HR Analytics Using Statistical Analysis

What is HR Analytics

HR Analytics is defined as a specialized form of data analytics that involves usage of employee-related data and analytical processes to improve HR performance level and employee retention. The data collected is used to help the management make informed decisions with respect to attrition rates and employee retention.

HR analytics aims at answering the following questions:

1. What is the employee value and retention rate?
2. What is the approximate attrition rate?
3. How many employees deserve a promotion?
4. What is the employee turnover rate?

Benifits of HR Analytics

1. HR Management Based on Evidence
2. Improves Talent Acquisition
3. Assessing Employee Performance and Productivity
4. Avoid Pay Disparities and Improve Benifits
5. Better Workforce Planning
6. Understanding Skill Gaps
7. Improve Learning and Development
8. Reducing Employee Trurnover
9. Improving Candidate Experience
10. Identifying HR Inefficiencies

Problem Statement

- Gadget Tank, a growing company is facing a high attrition rate among their employees which in turn affects their business due to lack of expertise and experience.
- Their HR department is assigned the task to reduce the attrition rate by retaining employees who are about to churn out.
- They need to recommend special plans or strategies which will help them to retain their employees which in turn will help them to grow bigger as a company

Importing libraries

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
df = pd.read_csv('Employee Attrition Data.csv')  #Importing Employees Data Set
```

Checking Data

In [3]:
```
df.size   #total no. of records
```

Out[3]: 149940

In [4]:
```
df.shape   #total no. of rows and columns
```

Out[4]: (14994, 10)

In [5]:
```
df.sample(5)    #Sample of DataSet
```

Out[5]:

	satisfactoryLevel	lastEvaluation	numberOfProjects	avgMonthlyHours	timeSpent.company	workAccident	left	promotionInLast5years	dept	salary
1070	0.10	0.81	6	308	4	0	1	0	IT	medium
9740	0.09	0.94	6	257	4	0	1	0	sales	low
6170	0.76	0.55	4	163	2	1	0	0	hr	medium
4238	0.93	0.95	2	156	3	1	0	0	support	low
13711	0.20	0.38	6	212	6	0	0	0	sales	high

In [6]:
```
df.info();  #Information about Data
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14994 entries, 0 to 14993
Data columns (total 10 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   satisfactoryLevel      14994 non-null  float64
 1   lastEvaluation         14994 non-null  float64
 2   numberOfProjects       14994 non-null  int64  
 3   avgMonthlyHours        14994 non-null  int64  
 4   timeSpent.company      14994 non-null  int64  
 5   workAccident           14994 non-null  int64  
 6   left                   14994 non-null  int64  
 7   promotionInLast5years  14994 non-null  int64  
 8   dept                   14994 non-null  object 
 9   salary                 14994 non-null  object 
dtypes: float64(2), int64(6), object(2)
memory usage: 1.1+ MB
```

In [7]:
```
df.describe() #Statistical Summary of Data
```

Out[7]:

	satisfactoryLevel	lastEvaluation	numberOfProjects	avgMonthlyHours	timeSpent.company	workAccident	left	promotionInLast5years
count	14994.000000	14994.000000	14994.000000	14994.000000	14994.000000	14994.000000	14994.000000	14994.000000
mean	0.612849	0.716064	3.802588	201.039216	3.498199	0.144658	0.238095	0.021275
std	0.248596	0.171182	1.232350	49.940114	1.460260	0.351767	0.425932	0.144305
min	0.090000	0.360000	2.000000	96.000000	2.000000	0.000000	0.000000	0.000000
25%	0.440000	0.560000	3.000000	156.000000	3.000000	0.000000	0.000000	0.000000
50%	0.640000	0.720000	4.000000	200.000000	3.000000	0.000000	0.000000	0.000000
75%	0.820000	0.870000	5.000000	245.000000	4.000000	0.000000	0.000000	0.000000
max	1.000000	1.000000	7.000000	310.000000	10.000000	1.000000	1.000000	1.000000

In [8]:
```
df.columns  # Checking Columns
```

Out[8]:
```
Index(['satisfactoryLevel', 'lastEvaluation', 'numberOfProjects',
       'avgMonthlyHours', 'timeSpent.company', 'workAccident', 'left',
       'promotionInLast5years', 'dept', 'salary'],
      dtype='object')
```

Data Cleaning

In [9]:
```
df.rename(columns = {'timeSpent.company':'timeSpent_company'}, inplace = True)  #Renaming Column
```

In [10]:
```
df.isnull().sum()  #If Null values are present
```

Out[10]:
```
satisfactoryLevel        0
lastEvaluation           0
numberOfProjects         0
avgMonthlyHours          0
timeSpent_company        0
workAccident             0
left                     0
promotionInLast5years    0
dept                     0
salary                   0
dtype: int64
```

In [11]:
```
df.duplicated().sum()   #Check for Duplicates
```

Out[11]:
```
3007
```

In [12]:
```
df = df.drop_duplicates(keep='first')  #Removing Duplicates while keeping First Values
```

In [13]:
```
df.shape  #Data Reduced to 11991 items
```

Out[13]:
```
(11987, 10)
```

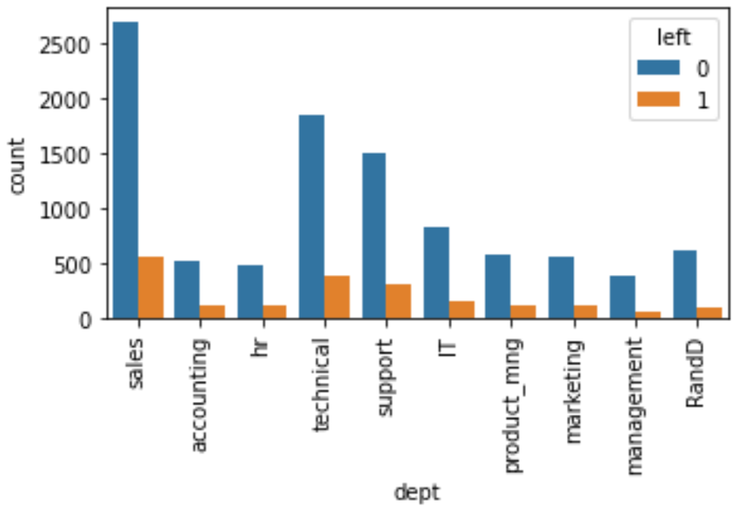
Using EDA

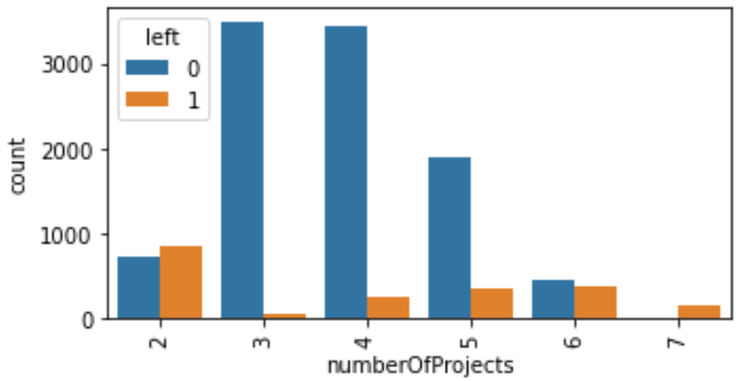
In [14]:
```
#First we will store all the independent column in a list

feature = ['dept','numberOfProjects','timeSpent_company','workAccident','promotionInLast5years','salary']
```

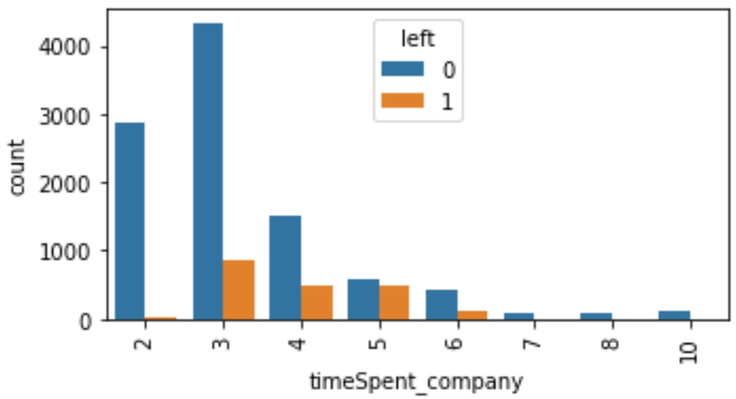
In [15]:
```
feature
```

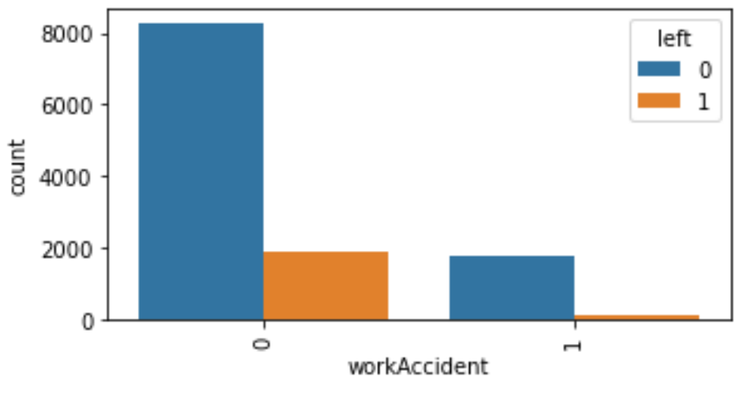
Out[15]:
```
['dept',
 'numberOfProjects',
 'timeSpent_company',
 'workAccident',
 'promotionInLast5years',
 'salary']
```

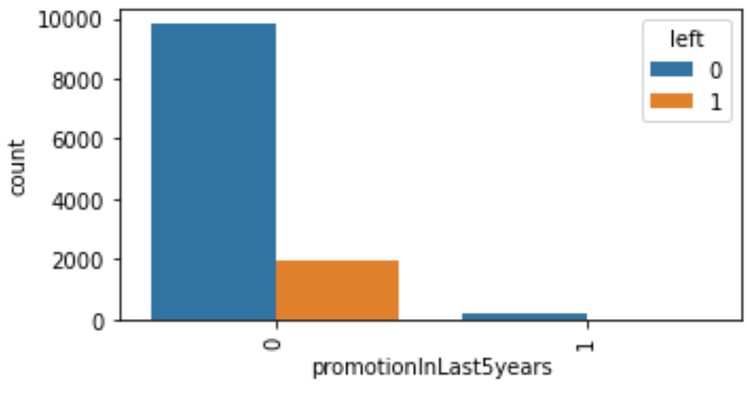
In [16]:
```
plt.figure(figsize=(10,10))
for p,q in enumerate(feature):
  plt.subplot(3,2,p+1)
  sns.countplot(x = q, hue = 'left', data = df)
  plt.xticks(rotation = 90)
  plt.tight_layout()
```

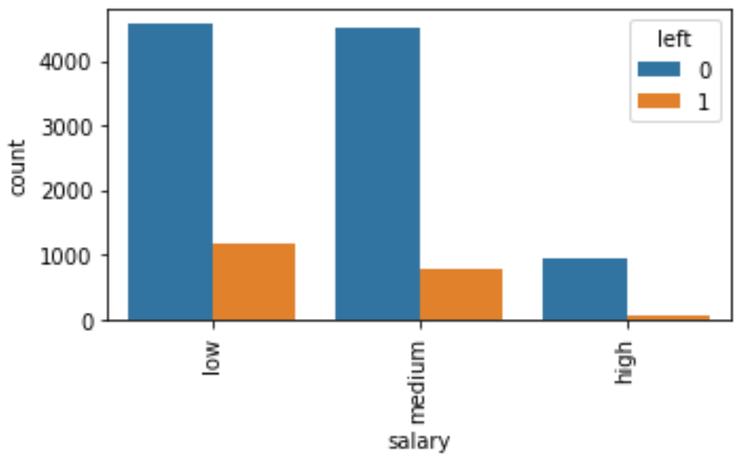

left
0
1
count
2500
2000
1500
1000
500
0
sales
accounting
hr
technical
support
IT
product_mng
marketing
management
RandD
dept


left
0
1
count
3000
2000
1000
0
2
3
4
5
6
7
numberOfProjects


left
0
1
count
4000
3000
2000
1000
0
2
3
4
5
6
7
8
10
timeSpent_company


left
0
1
count
8000
6000
4000
2000
0
0
1
workAccident


left
0
1
count
10000
8000
6000
4000
2000
0
0
1
promotionInLast5years


left
0
1
count
4000
3000
2000
1000
0
low
medium
high
salary

Conclusion Using EDA

1. The HR has to take care of Sales, Technical, and Support departments
2. The employees having less or more project are churning out. so optimal number of project is 3
3. The 3 - 5 years is the crucial time for employee who is churning out.
4. Note: work accident vs left --- it is not giving any information about employee
5. The employee is leaving if they are not getting promoted in 5 years.
6. The person having high salary are staying with the company whereas low salary is forcing them to leave or planning to leave.

Using Statistical Analysis

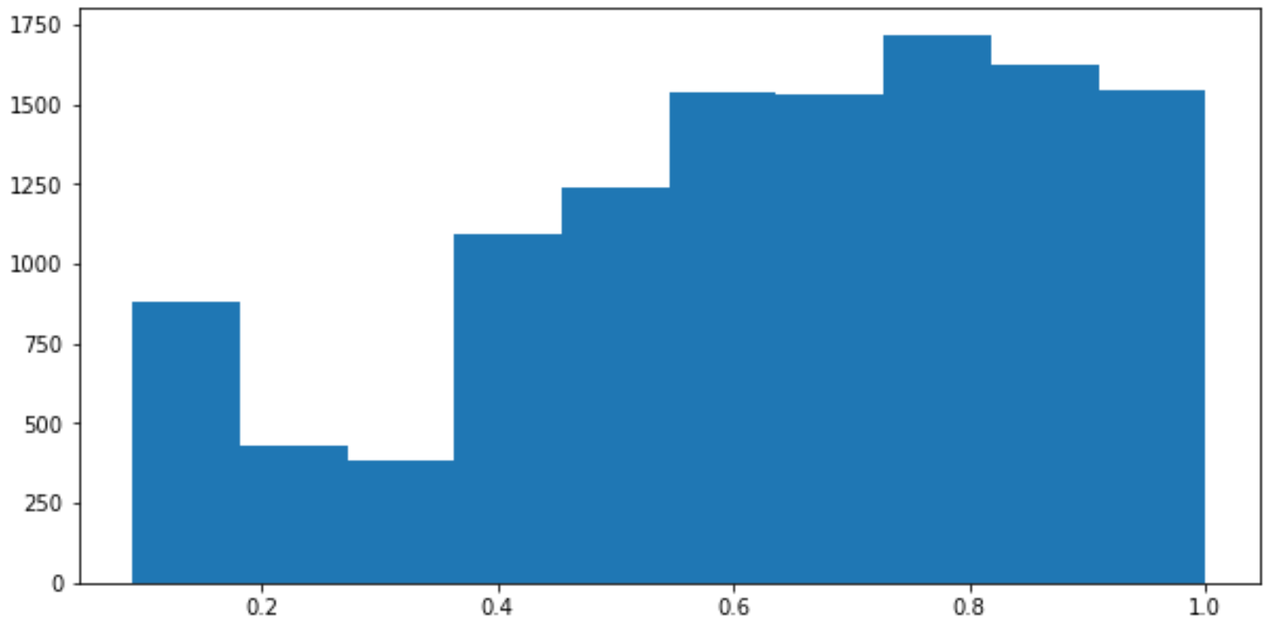
Cheking Normality Using

1. Visualization : Histogram and Skewness
2. Shapiro Wilk Test

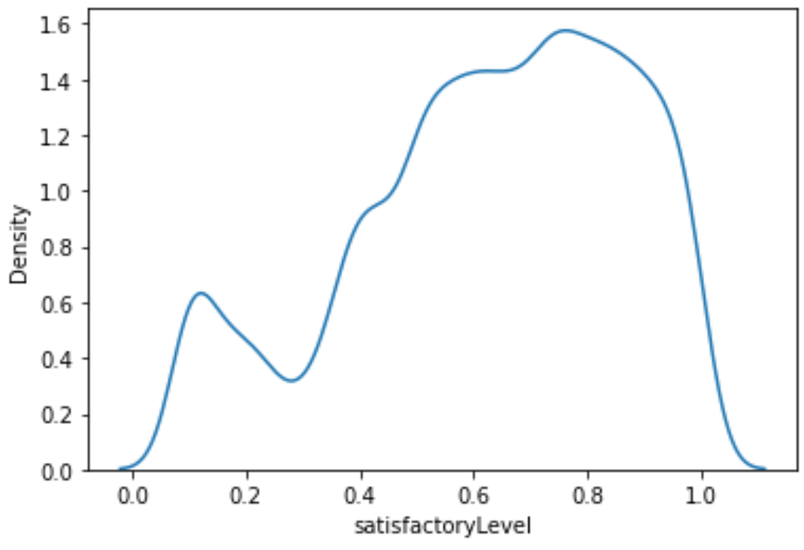
1. Visualization

Check whether the data is normally distributed or not in satisfactory level column using visualization

In [17]:
```
# plotting histogram to visualize the distribution of data
plt.figure(figsize=(10,5))
plt.hist(df["satisfactoryLevel"])
plt.show()
```



In [18]:
```
sns.distplot(df["satisfactoryLevel"], hist = False);
```



In [19]:
```
df['satisfactoryLevel'].skew()  #Negatively Skewed
```

Out[19]:
```
-0.5387089777913757
```

2. Using Shapiro Wilk Test

Check whether the data is normally distributed or not in satisfactory level column using shapiro-wilk test

In [20]:
```
from scipy.stats import shapiro
```

Hypothesis for Shapiro

1. **Null Hypothesis (h0)** - data is normally distributed
2. **Alternate Hypothesis (h1)** - data is not normally distributed

In [21]:
```
stat,p_value=shapiro(df["satisfactoryLevel"])
```

In [22]:
```
print(p_value)
```

```
0.0
```

In [23]:
```
print(stat)
```

```
0.9526721239089966
```

Conclusion About Normality:

Since p value is less than 0.05 reject null hypothesis, data is not normally distributed

Which Means our data is not Normally Distributed

Conversion of Categorical Data Using Label Encoding

Lets Convert Salary and Department into Numerical Data

In [24]:
```
# salary is categorical data
df["salary"].unique()
```

Out[24]:
```
array(['low', 'medium', 'high'], dtype=object)
```

In [25]:
```
# dept is also categorical data
df["dept"].unique()
```

Out[25]:
```
array(['sales', 'accounting', 'hr', 'technical', 'support', 'IT',
       'product_mng', 'marketing', 'management', 'RandD'], dtype=object)
```

In [26]:
```
df1=df  #copy of our dataset for further analysis
```

In [27]:
```
df1[["salary", "dept"]]
```

Out[27]:

	salary	dept
0	low	sales
1	medium	sales
2	medium	sales
3	low	sales
4	low	sales
...	...	...
14986	medium	RandD
14989	medium	product_mng
14990	high	technical
14991	medium	IT
14992	low	hr

11987 rows × 2 columns

In [28]:
```
# Converting the categorical data into num, using Label Encoder
from sklearn.preprocessing import LabelEncoder
l1=LabelEncoder()
df1["salary"]= l1.fit_transform(df1["salary"])
df1["dept"]= l1.fit_transform(df1["dept"])
```

In [29]:
```
df1.head()
```

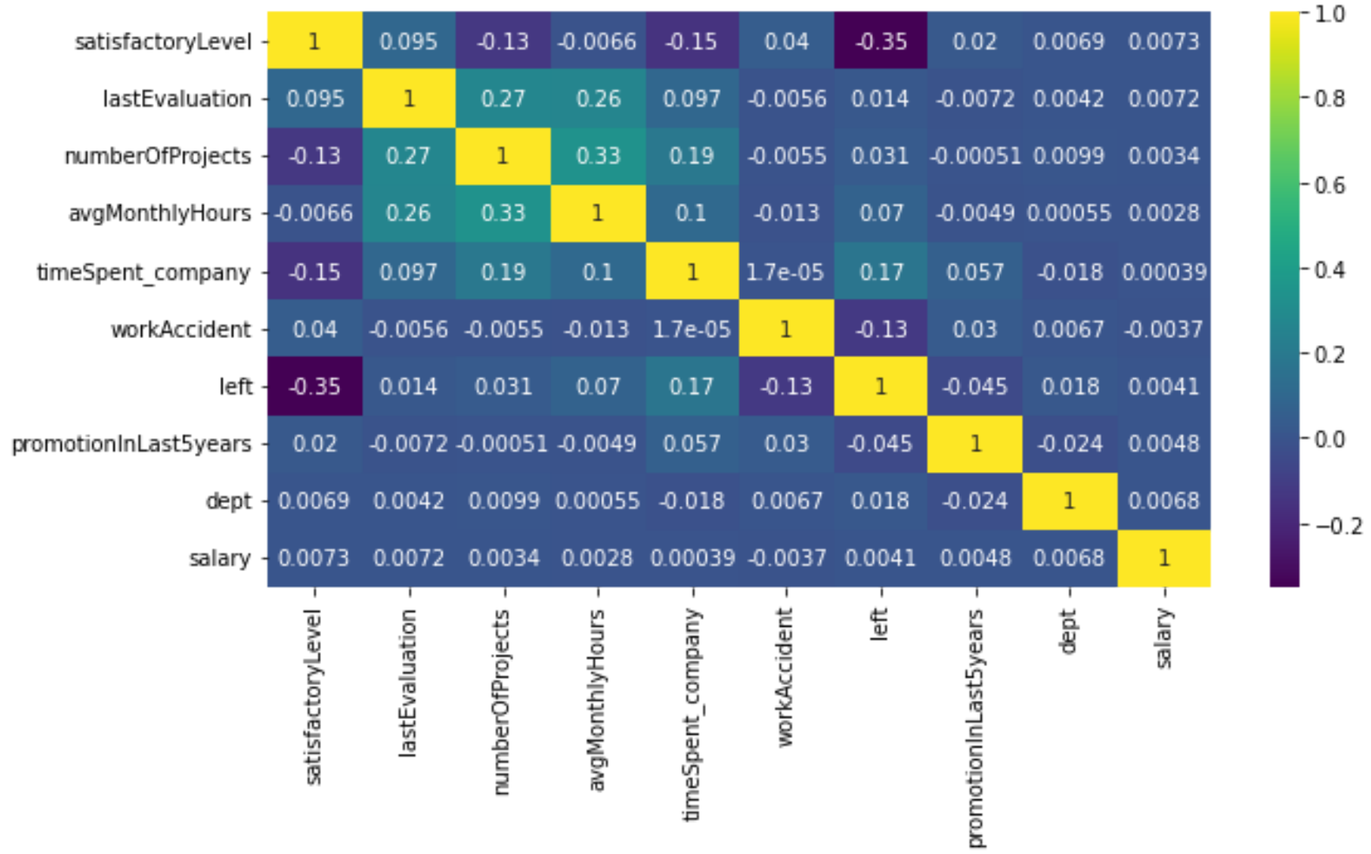
Out[29]:

	satisfactoryLevel	lastEvaluation	numberOfProjects	avgMonthlyHours	timeSpent_company	workAccident	left	promotionInLast5years	dept	salary
0	0.38	0.53	2	157	3	0	1	0	7	1
1	0.80	0.86	5	262	6	0	1	0	7	2
2	0.11	0.88	7	272	4	0	1	0	7	2
3	0.37	0.52	2	159	3	0	1	0	7	1
4	0.41	0.50	2	153	3	0	1	0	7	1

Check for Correlation

Correlation Graph

In [30]:
```
plt.figure(figsize = (10,5))
sns.heatmap(df1.corr(), annot=True, cmap = 'viridis');
```



Correlation has no enough evidence or we can say in this case is not helping us to make any inferences. So we will go with a random Experiment

Descriptive statistics

In [31]:
```
df.describe()  #Descriptive Analysis
```

Out[31]:

	satisfactoryLevel	lastEvaluation	numberOfProjects	avgMonthlyHours	timeSpent_company	workAccident	left	promotionInLast5years	dept
count	11987.000000	11987.000000	11987.000000	11987.000000	11987.000000	11987.000000	11987.000000	11987.000000	11987.000000
mean	0.629641	0.716647	3.802536	200.465588	3.364812	0.154334	0.166097	0.016935	5.870526
std	0.241057	0.168355	1.163205	48.726030	1.330302	0.361284	0.372183	0.129033	2.899263
min	0.090000	0.360000	2.000000	96.000000	2.000000	0.000000	0.000000	0.000000	0.000000
25%	0.480000	0.570000	3.000000	157.000000	3.000000	0.000000	0.000000	0.000000	4.000000
50%	0.660000	0.720000	4.000000	200.000000	3.000000	0.000000	0.000000	0.000000	7.000000
75%	0.820000	0.860000	5.000000	243.000000	4.000000	0.000000	0.000000	0.000000	8.000000
max	1.000000	1.000000	7.000000	310.000000	10.000000	1.000000	1.000000	1.000000	9.000000

Random Experiment

Since we are concerned about an employee's leaving the organisation so on the basis of that we will perform a Random Experiment i.e.,

- **Employee with satisfactoryLevel between 0 and 0.5**
  - Employees who are less satisfied are more prone to leave**
- TimeSpent in Company == 2 Years
  - Employee with less experience often look for change
- Average Monthly Hours Spent between 130 and 200
  - People are gullible to leave if workload is more

In [32]:
```
# Random experiment
emp = df[(df.satisfactoryLevel>=0)&(df.satisfactoryLevel<=0.50)&(df.timeSpent_company==2)&(df.avgMonthlyHours>=130)&(df.avgMonthlyHo
```

In [33]:
```
emp.shape
```

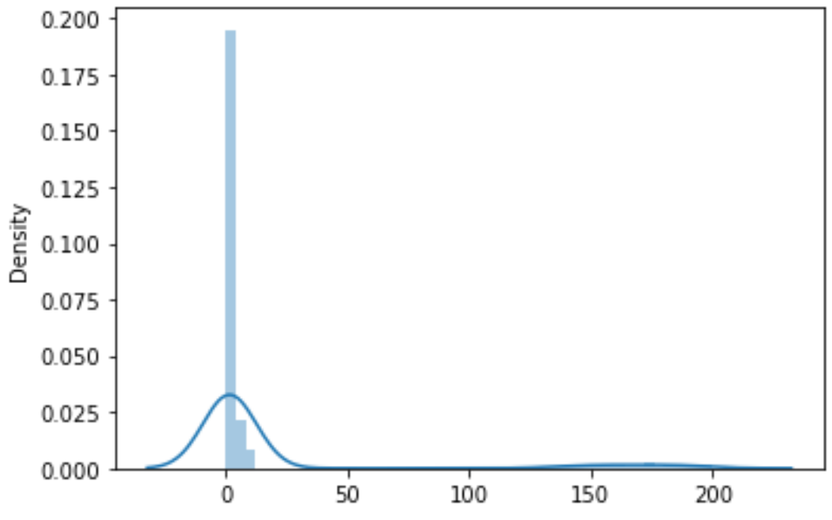
Out[33]: (217, 10)

In [34]:
```
emp.head(3)
```

Out[34]:

	satisfactoryLevel	lastEvaluation	numberOfProjects	avgMonthlyHours	timeSpent_company	workAccident	left	promotionInLast5years	dept	salary
35	0.13	0.78	6	152	2	0	1	0	8	1
379	0.48	0.78	2	198	2	0	1	0	9	2
413	0.34	0.67	4	141	2	0	1	0	7	1

In [35]:
```
sns.distplot(emp);  #our sample follows normality
```



In [36]:
```
emp["left"].value_counts() #Only 6 People are leaving
```

Out[36]:
```
0    211
1      6
Name: left, dtype: int64
```

In [37]:
```
emp["avgMonthlyHours"].mean()  #We will Test this statistic
```

Out[37]:
```
167.2258064516129
```

By Looking at the above data we found out 167.225 is the average monthly hours for employee with 2 Years of Experience. We will check if it is same for people with more years of experience with the help of hypothesis testing.

We assume if People with less experience are getting to work more than people with higher work experience

Hypothesis Testing

1. T-test

Used for checking difference in means between samples/popluation

a. One sample T-test for Mean

It tells us whether the mean of sample and population are different or not

Problem Statement

The average monthly hours of a employee having 2 years experience is 167. Is it same for employees having more than 2 years experience?

`Condition` - Satisfactory level of a employee is from 0-0.5 and AvgMonthlyhours is from 130-200

In [38]:
```
employee = df[(df.satisfactoryLevel>=0)&(df.satisfactoryLevel<=0.50)&(df.timeSpent_company>=3)&(df.avgMonthlyHours>=130)&(df.avgMont
```

In [39]:
```
employee.head(3)
```

Out[39]:

	satisfactoryLevel	lastEvaluation	numberOfProjects	avgMonthlyHours	timeSpent_company	workAccident	left	promotionInLast5years	dept	salary
0	0.38	0.53	2	157	3	0	1	0	7	1
3	0.37	0.52	2	159	3	0	1	0	7	1
4	0.41	0.50	2	153	3	0	1	0	7	1

In [40]:
```
employee.shape
```

Out[40]:
```
(1461, 10)
```

State Hypothesis

In [41]:
```
#Null hypothesis: avg monthly hours of a employee having 2 yrs exp and the employee more than that is same i.e, 167 hrs
```

In [42]:
```
#Alternate hypothesis: avg monthly hours of a employee having 2 yrs exp doesnot have same avg monthly hours with more than 2 yrs exp
```

Sampling

In [43]:
```
# selecting a random sample
sample_size = 100
sample1 = employee.sample(sample_size,random_state=0)
```

Population Parameter vs. Sample Statistic

In [44]:
```
# population mean
population_mean=167
```

In [45]:
```
# sample mean
print(sample1["avgMonthlyHours"].mean())
```

```
155.03
```

In [46]:
```
from scipy.stats import ttest_1samp
```

P Value Approach

In [47]:
```
statistics,pvalue=ttest_1samp(sample1["avgMonthlyHours"],population_mean)
print(statistics,pvalue)
```

```
-6.456739354158406 4.003623439248421e-09
```

The above p-value is in Exponentials. Hence Rejecting Null Hypothesis

Critical Value Approach

In [48]:
```
# Degrees of freedom for Sample
dof=100-1
print(dof)

#degree of freedome means except for our one value ever other value is free to change
```

```
99
```

In [49]:
```
#Confidence level = 0.95
alpha= 0.05
CL = 1-alpha
```

We Can Check Critical Value Using T Student Distribution Table or Else:

In [50]:
```
from scipy.stats import t
```

In [51]:
```
#Critical Value

cv= t.ppf([alpha/2, 1-alpha/2], dof)  #ppf = percent point function #Two Tailed Test
print(cv)
```

```
[-1.98421695  1.98421695]
```

One Sample T-test Conclusion

In [52]:
```
# p value is less than 0.05
#reject null hypothesis,

#avg monthly hours is not 167 hours for employees having more than 2 yrs of exp
```

b. One sample Z-test for Proportions

proportion = 6/211 = 3%

Problem Statement

The percentage of employee leaving the company is 3% having experience of 2 years. Is it same for employees having more than 2 years experience?

In [53]:
```
# Null hypothesis - percentage of employee leaving the company having the exp of 2 years is same as employee having exp more than 2
# Alternate hypothesis - percentage of employee leaving the company having the exp of 2 years is different from the employee having
```

In [54]:
```
from statsmodels.stats.proportion import proportions_ztest
```

In [55]:
```
employee.shape
```

Out[55]:
```
(1461, 10)
```

In [56]:
```
sample_size=100
```

In [57]:
```
sample1=employee.sample(sample_size,random_state=0)
```

In [58]:
```
count=sample1["left"].value_counts()
count
```

Out[58]:
```
1    58
0    42
Name: left, dtype: int64
```

In [59]:
```
nobs=len(sample1["left"])
```

In [60]:
```
nobs  #number of observations
```

Out[60]:
```
100
```

In [61]:
```
p0 = 0.3
```

In [62]:
```
sample1["left"].value_counts()/nobs
```

Out[62]:
```
1    0.58
0    0.42
Name: left, dtype: float64
```

In [63]:
```
statistic_oneprop,pvalue_oneprop=proportions_ztest(count=count,nobs=nobs,value=p0,alternative="two-sided",prop_var=False)
```

P Value Approach

In [64]:
```
print(statistic_oneprop,pvalue_oneprop)
```

```
-1.9798989873223334 0.047714880237351126
```

Critical Value Approach

In [65]:
```
#Critical Value

from scipy.stats import norm
cv_norm=norm.ppf([alpha/2,1-alpha/2])
print(cv_norm)
```

```
[-1.95996398  1.95996398]
```

One Proportion Z-test Conclusion

In [66]:
```
# p value is greater than 0.05 accept null hypothesis and reject alternate hypothesis
# percentage of employee leaving the company having the exp of 2 years is same as employee having exp more than 2 yrs
```

c. Two sample T-test for Mean

In [67]:
```
# Two sample test for means - compared the means of a two independent groups
```

In [68]:
```
df1.head(3)
```

Out[68]:

	satisfactoryLevel	lastEvaluation	numberOfProjects	avgMonthlyHours	timeSpent_company	workAccident	left	promotionInLast5years	dept	salary
0	0.38	0.53	2	157	3	0	1	0	7	1
1	0.80	0.86	5	262	6	0	1	0	7	2
2	0.11	0.88	7	272	4	0	1	0	7	2

Problem Statement

Is the mean avg monthly hours of a employee having experience of 2-5 yrs is the same as that for employee having exp 6 - 10 yrs ?

In [69]:
```
# Null hypothesis - Means are same
# Alternate hypothesis - Means are not same
```

In [70]:
```
e1=df1[(df1.timeSpent_company>=2) & (df1.timeSpent_company<=5)]
e2=df1[(df1.timeSpent_company>=6) & (df1.timeSpent_company<=10)]
```

In [71]:
```
e1.head(2)
```

Out[71]:

	satisfactoryLevel	lastEvaluation	numberOfProjects	avgMonthlyHours	timeSpent_company	workAccident	left	promotionInLast5years	dept	salary
0	0.38	0.53	2	157	3	0	1	0	7	1
2	0.11	0.88	7	272	4	0	1	0	7	2

In [72]:
```
e1.shape
```

Out[72]:
```
(11163, 10)
```

In [73]:
```
e2.head(2)
```

Out[73]:

	satisfactoryLevel	lastEvaluation	numberOfProjects	avgMonthlyHours	timeSpent_company	workAccident	left	promotionInLast5years	dept	salary
1	0.80	0.86	5	262	6	0	1	0	7	2
13	0.78	0.99	4	255	6	0	1	0	7	1

In [74]:
```
e2.shape
```

Out[74]:
```
(824, 10)
```

In [75]:
```
s1=e1.sample(200,random_state=0)
s2=e2.sample(200,random_state=0)
```

In [76]:
```
from scipy.stats import ttest_ind
```

P Value Approach

In [77]:
```
ttest_ind(s1["avgMonthlyHours"],s2["avgMonthlyHours"])
```

Out[77]:
```
Ttest_indResult(statistic=0.559273884718837, pvalue=0.576289384564243)
```

Two Sample T-Test Conclusion

In [78]:
```
# p value > 0.05 Hence accept null hypothesis
# The mean avg monthly hours of a employee having experience of 2-5 yrs is the same as that for employee having exp 6 - 10 yrs
```

d. F-Test for Variance

Problem

Compute the f-statistics of the previous problem statement

In [79]:
```
# Null hypothesis - Variances are same
# Alternate hypothesis - Variances are not same
```

In [80]:
```
# F-test for variance is used to test if the variances of two populations are equal.
```

In [81]:
```
# Sample Variance
print(s1.avgMonthlyHours.var())
print(s2.avgMonthlyHours.var())
```

```
2225.241306532664
2680.904522613066
```

In [82]:
```
# Degrees offreedom for sample
df1=len(s1)-1
df2=len(s2)-1
```

P-Value Approach

In [83]:
```
# Computing f statistic
from scipy.stats import f
F=s1.avgMonthlyHours.var()/s2.avgMonthlyHours.var()
print(F)

#P Value Greater than 0.05, Hence Accept Null Hypothesis
```

```
0.8300337769447048
```

In [84]:
```
import scipy.stats
```

Critical Value Approach

In [85]:
```
cv = scipy.stats.f.cdf(F, df1, df2) #Critical Value
```

In [86]:
```
f.ppf([alpha/2,1-alpha/2],df1, df2)
```

Out[86]:
```
array([0.75678659, 1.32137648])
```

Two Variance F-Test Conclusion

In [87]:
```
# p value is >0.05, accept null hypothesis, equal variances
```

Conclusions Using Statistical Analysis

- On the basis of one sample T-Test, we found out that average monthly hours for employees with 2 years of experience 167 hours wjile i is is not 167 hours for employees having more than 2 yrs of experience. Therefore, the reason for employees leaving might be workload due to extra working hours
- On the basis one sample proportion test, we found out percentage of employee leaving the company having the experience of 2 years is same as employee having experience more than 2 yrs, so experience might not be an issue as we have strong issues like number of projects, promotion which may lead to high attrition
- On the basis of two sample T-Test, we found out The mean average monthly hours of an employee having experience of 2-5 yrs is the same as that for employee having exp 6 - 10 yrs but from EDA we know for employees with less than 2 Years of experience, the average monthly work hours are pretty high and add up as work stress.