## ASSIGNMENT/ TASK 9

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Predict retention of an employee within an organization such that whether the employee will leave the company or continue with it. An organization is only as good as its employees, and these people are the true source of its competitive advantage. Dataset is downloaded from Kaggle. Link: <a href="https://www.kaggle.com/giripujar/hr-analytics">https://www.kaggle.com/giripujar/hr-analytics</a>

First do data exploration and visualization, after this create a logistic regression model to predict Employee Attrition Using Machine Learning & Python.

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import sklearn
from sklearn.linear_model import LinearRegression

dataset=pd.read_csv('/content/HR_comma_sep.csv')
dataset.head()
```

	satisfaction_level	last_evaluation	number_project	average_montly_hours	time_s
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	

satisfaction_level	last_evaluation	number_project	average_montly_hours	ti
14999.000000	14999.000000	14999.000000	14999.000000	
0.612834	0.716102	3.803054	201.050337	
0.248631	0.171169	1.232592	49.943099	
	14999.000000 0.612834	14999.000000 14999.000000 0.612834 0.716102	14999.000000 14999.000000 14999.000000 0.612834 0.716102 3.803054	0.612834

dataset.columns

1 000000 1 000000 7 000000 310 000000

dataset.dtypes

satisfaction_level	float64
last_evaluation	float64
number_project	int64
average_montly_hours	int64
time_spend_company	int64
Work_accident	int64
left	int64
<pre>promotion_last_5years</pre>	int64
Department	object
salary	object
dtype: object	

dataset.corr()

	satisfaction_level	last_evaluation	number_project	average_m
satisfaction_level	1.000000	0.105021	-0.142970	
last_evaluation	0.105021	1.000000	0.349333	
number_project	-0.142970	0.349333	1.000000	
average_montly_hours	-0.020048	0.339742	0.417211	
time_spend_company	-0.100866	0.131591	0.196786	
Work_accident	0.058697	-0.007104	-0.004741	
left	-0.388375	0.006567	0.023787	
promotion_last_5years	0.025605	-0.008684	-0.006064	

dataset.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
                           14999 non-null
    left
                                           int64
6
7
    promotion_last_5years
                           14999 non-null
                                            int64
8
    Department
                           14999 non-null
                                            object
    salary
                           14999 non-null
                                            object
```

dtypes: float64(2), int64(6), object(2)

memory usage: 1.1+ MB

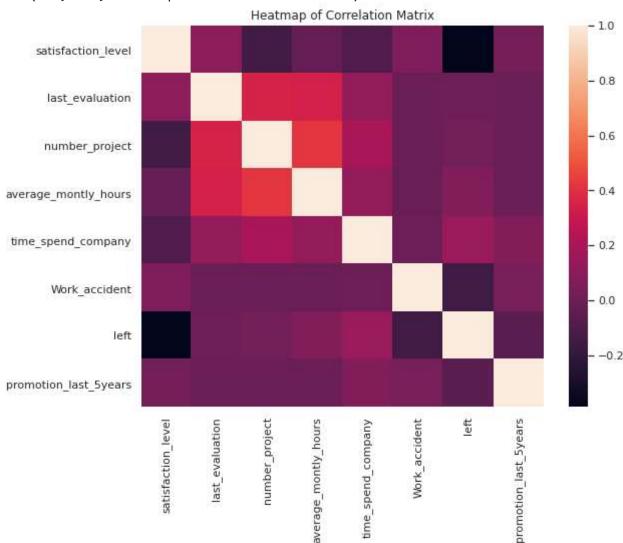
import seaborn as sns

sns.set(rc={'figure.figsize':(9,7)})
correlation\_matrix = dataset.corr().round(2)
sns.heatmap(data=correlation\_matrix, annot=True)

<matplotlib.axes.\_subplots.AxesSubplot at 0x7f5d820e86d0>



```
corr=dataset.corr()
corr =(corr)
sns.heatmap(corr, xticklabels=corr.columns.values,yticklabels=corr.columns.values)
plt.title('Heatmap of Correlation Matrix')
```



Text(0.5, 1.0, 'Heatmap of Correlation Matrix')

dataset.groupby('salary').mean()

 ${\tt satisfaction\_level\ last\_evaluation\ number\_project\ average\_montly\_hours}$ 

salary	alary					
high	0.637470	0.704325	3.767179	199.867421		
low	0.600753	0.717017	3.799891	200.996583		
medium	0.621817	0.717322	3.813528	201.338349		

emp\_population\_satisfaction =dataset['satisfaction\_level'].mean()
emp\_turnover\_satisfaction =dataset[dataset['left']==1]['satisfaction\_level'].mean()
print('the mean for population is:'+str(emp\_population\_satisfaction))
print('the mean for the employe is:'+str(emp\_turnover\_satisfaction))

the mean for population is:0.6128335222348166 the mean for the employe is:0.44009801176140917

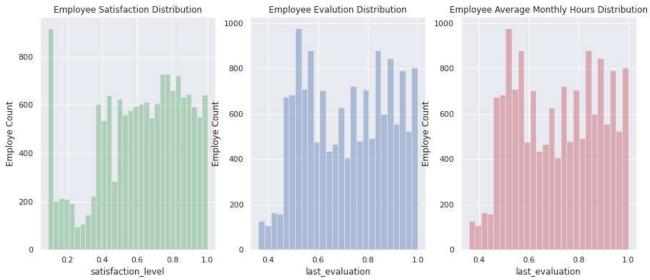
f, axes=plt.subplots(ncols=3,figsize=(15, 6))
sns.distplot(dataset.satisfaction\_level,kde=False,color="g",ax=axes[0]).set\_title('Employe
axes[0].set\_ylabel('Employe Count')

sns.distplot(dataset.last evaluation.kde=False.color="b".ax=axes[1]).set title('Employee E https://colab.research.google.com/drive/1KA4J4ygbKcuQHHFUYhF227OgqiimlZ2L#scrollTo=X\_0k45AF9zJm&printMode=true 4/9

axes[1].set\_ylabel('Employe Count')
sns.distplot(dataset.last\_evaluation,kde=False,color="r",ax=axes[2]).set\_title('Employee A
axes[2].set\_ylabel('Employe Count')

/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2557: FutureWarning: warnings.warn(msg, FutureWarning)

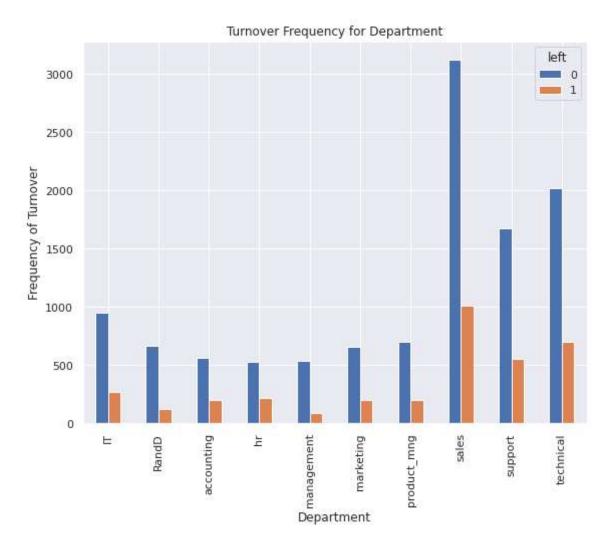
Text(0, 0.5, 'Employe Count')



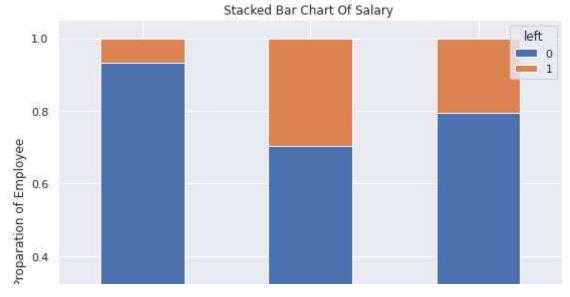
sns.countplot(x='Department',data=dataset).set\_title("Employe Department");

## **Employe Department**

```
pd.crosstab(dataset.Department,dataset.left).plot(kind='bar')
plt.title('Turnover Frequency for Department')
plt.xlabel('Department')
plt.ylabel('Frequency of Turnover')
plt.savefig('Department_bar_chart')
```



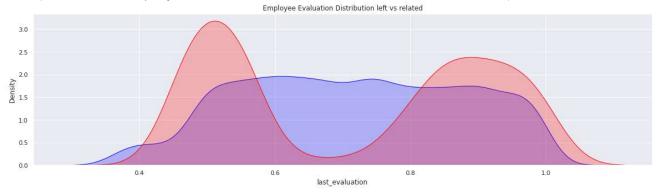
```
table=pd.crosstab(dataset.salary,dataset.left)
table.div(table.sum(1).astype(float),axis=0).plot(kind='bar',stacked=True)
plt.title("Stacked Bar Chart Of Salary ")
plt.xlabel('Salary Level')
plt.ylabel('Proparation of Employee')
plt.savefig('salary_bar_chart')
```



fig=plt.figure(figsize=(20,5))

ax=sns.kdeplot(dataset.loc[(dataset["left"]==0),'last\_evaluation'],color='blue',shade=True
ax=sns.kdeplot(dataset.loc[(dataset["left"]==1),'last\_evaluation'],color='red',shade=True)
plt.title('Employee Evaluation Distribution left vs related')

Text(0.5, 1.0, 'Employee Evaluation Distribution left vs related')



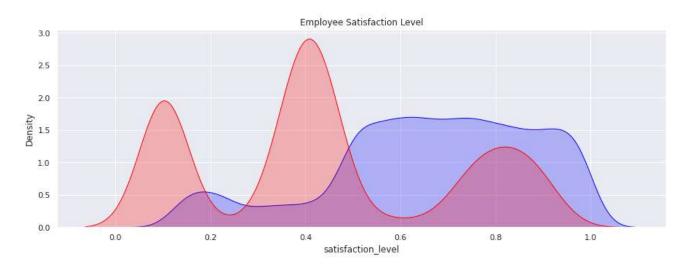
fig=plt.figure(figsize=(15,5))

ax=sns.kdeplot(dataset.loc[(dataset["left"]==0), 'average\_montly\_hours'], color='blue', shade
ax=sns.kdeplot(dataset.loc[(dataset["left"]==1), 'average\_montly\_hours'], color='red', shade=
plt.title('Employee Evaluation Distribution left vs relained')

Text(0.5, 1.0, 'Employee Evaluation Distribution left vs relained')



fig=plt.figure(figsize=(15,5))
ax=sns.kdeplot(dataset.loc[(dataset["left"]==0),'satisfaction\_level'],color='blue',shade=T
ax=sns.kdeplot(dataset.loc[(dataset["left"]==1),'satisfaction\_level'],color='red',shade=Tr
plt.title('Employee Satisfaction Level')



```
from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
dataset['Department']=le.fit_transform(dataset['Department'])
from sklearn.model selection import train test split
```

x=dataset.Department
y=dataset.salary
xtrain, xtest,ytrain,ytest = train\_test\_split(x,y,test\_size=0.30,random\_state=99)
xtrain.shape,xtest.shape,ytrain.shape,ytest.shape

((10499,), (4500,), (10499,), (4500,))

from sklearn.linear\_model import LogisticRegression
model=LogisticRegression()
print(model)

LogisticRegression(C=1.0, class\_weight=None, dual=False, fit\_intercept=True, intercept\_scaling=1, l1\_ratio=None, max\_iter=100, multi\_class='auto', n\_jobs=None, penalty='l2', random\_state=None, solver='lbfgs', tol=0.0001, verbose=0, warm\_start=False)

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