Activity_ Course 7 Salifort Motors project lab

May 31, 2023

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.

PACE stages

- Section **??**
- Section **??**
- Section **??**
- Section **??**

2 Pace: Plan Stage

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

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.

2.0.1 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?

[20]:
```python
## Relevant Imports for now, will require more later

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

[21]:
```python
## Reading in Data

df0 = pd.read_csv("HR_capstone_dataset.csv")
df0
```

[21]:
```
       satisfaction_level  last_evaluation  number_project  \
0                    0.38             0.53               2
1                    0.80             0.86               5
2                    0.11             0.88               7
3                    0.72             0.87               5
4                    0.37             0.52               2
…                     …               …              …
14994                0.40             0.57               2
14995                0.37             0.48               2
14996                0.37             0.53               2
14997                0.11             0.96               6
14998                0.37             0.52               2

       average_montly_hours  time_spend_company  Work_accident  left  \
0                       157                   3              0     1
1                       262                   6              0     1
2                       272                   4              0     1
3                       223                   5              0     1
4                       159                   3              0     1
…                     …                   …             …    …
14994                   151                   3              0     1
14995                   160                   3              0     1
14996                   143                   3              0     1
14997                   280                   4              0     1
14998                   158                   3              0     1

       promotion_last_5years Department  salary
0                          0      sales     low
1                          0      sales  medium
2                          0      sales  medium
3                          0      sales     low
4                          0      sales     low
…                        …        …     …
14994                      0    support     low
14995                      0    support     low
14996                      0    support     low
```

```
14997                        0    support     low
14998                        0    support     low

[14999 rows x 10 columns]
```

[22]:
```
## Exploring Data

df0.info()
```

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

[4]:
```
df0.describe()
```

[4]:
```
       satisfaction_level  last_evaluation  number_project  \
count        14999.000000     14999.000000    14999.000000
mean             0.612834         0.716102        3.803054
std              0.248631         0.171169        1.232592
min              0.090000         0.360000        2.000000
25%              0.440000         0.560000        3.000000
50%              0.640000         0.720000        4.000000
75%              0.820000         0.870000        5.000000
max              1.000000         1.000000        7.000000

       average_montly_hours  time_spend_company  Work_accident          left  \
count          14999.000000        14999.000000   14999.000000  14999.000000
mean             201.050337            3.498233       0.144610      0.238083
std               49.943099            1.460136       0.351719      0.425924
min               96.000000            2.000000       0.000000      0.000000
25%              156.000000            3.000000       0.000000      0.000000
50%              200.000000            3.000000       0.000000      0.000000
75%              245.000000            4.000000       0.000000      0.000000
```

```
max                310.000000            10.000000       1.000000       1.000000

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

[7]:
```
df0.columns
```

[7]:
```
Index(['satisfaction_level', 'last_evaluation', 'number_project',
       'average_montly_hours', 'time_spend_company', 'Work_accident', 'left',
       'promotion_last_5years', 'Department', 'salary'],
      dtype='object')
```

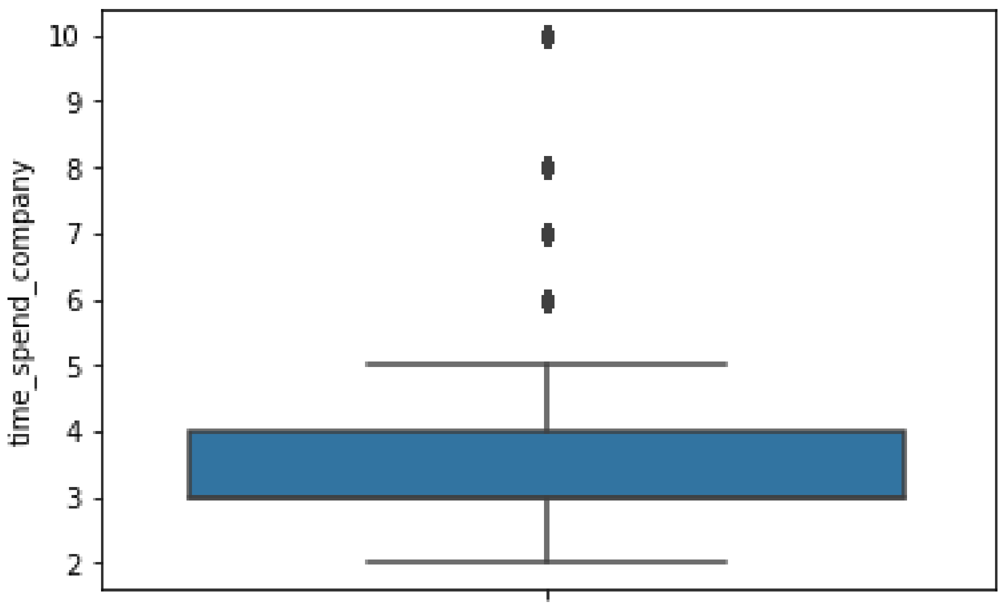
[38]:
```
## Renaming Columns such that they are consistent

df1 = df0.rename(columns={'Work_accident':'work_accident','Department':
↪'department','average_montly_hours':'average_monthly_hours'})
```

[39]:
```
## Checking for null values

df1.isna().sum()
```

[39]:
```
satisfaction_level       0
last_evaluation          0
number_project           0
average_monthly_hours    0
time_spend_company       0
work_accident            0
left                     0
promotion_last_5years    0
department               0
salary                   0
dtype: int64
```

[47]:
```
## Checking for outliers in time spent at the company

sns.boxplot(data = df1, y='time_spend_company')
```

[47]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fba39d47d50>
```



[49]:
```
## Getting rid of outliers
q1 = df1['time_spend_company'].quantile(0.25)
q3 = df1['time_spend_company'].quantile(0.75)

iqr = q3-q1
print('q1 = ',q1)
print('q3 = ',q3)
print('IQR = ',iqr)
```

```
q1 =  3.0
q3 =  4.0
IQR =  1.0
```

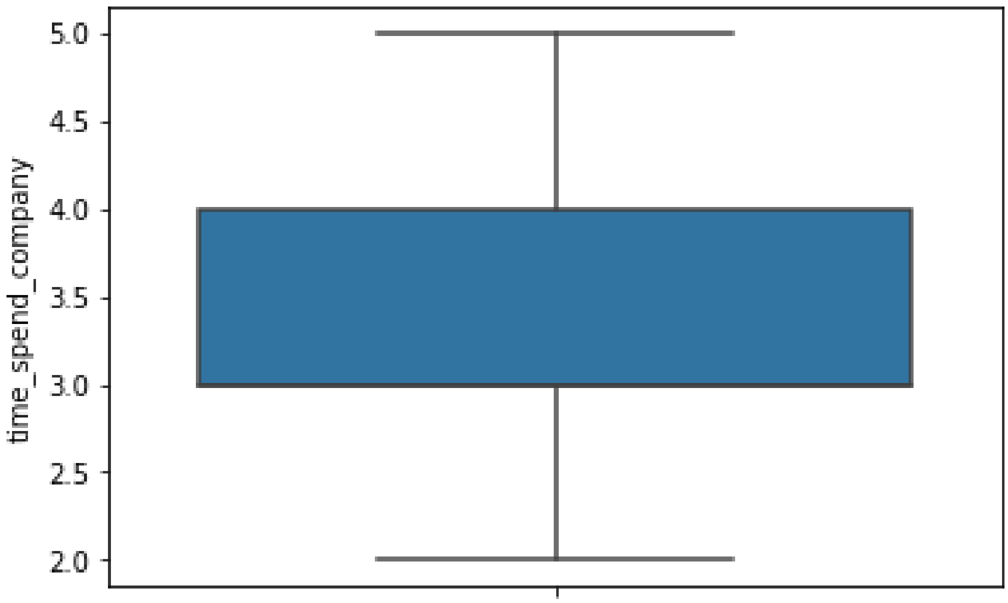
[50]:
```
upper_limit = q3 + 1.5*iqr
lower_limit = q1 - 1.5*iqr
print('Lower limit = ',lower_limit)
print('Upper limit = ',upper_limit)
```

```
Lower limit =  1.5
Upper limit =  5.5
```

[52]:
```
## Removing outliers from data set as new data set

df2 = df1.drop(df1[(df1['time_spend_company'] < 1.5) |␣
 ↪(df1['time_spend_company'] > 5.5)].index)
```

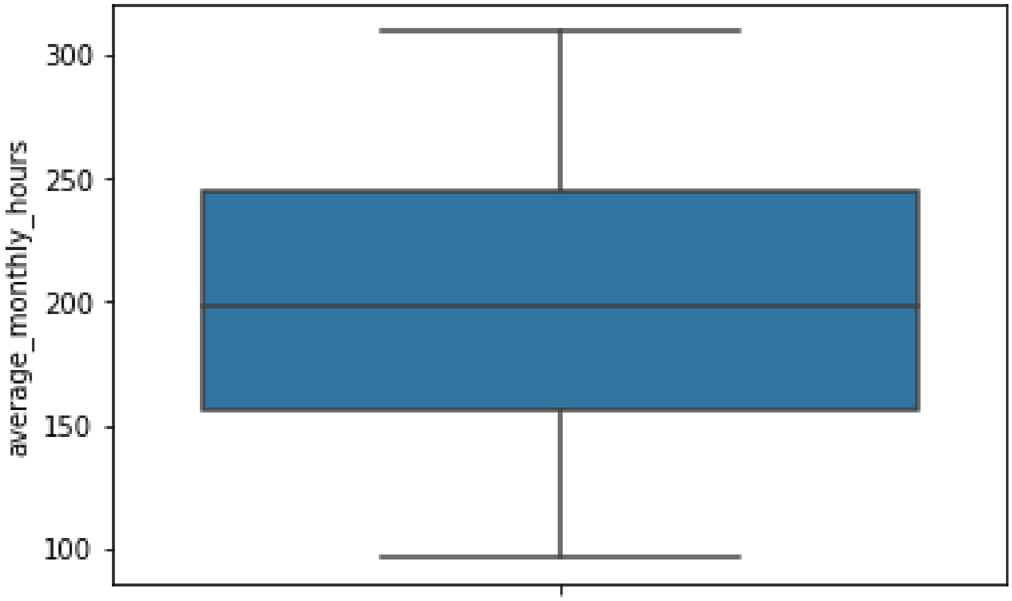
[54]:
```
## Displaying Results

sns.boxplot(data = df2, y='time_spend_company')
```

[54]: <matplotlib.axes._subplots.AxesSubplot at 0x7fba37446990>



[56]:
```
## Checking for outliers in average monthly hours

sns.boxplot(data = df2, y='average_monthly_hours')
```

[56]: <matplotlib.axes._subplots.AxesSubplot at 0x7fba34f49250>



2.0.2 Data visualizations

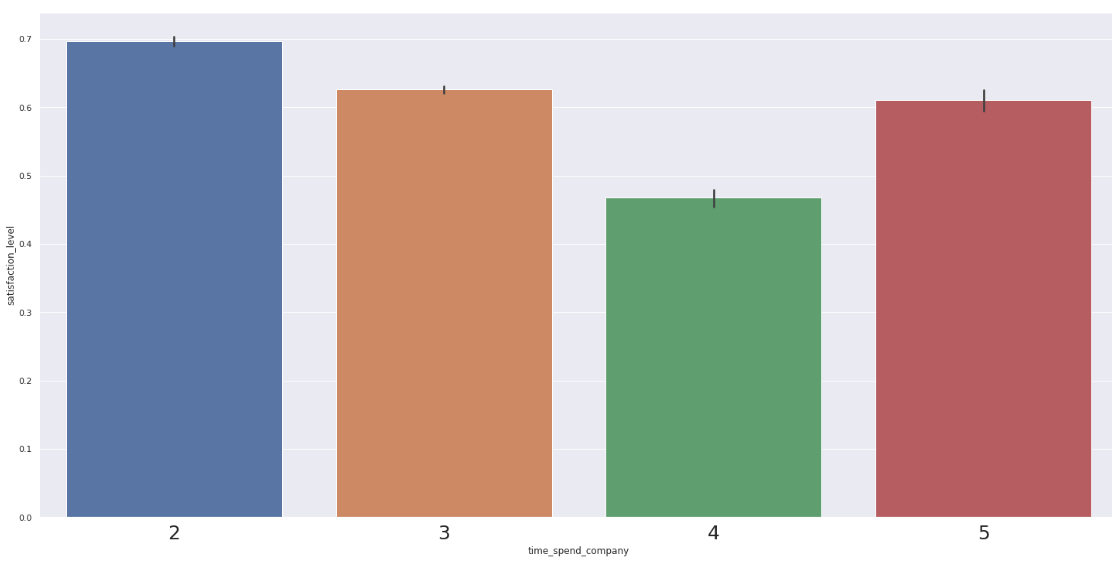
Plotting relevant variables

[94]:
```
df2.reset_index(inplace=True,drop=True)
df2
```

[94]:
```
       satisfaction_level  last_evaluation  number_project  \
0                    0.38             0.53               2
1                    0.11             0.88               7
2                    0.72             0.87               5
3                    0.37             0.52               2
4                    0.41             0.50               2
…                       …                …               …
13712                0.40             0.57               2
13713                0.37             0.48               2
13714                0.37             0.53               2
13715                0.11             0.96               6
13716                0.37             0.52               2

       average_monthly_hours  time_spend_company  work_accident  left  \
0                        157                   3              0     1
1                        272                   4              0     1
2                        223                   5              0     1
3                        159                   3              0     1
4                        153                   3              0     1
```

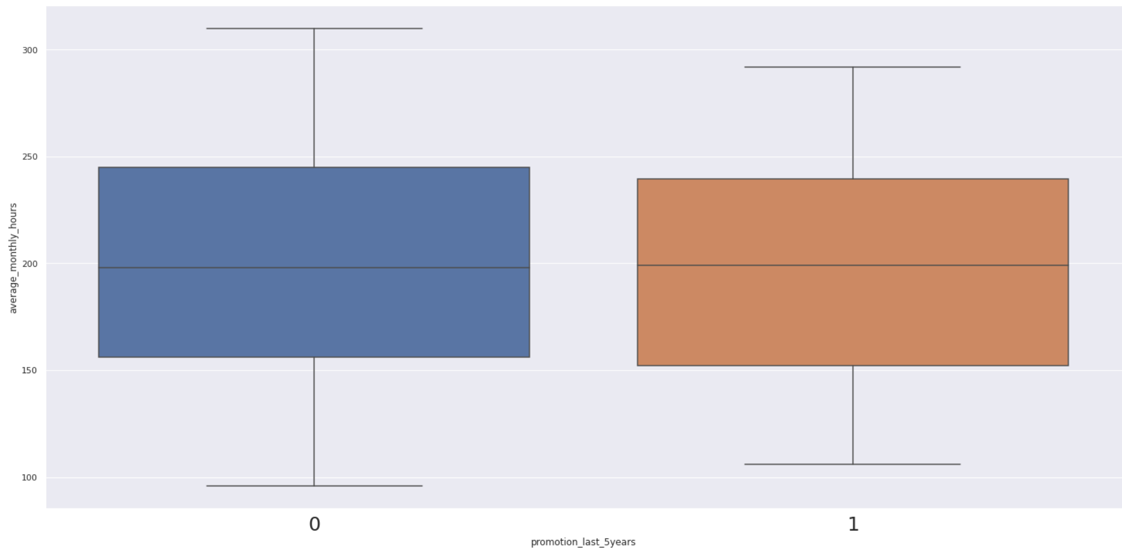
```
…                        …                 …             …    …
13712                   151                3             0      1
13713                   160                3             0      1
13714                   143                3             0      1
13715                   280                4             0      1
13716                   158                3             0      1

       promotion_last_5years department  salary
0                          0      sales     low
1                          0      sales  medium
2                          0      sales     low
3                          0      sales     low
4                          0      sales     low
…                        …        …      …
13712                      0    support     low
13713                      0    support     low
13714                      0    support     low
13715                      0    support     low
13716                      0    support     low

[13717 rows x 10 columns]
```

[89]:
```
sns.barplot(data=df2, x='time_spend_company', y='satisfaction_level')
plt.xticks(rotation=0,fontsize=25)
sns.set(rc={'figure.figsize':(25,12)})
```



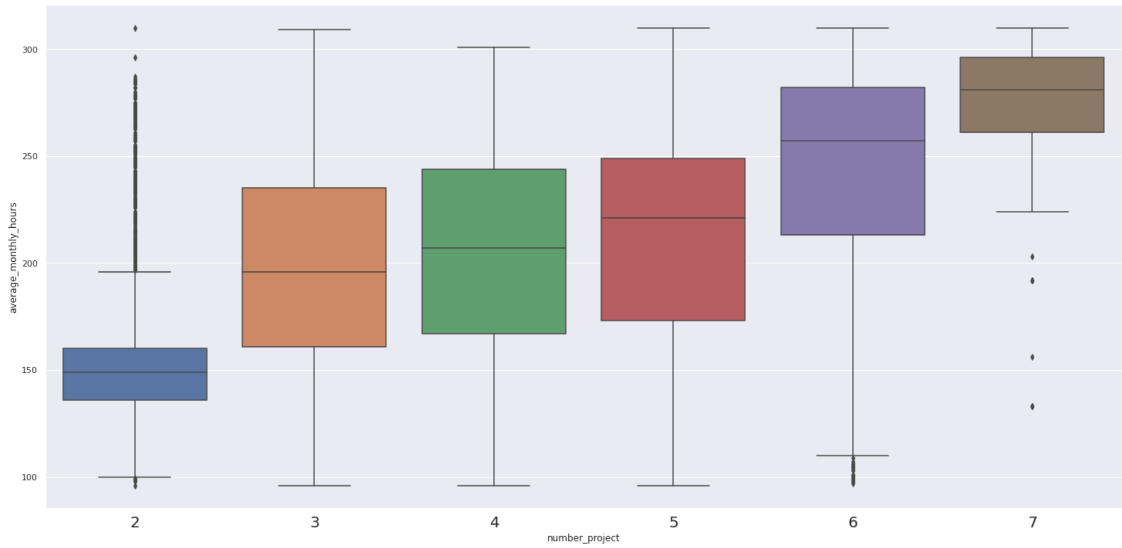
Satisfaction trends downward with time spend at company

```
[90]: sns.boxplot(data=df2, x='promotion_last_5years', y='average_monthly_hours')
plt.xticks(rotation=0,fontsize=25)
sns.set(rc={'figure.figsize':(25,12)})
```



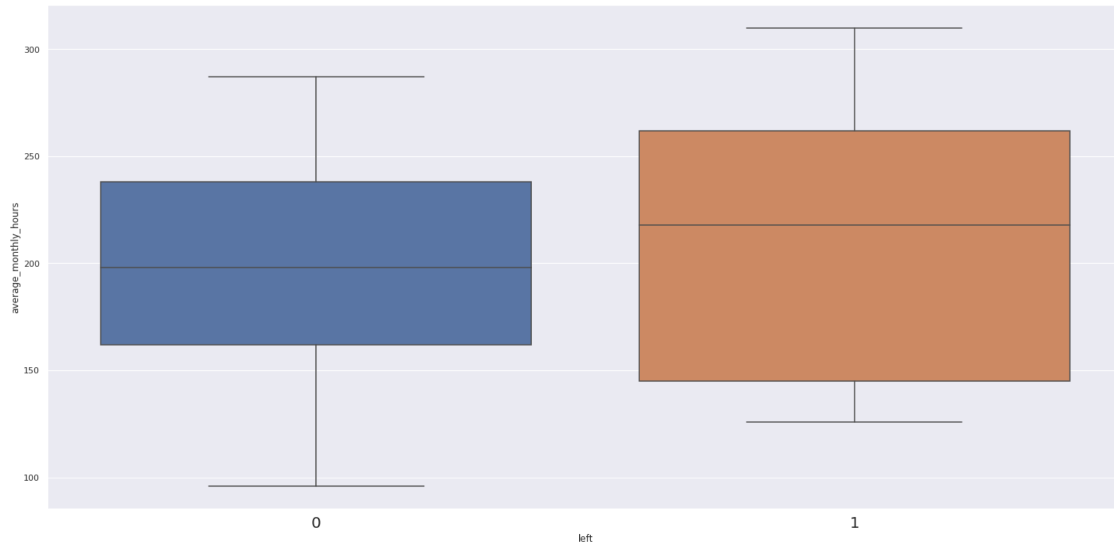
Average monthly hours is not strongly correlated to whether they've had a promotion in the last 5 years

```
[81]: sns.boxplot(data=df2, x='number_project', y='average_monthly_hours')
plt.xticks(rotation=0,fontsize=20)
sns.set(rc={'figure.figsize':(25,12)})
```



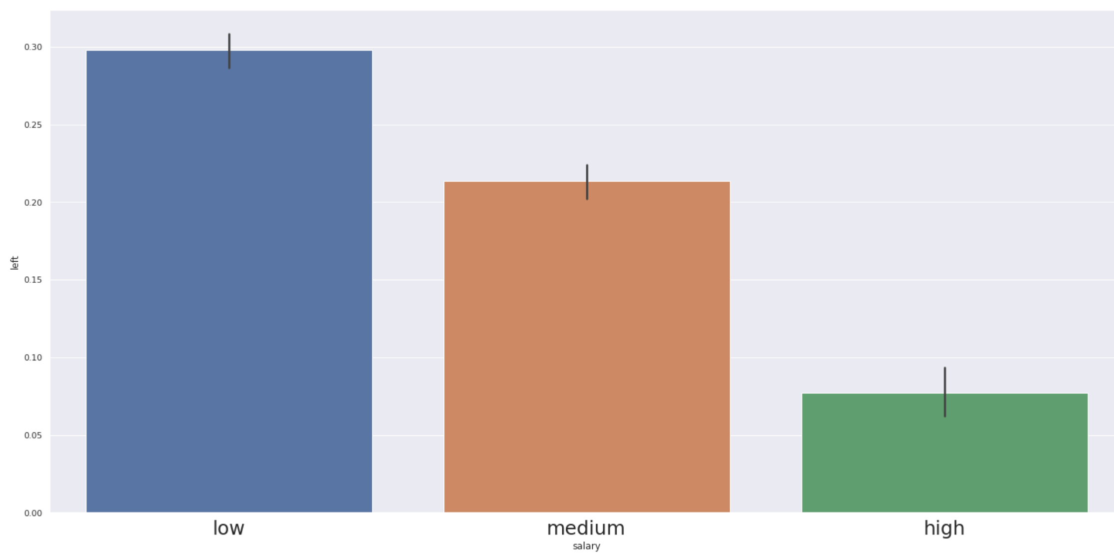
The more projects an employee contributes to is a good indicator of how many hours they average per month

[82]:
```
sns.boxplot(data=df2, x='left', y='average_monthly_hours')
plt.xticks(rotation=0,fontsize=20)
sns.set(rc={'figure.figsize':(25,12)})
```



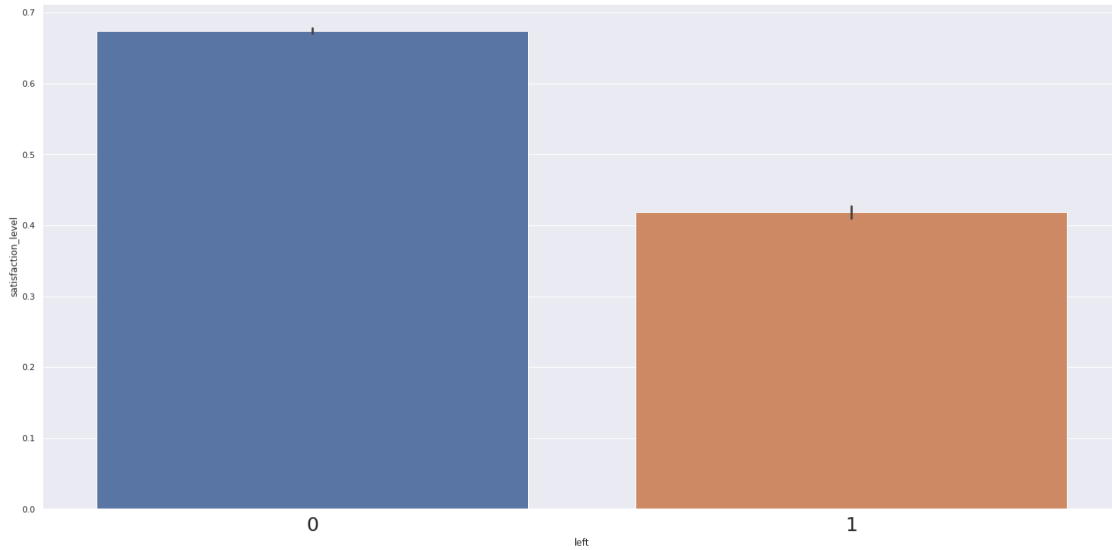
The employees that were working the most hours per month on average are more likely to have left

[92]:
```
sns.barplot(data=df2, x='salary', y='left')
plt.xticks(rotation=0,fontsize=25)
sns.set(rc={'figure.figsize':(25,12)})
```



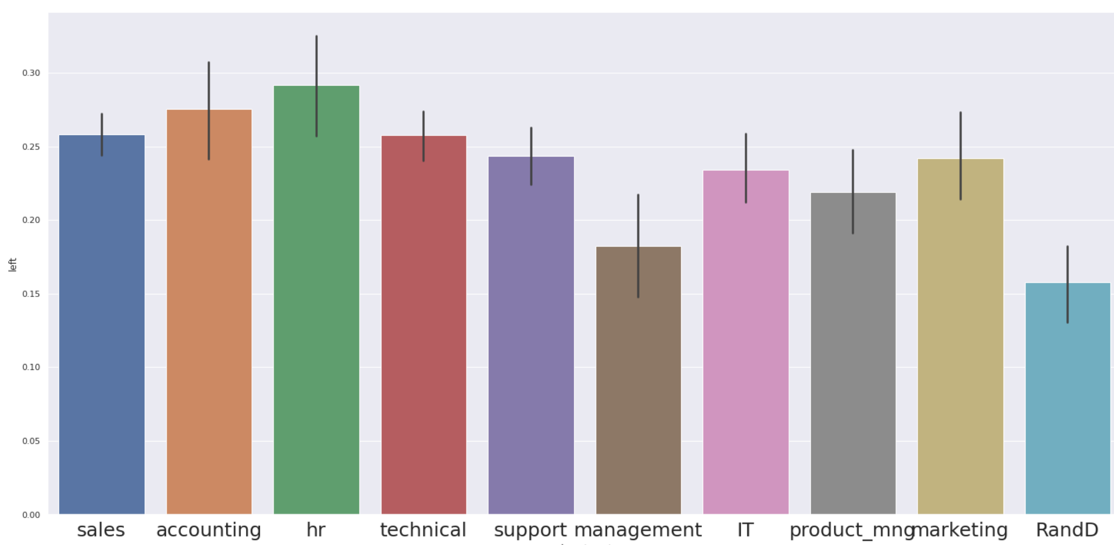
Less likely to leave with higher salary

[93]:
```
sns.barplot(data=df2, x='left', y='satisfaction_level')
plt.xticks(rotation=0,fontsize=25)
sns.set(rc={'figure.figsize':(25,12)})
```



Those that leave have a lower satisfaction level

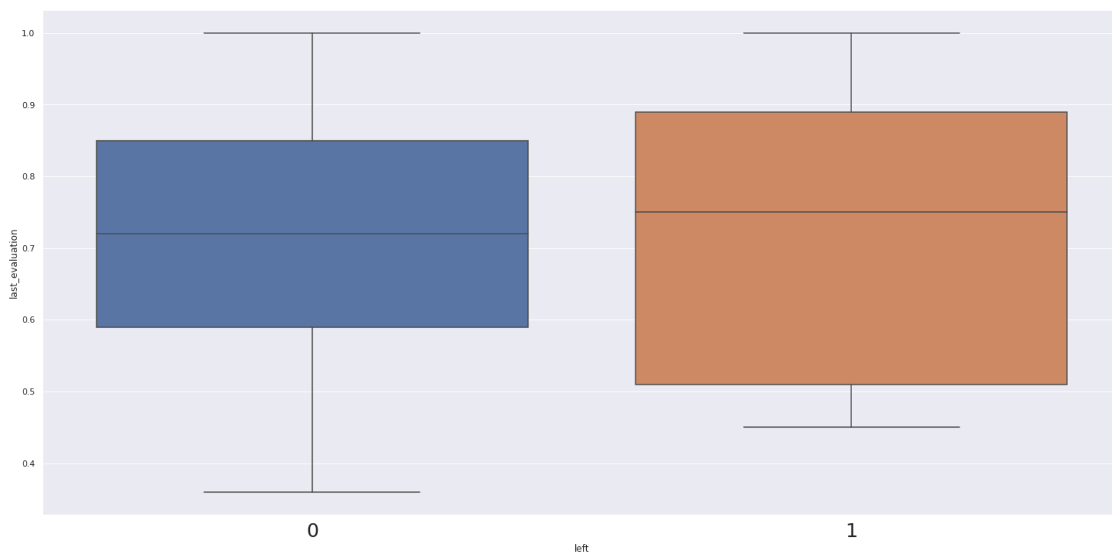
[95]:
```
sns.barplot(data=df2, x='department', y='left')
plt.xticks(rotation=0,fontsize=25)
sns.set(rc={'figure.figsize':(25,12)})
```



[111]:
```
## Validating barplot

sales = df2[df2['department'] == 'sales']
sales_left = sales.left.sum()
sales_emp = len(sales)
print(sales_left)
print(sales_emp)
percent = sales_left / sales_emp
print(percent)
```

```
966
3739
0.25835784969243114
```

[112]:
```
sns.boxplot(data=df2, x='left', y='last_evaluation')
plt.xticks(rotation=0,fontsize=25)
sns.set(rc={'figure.figsize':(25,12)})
```



Not highly correlated

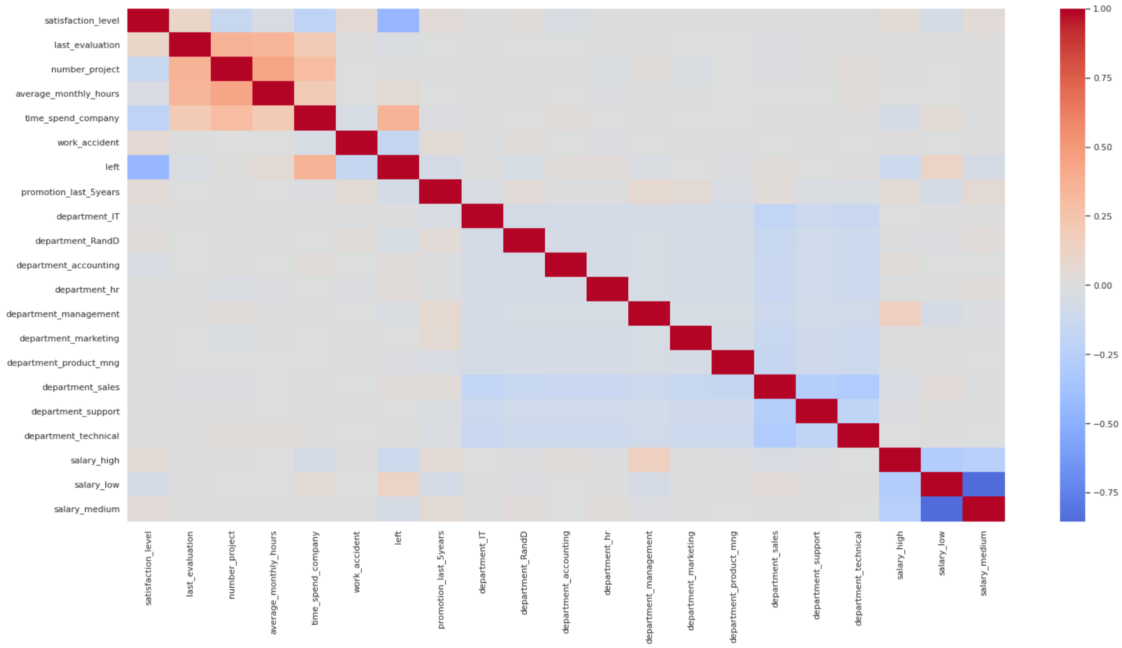
[119]:
```
## Going to create a heatmap for visualzing correlation matrix of the data, to␣
↪do this I need all categorical variables to be dummied

df3 = pd.get_dummies(df2, columns=['department','salary'])
df3
```

```
[119]:        satisfaction_level  last_evaluation  number_project  \
       0                    0.38             0.53               2
       1                    0.11             0.88               7
       2                    0.72             0.87               5
       3                    0.37             0.52               2
       4                    0.41             0.50               2
       …                     …                …               …
       13712                0.40             0.57               2
       13713                0.37             0.48               2
       13714                0.37             0.53               2
       13715                0.11             0.96               6
       13716                0.37             0.52               2

              average_monthly_hours  time_spend_company  work_accident  left  \
       0                        157                   3              0     1
       1                        272                   4              0     1
       2                        223                   5              0     1
       3                        159                   3              0     1
       4                        153                   3              0     1
       …                         …                   …              …    …
       13712                    151                   3              0     1
       13713                    160                   3              0     1
       13714                    143                   3              0     1
       13715                    280                   4              0     1
       13716                    158                   3              0     1

              promotion_last_5years  department_IT  department_RandD  …  \
       0                          0              0                 0  …
       1                          0              0                 0  …
       2                          0              0                 0  …
       3                          0              0                 0  …
       4                          0              0                 0  …
       …                         …              …                …  …
       13712                      0              0                 0  …
       13713                      0              0                 0  …
       13714                      0              0                 0  …
       13715                      0              0                 0  …
       13716                      0              0                 0  …

              department_hr  department_management  department_marketing  \
       0                  0                      0                     0
       1                  0                      0                     0
       2                  0                      0                     0
       3                  0                      0                     0
       4                  0                      0                     0
       …                 …                      …                     …
       13712              0                      0                     0
```

```
13713                0                       0                     0
14714                0                       0                     0
13715                0                       0                     0
13716                0                       0                     0

       department_product_mng  department_sales  department_support  \
0                           0                 1                   0
1                           0                 1                   0
2                           0                 1                   0
3                           0                 1                   0
4                           0                 1                   0
…                         …                 …                   …
13712                       0                 0                   1
13713                       0                 0                   1
13714                       0                 0                   1
13715                       0                 0                   1
13716                       0                 0                   1

       department_technical  salary_high  salary_low  salary_medium
0                         0            0           1              0
1                         0            0           0              1
2                         0            0           1              0
3                         0            0           1              0
4                         0            0           1              0
…                       …          …          …            …
13712                     0            0           1              0
13713                     0            0           1              0
13714                     0            0           1              0
13715                     0            0           1              0
13716                     0            0           1              0

[13717 rows x 21 columns]
```

[120]:
```python
from scipy import stats

fig = df3.corr()

sns.heatmap(fig, cmap='coolwarm', center=0)
```

[120]: <matplotlib.axes._subplots.AxesSubplot at 0x7fba20205590>



Whether an employee leaves is most highly correlated to their time spent at the company, whether they've had a work accident, and their salary.

2.0.3 Modeling

[139]:
```
## First going to check the ratio of employees that have left and not,
## to make sure their is a relatively equal balance

left_df = df3[df3['left'] == 1]
stayed_df = df3[df3['left'] == 0]
left = len(left_df)
stayed = len(stayed_df)
percent = left / (left + stayed)
print(left)
print(stayed)
print(percent * 100)
```

```
3362
10355
24.509732448786178
```

25% is very acceptable so we do not need to upsample or downsample

[143]:
```
## Going to use an XGB Classifer to predict whether an employee is likely to␣
↪leave
```

```python
from sklearn.model_selection import GridSearchCV, train_test_split
from sklearn.metrics import accuracy_score, precision_score, recall_score,\
f1_score, confusion_matrix, ConfusionMatrixDisplay
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from xgboost import plot_importance

## First need to Identify X and y variables

y = df3['left']

X = df3.drop(columns=['left'], axis = 1)

## Splitting up data into training and testing data
X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y,␣
 ↪test_size=0.2, random_state=42)
```

[142]:
```python
y_test
```

[142]:
```
11393    1
4677     0
10001    0
13495    1
8169     0
        ..
10982    0
12152    0
12441    0
5592     0
10645    0
Name: left, Length: 2744, dtype: int64
```

[125]:
```python
## Instantiating Classifier

xgb = XGBClassifier(objective='binary:logistic', random_state=42)
```

[126]:
```python
## Instantiating a GridSearch with hyper parameters
## Refitting with f1 score

cv_params = {'max_depth': [4,8,12],
             'min_child_weight': [3, 5],
             'learning_rate': [0.01, 0.1],
             'n_estimators': [300, 500]
             }

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

```
xgb_cv = GridSearchCV(xgb, cv_params, scoring=scoring, cv=4, refit='f1')
```

[127]:
```
## Fitting model to training data

xgb_cv.fit(X_train,y_train)
```

[127]:
```
GridSearchCV(cv=4, error_score=nan,
             estimator=XGBClassifier(base_score=None, booster=None,
                                     callbacks=None, colsample_bylevel=None,
                                     colsample_bynode=None,
                                     colsample_bytree=None,
                                     early_stopping_rounds=None,
                                     enable_categorical=False, eval_metric=None,
                                     gamma=None, gpu_id=None, grow_policy=None,
                                     importance_type=None,
                                     interaction_constraints=None,
                                     learning_rate=None, max…
                                     num_parallel_tree=None,
                                     objective='binary:logistic',
                                     predictor=None, random_state=42,
                                     reg_alpha=None, …),
             iid='deprecated', n_jobs=None,
             param_grid={'learning_rate': [0.01, 0.1], 'max_depth': [4, 8, 12],
                         'min_child_weight': [3, 5],
                         'n_estimators': [300, 500]},
             pre_dispatch='2*n_jobs', refit='f1', return_train_score=False,
             scoring={'recall', 'accuracy', 'precision', 'f1'}, verbose=0)
```

2.0.4 Evaluation

[128]:
```
xgb_cv.best_params_
```

[128]:
```
{'learning_rate': 0.1,
 'max_depth': 12,
 'min_child_weight': 3,
 'n_estimators': 300}
```

[129]:
```
xgb_cv.best_score_
```

[129]:
```
0.9706812495308832
```

[131]:
```
## Evaluating on test data now

y_pred = xgb_cv.predict(X_test)
```

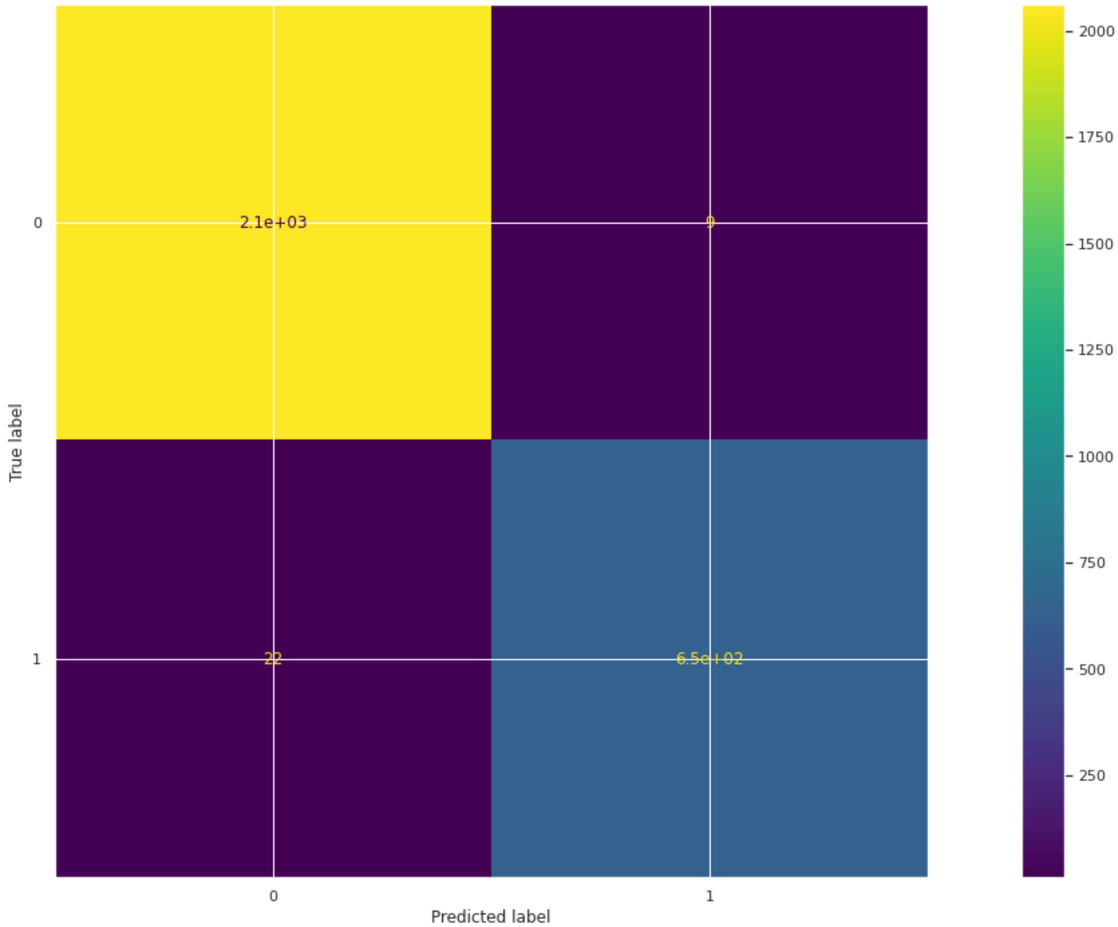
[134]:
```python
def get_test_scores(model_name:str, preds, y_test_data):

    accuracy = round(accuracy_score(y_test_data, preds), 3)
    precision = round(precision_score(y_test_data, preds), 3)
    recall = round(recall_score(y_test_data, preds), 3)
    f1 = round(f1_score(y_test_data, preds), 3)

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

    return table
```

[135]:
```python
get_test_scores('XGBClassifier', y_pred, y_test)
```

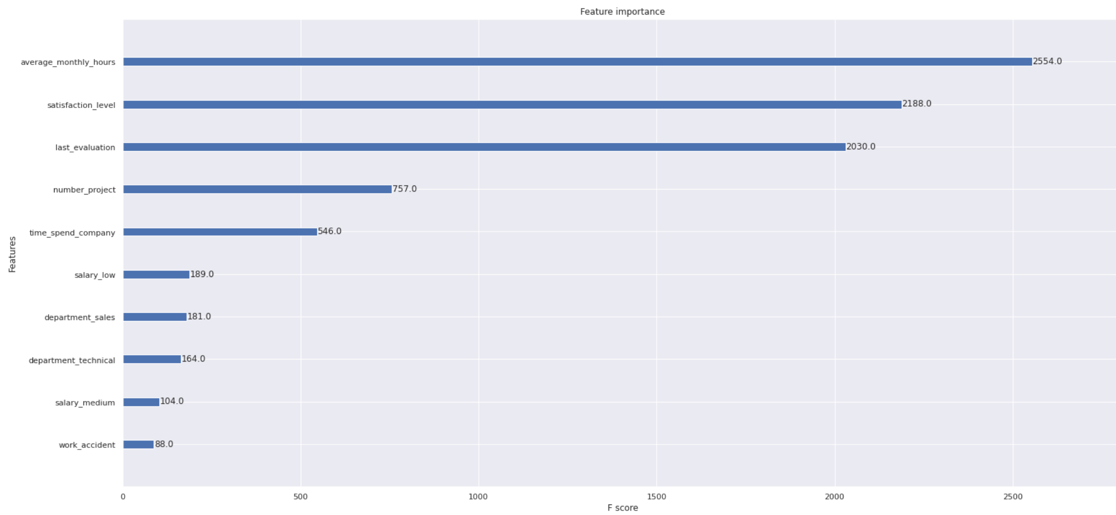
[135]:

	model	precision	recall	f1	accuracy
0	XGBClassifier	0.986	0.967	0.977	0.989

[137]:
```python
## Plotting confusion matrix to visualse model performance

cm = confusion_matrix(y_test, y_pred, labels=xgb_cv.classes_)

disp = ConfusionMatrixDisplay(confusion_matrix=cm,
                              display_labels=xgb_cv.classes_)
disp.plot();
```



[141]:
```
## Plotting relative importance of each variable used to determine whether
## Employee is likely to leave or not

plot_importance(xgb_cv.best_estimator_, max_num_features=10);
```



Model summary: 2100 true negatives, 650 true positives, 22 false negatives, 9 false positives

Overall very strong model, would reccomend to use this model to predict whether future employees are likely to leave based on metrics given initially. From the feature importance graph, we can see that employees who worked longer hours are more likely to leave, can be interpretted as overworked. Employees with low satisfaction scores are also more likely to leave. And employees with low evaluation scores are likely to leave.