Activity_ Course 7 Salifort Motors project lab

January 16, 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?

  - Who are your stakeholders for this project?
    - senior leadership
  - What are you trying to solve or accomplish?
    - Predicting the factors that contribute most to turnover
  - What are your initial observations when you explore the data?

  - "left" is my label
  - I predict the "satisfaction_level" feature wont be a quientissential contributor to the prediction
  - I predict "pay" and "hours" worked will be
  - Engineer : burnout variable with hours worked with accidents
  - Engineer : not being paid enough for good performance
- What resources do you find yourself using as you complete this stage? (Make sure to include the links.)
  - Previous courses and Kaggle
- Do you have any ethical considerations in this stage?
  - Employeer could misuse this information to terminate/harass employees

2.2 Step 1. Imports

- Import packages
- Load dataset

2.2.1 Import packages

[1]:
```
# Import packages
import numpy as np
import pandas as pd

import pickle as pkl

from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split, PredefinedSplit,␣
↪GridSearchCV
from sklearn.metrics import f1_score, precision_score, recall_score,␣
↪accuracy_score
import sklearn.metrics as metrics
from sklearn.tree import plot_tree

import matplotlib.pyplot as plt
import seaborn as sns
```

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.
```

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


# Display first few rows of the dataframe
df.head(25)
```

[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
5                 0.41             0.50               2                   153
6                 0.10             0.77               6                   247
7                 0.92             0.85               5                   259
8                 0.89             1.00               5                   224
9                 0.42             0.53               2                   142
10                0.45             0.54               2                   135
11                0.11             0.81               6                   305
12                0.84             0.92               4                   234
13                0.41             0.55               2                   148
14                0.36             0.56               2                   137
15                0.38             0.54               2                   143
16                0.45             0.47               2                   160
17                0.78             0.99               4                   255
18                0.45             0.51               2                   160
19                0.76             0.89               5                   262
20                0.11             0.83               6                   282
21                0.38             0.55               2                   147
22                0.09             0.95               6                   304
23                0.46             0.57               2                   139
24                0.40             0.53               2                   158

    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
5                    3              0     1                      0      sales
6                    4              0     1                      0      sales
7                    5              0     1                      0      sales
8                    5              0     1                      0      sales
9                    3              0     1                      0      sales
10                   3              0     1                      0      sales
```

```
11                     4              0     1                      0      sales
12                     5              0     1                      0      sales
13                     3              0     1                      0      sales
14                     3              0     1                      0      sales
15                     3              0     1                      0      sales
16                     3              0     1                      0      sales
17                     6              0     1                      0      sales
18                     3              1     1                      1      sales
19                     5              0     1                      0      sales
20                     4              0     1                      0      sales
21                     3              0     1                      0      sales
22                     4              0     1                      0      sales
23                     3              0     1                      0      sales
24                     3              0     1                      0      sales

    salary
0      low
1   medium
2   medium
3      low
4      low
5      low
6      low
7      low
8      low
9      low
10     low
11     low
12     low
13     low
14     low
15     low
16     low
17     low
18     low
19     low
20     low
21     low
22     low
23     low
24     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 ###
df.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 ###
df.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, 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 ###
df.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
### YOUR CODE HERE ###
df = df.rename(columns={'satisfaction_level':'satisfaction',␣
↪'time_spend_company':'tenure', 'Work_accident':'work_accident', 'Department':
↪'department', 'average_montly_hours':'average_monthly_hours'})

# Display all column names after the update
### YOUR CODE HERE ###
df.columns
```

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

2.3.4 Check missing values

Check for any missing values in the data.

[7]:
```
# Check for missing values
### YOUR CODE HERE ###
df.isnull().nunique(axis=0)
```

[7]:
```
satisfaction             1
last_evaluation          1
number_project           1
average_monthly_hours    1
tenure                   1
work_accident            1
left                     1
promotion_last_5years    1
department               1
salary                   1
dtype: int64
```

2.3.5 Check duplicates

Check for any duplicate entries in the data.

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

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

[9]:
```
# Inspect some rows containing duplicates as needed
### YOUR CODE HERE ###
df.loc[df.duplicated() == True]
```

[9]:
```
       satisfaction  last_evaluation  number_project  average_monthly_hours  \
396            0.46             0.57               2                    139
866            0.41             0.46               2                    128
1317           0.37             0.51               2                    127
1368           0.41             0.52               2                    132
1461           0.42             0.53               2                    142
…               …                …              …                    …
14994          0.40             0.57               2                    151
14995          0.37             0.48               2                    160
14996          0.37             0.53               2                    143
14997          0.11             0.96               6                    280
```

```
14998         0.37             0.52            2                    158

       tenure  work_accident  left  promotion_last_5years  department  salary
396         3              0     1                      0       sales     low
866         3              0     1                      0  accounting     low
1317        3              0     1                      0       sales  medium
1368        3              0     1                      0       RandD     low
1461        3              0     1                      0       sales     low
…         …            …   …                    …         …     …
14994       3              0     1                      0     support     low
14995       3              0     1                      0     support     low
14996       3              0     1                      0     support     low
14997       4              0     1                      0     support     low
14998       3              0     1                      0     support     low

[3008 rows x 10 columns]
```

[10]:

```python
# Drop duplicates and save resulting dataframe in a new variable as needed
### YOUR CODE HERE ###
df_clean = df.drop_duplicates()

# Display first few rows of new dataframe as needed
### YOUR CODE HERE ###
df_clean.head(15)
```

[10]:

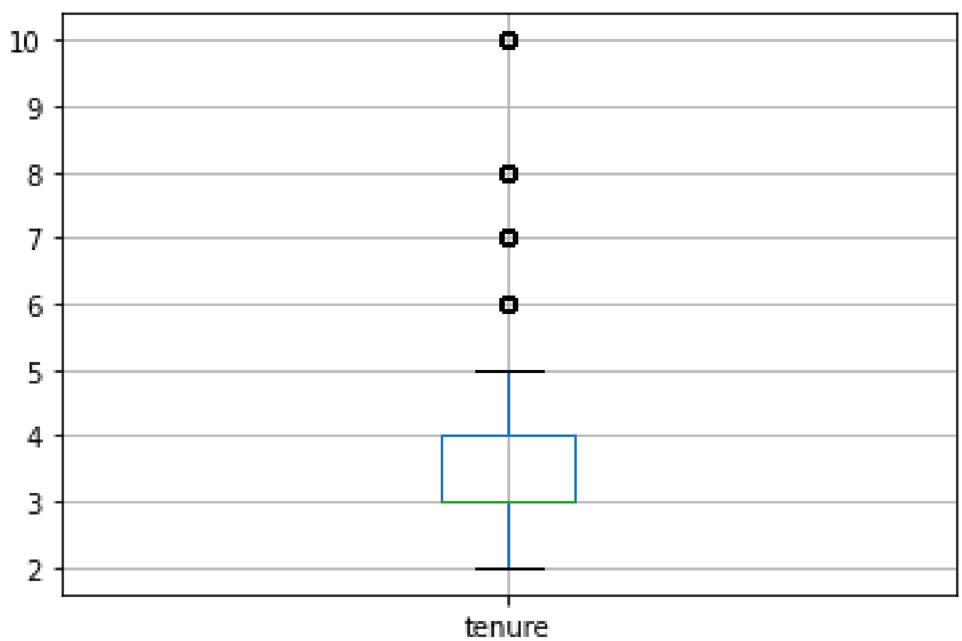
```
    satisfaction  last_evaluation  number_project  average_monthly_hours  \
0           0.38             0.53               2                    157
1           0.80             0.86               5                    262
2           0.11             0.88               7                    272
3           0.72             0.87               5                    223
4           0.37             0.52               2                    159
5           0.41             0.50               2                    153
6           0.10             0.77               6                    247
7           0.92             0.85               5                    259
8           0.89             1.00               5                    224
9           0.42             0.53               2                    142
10          0.45             0.54               2                    135
11          0.11             0.81               6                    305
12          0.84             0.92               4                    234
13          0.41             0.55               2                    148
14          0.36             0.56               2                    137

    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
5	3	0	1	0	sales	low
6	4	0	1	0	sales	low
7	5	0	1	0	sales	low
8	5	0	1	0	sales	low
9	3	0	1	0	sales	low
10	3	0	1	0	sales	low
11	4	0	1	0	sales	low
12	5	0	1	0	sales	low
13	3	0	1	0	sales	low
14	3	0	1	0	sales	low

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 ###
boxplot = df.boxplot(column=['tenure'])
```



[12]:
```
# Determine the number of rows containing outliers
### YOUR CODE HERE ###
print(f"Number of outliers : {df[df['tenure'] > 5].count()[0]}")
```

```
print(f"Number of outliers that left: {df[ (df['tenure'] > 5) &␣
↪(df['left']==1)].count()[0]}")
```

```
Number of outliers : 1282
Number of outliers that left: 209
```

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.

[13]:
```
# Get numbers of people who left vs. stayed
### YOUR CODE HERE ###
print(f"Number of employees that left: {df['left'].value_counts()[1]}")
print(f"Number of employees retained: {df['left'].value_counts()[0]}")

# Get percentages of people who left vs. stayed
### YOUR CODE HERE ###
x = df['left'].value_counts(normalize=True)
print(f"{100*x[0]:2.2f}% of employees stayed while {100*x[1]:2.2f}% left" )

print("\nClasses are not too unbalanced (>=90%) s.t. sampling techniques are␣
↪required.\nThis could change if outliers above were removed.")
```

```
Number of employees that left: 3571
Number of employees retained: 11428
76.19% of employees stayed while 23.81% left
```

```
Classes are not too unbalanced (>=90%) s.t. sampling techniques are required.
This could change if outliers above were removed.
```

- What am I trying to prove here?

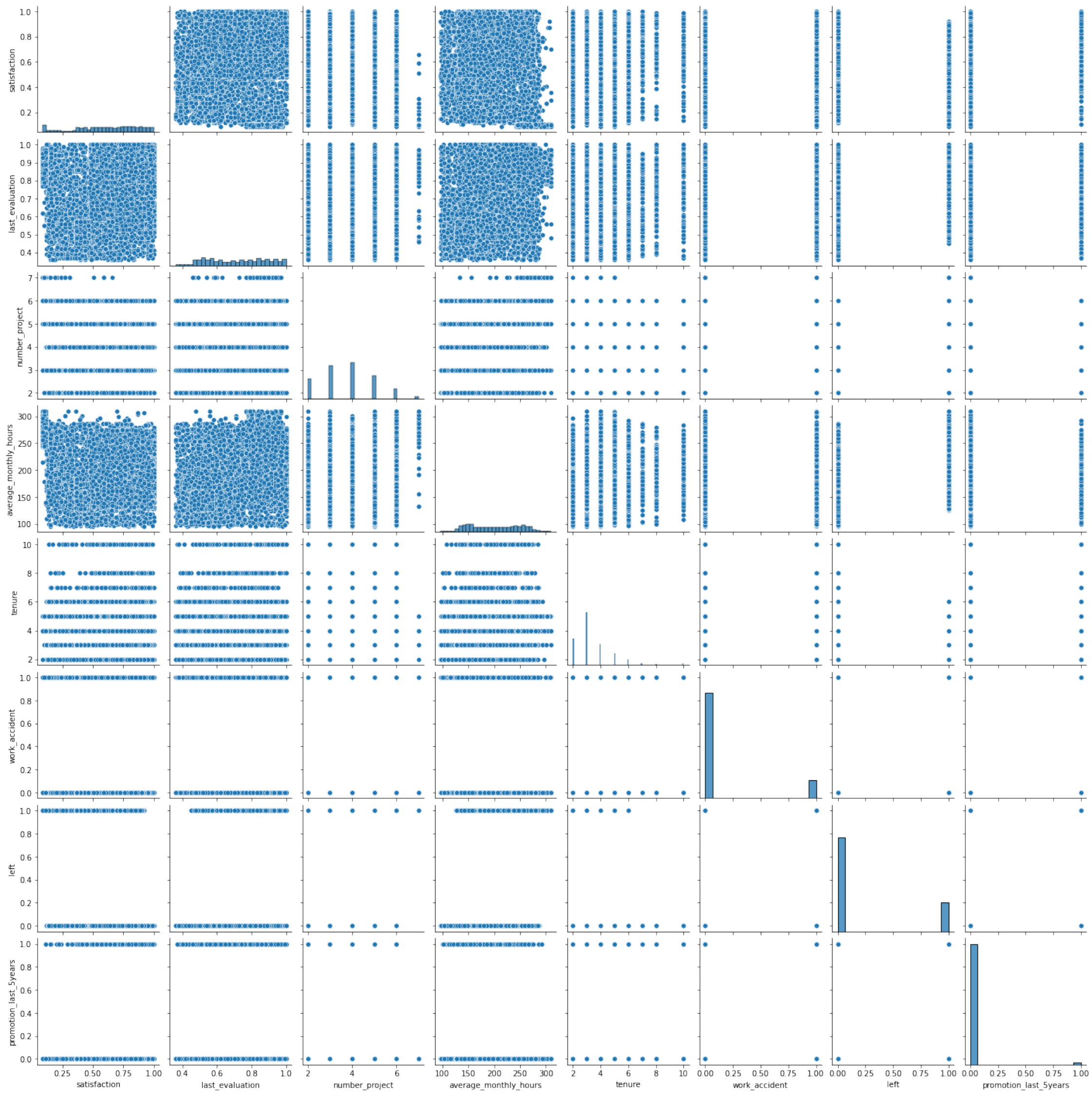
Lets first try Binomial logistic regression by testing assumptions (if using this model) 1. Linearity: Each feature is linearly related to the outcome variable (Verify with pairwise scatterplot) 2. Independent Observation (Assuming valid data collection - no action needed) 3. No multicollinearity - There is not a linear relationship between features (Verify with pairwise scatterplot) 4. No extreme outliers

OR use ML that don't require assumptions

[14]:
```python
#TODO : Convert datatype
df_subset = df.copy()

df_subset['number_project'] = df_subset['number_project'].astype(float)
df_subset['average_monthly_hours'] = df_subset['average_monthly_hours'].
↪astype(float)
df_subset['tenure'] = df_subset['tenure'].astype(float)
df_subset['work_accident'] = df_subset['work_accident'].astype(float)
df_subset['promotion_last_5years'] = df_subset['promotion_last_5years'].
↪astype(float)

df_subset.info()
```

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

[15]:
```python
# Assess logistic regression assumptions
#df_subset = pd.get_dummies(df_subset, columns=['department', 'salary'])
sns.pairplot(df_subset);
```



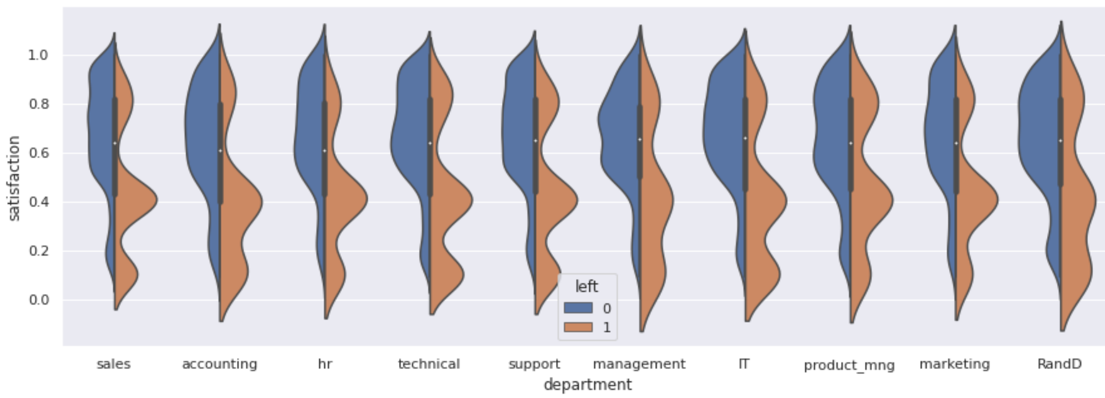
3.1.1 Data visualizations

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

[16]:
```
# finding the relationship between satisfaction and leaving by department
sns.set(rc={"figure.figsize":(15, 5)}) #width=6, height=5
sns.violinplot(data = df, y=df['satisfaction'], x = df['department'],␣
↪hue=df['left'], split=True, height=10, aspect=2)


# Looks like more people leave if they are less satisfied with their job.
# Department looks like it doesnt matter
```

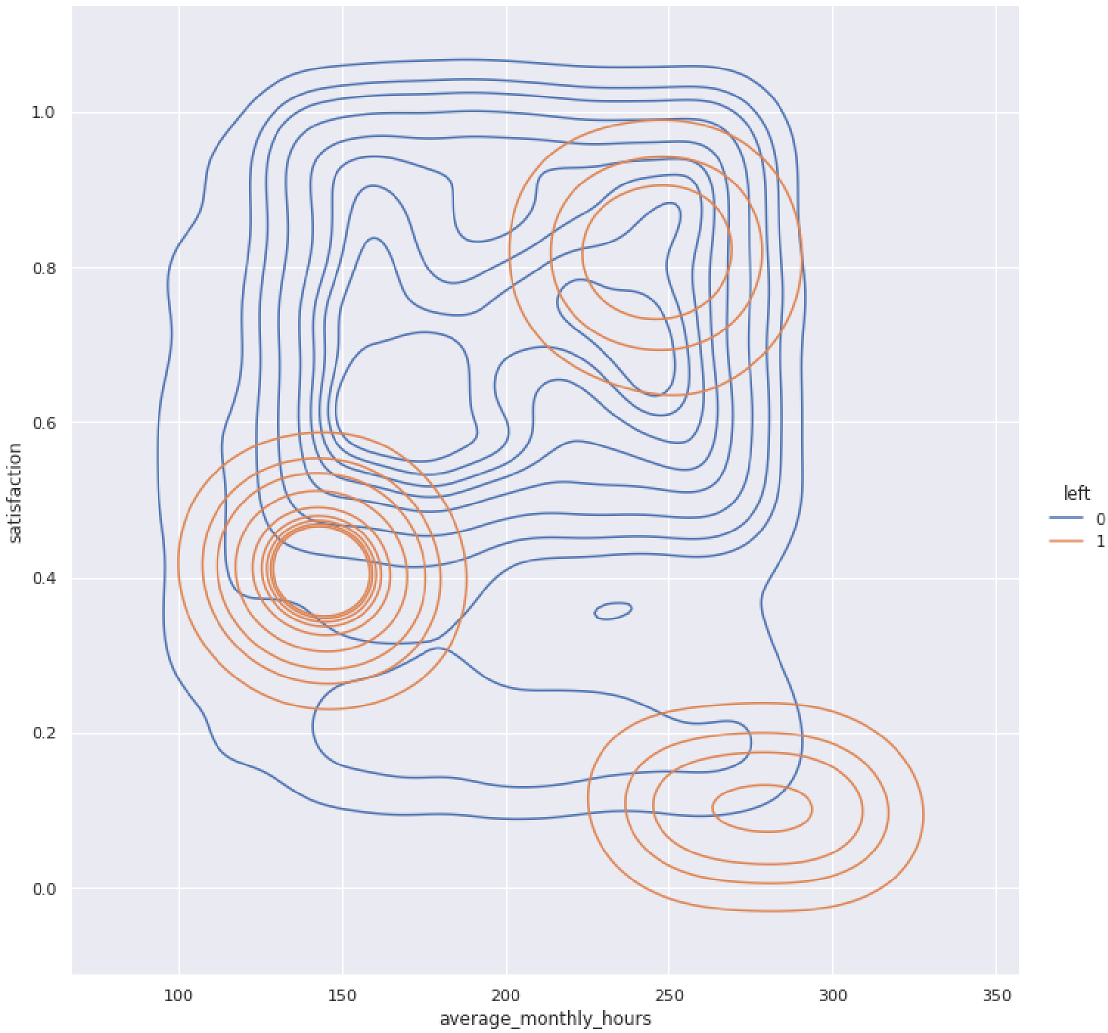
```
# What causes low job satisfaction? Let's start with average_hours_worked
```

[16]: <matplotlib.axes._subplots.AxesSubplot at 0x7f79c8104190>



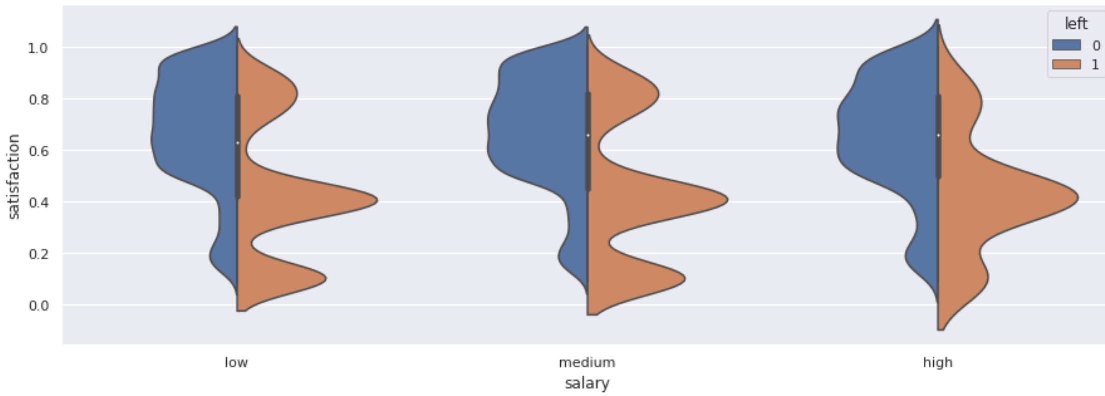
[17]:
```
#finding the relationship between satisfaction and hours
sns.displot(data = df, y=df['satisfaction'], x = df['average_monthly_hours'],␣
↪hue=df['left'], kind='kde', height=10, aspect=1)

# There are unique combinations of hours worked and satisfaction that lead to␣
↪employees leaving.
# How does pay contribute to satisfaction?
```

[17]: <seaborn.axisgrid.FacetGrid at 0x7f79c86bc710>



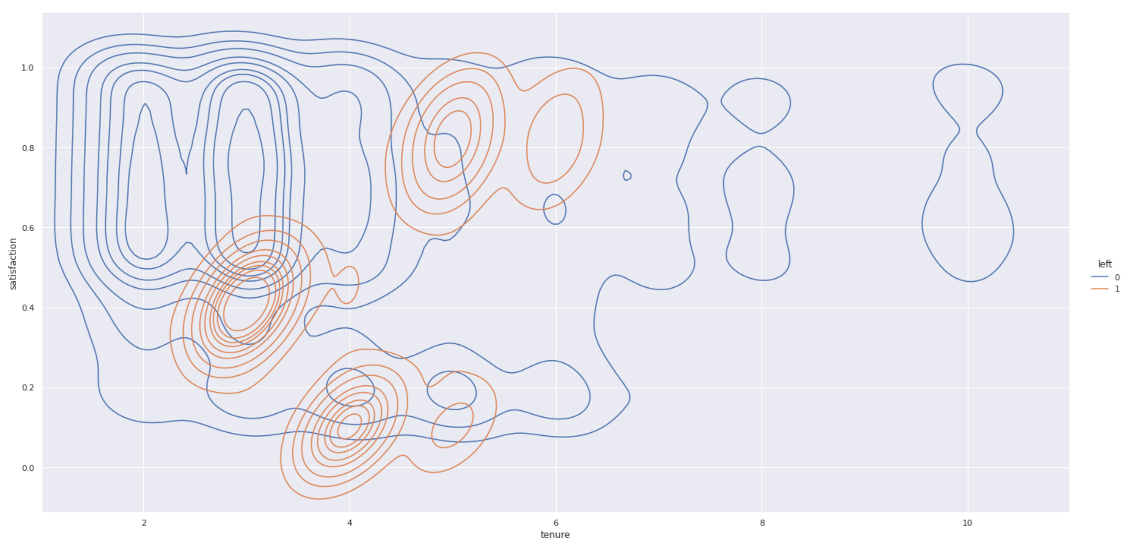
[18]:
```
sns.violinplot(data = df, y=df['satisfaction'], x = df['salary'],
 ↪hue=df['left'], split=True, height=10, aspect=1)

# Looks like pay ranges have similar satisfaction shapes. Pay range might not
 ↪be an important factor
```

[18]: <matplotlib.axes._subplots.AxesSubplot at 0x7f79c5ea6ad0>



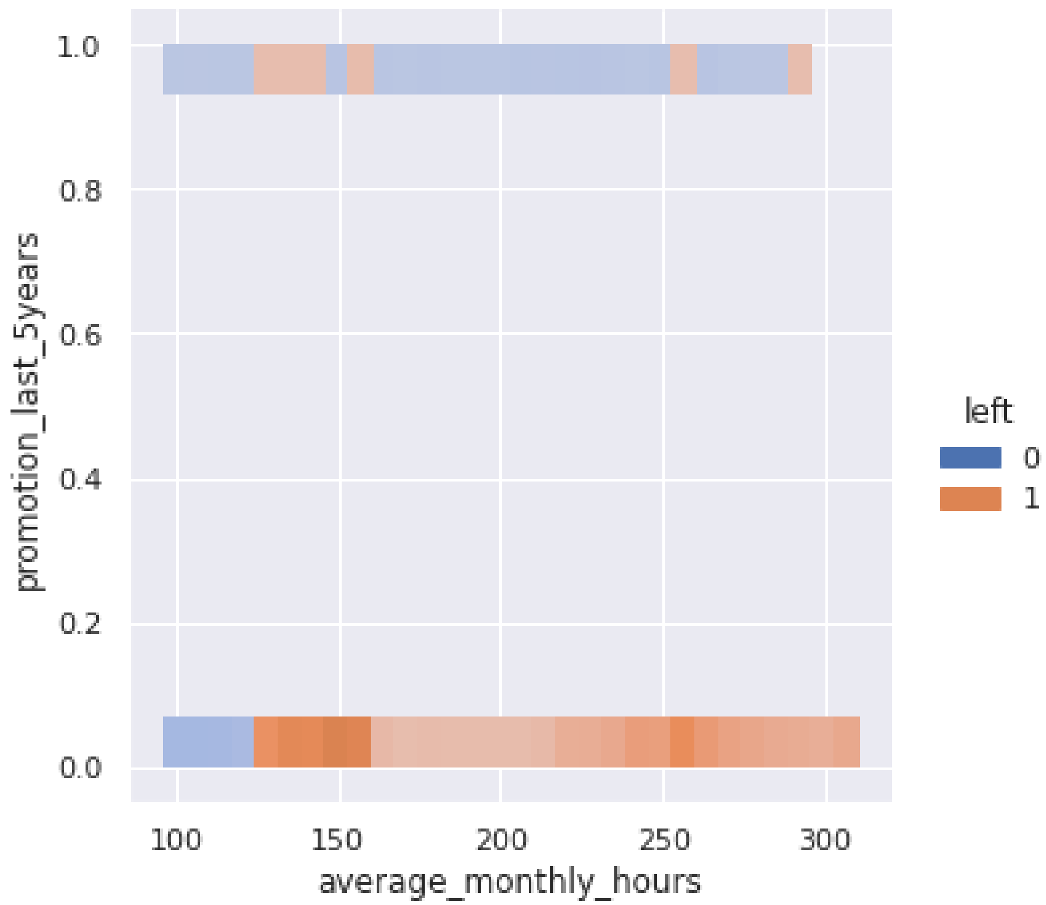
[19]:
```
# Does satisfaction get better with time?
sns.displot(data = df, y=df['satisfaction'], x = df['tenure'], hue=df['left'],␣
↪kind='kde', height=10, aspect=2)

# There exist unique pockets with high numbers of people leaving
# After 7 years, most people stay
# Most people start to leave after 2 years
```

[19]: <seaborn.axisgrid.FacetGrid at 0x7f79c803d6d0>



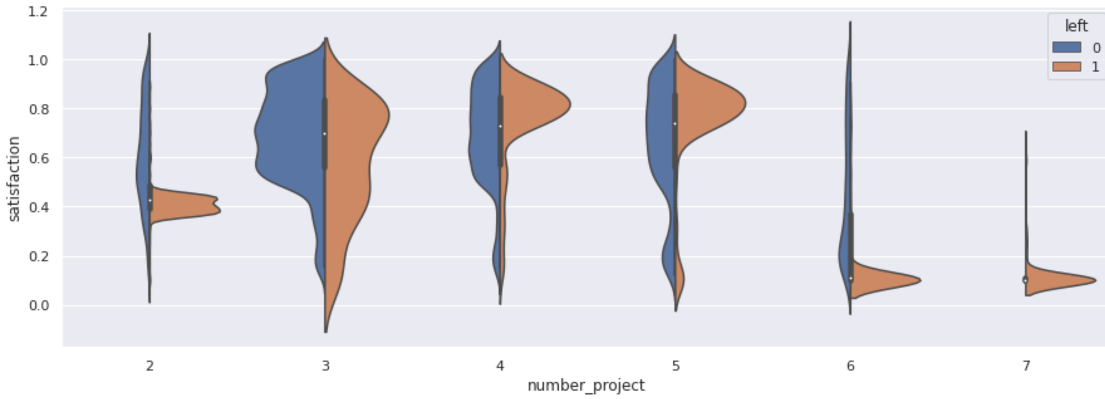
[20]:
```
# Comparing promotion and hourly
sns.displot(data = df, y=df['promotion_last_5years'], x =␣
↪df['average_monthly_hours'], hue=df['left'])
```

[20]: <seaborn.axisgrid.FacetGrid at 0x7f79c5ef5910>



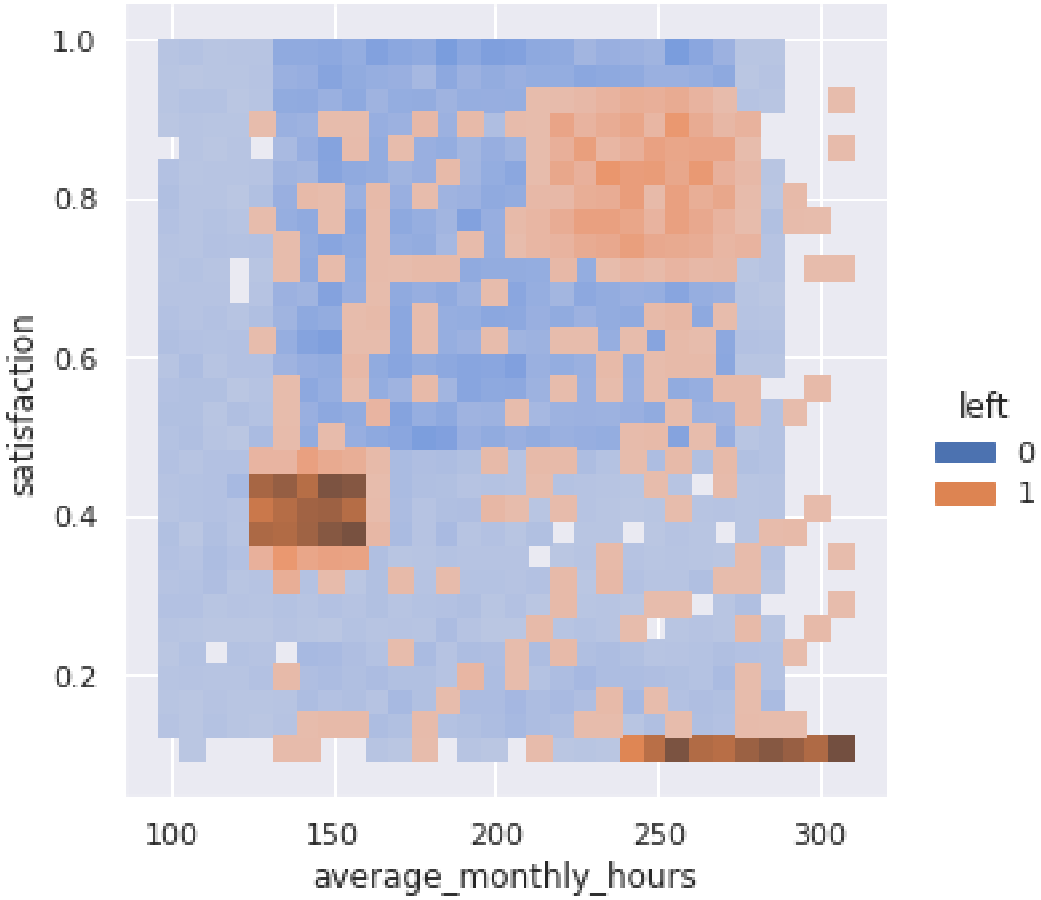

```
[21]: # Comparing satisfaction and number of projects
      #sns.displot(data = df, y=df['number_project'], x =␣
       ↪df['average_monthly_hours'], hue=df['left'], kind='kde')
      sns.violinplot(data = df, y=df['satisfaction'], x = df['number_project'],␣
       ↪hue=df['left'], split=True, height=10, aspect=2)

      # People who get 6+ projects have low satisfaction and tend to leave␣
       ↪(Overworked?)
      # People who get 2- projects and have a mid-level satisfaction tend to leave␣
       ↪(Bored?)
      # Most people have 3-5 projects.
          # 4-5 project people have higher satisfaction but might leave
```

```
[21]: <matplotlib.axes._subplots.AxesSubplot at 0x7f79c83cf690>
```



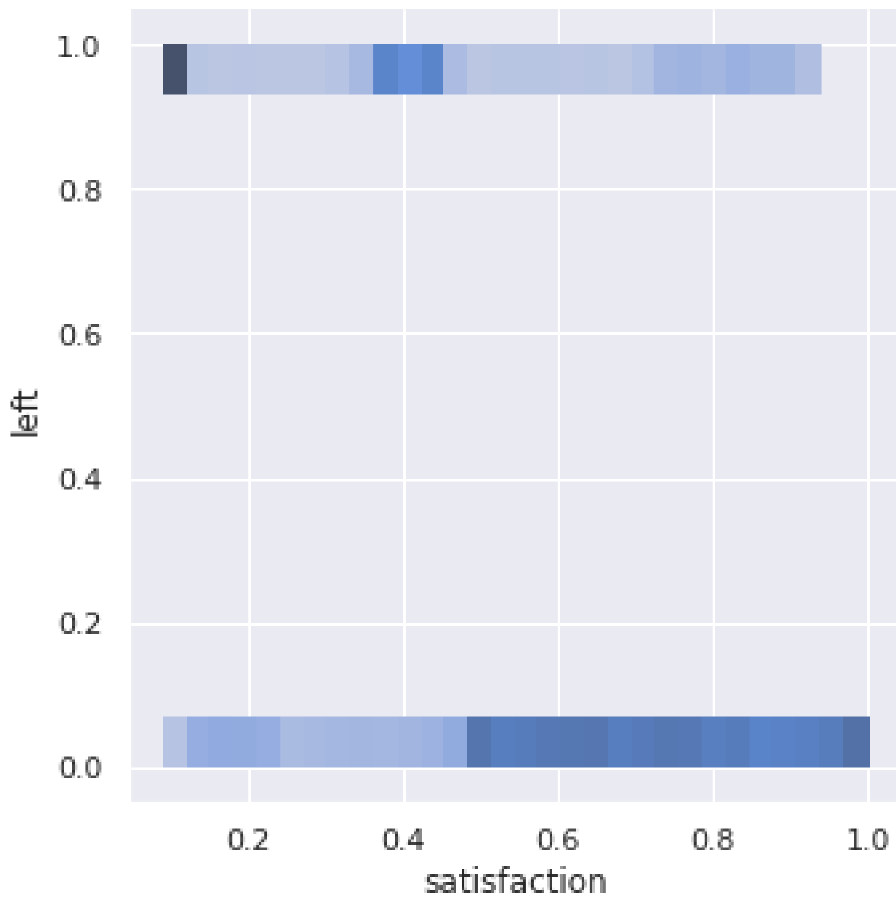
[22]:
```
#Final look at data
sns.displot(data=df, y = df['satisfaction'], x = df['average_monthly_hours'],␣
↪hue=df['left'])

#Looks like there are outliers after 300 hours
```

[22]:
```
<seaborn.axisgrid.FacetGrid at 0x7f79c814e910>
```



[23]:
```
# Plot 6 : Left vs Satisfaction
sns.displot(data = df, y=df['left'], x = df['satisfaction'], legend=True)
```

[23]: <seaborn.axisgrid.FacetGrid at 0x7f79c5f1bb90>



3.1.2 Insights

3.1.3 Graph 1 (Satisfaction vs Department):

- People with lower satisfaction tend to leave.
- All departments see the same three bumps trend in satisfaction that leads people to leave.

  Therefore people with lower satisfaction tend to leave

3.1.4 Graph 2 (Satisfaction vs Average Monthly Hours):

- Dense pocket of people who leave :
  1. Satisfaction approx 0.4 in hours range [125, 170]
  2. Satisfaction approx 0.1 in hours range [230, 300+]
- Broad pocket of people who have not left with satisfaction [0.5, 0.9] in hour range [130, 275]

  - Subset of left employees in here too : satisfaction approx [0.7, 0.9] in hour range of [200, 275].

  Unique pockets of satisfaction vs Hours Worked have high leave zones.

3.1.5 Graph 3 (Satisfaction vs Salary):

- The satisfaction proportions look similar regardless of pay level.

  Pay may not have an impact on job satisfaction.

3.1.6 Graph 4 (Satisfaction vs Tenure):

- Large pockets of people who leave in years [3, 7] at various levels of satisfaction
- People dont tend to leave before 2 years and after 7 years.
- There is usually high satisfaction the first year of working

  Tenure has pockets of people leaving at various levels of satifaction

3.1.7 Graph 4 (Promotion vs Average Monthly Hours)

- More people quit if they are not promoted. Note that some people so not make it to the 5 year mark here.
- Higher density pockets around 150 hours and 250 hours.

  People who are not promoted tend to leave.

3.1.8 Graph 5 (Satisfaction vs Number of Projects):

- People like getting 3-5 projects
- Satisfaction in the 3-5 project-range is high but people tend to still leave/stay

  People like 3-5 projects, outside of this range and they are very likely 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 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

Assumptions are not met for binomial logistical regression b/c: 1. The relationship between feature and label is not linear - linearity assumption not met 2. Relationships between data is hard to verify.

Therefore, I'll opt for a machine learning approach Note: - Outliers exist - 75/25 sample balance - Features may NOT be independent from each other (Dont use native bayes)

Lets try random forest = bagging + decision tree.

[24]:
```
#Lets one=hot encode the object items before building up the model.
df_subset = pd.get_dummies(df, columns=['department', 'salary'])
```

[25]:
```
# Separating the label from the features
y = df_subset['left']
X = df_subset.drop('left', axis=1)
```

[26]:
```
# Double checking sizes
print(y.shape)
X.info()
```

```
(14999,)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14999 entries, 0 to 14998
Data columns (total 20 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   satisfaction            14999 non-null  float64
 1   last_evaluation         14999 non-null  float64
 2   number_project          14999 non-null  int64
 3   average_monthly_hours   14999 non-null  int64
 4   tenure                  14999 non-null  int64
 5   work_accident           14999 non-null  int64
 6   promotion_last_5years   14999 non-null  int64
 7   department_IT           14999 non-null  uint8
 8   department_RandD        14999 non-null  uint8
 9   department_accounting   14999 non-null  uint8
 10  department_hr           14999 non-null  uint8
 11  department_management   14999 non-null  uint8
 12  department_marketing    14999 non-null  uint8
 13  department_product_mng  14999 non-null  uint8
 14  department_sales        14999 non-null  uint8
 15  department_support      14999 non-null  uint8
 16  department_technical    14999 non-null  uint8
 17  salary_high             14999 non-null  uint8
 18  salary_low              14999 non-null  uint8
```

```
 19  salary_medium           14999 non-null  uint8
dtypes: float64(2), int64(5), uint8(13)
memory usage: 1010.8 KB
```

[27]:
```
# Allocating data for testing (tr(56%), val(19%), test(25%))
# Using a validation set in case more algos are tried.

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25,␣
 ↪random_state = 0)
X_tr, X_val, y_tr, y_val = train_test_split(X_train, y_train, test_size = 0.25,␣
 ↪random_state = 0)
```

[28]:
```
# Defining the hyperparameters
cv_params = {'n_estimators' : [50,100],
              'max_depth' : [10,50],
              'min_samples_leaf' : [0.5,1],
              'min_samples_split' : [0.001, 0.01],
              'max_features' : ["sqrt"],
              'max_samples' : [.5,.9]}
```

[29]:
```
# Scoring Method
scoring = 'f1' # Using the harmonic mean
```

[30]:
```
#Create list of split indicies
split_index = [0 if x in X_val.index else -1 for x in X_train.index]
custom_split = PredefinedSplit(split_index)
```

[31]:
```
#Instantiate Model
rf = RandomForestClassifier(random_state=0)
```

[32]:
```
#Search over specific param
rf_val=GridSearchCV(rf, cv_params, cv=custom_split, refit=scoring, n_jobs = -1,␣
 ↪verbose = 2)
```

[34]:
```
# Fit the model
#%%time

rf_val.fit(X_train, y_train)
```

```
Fitting 1 folds for each of 32 candidates, totalling 32 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done  32 out of  32 | elapsed:    5.0s finished
```

[34]:
```
GridSearchCV(cv=PredefinedSplit(test_fold=array([-1, -1, …, -1,  0])),
             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_weigh…
                                              n_estimators=100, n_jobs=None,
                                              oob_score=False, random_state=0,
                                              verbose=0, warm_start=False),
             iid='deprecated', n_jobs=-1,
             param_grid={'max_depth': [10, 50], 'max_features': ['sqrt'],
                         'max_samples': [0.5, 0.9],
                         'min_samples_leaf': [0.5, 1],
                         'min_samples_split': [0.001, 0.01],
                         'n_estimators': [50, 100]},
             pre_dispatch='2*n_jobs', refit='f1', return_train_score=False,
             scoring=None, verbose=2)
```

[35]:
```
#Capturing the best param values
rf_val.best_params_
```

[35]:
```
{'max_depth': 50,
 'max_features': 'sqrt',
 'max_samples': 0.9,
 'min_samples_leaf': 1,
 'min_samples_split': 0.001,
 'n_estimators': 100}
```

[36]:
```
#Loading optimal values
rf_opt = RandomForestClassifier(max_depth = 50,
                                max_features = 'sqrt',
                                max_samples = 0.9,
                                min_samples_leaf = 1,
                                min_samples_split = 0.001,
                                n_estimators = 100,
                                random_state = 0)
```

[37]:
```
#Retraining the model
rf_opt.fit(X_train, y_train)
```

[37]:
```
RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=None,
                       criterion='gini', max_depth=50, max_features='sqrt',
                       max_leaf_nodes=None, max_samples=0.9,
                       min_impurity_decrease=0.0, min_impurity_split=None,
```

```
                             min_samples_leaf=1, min_samples_split=0.001,
                             min_weight_fraction_leaf=0.0, n_estimators=100,
                             n_jobs=None, oob_score=False, random_state=0, verbose=0,
                             warm_start=False)
```

[38]:
```
#Predict on test set
y_pred = rf_opt.predict(X_test)
```

Reflect on these questions as you complete the constructing stage.

1. 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?

    1. Outliers exist and groupings exist

    - I plan to use all variables for the random forest model
    - The assumptions for logistic regression are not met - it doesnt appear that the features are linearly related to the labels
    - The random forest model fit well but maybe too well. Overfitting might have occured - more testing is needed to confirm.
    - There are boosting techniques that might help here but performance gains will most likely be small.
    - The Sklearn and pandas reference guides are very useful - old course material as well.
    - I hope this prediction model won't single out employees - data collection should be stripping personal info that could be used to identify a person. Wages didn't significantly contribute to retension - I hope wages keep up with inflation.

5 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?

  - Satisfaction was a large contributor in predicting retension with a handful of other items.
  - Focus should be on employee satisfaction, tenure, the number of projects, average monthly hours, and the last evaluation score. These items contribute the most to prediction employee retention
  - Another trade study is required to understand what contributes to satisfaction. Features s.a. number of projects and hours worked could contribute to satisfaction but data should be collected to understand this metric.
  - I want to try more models to see if boosting would get better results
  -
  - Course material and the pandas/sklearn reference guides
  - Keeping the data private and making sure the data isnt used to single people out or pay people less.

5.1 Step 4. Results and Evaluation

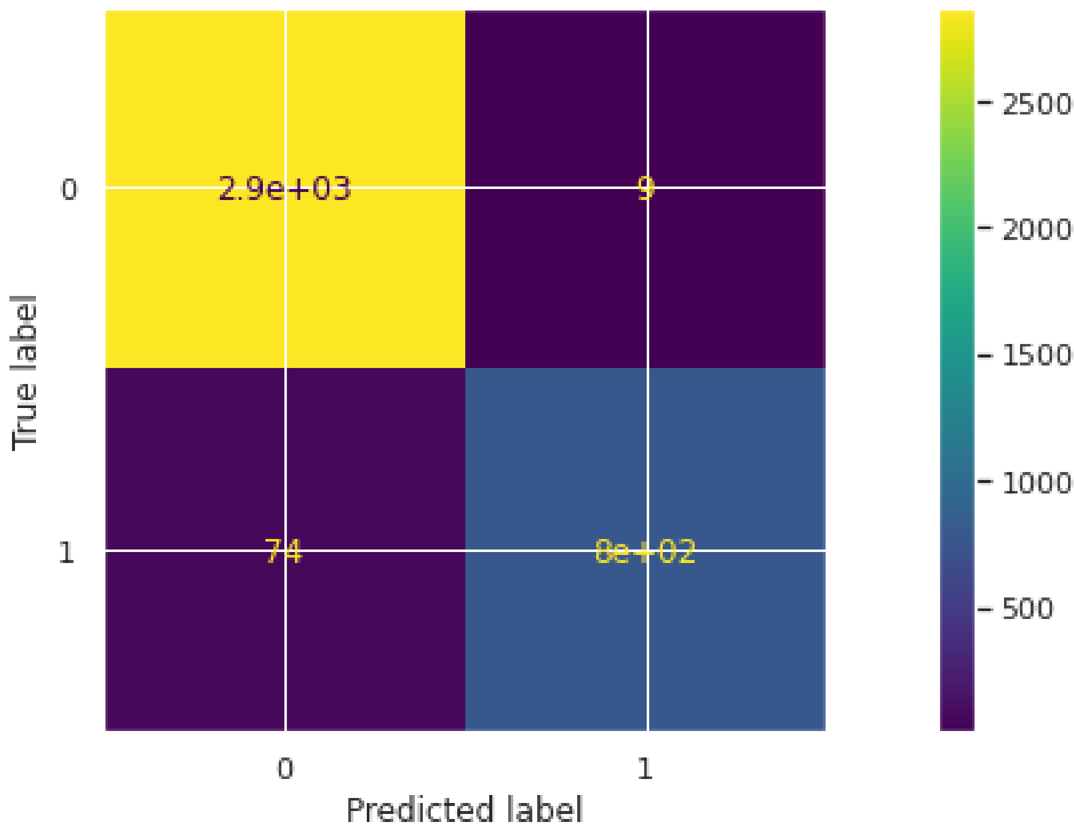
- Interpret model
- Evaluate model performance using metrics
- Prepare results, visualizations, and actionable steps to share with stakeholders

[43]:
```
# Getting score from test
pc_test = precision_score(y_test, y_pred)
rc_test = recall_score(y_test, y_pred)
ac_test = accuracy_score(y_test, y_pred)
f1_test = f1_score(y_test, y_pred)

print("The F1 score is {f1:.3f}".format(f1 = f1_test))
print("The accuracy score is {ac:.3f}".format(ac = ac_test))
print("The recall score is {rc:.3f}".format(rc = rc_test))
print("The precision score is {pc:.3f}".format(pc = pc_test))

cm = metrics.confusion_matrix(y_test, y_pred, labels = rf_opt.classes_)
```

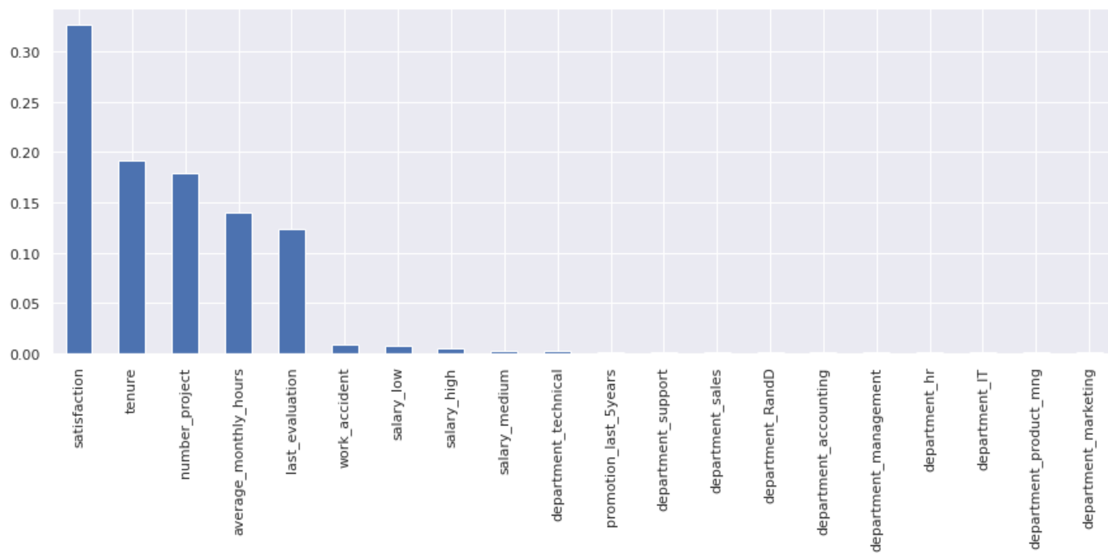
```
disp = metrics.ConfusionMatrixDisplay(confusion_matrix = cm,display_labels =␣
 ↪rf_opt.classes_)
disp.plot()
```

```
The F1 score is 0.950
The accuracy score is 0.978
The recall score is 0.915
The precision score is 0.989
```

[43]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7f79c80646d0>



[44]:
```
# Feature Importance
importances = rf_opt.feature_importances_
rf_importances = pd.Series(importances, index=X.columns).
 ↪sort_values(ascending=False)

fig, ax = plt.subplots()
rf_importances.plot.bar(ax=ax);
```



5.1.1 Summary of model results

[Double-click to enter your summary here.]

5.1.2 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.