

```

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')

df = pd.read_excel('F:/simplilearn/projects/ml projects/employee
turnover analytics/dataset.xlsx')

```

```
df
```

	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	

left	average_monthly_hours	time_spend_company	Work_accident	
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    sales    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]

```
df.shape
```

```
(14999, 10)
```

```

df=df.rename(columns={'average_monthly_hours':'average_weekly_hours','sales':'department'})
df['average_weekly_hours']=df['average_weekly_hours']*12/52
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_weekly_hours	14999 non-null	float64
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(3), int64(5), object(2)
```

```
memory usage: 1.1+ MB
```

```
# no null values
```

```
df.isna().sum()
```

```

satisfaction_level    0
last_evaluation        0
number_project         0
average_weekly_hours  0
time_spend_company    0
Work_accident         0

```

```

left                                0
promotion_last_5years              0
department                        0
salary                            0
dtype: int64

df = df.loc[:,~df.T.duplicated(keep='first')]

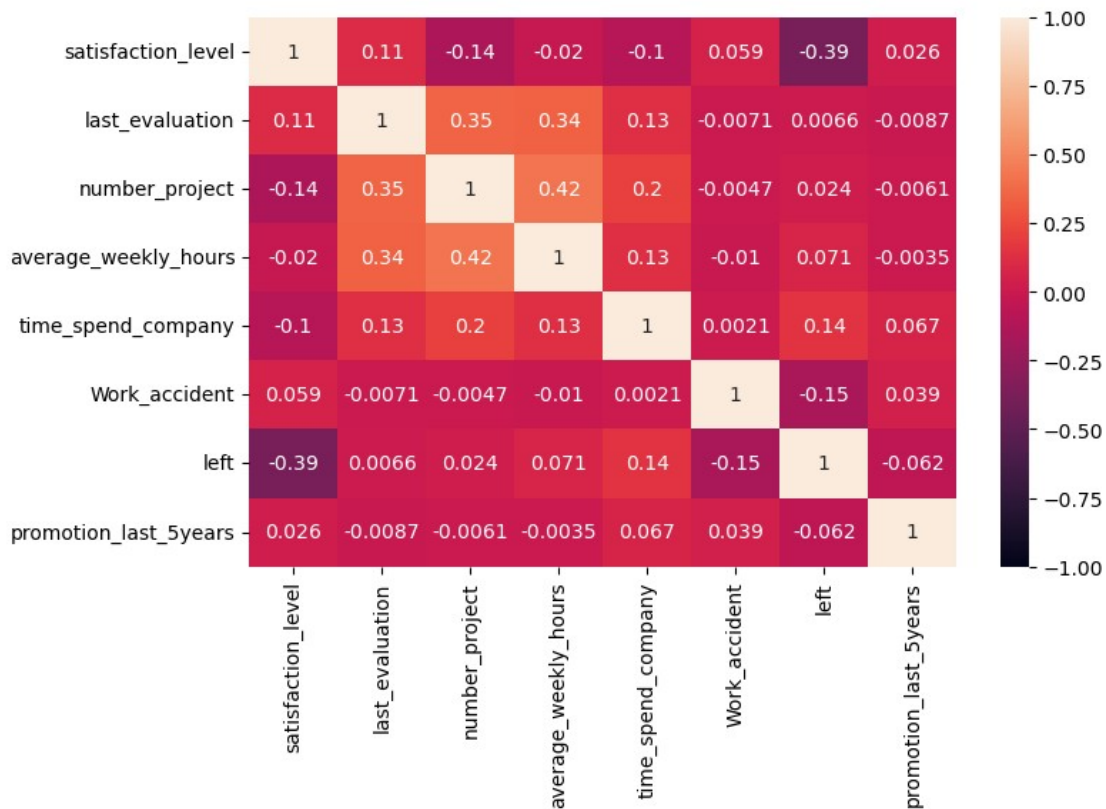
df.shape

(14999, 10)

# factors that contributed more to employee turn over
plt.figure(figsize=(8,5))
sns.heatmap(df.corr(),annot=True,vmin=-1,vmax=1)
plt.show()

<IPython.core.display.Javascript object>

```



only the satisfaction level shows some strong negative relation with ETO with a pearson correlation of -0.39

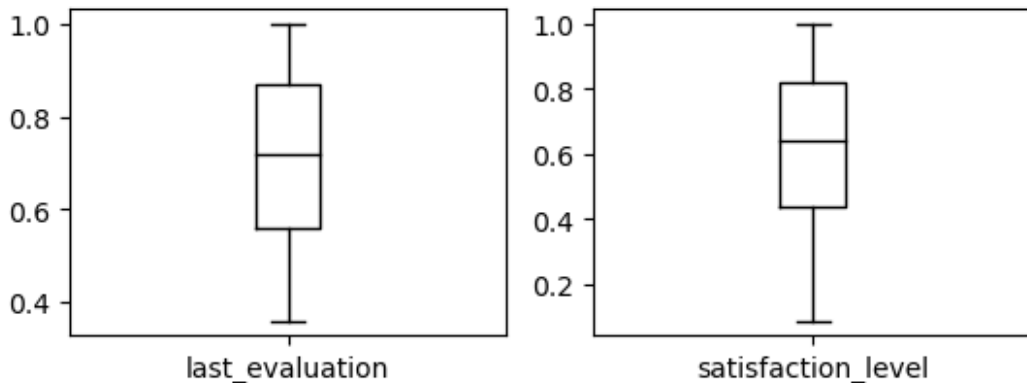
```

from sklearn.decomposition import PCA
from sklearn.cluster import KMeans

df[['last_evaluation','satisfaction_level']].plot(kind =
'box',subplots = True, layout = (2,2), sharex = False, sharey =

```

```
False,color='black')
plt.show()
```



```
df[['last_evaluation','satisfaction_level']].describe()
```

	last_evaluation	satisfaction_level
count	14999.000000	14999.000000
mean	0.716102	0.612834
std	0.171169	0.248631
min	0.360000	0.090000
25%	0.560000	0.440000
50%	0.720000	0.640000
75%	0.870000	0.820000
max	1.000000	1.000000

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

out of every 4 employees 1 employee has left the company

```
0    11428
1     3571
Name: left, dtype: int64
```

```
df[['Work_accident']].value_counts()
```

```
Work_accident
0           12830
1           2169
dtype: int64
```

we can say the following

they have a relatively short tenure with the firm (average of 3.5 years, max of 10 years)

they are generally more satisfied than not (.61 average satisfaction level)

they are generally above average performers (.716 average rating in their last evaluation)

14.46% (approximately 1 in 7) of the people have had work accidents

```
df.describe()
```

	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_weekly_hours	time_spend_company	Work_accident
left \			
count	14999.000000	14999.000000	14999.000000
14999.000000			
mean	46.396232	3.498233	0.144610
0.238083			
std	11.525331	1.460136	0.351719
0.425924			
min	22.153846	2.000000	0.000000
0.000000			
25%	36.000000	3.000000	0.000000
0.000000			
50%	46.153846	3.000000	0.000000
0.000000			
75%	56.538462	4.000000	0.000000
0.000000			
max	71.538462	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

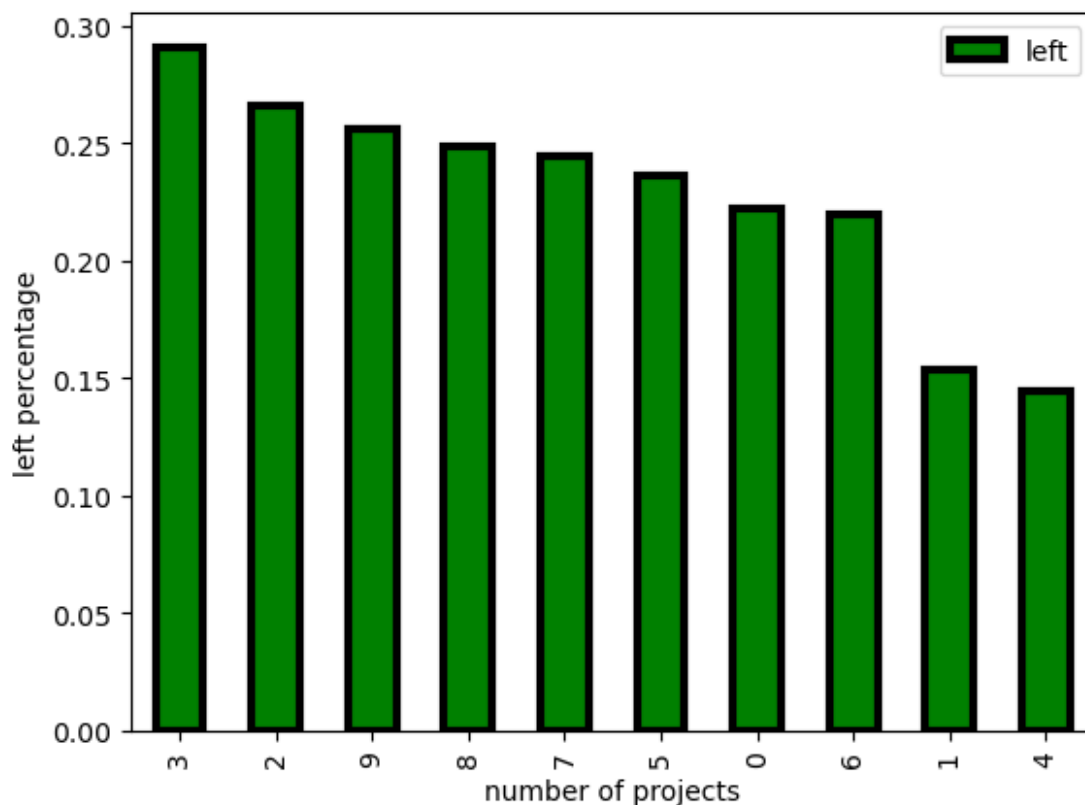
```
df.describe(include='O')
```

	department	salary
count	14999	14999
unique	10	3
top	sales	low
freq	4140	7316

```
print(df[['department', 'left']].groupby('department', as_index=False).mean().sort_values(by=['left'], ascending=False))
df[['department', 'left']].groupby('department', as_index=False).mean().sort_values(by=['left'], ascending=False).plot(kind='bar', color='g', edg
```

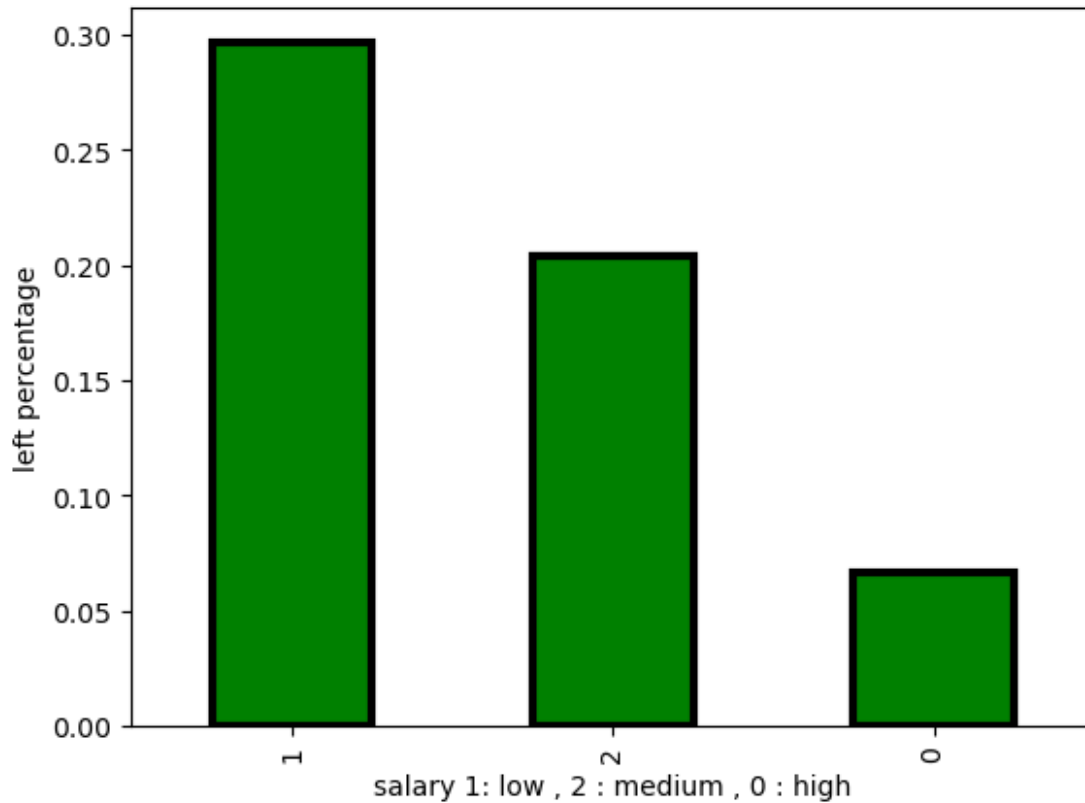
```
ecolor='black',linewidth=3)
plt.xlabel('number of projects')
plt.ylabel('left percentage')
plt.show()
```

	department	left
3	hr	0.290934
2	accounting	0.265971
9	technical	0.256250
8	support	0.248991
7	sales	0.244928
5	marketing	0.236597
0	IT	0.222494
6	product_mng	0.219512
1	RandD	0.153748
4	management	0.144444



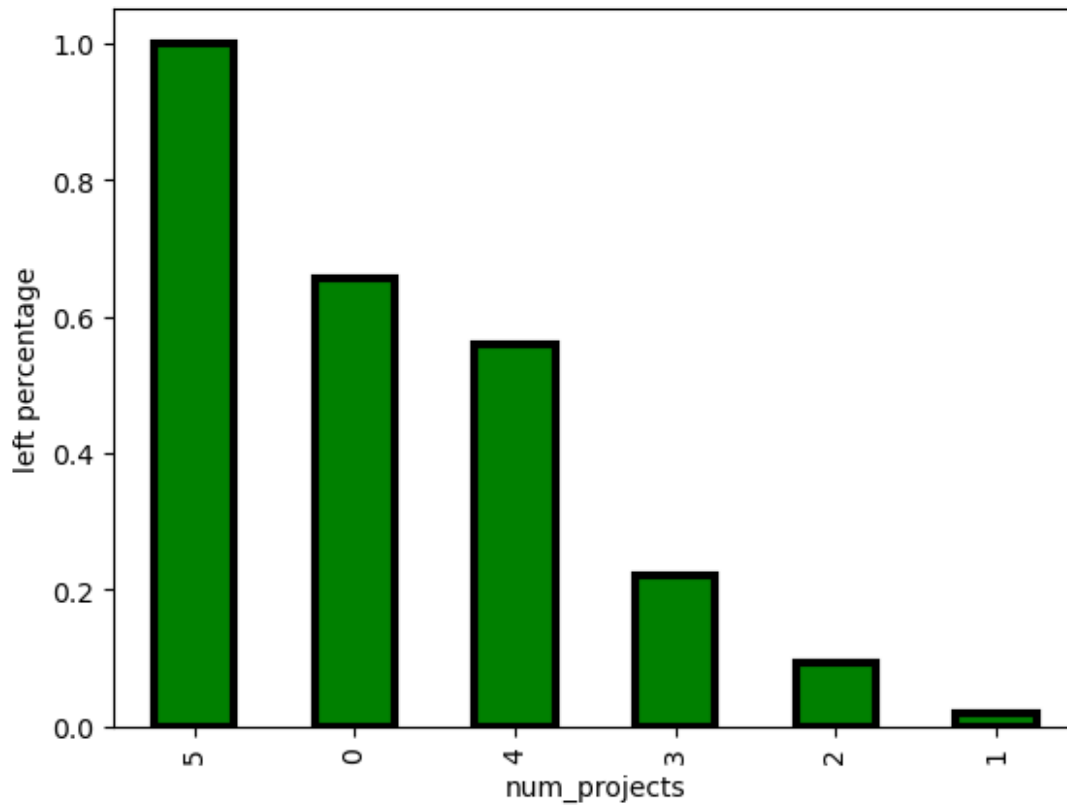
```
print(df[['salary', 'left']].groupby('salary',as_index=False).mean().sort_values(by=['left'],ascending=False))
df[['salary', 'left']].groupby('salary',as_index=False).mean().sort_values(by=['left'],ascending=False)
['left'].plot(kind='bar',color='g',edgecolor='black',linewidth=3)
plt.xlabel('salary 1: low , 2 : medium , 0 : high')
plt.ylabel('left percentage')
plt.show()
```

	salary	left
1	low	0.296884
2	medium	0.204313
0	high	0.066289



```
print(df[['number_project', 'left']].groupby('number_project', as_index=False).mean().sort_values(by=['left'], ascending=False))
df[['number_project', 'left']].groupby('number_project', as_index=False).mean().sort_values(by=['left'], ascending=False)
['left'].plot(kind='bar', color='g', edgecolor='black', linewidth=3)
plt.xlabel('num_projects')
plt.ylabel('left percentage')
plt.show()
```

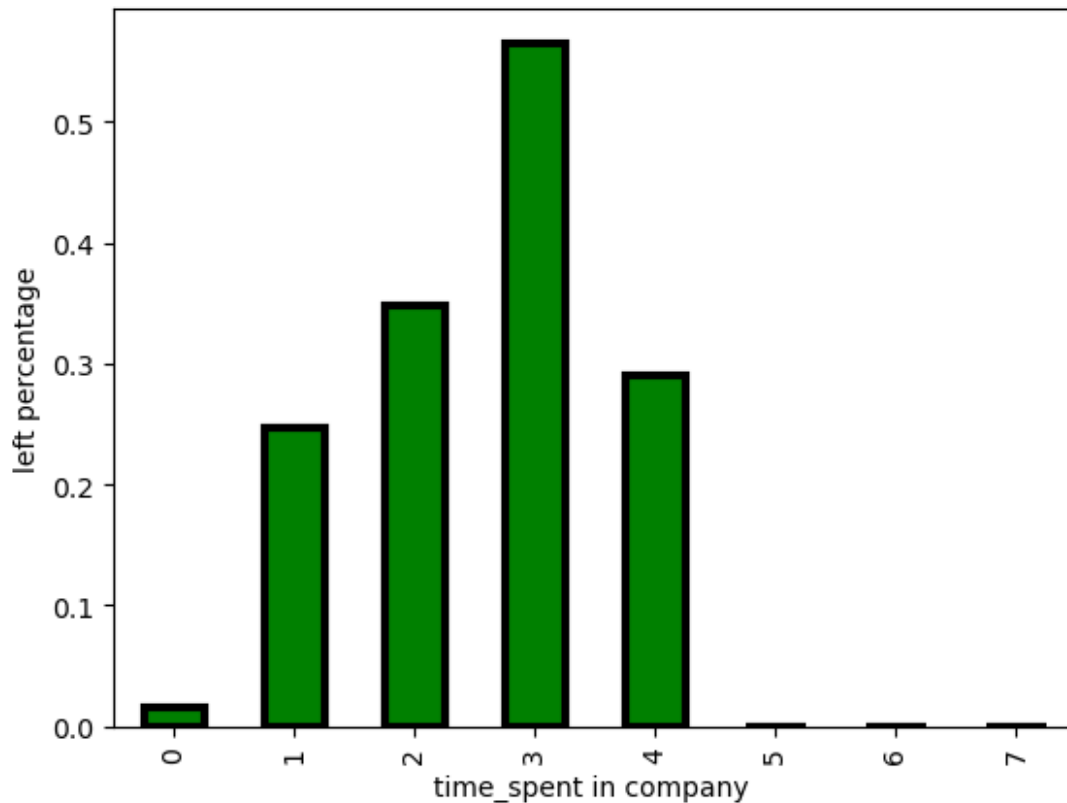
number_project	left
5	7 1.000000
0	2 0.656198
4	6 0.557922
3	5 0.221659
2	4 0.093700
1	3 0.017756



```
print(df[['time_spend_company',
'left']].groupby(['time_spend_company'],
as_index=False).mean().sort_values(by='time_spend_company'))
df[['time_spend_company', 'left']].groupby(['time_spend_company'],
as_index=False).mean().sort_values(by='time_spend_company')
['left'].plot(kind='bar',color='g',edgecolor='black',linewidth=3)
```

```
plt.xlabel('time_spent in company ')
plt.ylabel('left percentage')
plt.show()
```

	time_spend_company	left
0	2	0.016338
1	3	0.246159
2	4	0.348064
3	5	0.565513
4	6	0.291086
5	7	0.000000
6	8	0.000000
7	10	0.000000



```
df[['average_weekly_hours', 'number_project']].corr()
```

	average_weekly_hours	number_project
average_weekly_hours	1.000000	0.417211
number_project	0.417211	1.000000

Observations:

We observe that lower satisfaction levels are associated with higher levels of turnover, as expected

Regarding evaluation scores, it's interesting to note the two "clusters" that form; the people who leave tend to either have received low scores (.6 and below) or very high scores (.8 and above). Employees scoring in the middle rarely left.

A similar clustering effect is shown for the weekly hours graph as well. People tend to leave when they are overworked or underworked. We also observe that the pattern we see for the weekly hours feature is similar to that of the number of projects feature.

Conclusions:

Use the satisfaction_level feature in our model

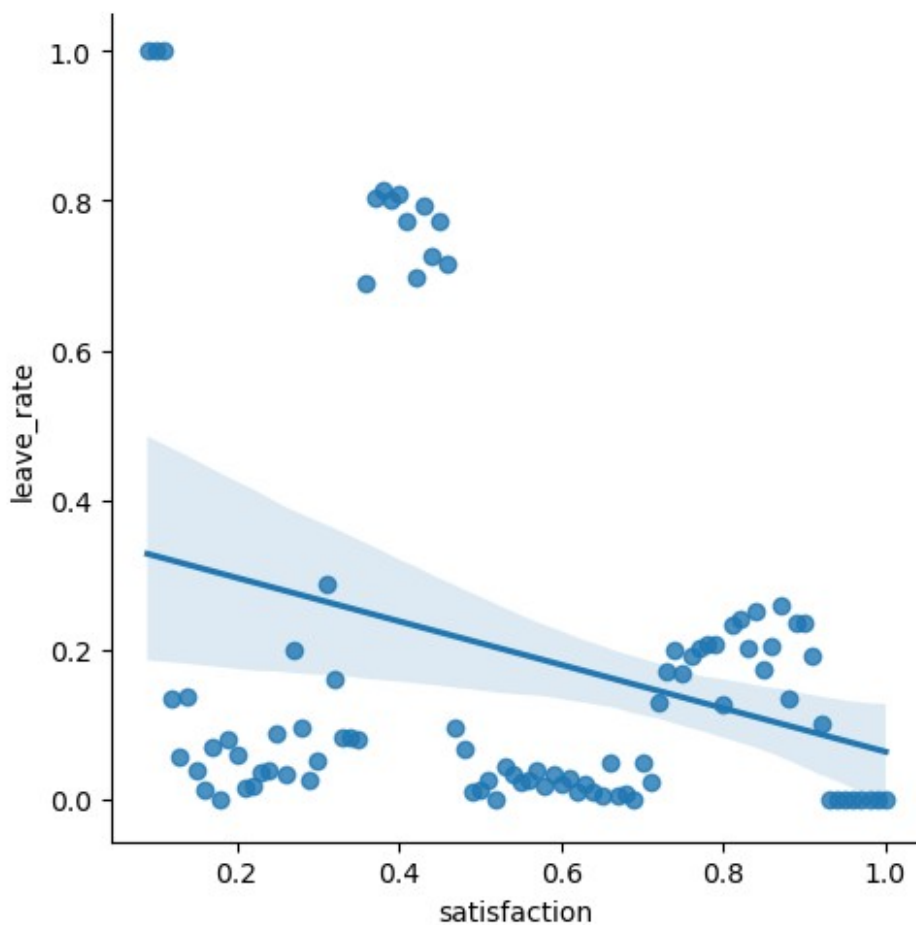
We may need to do some data wrangling on the last_evaluation feature. Consider creating two bands, exceptional scores (both really good and really bad evaluations) vs. the rest.

Given that both the weekly hours feature and number of projects

feature exhibit a comparable clustering effect and that there is a moderate correlation between these variables (.417, as calculated earlier), I will only use the number of projects feature in my model and discard the weekly hours feature for simplicity.

```
leave_sat=df.groupby('satisfaction_level').agg({'left': lambda x:
len(x[x==1])})
leave_sat['total']=df.groupby('satisfaction_level').agg({'left': len})
leave_sat['leave_rate']=leave_sat['left']/leave_sat['total']
leave_sat['satisfaction']=df.groupby('satisfaction_level').agg({'satis
faction_level': 'mean'})
g=sns.lmplot('satisfaction', 'leave_rate',data=leave_sat)
```

<IPython.core.display.Javascript object>

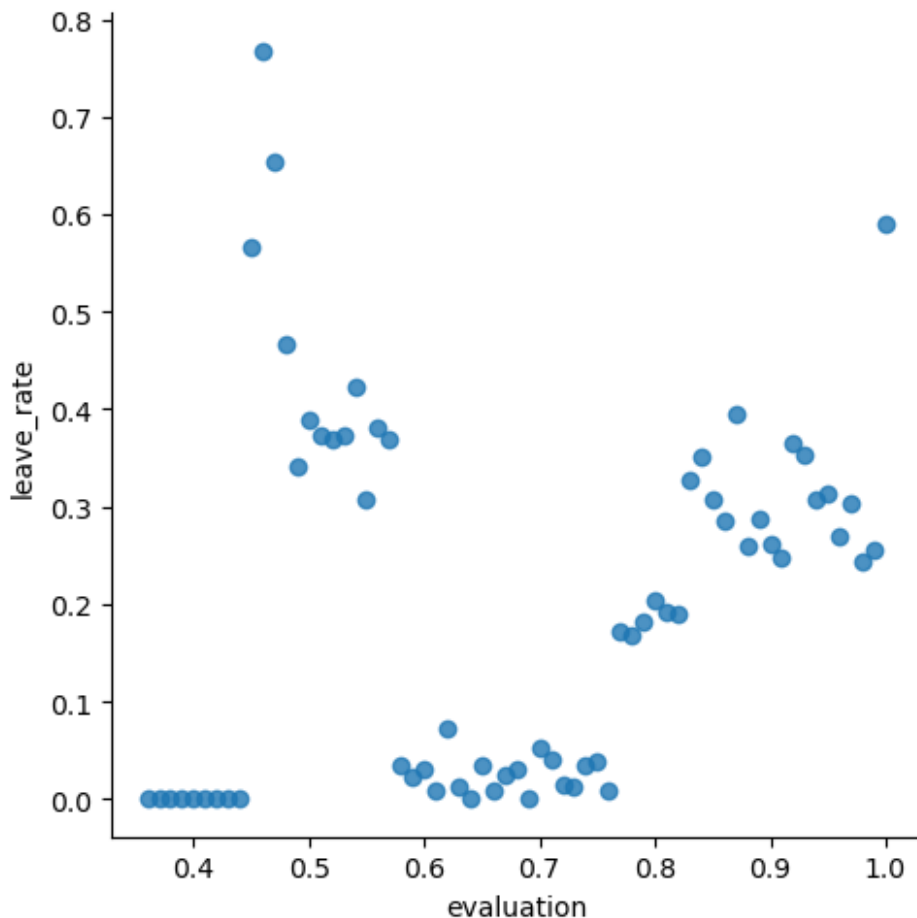


the more the satisfaction is the lesser is hte leaving rate

```
leave_eval=df.groupby('last_evaluation').agg({'left': lambda x:
len(x[x==1])})
leave_eval['total']=df.groupby('last_evaluation').agg({'left': len})
leave_eval['leave_rate']=leave_eval['left']/leave_eval['total']
leave_eval['evaluation']=df.groupby('last_evaluation').agg({'last_eval
uation': 'mean'})
```

```
gr=sns.lmplot('evaluation',
'leave_rate',data=leave_eval,fit_reg=False)
```

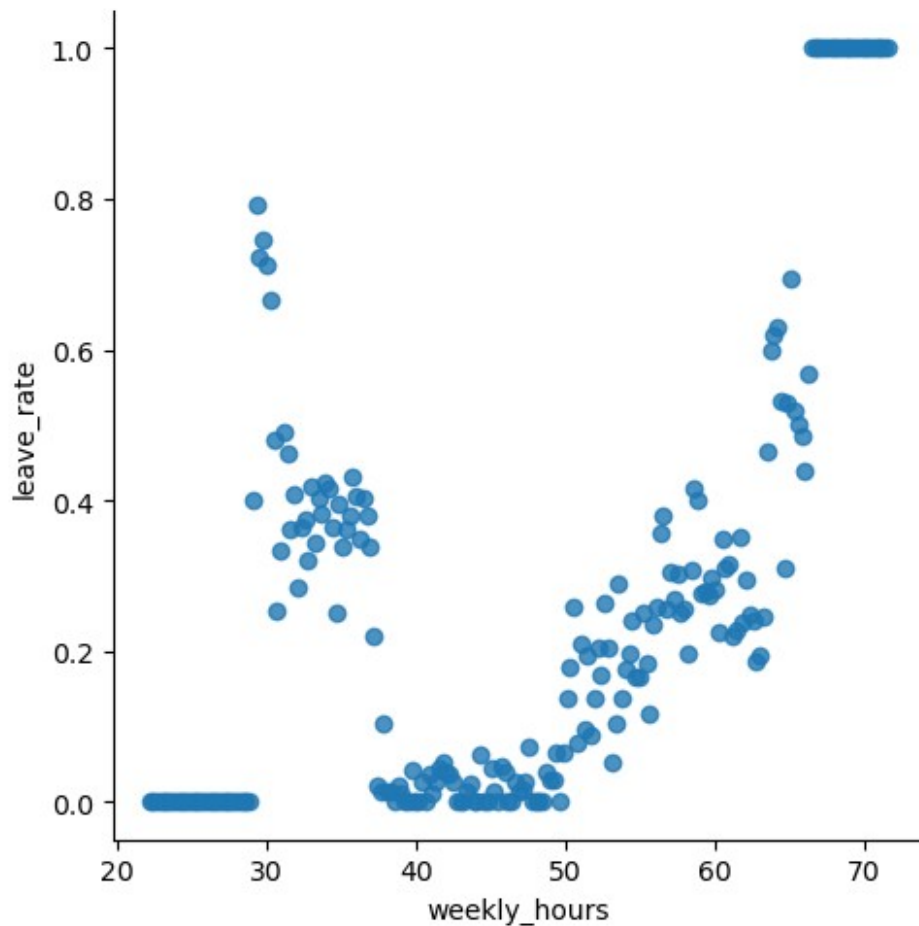
<IPython.core.display.Javascript object>



employees at a evalation score between 0.55 to 0.78 tend to leave less

```
leave_hours=df.groupby('average_weekly_hours').agg({'left': lambda x:
len(x[x==1])})
leave_hours['total']=df.groupby('average_weekly_hours').agg({'left':
len})
leave_hours['leave_rate']=leave_hours['left']/leave_hours['total']
leave_hours['weekly_hours']=df.groupby('average_weekly_hours').agg({'a
verage_weekly_hours': 'mean'})
grid=sns.lmplot('weekly_hours',
'leave_rate',data=leave_hours,fit_reg=False)
```

<IPython.core.display.Javascript object>



```
df[['department', 'average_weekly_hours']].groupby(['department'],
as_index=False).mean().sort_values(by='average_weekly_hours',
ascending=False)
```

	department	average_weekly_hours
9	technical	46.730175
0	IT	46.665225
4	management	46.442125
2	accounting	46.422224
7	sales	46.364158
1	RandD	46.338579
8	support	46.328813
6	product_mng	46.145915
5	marketing	46.012103
3	hr	45.850317

```
ll =
df[['promotion_last_5years', 'left']].groupby('promotion_last_5years').
sum(['left'])
ll['value_counts'] = df['promotion_last_5years'].value_counts()
ll
```

we can see addning prmotion in our predictions doesnt make it meaningful

```

           left  value_counts
promotion_last_5years
0           3552           14680
1             19             319
```

```
df[['department', 'average_weekly_hours']].groupby(['department']).mean(
(['average_weekly_hours'])
```

it doesnt make sense to use the working hours as all show close mean

```

           average_weekly_hours
department
IT           46.665225
RandD        46.338579
accounting    46.422224
hr            45.850317
management    46.442125
marketing     46.012103
product_mng   46.145915
sales         46.364158
support       46.328813
technical     46.730175
```

```
df=df.drop(['Work_accident', 'department', 'average_weekly_hours', 'promo
tion_last_5years'],axis=1)
```

```
df.columns
```

```
Index(['satisfaction_level', 'last_evaluation', 'number_project',
       'time_spend_company', 'left', 'salary'],
      dtype='object')
```

```
df.head()
```

```

satisfaction_level  last_evaluation  number_project
time_spend_company \
0                 0.38             0.53             2
3
1                 0.80             0.86             5
6
2                 0.11             0.88             7
4
3                 0.72             0.87             5
5
4                 0.37             0.52             2
3
```

```

left  salary
0     1    low
1     1  medium
```

```
2      1  medium
3      1    low
4      1    low
```

```
df['salary'] =
df['salary'].map({'low':0,'medium':1,'high':2}).astype('int')
```

```
df
```

	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	

	time_spend_company	left	salary
0	3	1	0
1	6	1	1
2	4	1	1
3	5	1	0
4	3	1	0
...
14994	3	1	0
14995	3	1	0
14996	3	1	0
14997	4	1	0
14998	3	1	0

```
[14999 rows x 6 columns]
```

```
df['number_project'].unique()
```

```
array([2, 5, 7, 6, 4, 3], dtype=int64)
```

```
# pd.cut for number_projects
```

```
probin = [0,2,5,10]
```

```
praname=[1,2,3]
```

```
df['cut_projects'] = pd.cut(df['number_project'],bins = probin ,
labels = praname )
```

```
# pd.cut for years at company
```

```
yearbin = [0,1,2,3,4,5,6,100]
```

```
yearlab = [1,2,3,4,5,6,7]
```

```
df['cut_year'] =
```

```
pd.cut(df['time_spend_company'],bins=yearbin,labels=yearlab)
```

```
#banding last_evaluation
```

```
evalbin=[0,.6,.8,1]
```

```
evalname=[0,1,2]
```

```
df['cut_eval']=pd.cut(df['last_evaluation'],bins =  
evalbin,labels=evalname)
```

```
df.head()
```

	satisfaction_level	last_evaluation	number_project
0	0.38	0.53	2
3			
1	0.80	0.86	5
6			
2	0.11	0.88	7
4			
3	0.72	0.87	5
5			
4	0.37	0.52	2
3			

	left	salary	cut_projects	cut_year	cut_eval
0	1	0	1	3	0
1	1	1	2	6	2
2	1	1	3	4	2
3	1	0	2	5	2
4	1	0	1	3	0

```
df =
```

```
df.drop(['number_project','time_spend_company','last_evaluation'],axis  
=1)
```

```
df.head()
```

	satisfaction_level	left	salary	cut_projects	cut_year	cut_eval
0	0.38	1	0	1	3	0
1	0.80	1	1	2	6	2
2	0.11	1	1	3	4	2
3	0.72	1	0	2	5	2
4	0.37	1	0	1	3	0

```
df.dtypes
```

```
satisfaction_level    float64  
left                  int64  
salary                int32  
cut_projects          category  
cut_year              category  
cut_eval              category  
dtype: object
```

```
df[['cut_projects','cut_year','cut_eval']] =
```

```
df[['cut_projects','cut_year','cut_eval']].astype('int64')
```

```
df.head()
```

	satisfaction_level	left	salary	cut_projects	cut_year	cut_eval
0	0.38	1	0	1	3	0
1	0.80	1	1	2	6	2
2	0.11	1	1	3	4	2
3	0.72	1	0	2	5	2
4	0.37	1	0	1	3	0

```
df.dtypes
```

```
satisfaction_level    float64
left                  int64
salary                int32
cut_projects          int64
cut_year              int64
cut_eval              int64
dtype: object
```

models using different techniques

```
from sklearn.linear_model import LogisticRegression as lr_
from sklearn.svm import SVC as svc_
from sklearn.neighbors import KNeighborsClassifier as knn_
from sklearn.naive_bayes import GaussianNB as gnb_
from sklearn.tree import DecisionTreeClassifier as dtc_
```

```
from sklearn.model_selection import train_test_split
```

```
x_train, x_test, y_train, y_test =
train_test_split(df, df['left'], test_size=.2)
x_train = x_train.drop('left', axis=1)
x_test = x_test.drop('left', axis=1)
print(x_train.shape, y_train.shape)
print(x_test.shape, y_test.shape)
```

```
(11999, 5) (11999,)
(3000, 5) (3000,)
```

```
models = [lr_(), knn_(), dtc_(), gnb_(), svc_()]
model_names = ['log reg', 'KNN', 'DTC', 'GNB', 'SVC']
for i in range(len(models)):
    ind_model = models[i].fit(x_train, y_train)
    print(f'{model_names[i]} :::: training score :
{round(ind_model.score(x_train, y_train)*100, 1)} test score :
{round(ind_model.score(x_test, y_test)*100, 1)}')
```

```
log reg :::: training score : 78.9      test score : 78.8
KNN :::: training score : 97.5      test score : 96.3
DTC :::: training score : 98.5      test score : 97.3
GNB :::: training score : 83.8      test score : 83.1
SVC :::: training score : 94.9      test score : 95.1
```



```

models_scores = pd.DataFrame()
models = [lr_(),knn_(),dtc_(),gnb_(),svc_()]
model_names = ['log reg','KNN','DTC','GNB','SVC']
train_scores=[]
test_scores= []
for i in range(len(models)):
    ind_model = models[i].fit(x_train,y_train)
    models_scores['model name'] = model_names[i]
    train_scores.append(ind_model.score(x_train,y_train))
    test_scores.append(ind_model.score(x_test,y_test))

models_scores = pd.DataFrame()
models_scores['model name'] = model_names
models_scores['train scores'] =train_scores
models_scores['test scores'] = test_scores

```

```
models_scores
```

	model name	train scores	test scores
0	log reg	0.789399	0.787667
1	KNN	0.974665	0.963333
2	DTC	0.985415	0.972667
3	GNB	0.837986	0.831000
4	SVC	0.949329	0.951000