MSDS Practicum I - HR analysis

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0.3.1 Spring 2020

0.3.2 Purpose of project:

Showcase skills in data manipulation and engineering, exploratory data analysis, visualizations and Machine leaning.

0.3.3 The problems to solve are:

1. what main characteristics contribute to the reason of why employees are leaving?
2. Which learning model appears to be better for predicting which employees will leave.

0.3.4 About the Dataset:

The dataset belongs to William Walter. Data can be found at "https://www.kaggle.com/colara/human-resource"

0.3.5 Other Resources used:

"Pandas for Everyone' by Daniel Chen

https://www.kaggle.com/colara/human-resources-analytics-a-descriptive-analysis

https://www.kaggle.com/daphnecor/predict-employee-turnover-rate-0

https://www.kaggle.com/henryshtang/hr-data-exploration

https://www.kaggle.com/rhuebner/human-resources-data-set/kernels

0.3.6 Import Libraries

[1]:
```
# import numpy, pandas. seaborn and matplotlib

import numpy as np
import pandas as pd
import sklearn
import seaborn as sns
```

```
sns.set()
import matplotlib.pyplot as plt
%matplotlib inline
# import warnings filter
from warnings import simplefilter
# ignore all future warnings
simplefilter(action='ignore', category=FutureWarning)
```

0.3.7 Upload Data

[2]:
```
# Use pandas to read the csv file

hr = pd.read_csv('C:/Users/spbro/OneDrive/Desktop/Human Resources.csv')
```

0.3.8 Eploratory Data Analysis

[3]:
```
# List the column names for the dataset
hr.columns
```

[3]:
```
Index(['satisfaction_level', 'last_evaluation', 'number_project',
       'average_montly_hours', 'time_spend_company', 'Work_accident', 'left',
       'promotion_last_5years', 'sales', 'salary'],
      dtype='object')
```

A closer look at the column names shows that some of the colums are not descriptive enough to help the analyst know what the column contains. For this reason the "Sales" column will need to be changed to "departments" and "average_montly_hours" will be changed to "average_monthly_hours". "Work_accidents" change to "work_accidents", "time_spend_company" to "time_spent_at_company", "number_project" to "number_of_projects"

[4]:
```
# use rename() to change column names

hr = hr.rename(columns = {'sales':'department'})
hr = hr.rename(columns = {'average_montly_hours':'average_monthly_hours'})
hr = hr.rename(columns = {'Work_accidents':'work_accident'})
hr = hr.rename(columns = {'time_spend_company':'time_spent_at_company'})
hr = hr.rename(columns = {'number_project':'number_of_projects'})
```

[5]:
```
# Display first 5 rows

hr.head()
```

[5]:
```
   satisfaction_level  last_evaluation  number_of_projects  \
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

   average_monthly_hours  time_spent_at_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

   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
```

[6]:
```
# Display last 5 rows

hr.tail()
```

[6]:
```
       satisfaction_level  last_evaluation  number_of_projects  \
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_monthly_hours  time_spent_at_company  Work_accident  left  \
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
14994                      0    support    low
14995                      0    support    low
14996                      0    support    low
14997                      0    support    low
14998                      0    support    low
```

[7]:
```
hr.shape

# There are 14999 rows and 10 columns
```

[7]: (14999, 10)

[8]:
```python
# A statistical description of each column

hr.describe()
```

[8]:
```
       satisfaction_level  last_evaluation  number_of_projects  \
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_monthly_hours  time_spent_at_company  Work_accident  \
count           14999.000000           14999.000000   14999.000000
mean              201.050337               3.498233       0.144610
std                49.943099               1.460136       0.351719
min                96.000000               2.000000       0.000000
25%               156.000000               3.000000       0.000000
50%               200.000000               3.000000       0.000000
75%               245.000000               4.000000       0.000000
max               310.000000              10.000000       1.000000

               left  promotion_last_5years
count  14999.000000           14999.000000
mean       0.238083               0.021268
std        0.425924               0.144281
min        0.000000               0.000000
25%        0.000000               0.000000
50%        0.000000               0.000000
75%        0.000000               0.000000
max        1.000000               1.000000
```

[9]:
```python
# check if data contains any null values

hr.isnull().any()
```

[9]:
```
satisfaction_level       False
last_evaluation          False
number_of_projects       False
average_monthly_hours    False
time_spent_at_company    False
Work_accident            False
left                     False
promotion_last_5years    False
department               False
```

```
salary                     False
dtype: bool
```

[10]:
```
# display more descriptive stats using .info()
hr.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14999 entries, 0 to 14998
Data columns (total 10 columns):
satisfaction_level       14999 non-null float64
last_evaluation          14999 non-null float64
number_of_projects       14999 non-null int64
average_monthly_hours    14999 non-null int64
time_spent_at_company    14999 non-null int64
Work_accident            14999 non-null int64
left                     14999 non-null int64
promotion_last_5years    14999 non-null int64
department               14999 non-null object
salary                   14999 non-null object
dtypes: float64(2), int64(6), object(2)
memory usage: 1.1+ MB
```

[11]:
```
# display unique values of hr['salary']

hr['salary'].unique()
```

[11]:
```
array(['low', 'medium', 'high'], dtype=object)
```

[12]:
```
5# Convert salary variable type to numeric
hr['salary'] = hr['salary'].map({'low':1, 'medium':2, 'high':3})

hr['salary'].unique()
```

[12]:
```
array([1, 2, 3], dtype=int64)
```

[13]:
```
# display unique values of hr['department']
hr['department'].unique()
```

[13]:
```
array(['sales', 'accounting', 'hr', 'technical', 'support', 'management',
       'IT', 'product_mng', 'marketing', 'RandD'], dtype=object)
```

[14]:
```
#numpy.where(condition[, x, y])
#Return elements, either from x or y, depending on condition.

# change 'support' category to 'technical' category
hr['department'] = np.where(hr['department'] == 'support', 'technical',␣
 ↪hr['department'])
```

```
# change 'IT' in 'technical'category'
hr['department'] = np.where(hr['department'] == 'IT' , 'technical',␣
↪hr['department'])

hr['department'].unique()
```

[14]:
```
array(['sales', 'accounting', 'hr', 'technical', 'management',
       'product_mng', 'marketing', 'RandD'], dtype=object)
```

explore the number of employees that left the company versus those that did not leave using count and groupby

[15]:
```
# how many people left the company using count

hr['left'].value_counts()
```

[15]:
```
0    11428
1     3571
Name: left, dtype: int64
```

[16]:
```
# (3571/14999)*100 = 23.808% This indicated that about 24% of the employees
# left the company
```

[17]:
```
# Use groupby to explore those who left per each cloumn using mean values

hr.groupby('left').mean()
```

[17]:
```
      satisfaction_level  last_evaluation  number_of_projects  \
left
0               0.666810         0.715473            3.786664
1               0.440098         0.718113            3.855503

      average_monthly_hours  time_spent_at_company  Work_accident  \
left
0                199.060203               3.380032       0.175009
1                207.419210               3.876505       0.047326

      promotion_last_5years    salary
left
0                  0.026251  1.650945
1                  0.005321  1.414730
```

0.4 Observations

- The average satisfaction level of employees who stayed with the company is higher (66%) than that of the employees who left(44%).

- The average monthly work hours of employees who left the company is more than that of the employees who stayed. The average hours worked per month of those who left the company was 207.4hrs and those who stayed was about 199hrs.
- The employees who had workplace accidents are less likely to leave than that of the employee who did not have workplace accidents.
- The employees who were promoted in the last five years are less likely to leave than those who did not get a promotion in the last five years.
- On face value, it appears there was no significant different in the mean between those who left and those who did not leave when it comes to 'last_evaluations' and 'number of projects'
- The average number of people who stayed because of salary was higher than those whose left.

[18]:
```
# Use groupby to explore the data using department

hr.groupby('department').mean()
```

[18]:
```
             satisfaction_level  last_evaluation  number_of_projects  \
department
RandD                  0.619822         0.712122            3.853875
accounting             0.582151         0.717718            3.825293
hr                     0.598809         0.708850            3.654939
management             0.621349         0.724000            3.860317
marketing              0.618601         0.715886            3.687646
product_mng            0.619634         0.714756            3.807095
sales                  0.614447         0.709717            3.776329
technical              0.613687         0.720976            3.839054

             average_monthly_hours  time_spent_at_company  Work_accident  \
department
RandD                   200.800508               3.367217       0.170267
accounting              201.162973               3.522816       0.125163
hr                      198.684709               3.355886       0.120433
management              201.249206               4.303175       0.163492
marketing               199.385781               3.569930       0.160839
product_mng             199.965632               3.475610       0.146341
sales                   200.911353               3.534058       0.141787
technical               201.813795               3.416127       0.144106

                 left  promotion_last_5years    salary
department
RandD        0.153748               0.034307  1.602287
accounting   0.265971               0.018253  1.629726
hr           0.290934               0.020298  1.607578
management   0.144444               0.109524  2.071429
marketing    0.236597               0.050117  1.624709
product_mng  0.219512               0.000000  1.575388
```

```
sales          0.244928                 0.024155   1.557971
technical      0.246924                 0.008258   1.562500
```

0.5 Observations

- Management department had the most satisfaction level
- The department with the highest average of people who left was hr and management had the least.
- the satisfaction level for hr was about 59%. Accounting has the lowest average satisfaction level at about 58%.
- It can be observed that satisfaction level may not be the only criteria for leaving, given that accounting did not become the department with the most number of people who left seeing that their satisfaction level was the lowest in the company. In other words, other tools like correlation analysis may have to be used to estimate what combinations of factors may be a better predictor of does who left the company.

[19]:
```python
# Use groupby to explore the data using salary

hr.groupby('salary').mean()
```

[19]:
```
        satisfaction_level  last_evaluation  number_of_projects  \
salary
1                 0.600753         0.717017            3.799891
2                 0.621817         0.717322            3.813528
3                 0.637470         0.704325            3.767179

        average_monthly_hours  time_spent_at_company  Work_accident      left  \
salary
1                  200.996583               3.438218       0.142154  0.296884
2                  201.338349               3.529010       0.145361  0.204313
3                  199.867421               3.692805       0.155214  0.066289

        promotion_last_5years
salary
1                    0.009021
2                    0.028079
3                    0.058205
```

0.6 Observations

- Given that 1 is low salary and 3 is for high salary, it appears that those with the high salary are usually the most satisfied as well.
- Those with the high salary appear to also have teh lowest average of people who left.

0.7 Additional Questions that can be answered through more EDA

[20]:
```python
# How many employees work in each department?

hr['department'].value_counts()
```

[20]:
```
technical      6176
sales          4140
product_mng     902
marketing       858
RandD           787
accounting      767
hr              739
management      630
Name: department, dtype: int64
```

[21]:
```python
# How many emplpoyes per Salary range?

hr['salary'].value_counts()
```

[21]:
```
1    7316
2    6446
3    1237
Name: salary, dtype: int64
```

[22]:
```python
# How many employees per salary range and department?

table = hr.pivot_table(values="satisfaction_level", index="department",␣
↪columns="salary",aggfunc=np.count_nonzero)

table
```

[22]:

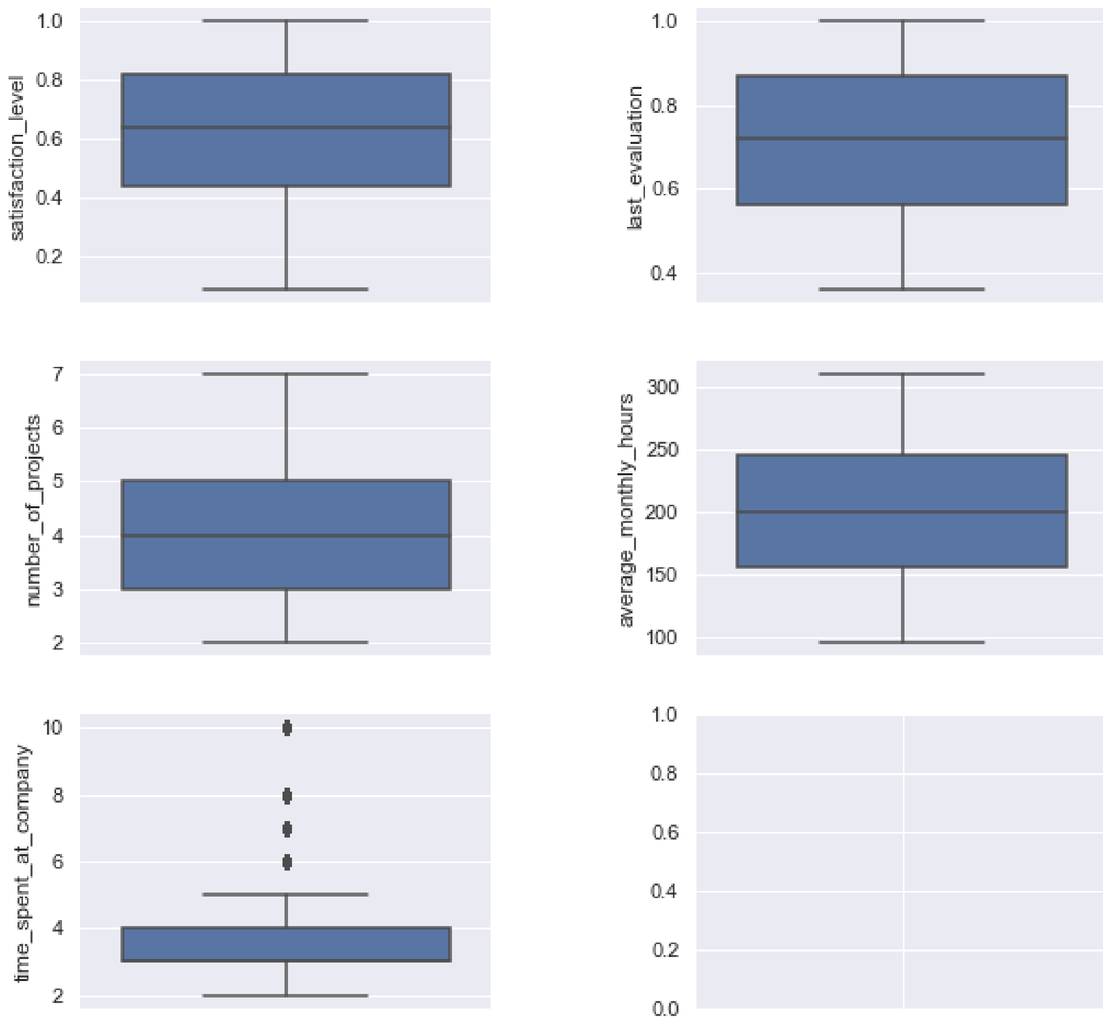
salary	1	2	3
department			
RandD	364.0	372.0	51.0
accounting	358.0	335.0	74.0
hr	335.0	359.0	45.0
management	180.0	225.0	225.0
marketing	402.0	376.0	80.0
product_mng	451.0	383.0	68.0
sales	2099.0	1772.0	269.0
technical	3127.0	2624.0	425.0

0.8 Data Visualization

0.8.1 BOXPLOTS

[23]:
```
f, axes = plt.subplots(3,2, figsize=(10,10), sharex=True)

plt.subplots_adjust(wspace=0.5) # adjust the space between the plots

sns.despine(left=True)

# plot a boxplot of satisfaction_level to see if there is outliers
sns.boxplot( x= 'satisfaction_level',  data=hr, orient='v',ax=axes[0,0])

# plot a boxplot of last_evaluation to see if there is outliers
sns.boxplot( x= 'last_evaluation',  data=hr, orient='v',ax=axes[0,1])

# plot a boxplot of number_project to see if there is outliers
sns.boxplot( x= 'number_of_projects',  data=hr, orient='v',ax=axes[1,0])

# plot a boxplot of average_montly_hours to see if there is outliers
sns.boxplot( x= 'average_monthly_hours',  data=hr, orient='v',ax=axes[1,1])

# plot a boxplot of time_spent_at_company to see if there is outliers
sns.boxplot( x= 'time_spent_at_company',  data=hr, orient='v',ax=axes[2,0])
```

[23]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1772a891748>
```



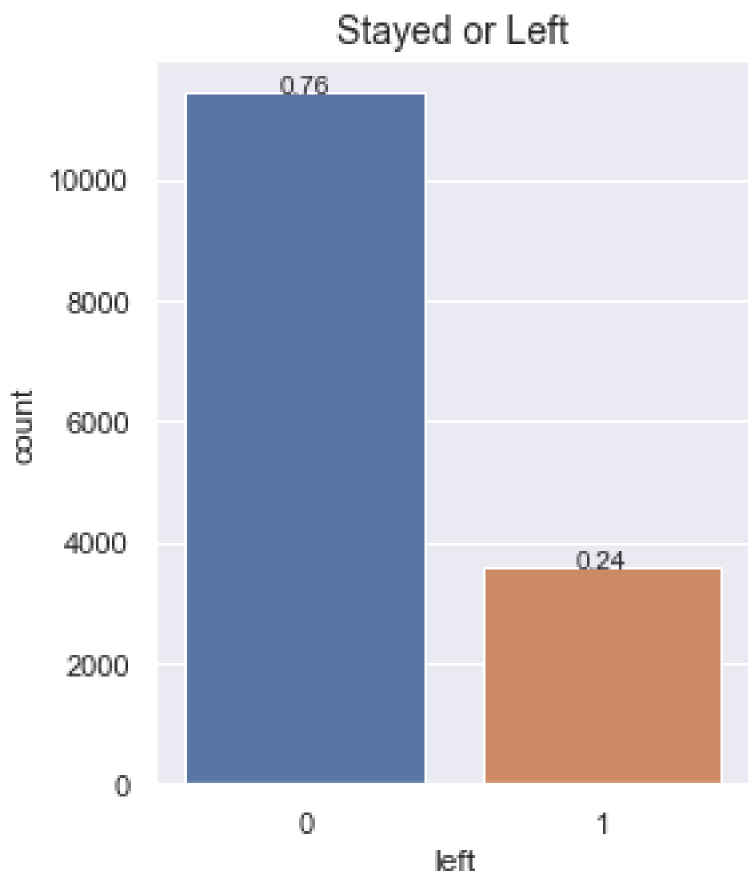
0.9 Observation

Time spent at the company has outliers. The company also appears to be a young company.

0.10 BAR PLOT

[24]:
```
# The plot shows the amount of employees that stayed and left the company.

plt.figure(figsize=(4,5))
ax = sns.countplot(hr.left)
total = float(len(hr))

for p in ax.patches:
    height = p.get_height()
    ax.text(p.get_x()+p.get_width()/2.,
```

```
            height + 3,
            '{:1.2f}'.format(height/total),
            ha="center")
plt.title('Stayed or Left', fontsize=14);
```

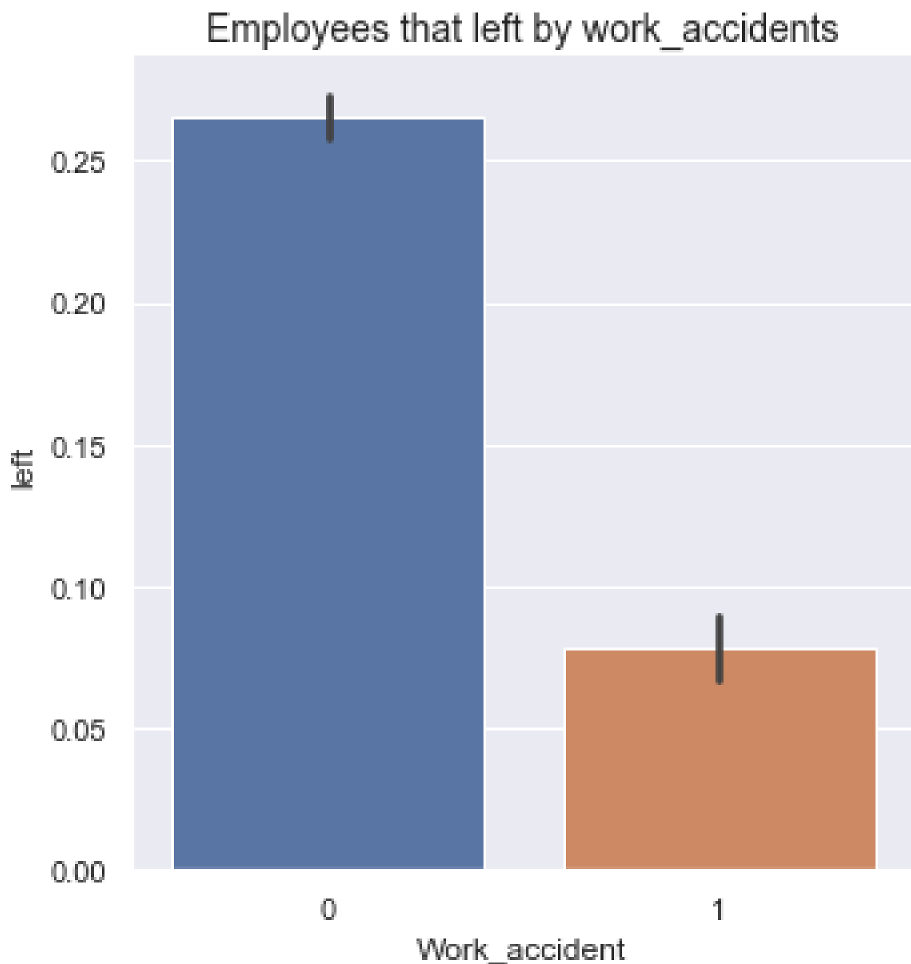


[25]:
```
# plot of Employees that left by Salary level

j = sns.catplot(x='salary', y='left', kind='bar', data=hr)
plt.title('Employees that left by salary level', fontsize=14)
j.set_xticklabels(['Low', 'Medium', 'High'])
```

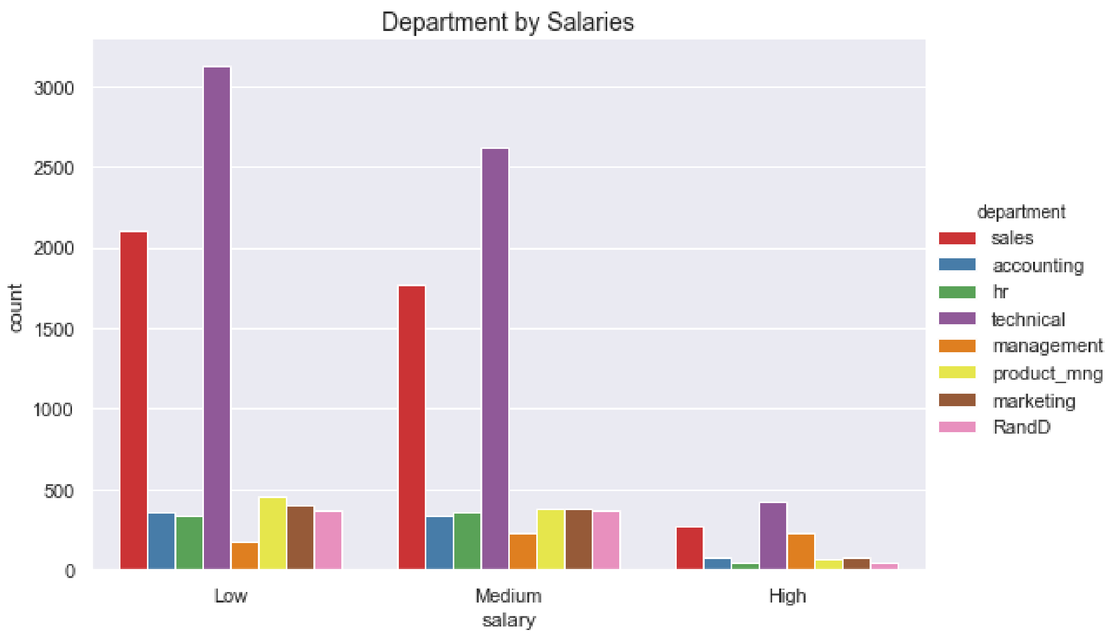
[25]: <seaborn.axisgrid.FacetGrid at 0x17728efebc8>

[26]:
```
# plot of Employees that left by Salary level

j = sns.catplot(x='Work_accident', y='left', kind='bar', data=hr)
plt.title('Employees that left by work_accidents', fontsize=14)
```

[26]:
```
Text(0.5, 1, 'Employees that left by work_accidents')
```



[27]:
```
# plot of departments by salary level

h = sns.catplot(x = 'salary', hue='department', kind ='count', height =␣
↪5,aspect=1.5, data=hr, palette='Set1' )
plt.title("Department by Salaries", fontsize=14)
h.set_xticklabels(['Low', 'Medium', 'High']);
```

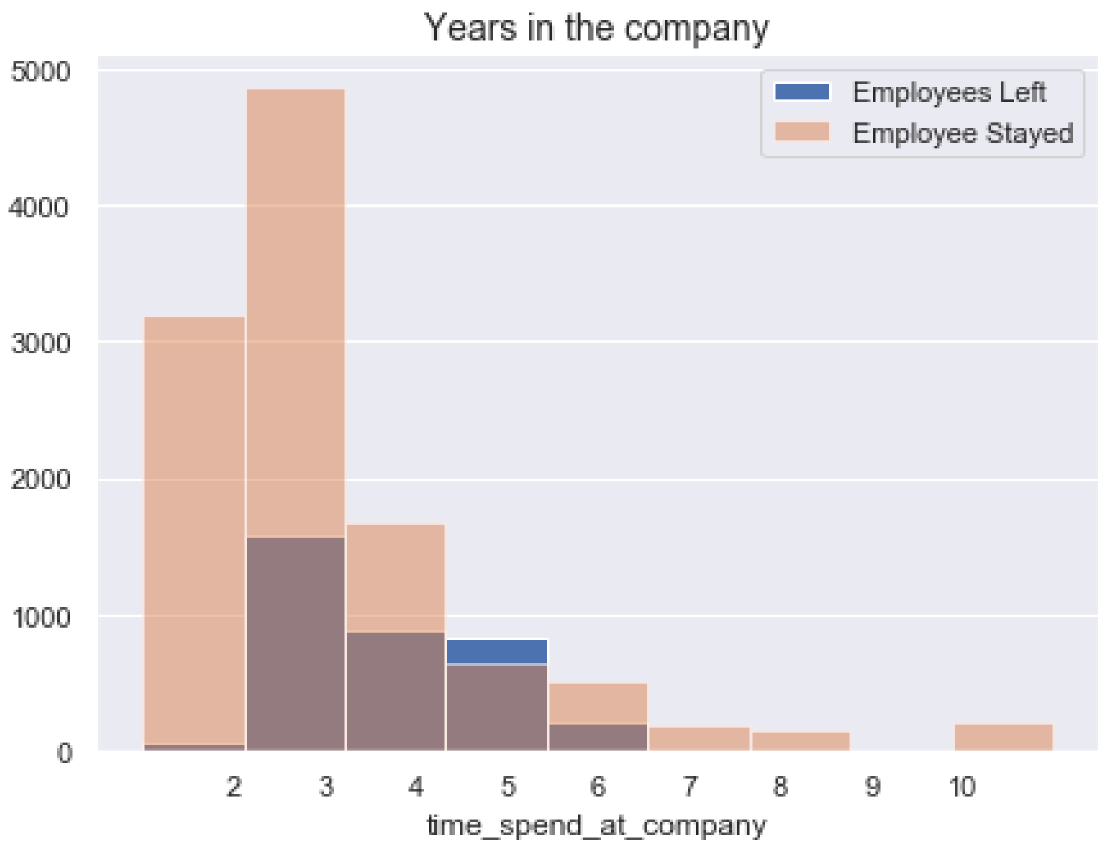


0.11 OBSERVATION

- Most of the employees of the technical department have low or medium salaries.
- Sales department is in the second place where most of the employees receives low and medium salaries.

[28]:

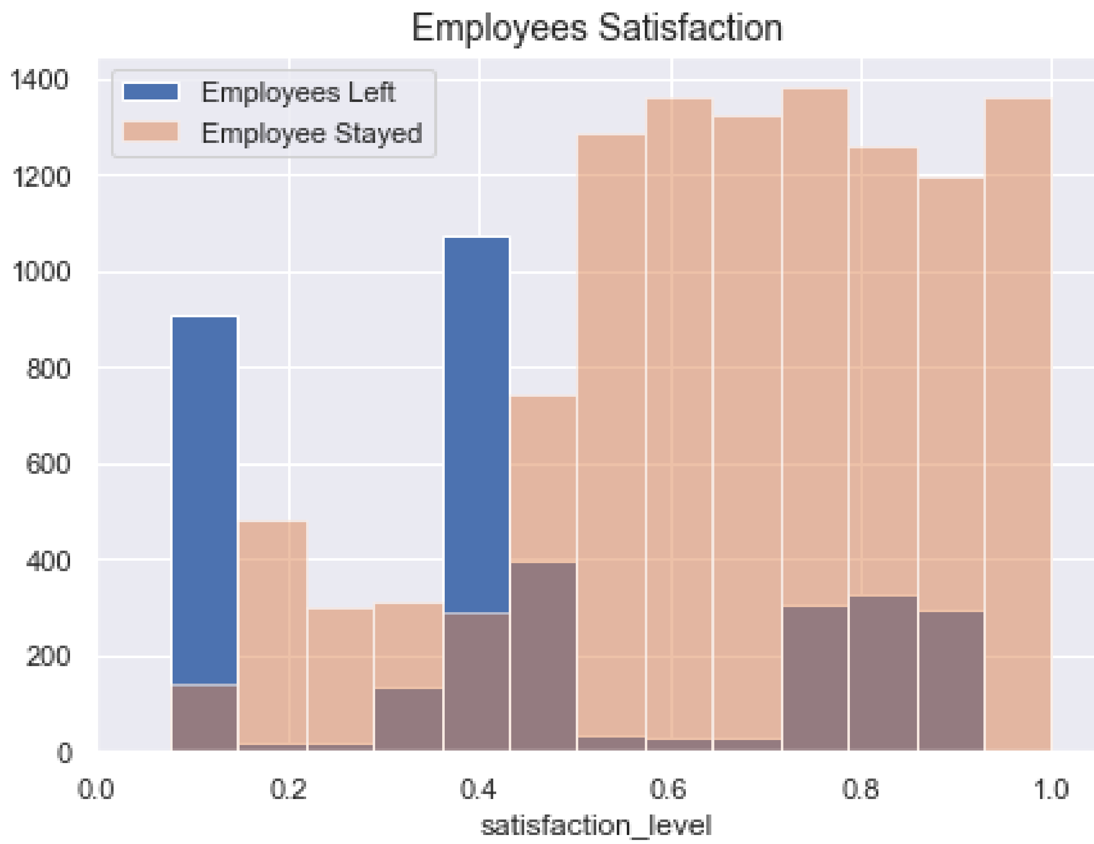
```
# Plot comparing employees that left with years in company

plt.figure(figsize =(7,5))
bins = np.linspace(1.0, 11,10)
plt.hist(hr[hr['left']==1]['time_spent_at_company'], bins=bins, alpha=1,␣
 ↪label='Employees Left')
plt.hist(hr[hr['left']==0]['time_spent_at_company'], bins=bins, alpha = 0.5,␣
 ↪label = 'Employee Stayed')
plt.grid(axis='x')
plt.xticks(np.arange(2,11))
plt.xlabel('time_spend_at_company')
plt.title('Years in the company', fontsize=14)
plt.legend(loc='best');
```



0.12 OBSERVATION

- Employees with 7 or more years did not leave.
- In year 1, new hires hardly leave the company, if they do the number is very low. The problem starts when the employees have more than 3 years and get worst when they achieve 5 years.

[29]:
```
# Plot comparing employees that left with satisfaction

plt.figure(figsize =(7,5))
bins = np.linspace(0.006,1.000, 15)
plt.hist(hr[hr['left']==1]['satisfaction_level'], bins=bins, alpha=1,␣
 ↪label='Employees Left')
plt.hist(hr[hr['left']==0]['satisfaction_level'], bins=bins, alpha = 0.5, label␣
 ↪= 'Employee Stayed')
plt.title('Employees Satisfaction', fontsize=14)
plt.xlabel('satisfaction_level')
plt.xlim((0,1.05))
plt.legend(loc='best');
```




```
[ ]:
```

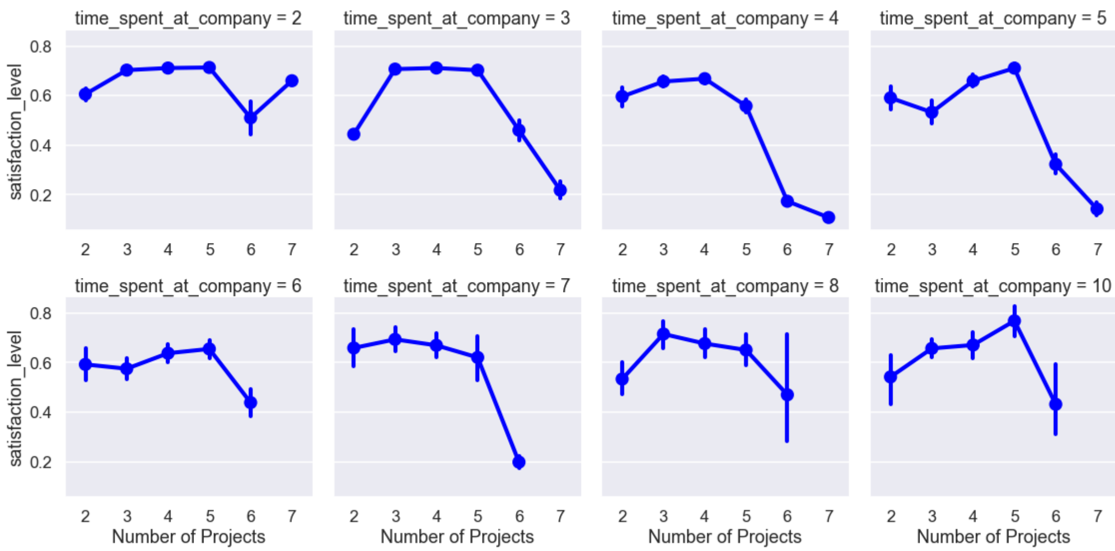
0.13 OBSERVATION

- We have a peak at about 0.1 satisfaction level. These are employees who are totally disappointed.
- Another peak at 0.4 satsfaction level, representing another group with the satisfaction level below the average.
- And another amount in the range 0.7 and 0.9, with employees that left, although the high satisfaction.

0.14 LINE CHART

```
[45]: sns.set()
sns.set_context("talk")
ax = sns.factorplot(x="number_of_projects", y="satisfaction_level",␣
 ↪col="time_spent_at_company",col_wrap=4, height=4, color='blue',sharex=False,␣
 ↪data=hr)
ax.set_xlabels('Number of Projects')
```

[45]: <seaborn.axisgrid.FacetGrid at 0x177315c62c8>



0.15 OBSERVATION

It appears clear that there is a drop in satisfaction when employees are working on 6 or more projects.

0.16 Summary of the Exploratory Data Analysis

- It is a relatively young company, on average, employees have 3 or 4 years in the company and the oldest employee has been working there for 10 years.
- In five years only 2% of the employees were promoted. Is possible that many employees get unmotivated and start planning to leave.
- Employees with 7 or more years in the company did not left. Employees with 5 years have a greater chance to leaving. Management may have to plan an incentive package to retain emplopyees who work for five years.
- The employees with 4 years in the company have the lowest average satisfaction level of all the company with (0.47).
- The satisfaction drops when the employees are working on 5 or more projects. A number of 3 or 4 projects seems to be ideal independent of the time spent in the company.

0.17 MACHINE LEARNING

Now we have to predict who will leave the company

[31]:
```
#sklearn libraries needed for machine learning

from sklearn.model_selection import train_test_split
```

```python
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import cross_val_score
from sklearn.metrics import confusion_matrix, accuracy_score
from sklearn import tree
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
```

[32]:
```python
#Train-Test split
y = hr['left']
X = hr.drop(['left','department'], axis=1)

X.head()
```

[32]:
```
   satisfaction_level  last_evaluation  number_of_projects  \
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

   average_monthly_hours  time_spent_at_company  Work_accident  \
0                    157                      3              0
1                    262                      6              0
2                    272                      4              0
3                    223                      5              0
4                    159                      3              0

   promotion_last_5years  salary
0                      0       1
1                      0       2
2                      0       2
3                      0       1
4                      0       1
```

[33]:
```python
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.
↪30,random_state=123)
```

[34]:
```python
from sklearn.preprocessing import StandardScaler
Scaler_X = StandardScaler()
X_train = Scaler_X.fit_transform(X_train)
X_test = Scaler_X.transform(X_test)
```

[35]:
```python
#Logistic Regression
logis = LogisticRegression()
logis.fit(X_train, y_train)
```

```python
logis_score_train = logis.score(X_train, y_train)
print("Training score: ",logis_score_train)
logis_score_test = logis.score(X_test, y_test)
print("Testing score: ",logis_score_test)
```

```
Training score:  0.7904562339270407
Testing score:  0.7857777777777778
```

[36]:
```python
# Accuracy Maxtix
pred=logis.predict(X_test)
print(accuracy_score(y_test,pred))
print(confusion_matrix(y_test,pred))
```

```
0.7857777777777778
[[3183  246]
 [ 718  353]]
```

[37]:
```python
# display table of correlation for each column
coeff_df = pd.DataFrame(X.columns)
coeff_df.columns = ['Features']
coeff_df["Correlation"] = pd.Series(logis.coef_[0])

coeff_df.sort_values(by='Correlation', ascending=False)
```

[37]:

	Features	Correlation
4	time_spent_at_company	0.370398
3	average_monthly_hours	0.219374
1	last_evaluation	0.157843
6	promotion_last_5years	-0.195991
2	number_of_projects	-0.385212
7	salary	-0.440508
5	Work_accident	-0.554016
0	satisfaction_level	-1.027387

[38]:
```python
#decision tree
dt = tree.DecisionTreeClassifier()
dt.fit(X_train, y_train)
dt_score_train = dt.score(X_train, y_train)
print("Training score: ",dt_score_train)
dt_score_test = dt.score(X_test, y_test)
print("Testing score: ",dt_score_test)
```

```
Training score:  1.0
Testing score:  0.9755555555555555
```

[39]:
```python
#decision tree
dt = RandomForestClassifier()
```

```
dt.fit(X_train, y_train)
dt_score_train = dt.score(X_train, y_train)
print("Training score: ",dt_score_train)
dt_score_test = dt.score(X_test, y_test)
print("Testing score: ",dt_score_test)
```

```
Training score:  0.9978093151728736
Testing score:  0.9877777777777778
```

[40]:
```
#kNN
knn = KNeighborsClassifier()
knn.fit(X_train, y_train)
knn_score_train = knn.score(X_train, y_train)
print("Training score: ",knn_score_train)
knn_score_test = knn.score(X_test, y_test)
print("Testing score: ",knn_score_test)
```

```
Training score:  0.9723783217449281
Testing score:  0.9568888888888889
```

[41]:
```
#SVM
svm = SVC()
svm.fit(X_train, y_train)
svm_score_train = svm.score(X_train, y_train)
print("Training score: ",svm_score_train)
svm_score_test = svm.score(X_test, y_test)
print("Testing score: ",svm_score_test)
```

```
Training score:  0.9665682445947233
Testing score:  0.9617777777777777
```

[42]:
```
#random forest
rfc = RandomForestClassifier()
rfc.fit(X_train, y_train)
rfc_score_train = rfc.score(X_train, y_train)
print("Training score: ",rfc_score_train)
rfc_score_test = rfc.score(X_test, y_test)
print("Testing score: ",rfc_score_test)
```

```
Training score:  0.9982855510048576
Testing score:  0.9897777777777778
```

[43]:
```
#Model comparison
models = pd.DataFrame({
        'Model'          : ['Logistic Regression', 'SVM', 'kNN', 'Decision␣
↪Tree', 'Random Forest'],
        'Training_Score' : [logis_score_train, svm_score_train,␣
↪knn_score_train, dt_score_train, rfc_score_train],
```

```
        'Testing_Score'  : [logis_score_test, svm_score_test, knn_score_test,␣
↪dt_score_test, rfc_score_test]
    })
models.sort_values(by='Testing_Score', ascending=False)
```

[43]:

	Model	Training_Score	Testing_Score
4	Random Forest	0.998286	0.989778
3	Decision Tree	0.997809	0.987778
1	SVM	0.966568	0.961778
2	kNN	0.972378	0.956889
0	Logistic Regression	0.790456	0.785778

0.18 Recommendations

- Satisfaction level is the major impact on whether employees stay or leave the company.
- Improve work life balance by having the right number of projects. Employees with 3-4 projects assigned tend to stay. Similarly, number of average hours a month plays a role in employees leaving or staying.
- Provide training so that their evaluation score can improve. The data shows that employees with a low evaluation score are likely to leave.