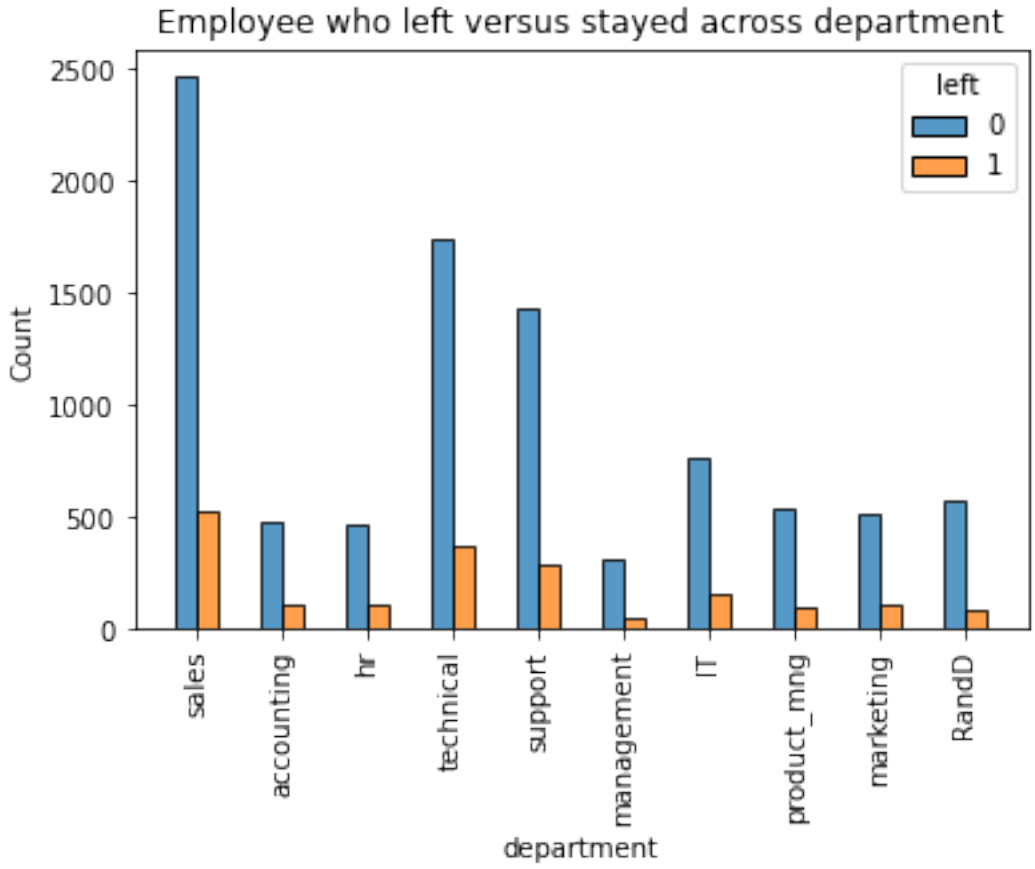
[94]:
```
# Create a heatmap to lookat how correlated data are
plt.figure(figsize = (16,8))

sns.
 ↪heatmap(df_enc[['satisfaction_level','number_project','average_montly_hours','last_pro_eval
 ↪corr(), annot = True, cmap='crest')
heatmap.set_title('Heatmap of the dataset')
plt.show()
```



Variables aren't highly correlated. Max 34

[95]:
```
```

```
# Salary by department who left and didn't
sns.histplot(data = df, x='department', hue='left', multiple='dodge', shrink =␣
↪0.5, color='mr')
plt.title('Employee who left versus stayed across department')
plt.xticks(rotation = 90, fontsize = 10)
plt.show()
```



[96]:
```
# Isolate the outcome variable
y = df_enc['left']
y.head()
```

[96]:
```
0    1
2    1
3    1
4    1
5    1
Name: left, dtype: int64
```

[97]:
```
# Select features wanted for analysis
x = df_enc.drop('left', axis = 1)
x.head()
```

[97]:

	satisfaction_level	number_project	average_montly_hours	\
0	0.38	2	157	
2	0.11	7	272	
3	0.72	5	223	
4	0.37	2	159	
5	0.41	2	153	

	promotion_last_5years	salary	last_pro_evaluation	work_accident	tenure	\
0	0	0	0.53	0	3	
2	0	1	0.88	0	4	
3	0	0	0.87	0	5	
4	0	0	0.52	0	3	
5	0	0	0.50	0	3	

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

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

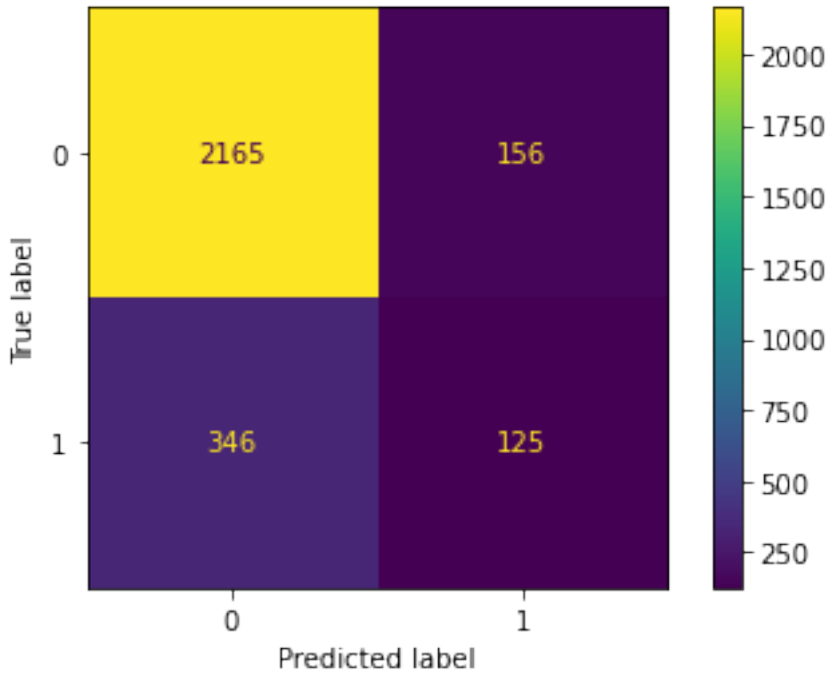
	department_sales	department_support	department_technical
0	1	0	0
2	1	0	0
3	1	0	0
4	1	0	0
5	1	0	0

[98]:
```
# Split the data to train the model
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.25,␣
 ↪stratify = y, random_state = 42)
```

[99]:
```
# Construct a logistic regression model
clf = LogisticRegression(random_state = 42, max_iter=500).fit(x_train, y_train)
```

[100]:
```
# Use the logistic regression model to get predictions on the test set
y_pred = clf.predict(x_test)
```

[101]:
```
log_cm = confusion_matrix(y_test, y_pred, labels=clf.classes_)

log_disp = ConfusionMatrixDisplay(confusion_matrix=log_cm, display_labels = clf.
↪classes_)

log_disp.plot(values_format='')

plt.show()
```



[102]:
```
df_enc['left'].value_counts(normalize=True)
```

[102]:
```
0    0.831468
1    0.168532
Name: left, dtype: float64
```

[103]:
```
# 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      0.27      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
```

Great for predicting employees who don't leave but bad for leaving employees. Must test another model

6 Tree based modeling

[104]:
```
y = df_enc['left']
y.head()
```

[104]:
```
0    1
2    1
3    1
4    1
5    1
Name: left, dtype: int64
```

[105]:
```
x = df_enc.drop('left', axis = 1)
x.head()
```

[105]:
```
   satisfaction_level  number_project  average_montly_hours  \
0                0.38               2                   157
2                0.11               7                   272
3                0.72               5                   223
4                0.37               2                   159
5                0.41               2                   153

   promotion_last_5years  salary  last_pro_evaluation  work_accident  tenure  \
0                      0       0                 0.53              0       3
2                      0       1                 0.88              0       4
3                      0       0                 0.87              0       5
4                      0       0                 0.52              0       3
5                      0       0                 0.50              0       3

   department_IT  department_RandD  department_accounting  department_hr  \
0              0                 0                      0              0
2              0                 0                      0              0
3              0                 0                      0              0
4              0                 0                      0              0
5              0                 0                      0              0
```

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

   department_sales  department_support  department_technical
0                 1                   0                     0
2                 1                   0                     0
3                 1                   0                     0
4                 1                   0                     0
5                 1                   0                     0
```

[106]:
```
# Split data into training and testing set
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.25,␣
↪stratify = y, random_state = 0)
```

[107]:
```
# 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')
```

[108]:
```
%%time
tree1.fit(x_train, y_train)
```

```
CPU times: user 4.35 s, sys: 1.63 ms, total: 4.35 s
Wall time: 4.43 s
```

[108]:
```
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', 'precision', 'roc_auc', 'f1', 'recall'},
             verbose=0)
```

[109]:
```
# Valeurs optimales
tree1.best_params_
```

[109]:
```
{'max_depth': 4, 'min_samples_leaf': 2, 'min_samples_split': 2}
```

[110]:
```
# Meilleur score
tree1.best_score_
```

[110]:
```
0.9741265306913758
```

[111]:
```
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
```

[112]:
```
# Get all CV scores
tree1_cv_results = make_results('decision tree cv', tree1, 'auc')
tree1_cv_results
```

[112]:

	model	precision	recall	F1	accuracy	auc
0	decision tree cv	0.95541	0.912133	0.933245	0.97803	0.974127

6.0.1 Random forest - Round 1

[113]:
```
# 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')
```

[114]:
```
%%time
rf1.fit(x_train, y_train) # --> Wall time: ~10min
```

```
CPU times: user 11min 42s, sys: 1.69 s, total: 11min 44s
Wall time: 11min 49s
```

[114]:
```
GridSearchCV(cv=4, error_score=nan,
             estimator=RandomForestClassifier(bootstrap=True, ccp_alpha=0.0,
                                              class_weight=None,
                                              criterion='gini', max_depth=None,
                                              max_features='auto',
                                              max_leaf_nodes=None,
                                              max_samples=None,
                                              min_impurity_decrease=0.0,
                                              min_impurity_split=None,
                                              min_samples_leaf=1,
                                              min_samples_split=2,
                                              min_weight_fraction_leaf=0.0,
                                              n_estimators=100, n_jobs=None,…
                                              verbose=0, warm_start=False),
             iid='deprecated', n_jobs=None,
             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]},
             pre_dispatch='2*n_jobs', refit='roc_auc', return_train_score=False,
             scoring={'accuracy', 'precision', 'roc_auc', 'f1', 'recall'},
             verbose=0)
```

[115]:
```
# Define a path to the folder where you want to save the model
path = '/home/jovyan/work/'
```

[116]:
```
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)
```

[117]:
```
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
```

[118]:
```
# Write pickle
write_pickle(path, rf1, 'hr_rf1')
```

[119]:
```
# Read pickle
rf1 = read_pickle(path, 'hr_rf1')
```

[120]:
```
# Check best AUC score on CV
rf1.best_score_
```

[120]:
```
0.9818301014715982
```

[121]:
```
# Check best params
rf1.best_params_
```

[121]:
```
{'max_depth': 5,
 'max_features': 1.0,
 'max_samples': 0.7,
 'min_samples_leaf': 1,
 'min_samples_split': 2,
 'n_estimators': 300}
```

[122]:
```
# 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    0.95541  0.912133  0.933245   0.97803  0.974127
                model  precision   recall        F1  accuracy      auc
0  random forest cv    0.970634  0.91497  0.941925  0.981015  0.98183
```

[123]:
```
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 yout␣
↪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
```

[124]:
```
# Get predictions on test data
rf1_test_scores = get_scores('random forest1 test', rf1,x_test, y_test)
rf1_test_scores
```

[124]:

	model	precision	recall	f1	accuracy	AUC
0	random forest1 test	0.967033	0.934183	0.950324	0.983524	0.96386

[125]:
```
df2 = df_enc.drop('satisfaction_level', axis=1)
df2.head()
```

[125]:

	number_project	average_montly_hours	left	promotion_last_5years	salary	\
0	2	157	1	0	0	
2	7	272	1	0	1	
3	5	223	1	0	0	

```
4                2                   159     1                       0       0
5                2                   153     1                       0       0

   last_pro_evaluation  work_accident  tenure  department_IT  \
0                 0.53              0       3              0
2                 0.88              0       4              0
3                 0.87              0       5              0
4                 0.52              0       3              0
5                 0.50              0       3              0

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

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

   department_sales  department_support  department_technical
0                 1                   0                     0
2                 1                   0                     0
3                 1                   0                     0
4                 1                   0                     0
5                 1                   0                     0
```

[126]:
```
df2["overworked"] = df2["average_montly_hours"]

print("Max hours:", df2["overworked"].max())
print("Min hours:", df2["overworked"].min())
```

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

Define overwork as over 175h per month

[127]:
```
df2['overworked'] = (df2['overworked'] > 175).astype(int)

df2['overworked'].head()
```

[127]:
```
0    0
2    1
3    1
```

```
4    0
5    0
Name: overworked, dtype: int64
```

[128]:
```
df2= df2.drop('average_montly_hours', axis = 1)
df2.head()
```

[128]:

	number_project	left	promotion_last_5years	salary	last_pro_evaluation	work_accident	tenure	department_IT	department_RandD	department_accounting	department_hr	department_management	department_marketing	department_product_mng	department_sales	department_support	department_technical	overworked
0	2	1	0	0	0.53	0	3	0	0	0	0	0	0	0	1	0	0	0
2	7	1	0	1	0.88	0	4	0	0	0	0	0	0	0	1	0	0	1
3	5	1	0	0	0.87	0	5	0	0	0	0	0	0	0	1	0	0	1
4	2	1	0	0	0.52	0	3	0	0	0	0	0	0	0	1	0	0	0
5	2	1	0	0	0.50	0	3	0	0	0	0	0	0	0	1	0	0	0

[129]:
```
y = df2['left']
y.head()

x = df2.drop('left', axis = 1)
x.head()
```

[129]:
```
   number_project  promotion_last_5years  salary  last_pro_evaluation  \
0               2                      0       0                 0.53
2               7                      0       1                 0.88
3               5                      0       0                 0.87
4               2                      0       0                 0.52
5               2                      0       0                 0.50

   work_accident  tenure  department_IT  department_RandD  \
0              0       3              0                 0
2              0       4              0                 0
3              0       5              0                 0
4              0       3              0                 0
5              0       3              0                 0

   department_accounting  department_hr  department_management  \
0                      0              0                     0
2                      0              0                     0
3                      0              0                     0
4                      0              0                     0
5                      0              0                     0

   department_marketing  department_product_mng  department_sales  \
0                     0                       0                 1
2                     0                       0                 1
3                     0                       0                 1
4                     0                       0                 1
5                     0                       0                 1

   department_support  department_technical  overworked
0                   0                     0           0
2                   0                     0           1
3                   0                     0           1
4                   0                     0           0
5                   0                     0           0
```

[130]:
```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.25,␣
↪stratify= y, random_state = 42)
```

[131]:
```
tree = RandomForestClassifier(random_state = 0)

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

scoring = {'accuracy','precision','recall','f1','roc_auc'}
```

```
tree2 = GridSearchCV(tree, cv_params, scoring = scoring, cv=4, refit =␣
↪'roc_auc')
```

[132]:
```
%%time
tree2.fit(x_train, y_train)
```

```
CPU times: user 59.9 s, sys: 209 ms, total: 1min
Wall time: 1min
```

[132]:
```
GridSearchCV(cv=4, error_score=nan,
             estimator=RandomForestClassifier(bootstrap=True, ccp_alpha=0.0,
                                              class_weight=None,
                                              criterion='gini', max_depth=None,
                                              max_features='auto',
                                              max_leaf_nodes=None,
                                              max_samples=None,
                                              min_impurity_decrease=0.0,
                                              min_impurity_split=None,
                                              min_samples_leaf=1,
                                              min_samples_split=2,
                                              min_weight_fraction_leaf=0.0,
                                              n_estimators=100, n_jobs=None,
                                              oob_score=False, random_state=0,
                                              verbose=0, warm_start=False),
             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', 'precision', 'roc_auc', 'f1', 'recall'},
             verbose=0)
```

[133]:
```
# check best parameters
tree2.best_params_
```

[133]:
```
{'max_depth': 8, 'min_samples_leaf': 1, 'min_samples_split': 6}
```

[134]:
```
tree2.best_score_
```

[134]:
```
0.9712019628363922
```

[135]:
```
# 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    0.95541  0.912133  0.933245   0.97803  0.974127
```

```
                  model  precision    recall        F1  accuracy       auc
0  decision tree2 cv   0.919953  0.885909  0.902543  0.967761  0.971202
```

[136]:
```
# 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 Grid Search
rf2 = GridSearchCV(rf, cv_params, scoring = scoring, cv= 4, refit='roc_auc')
```

[137]:
```
%%time
rf2.fit(x_train, y_train)
```

```
CPU times: user 8min 49s, sys: 1.67 s, total: 8min 51s
Wall time: 8min 53s
```

[137]:
```
GridSearchCV(cv=4, error_score=nan,
             estimator=RandomForestClassifier(bootstrap=True, ccp_alpha=0.0,
                                              class_weight=None,
                                              criterion='gini', max_depth=None,
                                              max_features='auto',
                                              max_leaf_nodes=None,
                                              max_samples=None,
                                              min_impurity_decrease=0.0,
                                              min_impurity_split=None,
                                              min_samples_leaf=1,
                                              min_samples_split=2,
                                              min_weight_fraction_leaf=0.0,
                                              n_estimators=100, n_jobs=None,…
                                              verbose=0, warm_start=False),
             iid='deprecated', n_jobs=None,
             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]},
```

```
                   pre_dispatch='2*n_jobs', refit='roc_auc', return_train_score=False,
                   scoring={'accuracy', 'precision', 'roc_auc', 'f1', 'recall'},
                   verbose=0)
```

[138]:
```
# Write pickle
write_pickle(path, rf2, 'hr_rf2')
```

[139]:
```
# Read in pickle
rf2 = read_pickle(path, 'hr_rf2')
```

[140]:
```
# check best parameters
tree2.best_params_
```

[140]:
```
{'max_depth': 8, 'min_samples_leaf': 1, 'min_samples_split': 6}
```

[141]:
```
# check best AUC score on CV
rf2.best_score_
```

[141]:
```
0.971112341529847
```

[146]:
```
# Get all CV scores
rf2_cv_results = make_results('random forest2 cv', rf2, 'auc')
print(tree2_cv_results)
print(rf2_cv_results)
```

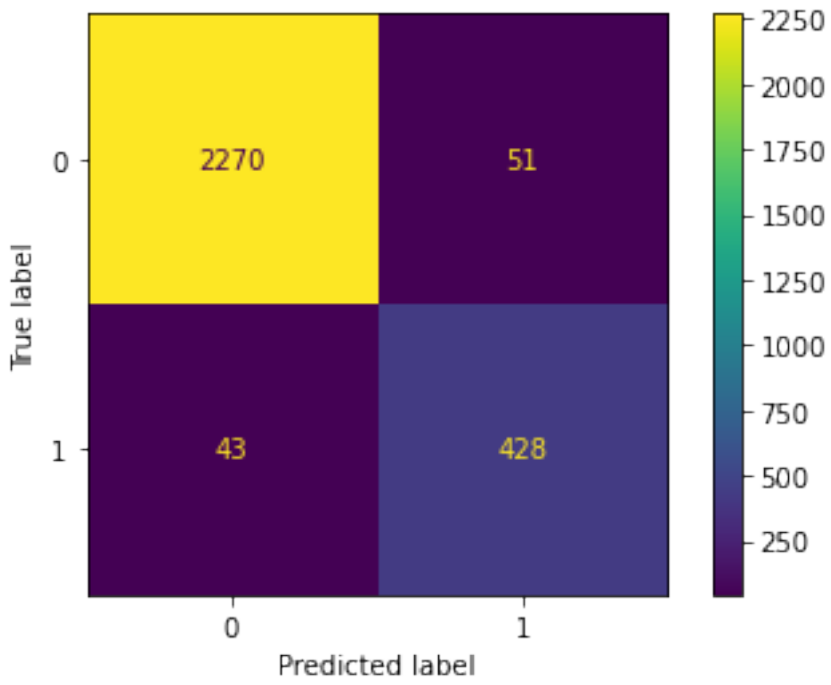
```
                model  precision    recall        F1  accuracy       auc
0  decision tree2 cv   0.919953  0.885909  0.902543  0.967761  0.971202
                model  precision    recall        F1  accuracy       auc
0  random forest2 cv   0.896338  0.906459  0.901303  0.966567  0.971112
```

[147]:
```
# Get predictions on test data
rf2_test_scores = get_scores('random forest2 test', rf2, x_test, y_test)
rf2_test_scores
```

[147]:

	model	precision	recall	f1	accuracy	AUC
0	random forest2 test	0.893528	0.908705	0.901053	0.966332	0.943366

[148]:
```
# 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='');
```



[150]:
```
# 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()
```

```
␣
↪---------------------------------------------------------------------------

AttributeError                            Traceback (most recent call␣
↪last)

<ipython-input-150-5c7440698070> in <module>
  1 # Plot the tree
  2 plt.figure(figsize=(85,20))
----> 3 plot_tree(tree2.best_estimator_, max_depth=6, fontsize=14,␣
↪feature_names=x.columns, class_names={0:'stayed', 1:'left'}, filled=True);
  4 plt.show()

/opt/conda/lib/python3.7/site-packages/sklearn/tree/_export.py in␣
↪plot_tree(decision_tree, max_depth, feature_names, class_names, label, filled,␣
↪impurity, node_ids, proportion, rotate, rounded, precision, ax, fontsize)
```

```
        174         proportion=proportion, rotate=rotate, rounded=rounded,
        175         precision=precision, fontsize=fontsize)
    --> 176     return exporter.export(decision_tree, ax=ax)
        177
        178


        /opt/conda/lib/python3.7/site-packages/sklearn/tree/_export.py in␣
    ↪export(self, decision_tree, ax)
        564         ax.clear()
        565         ax.set_axis_off()
    --> 566         my_tree = self._make_tree(0, decision_tree.tree_,
        567                                   decision_tree.criterion)
        568         draw_tree = buchheim(my_tree)


        AttributeError: 'RandomForestClassifier' object has no attribute 'tree_'
```

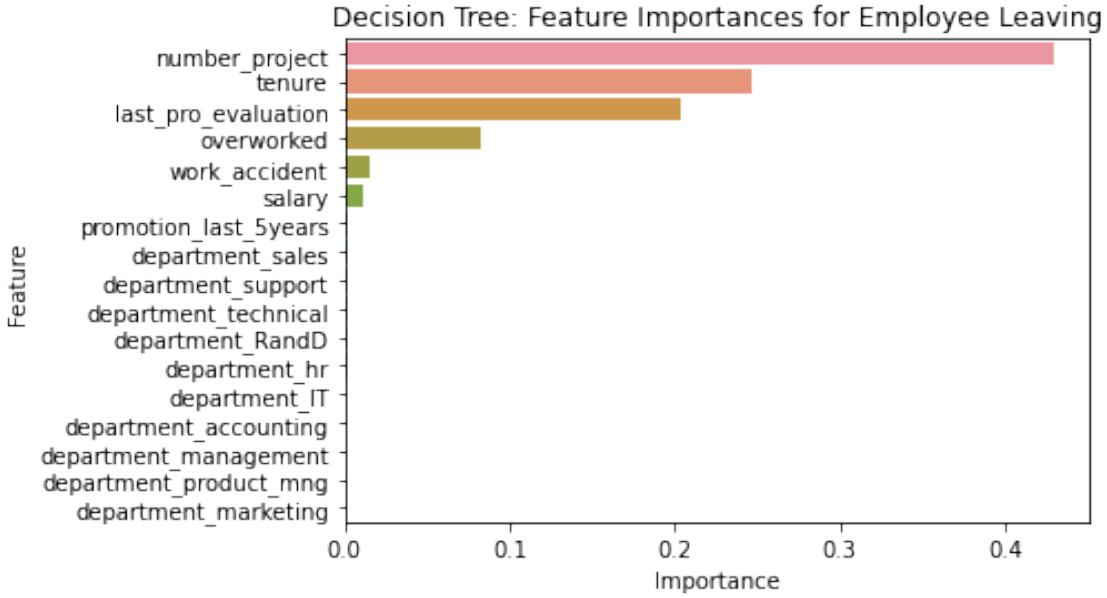
[151]:
```
#tree2_importances = pd.DataFrame(tree2.best_estimator_.feature_importances_,␣
 ↪columns=X.columns)
tree2_importances = pd.DataFrame(tree2.best_estimator_.feature_importances_,
                                 columns=['gini_importance'],
                                 index=x.columns
                                )
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
```

[151]:

	gini_importance
number_project	0.429134
tenure	0.246034
last_pro_evaluation	0.202845
overworked	0.082276

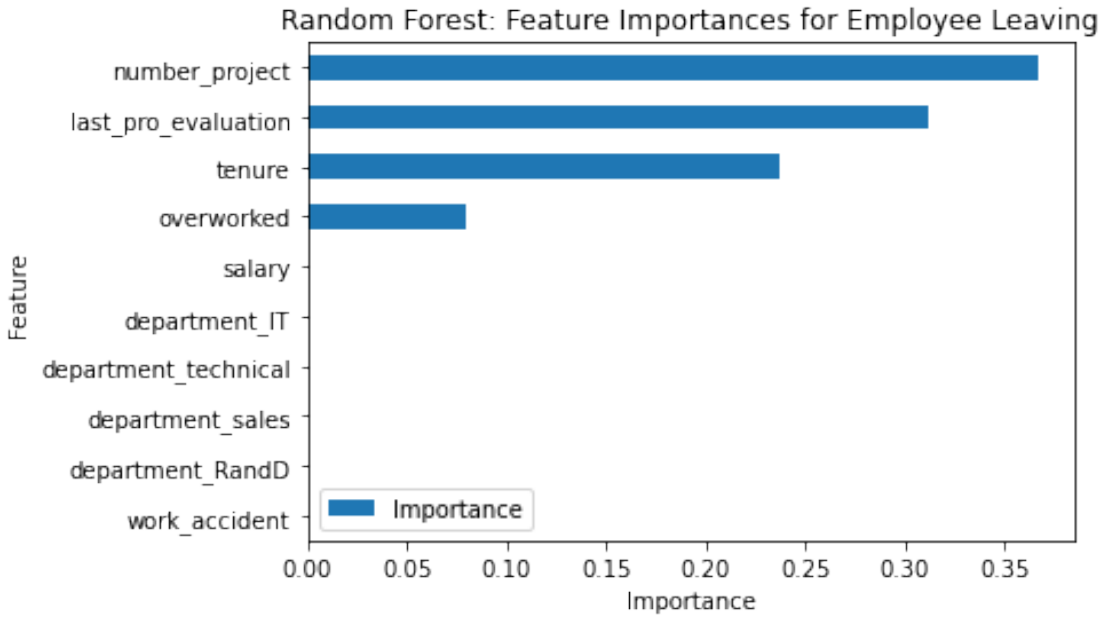
```
work_accident                0.015421
salary                       0.011081
promotion_last_5years        0.002012
department_sales             0.001716
department_support           0.001409
department_technical         0.001388
department_RandD             0.001259
department_hr                0.001240
department_IT                0.000900
department_accounting        0.000885
department_management        0.000840
department_product_mng       0.000813
department_marketing         0.000747
```

[152]:
```
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()
```



[154]:
```
# 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()
```



[ ]:

[ ]:

[ ]:

7 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.

Reflect on these questions as you complete the executing stage.

- What key insights emerged from your model(s)?
- What business recommendations do you propose based on the models built?
- What potential recommendations would you make to your manager/company?
- Do you think your model could be improved? Why or why not? How?
- Given what you know about the data and the models you were using, what other questions could you address for the team?
- What resources do you find yourself using as you complete this stage? (Make sure to include the links.)
- Do you have any ethical considerations in this stage?

Double-click to enter your responses here.

7.1 Step 4. Results and Evaluation

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

7.1.1 Summary of model results

[Double-click to enter your summary here.]

7.1.2 Conclusion, Recommendations, Next Steps

[Double-click to enter your conclusion, recommendations, and next steps here.]

Congratulations! You've completed this lab. However, you may not notice a green check mark next to this item on Coursera's platform. Please continue your progress regardless of the check mark. Just click on the "save" icon at the top of this notebook to ensure your work has been logged.