Untitled

June 26, 2024

[1]:
```
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
```

[2]:
```
df = pd.read_csv("HR.csv")
```

[3]:
```
df
```

[3]:
```
       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    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]
```

[4]:
```
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_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   sales                  14999 non-null  object
 9   salary                 14999 non-null  object
dtypes: float64(2), int64(6), object(2)
memory usage: 1.1+ MB
```

[5]:
```
df.isna().sum()
```

[5]:
```
satisfaction_level       0
last_evaluation          0
number_project           0
average_montly_hours     0
time_spend_company       0
Work_accident            0
left                     0
promotion_last_5years    0
sales                    0
```

```
salary                  0
dtype: int64
```

[6]:
```
df["left"].unique()
```

[6]:
```
array([1, 0])
```

[7]:
```
df["promotion_last_5years"].unique()
```

[7]:
```
array([0, 1])
```

[8]:
```
df["number_project"].unique()
```

[8]:
```
array([2, 5, 7, 6, 4, 3])
```

[9]:
```
df.satisfaction_level.unique()
```

[9]:
```
array([0.38, 0.8 , 0.11, 0.72, 0.37, 0.41, 0.1 , 0.92, 0.89, 0.42, 0.45,
       0.84, 0.36, 0.78, 0.76, 0.09, 0.46, 0.4 , 0.82, 0.87, 0.57, 0.43,
       0.13, 0.44, 0.39, 0.85, 0.81, 0.9 , 0.74, 0.79, 0.17, 0.24, 0.91,
       0.71, 0.86, 0.14, 0.75, 0.7 , 0.31, 0.73, 0.83, 0.32, 0.54, 0.27,
       0.77, 0.88, 0.48, 0.19, 0.6 , 0.12, 0.61, 0.33, 0.56, 0.47, 0.28,
       0.55, 0.53, 0.59, 0.66, 0.25, 0.34, 0.58, 0.51, 0.35, 0.64, 0.5 ,
       0.23, 0.15, 0.49, 0.3 , 0.63, 0.21, 0.62, 0.29, 0.2 , 0.16, 0.65,
       0.68, 0.67, 0.22, 0.26, 0.99, 0.98, 1.  , 0.52, 0.93, 0.97, 0.69,
       0.94, 0.96, 0.18, 0.95])
```

[10]:
```
df.last_evaluation.unique()
```

[10]:
```
array([0.53, 0.86, 0.88, 0.87, 0.52, 0.5 , 0.77, 0.85, 1.  , 0.54, 0.81,
       0.92, 0.55, 0.56, 0.47, 0.99, 0.51, 0.89, 0.83, 0.95, 0.57, 0.49,
       0.46, 0.62, 0.94, 0.48, 0.8 , 0.74, 0.7 , 0.78, 0.91, 0.93, 0.98,
       0.97, 0.79, 0.59, 0.84, 0.45, 0.96, 0.68, 0.82, 0.9 , 0.71, 0.6 ,
       0.65, 0.58, 0.72, 0.67, 0.75, 0.73, 0.63, 0.61, 0.76, 0.66, 0.69,
       0.37, 0.64, 0.39, 0.41, 0.43, 0.44, 0.36, 0.38, 0.4 , 0.42])
```

[11]:
```
df.time_spend_company.unique()
```

[11]:
```
array([ 3,  6,  4,  5,  2,  8, 10,  7])
```

[12]:
```
df.Work_accident.unique()
```

[12]:
```
array([0, 1])
```

[13]:
```
df.sales.unique()
```

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

[14]:
```
df.salary.unique()
```

[14]:
```
array(['low', 'medium', 'high'], dtype=object)
```

[15]:
```
df.corr()
```

```
/tmp/ipykernel_352/635785762.py:1: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numeric_only
to silence this warning.
  df.corr()
```

[15]:

	satisfaction_level	last_evaluation	number_project	\
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	

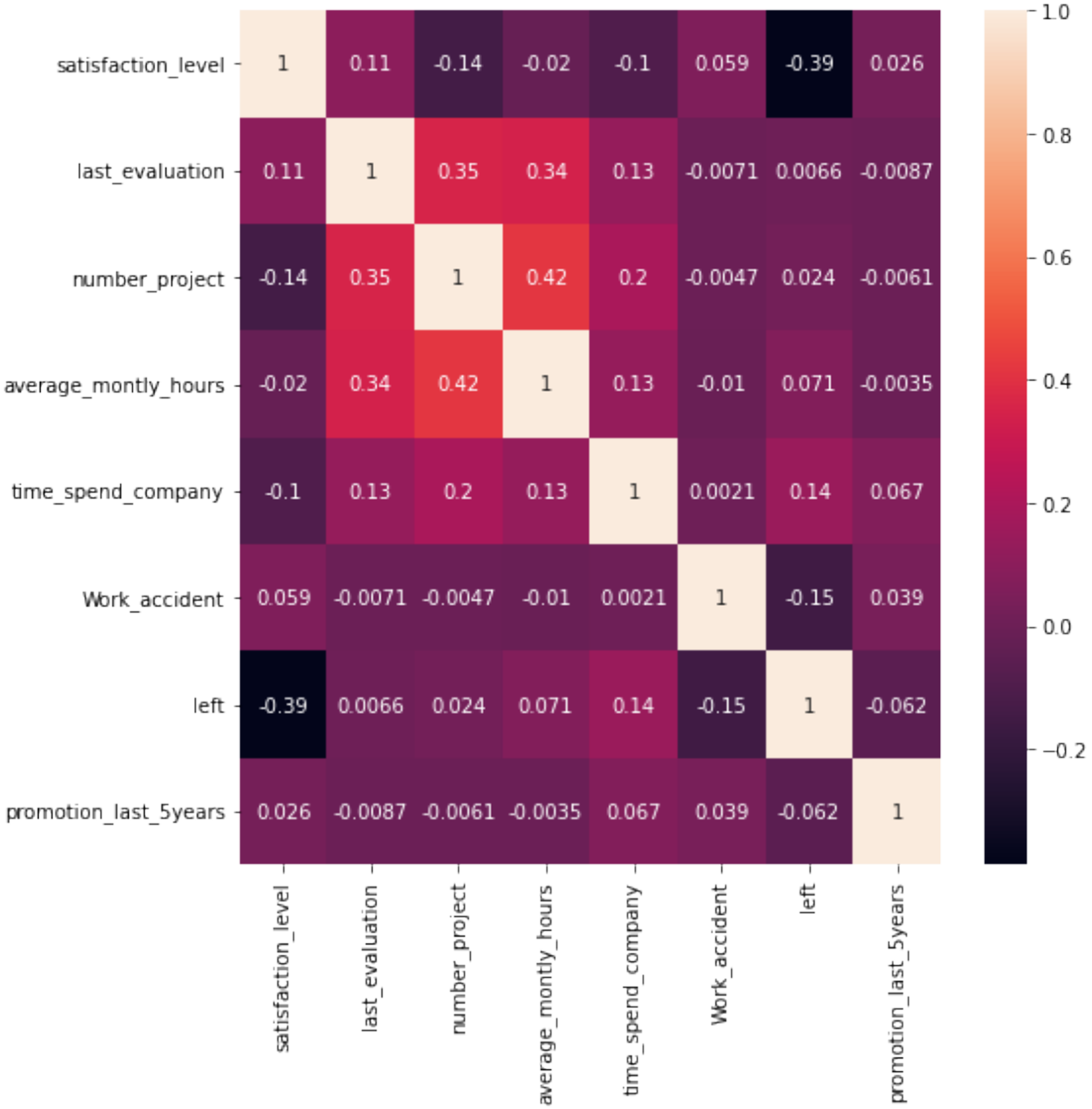
	average_montly_hours	time_spend_company	\
satisfaction_level	-0.020048	-0.100866	
last_evaluation	0.339742	0.131591	
number_project	0.417211	0.196786	
average_montly_hours	1.000000	0.127755	
time_spend_company	0.127755	1.000000	
Work_accident	-0.010143	0.002120	
left	0.071287	0.144822	
promotion_last_5years	-0.003544	0.067433	

	Work_accident	left	promotion_last_5years
satisfaction_level	0.058697	-0.388375	0.025605
last_evaluation	-0.007104	0.006567	-0.008684
number_project	-0.004741	0.023787	-0.006064
average_montly_hours	-0.010143	0.071287	-0.003544
time_spend_company	0.002120	0.144822	0.067433
Work_accident	1.000000	-0.154622	0.039245
left	-0.154622	1.000000	-0.061788
promotion_last_5years	0.039245	-0.061788	1.000000

[16]:
```
plt.figure(figsize=(8,8))
sns.heatmap(df.corr(),annot=True)
```

```
/tmp/ipykernel_352/609742482.py:2: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numeric_only
to silence this warning.
  sns.heatmap(df.corr(),annot=True)
```

[16]: <AxesSubplot: >



[17]:
```
df1= df.groupby(["sales"])["left"].value_counts().reset_index(name="count")
df1=pd.DataFrame(df1)
```

[18]:
```
df["sales"].value_counts()
```

[18]:
```
sales          4140
technical      2720
support        2229
IT             1227
product_mng     902
marketing       858
RandD           787
accounting      767
hr              739
management      630
Name: sales, dtype: int64
```

[19]:
```
dft=df["sales"].value_counts().reset_index(name="Total")
```

[20]:
```
dft=dft.rename(columns={"index":"sales"})
```

[21]:
```
dft
```

[21]:

	sales	Total
0	sales	4140
1	technical	2720
2	support	2229
3	IT	1227
4	product_mng	902
5	marketing	858
6	RandD	787
7	accounting	767
8	hr	739
9	management	630

[22]:
```
dfmer=df1.merge(dft,how="left")
```

[23]:
```
dfmer
```

[23]:

	sales	left	count	Total
0	IT	0	954	1227
1	IT	1	273	1227
2	RandD	0	666	787
3	RandD	1	121	787
4	accounting	0	563	767
5	accounting	1	204	767
6	hr	0	524	739
7	hr	1	215	739
8	management	0	539	630
9	management	1	91	630

```
10    marketing     0    655    858
11    marketing     1    203    858
12  product_mng     0    704    902
13  product_mng     1    198    902
14        sales     0   3126   4140
15        sales     1   1014   4140
16      support     0   1674   2229
17      support     1    555   2229
18    technical     0   2023   2720
19    technical     1    697   2720
```

[24]:
```
dfmer["normal"]=dfmer["count"].div(dfmer["Total"].values)
dfmer["normal"]=dfmer["normal"]*100
```

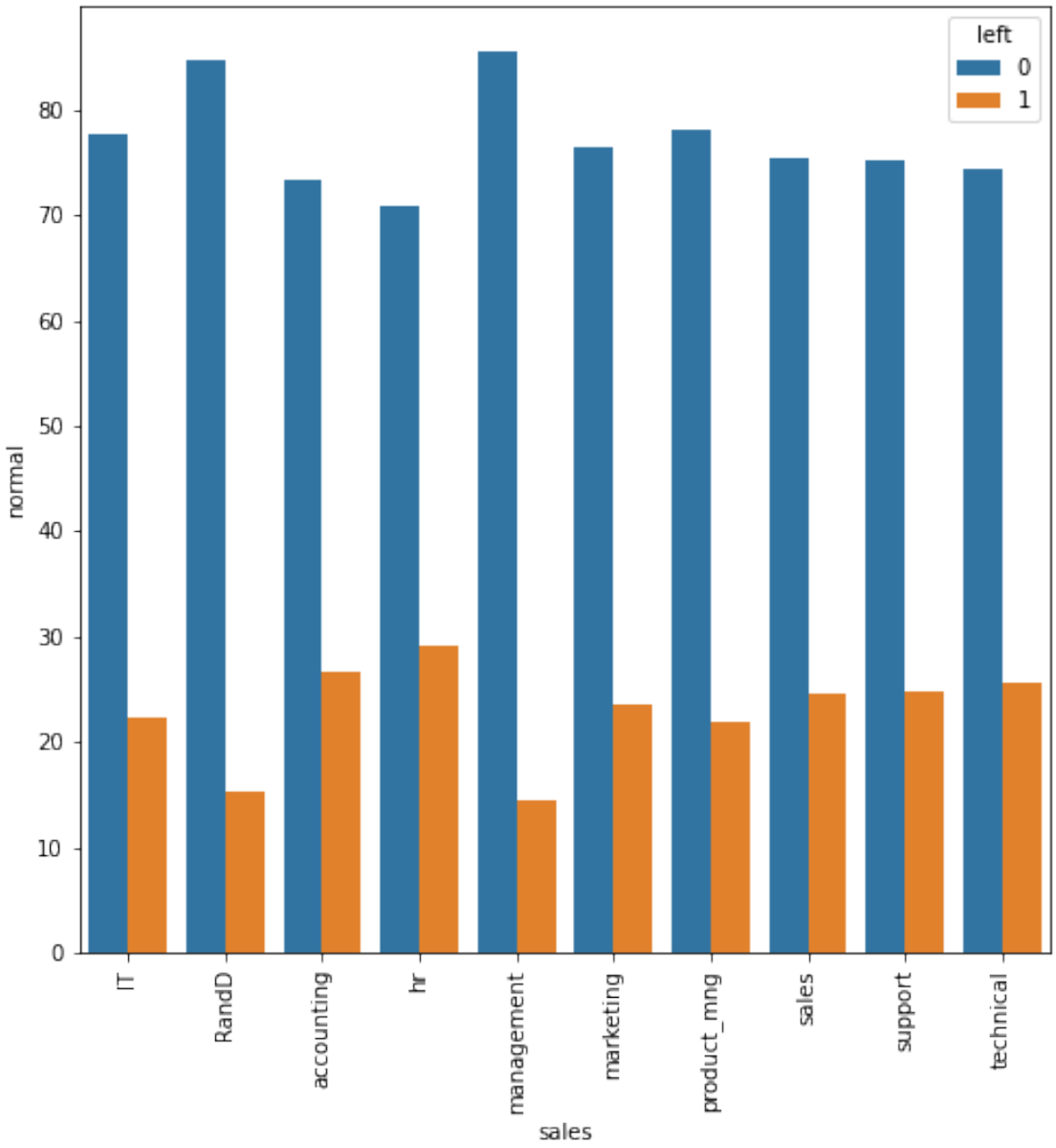
[25]:
```
dfmer
```

[25]:
```
          sales  left  count  Total     normal
0            IT     0    954   1227  77.750611
1            IT     1    273   1227  22.249389
2         RandD     0    666    787  84.625159
3         RandD     1    121    787  15.374841
4    accounting     0    563    767  73.402868
5    accounting     1    204    767  26.597132
6            hr     0    524    739  70.906631
7            hr     1    215    739  29.093369
8    management     0    539    630  85.555556
9    management     1     91    630  14.444444
10    marketing     0    655    858  76.340326
11    marketing     1    203    858  23.659674
12  product_mng     0    704    902  78.048780
13  product_mng     1    198    902  21.951220
14        sales     0   3126   4140  75.507246
15        sales     1   1014   4140  24.492754
16      support     0   1674   2229  75.100942
17      support     1    555   2229  24.899058
18    technical     0   2023   2720  74.375000
19    technical     1    697   2720  25.625000
```

[26]:
```
plt.figure(figsize=(8,8))
sns.barplot(x="sales",y='normal',hue="left",data=dfmer)
plt.xticks(rotation=90)
```

[26]:
```
(array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9]),
 [Text(0, 0, 'IT'),
  Text(1, 0, 'RandD'),
  Text(2, 0, 'accounting'),
```

```
Text(3, 0, 'hr'),
Text(4, 0, 'management'),
Text(5, 0, 'marketing'),
Text(6, 0, 'product_mng'),
Text(7, 0, 'sales'),
Text(8, 0, 'support'),
Text(9, 0, 'technical')])
```



[27]:

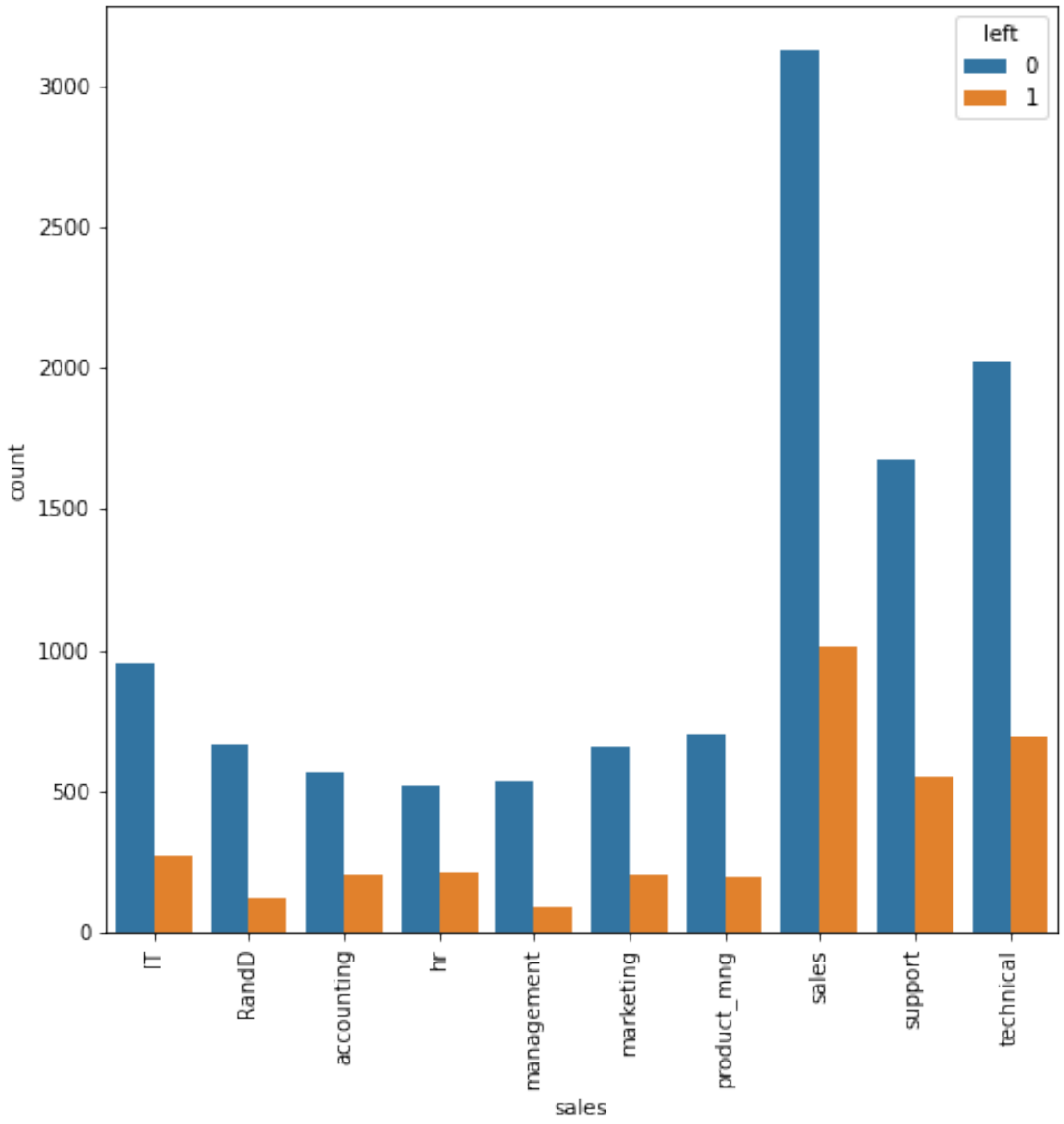
```
#People from the hr department are leaving the highest based on the normalized␣
 ↪data.The Hr department has the highest percentage. Normal = (Count of people␣
 ↪from leaving category in a department)/(Total number of people in that␣
 ↪department)*100
```

[28]:
```
df1.head()
```

[28]:
```
        sales  left  count
0          IT     0    954
1          IT     1    273
2       RandD     0    666
3       RandD     1    121
4  accounting     0    563
```

[29]:
```
plt.figure(figsize=(8,8))
sns.barplot(x="sales",y='count',hue="left",data=df1)
plt.xticks(rotation=90)
```

[29]:
```
(array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9]),
 [Text(0, 0, 'IT'),
  Text(1, 0, 'RandD'),
  Text(2, 0, 'accounting'),
  Text(3, 0, 'hr'),
  Text(4, 0, 'management'),
  Text(5, 0, 'marketing'),
  Text(6, 0, 'product_mng'),
  Text(7, 0, 'sales'),
  Text(8, 0, 'support'),
  Text(9, 0, 'technical')])
```



[30]:
```
#The people from the sales department are leaing the highest if we look at only␣
 ↪the count of leaving people.
```

[31]:
```
df2= df.groupby(["salary"])["left"].value_counts().reset_index(name="count")
df2=pd.DataFrame(df2)
```

[32]:
```
df2.head()
```

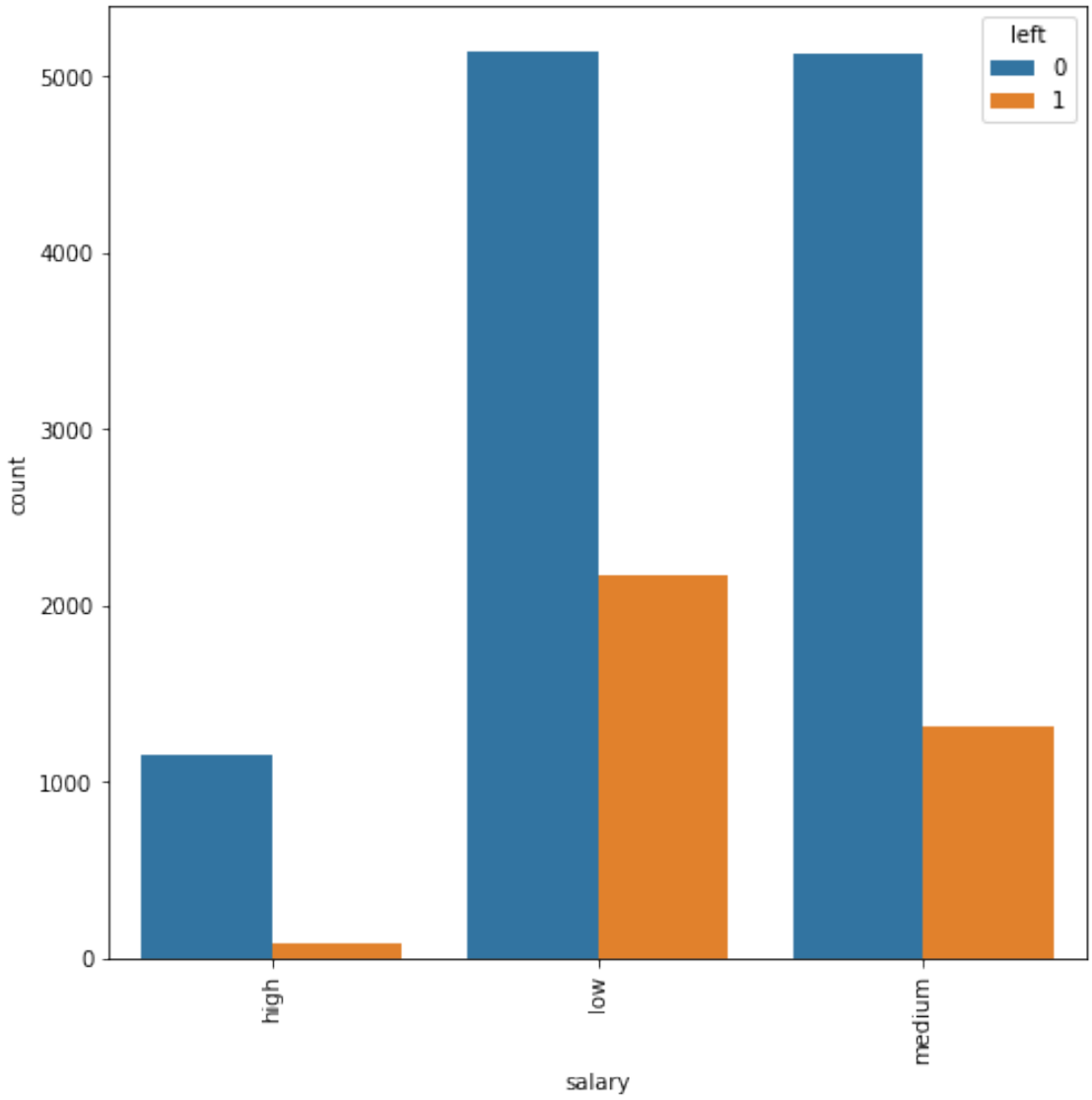
[32]:

	salary	left	count
0	high	0	1155
1	high	1	82

```
2      low      0   5144
3      low      1   2172
4   medium      0   5129
```

[33]:
```
plt.figure(figsize=(8,8))
sns.barplot(x="salary",y='count',hue="left",data=df2)
plt.xticks(rotation=90)
```

[33]:
```
(array([0, 1, 2]),
 [Text(0, 0, 'high'), Text(1, 0, 'low'), Text(2, 0, 'medium')])
```

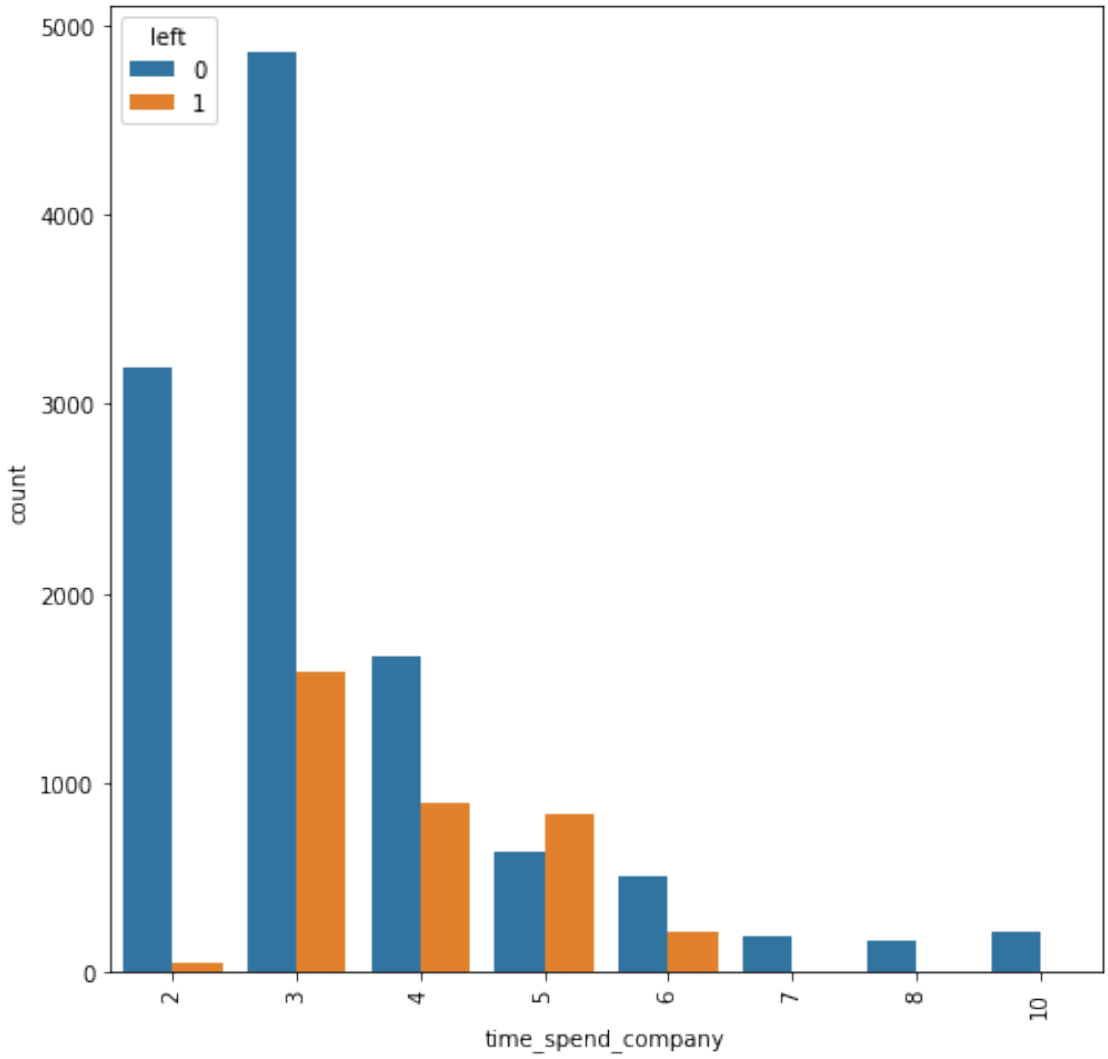


[34]:
```
#People with Lower Salaries are leaving the company
```

[35]:
```
df3= df.groupby(["time_spend_company"])["left"].value_counts().
  ↪reset_index(name="count")
df3=pd.DataFrame(df3)
```

[36]:
```
#time_spend_company
plt.figure(figsize=(8,8))
sns.barplot(x="time_spend_company",y='count',hue="left",data=df3)
plt.xticks(rotation=90)
```

[36]:
```
(array([0, 1, 2, 3, 4, 5, 6, 7]),
 [Text(0, 0, '2'),
  Text(1, 0, '3'),
  Text(2, 0, '4'),
  Text(3, 0, '5'),
  Text(4, 0, '6'),
  Text(5, 0, '7'),
  Text(6, 0, '8'),
  Text(7, 0, '10')])
```



[37]:
```
#People with experience of 3 to 5 years are leaving the comapny more.
```

[38]:
```
plt.figure(figsize=(8,8))
sns.countplot("Work_accident",hue="left",data=df)
plt.xticks(rotation=90)
```

```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
/tmp/ipykernel_352/83986659.py in <cell line: 2>()
      1 plt.figure(figsize=(8,8))
----> 2 sns.countplot("Work_accident",hue="left",data=df)
      3 plt.xticks(rotation=90)
      4
```

```
TypeError: countplot() got multiple values for argument 'data'
```

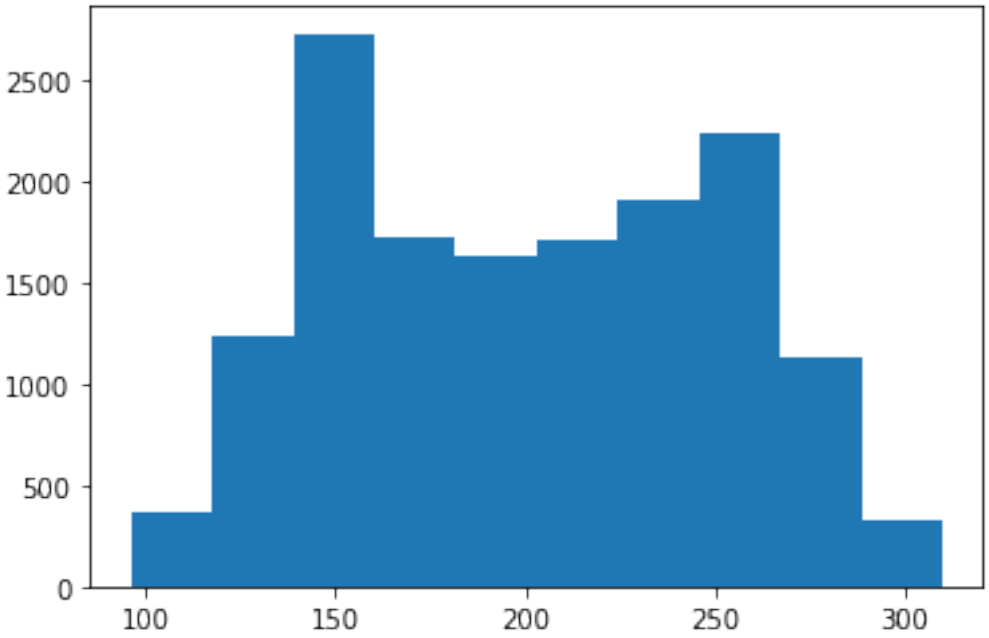
```
<Figure size 576x576 with 0 Axes>
```

[39]:
```
df.columns
```

[39]:
```
Index(['satisfaction_level', 'last_evaluation', 'number_project',
       'average_montly_hours', 'time_spend_company', 'Work_accident', 'left',
       'promotion_last_5years', 'sales', 'salary'],
      dtype='object')
```

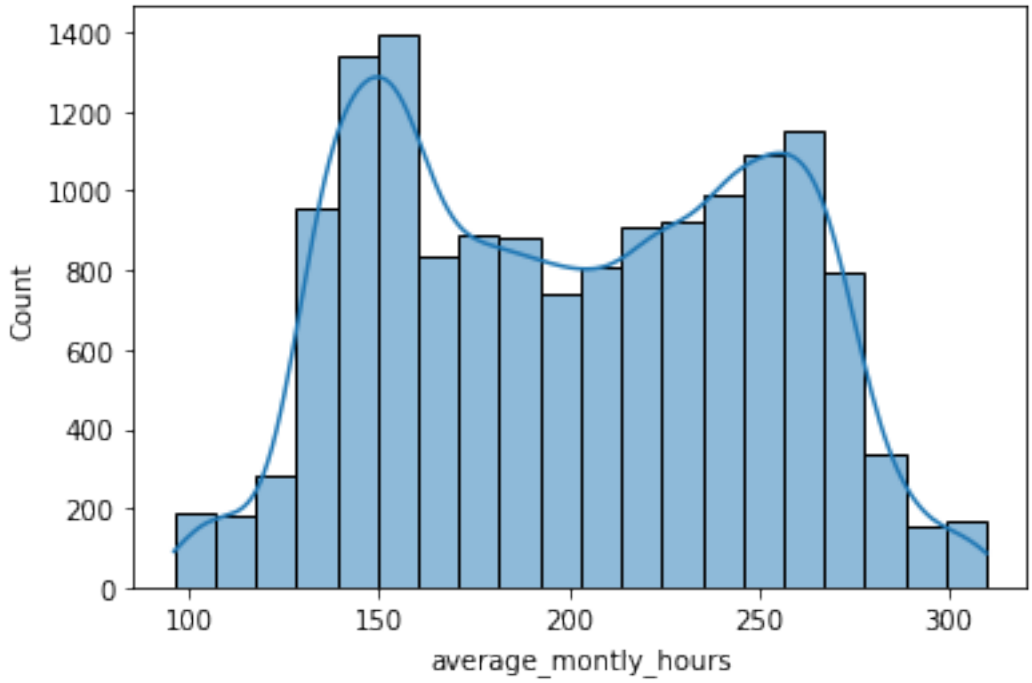
[40]:
```
plt.hist(df["average_montly_hours"])
```

[40]:
```
(array([ 367., 1240., 2733., 1722., 1628., 1712., 1906., 2240., 1127.,
         324.]),
 array([ 96. , 117.4, 138.8, 160.2, 181.6, 203. , 224.4, 245.8, 267.2,
        288.6, 310. ]),
 <BarContainer object of 10 artists>)
```



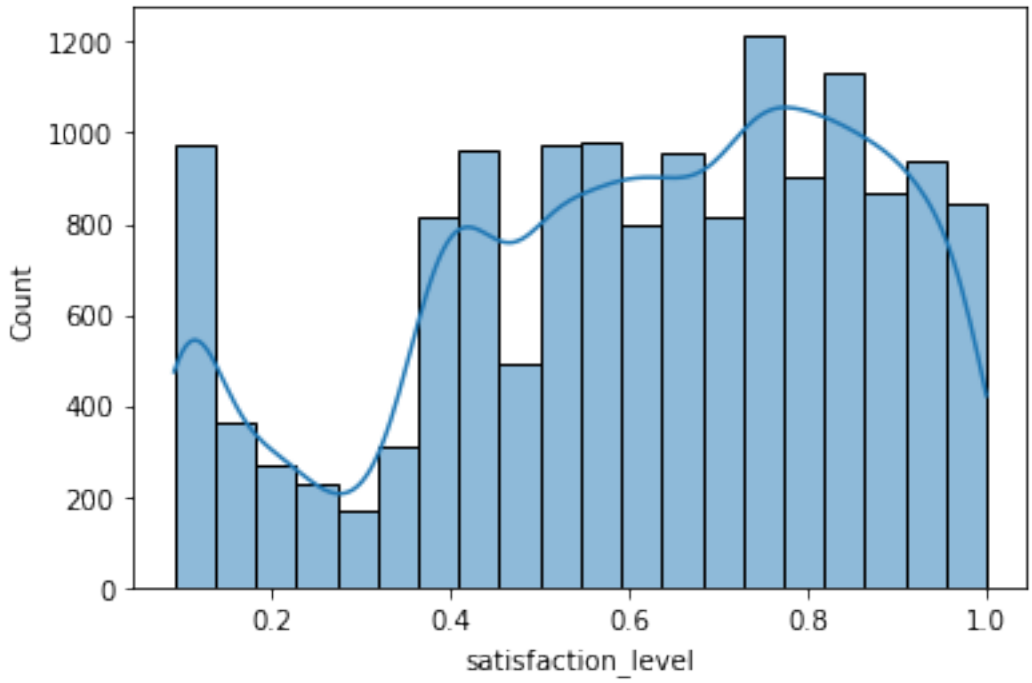
[41]:
```
sns.histplot(data = df,x="average_montly_hours", kde = True,bins=20)
```

[41]:
```
<AxesSubplot: xlabel='average_montly_hours', ylabel='Count'>
```



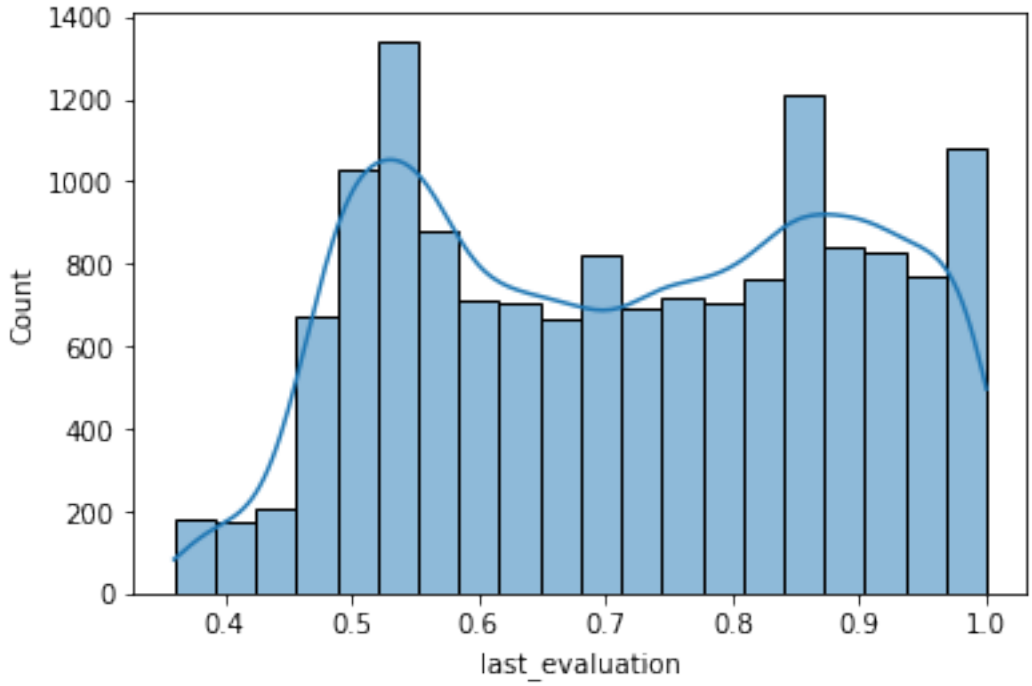
[42]:
```
sns.histplot(data = df,x="satisfaction_level", kde = True,bins=20)
```

[42]: <AxesSubplot: xlabel='satisfaction_level', ylabel='Count'>



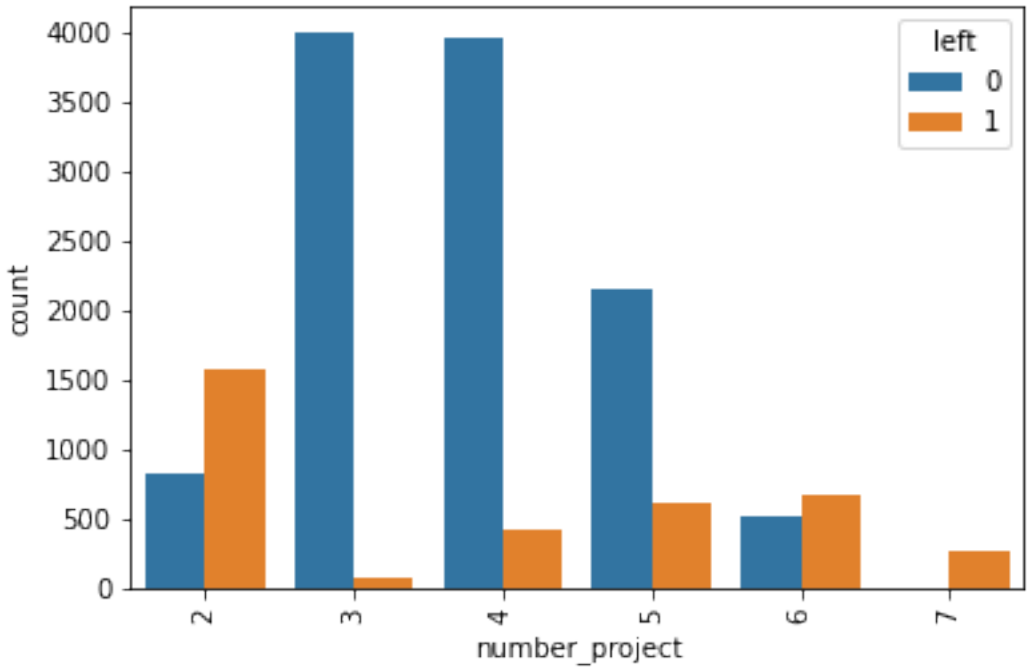
[43]:
```
sns.histplot(data = df,x="last_evaluation", kde = True,bins=20)
```

[43]:
```
<AxesSubplot: xlabel='last_evaluation', ylabel='Count'>
```



[44]:
```
sns.countplot(x="number_project",hue="left",data=df)
plt.xticks(rotation=90)
```

[44]:
```
(array([0, 1, 2, 3, 4, 5]),
 [Text(0, 0, '2'),
  Text(1, 0, '3'),
  Text(2, 0, '4'),
  Text(3, 0, '5'),
  Text(4, 0, '6'),
  Text(5, 0, '7')])
```



[45]:
```
#People who have worked on 3 or 4 projects have left the organisation more.
```

[46]:
```
dfclus = df[["satisfaction_level","last_evaluation","left"]]
```

[47]:
```
dfclus
```

[47]:

	satisfaction_level	last_evaluation	left
0	0.38	0.53	1
1	0.80	0.86	1
2	0.11	0.88	1
3	0.72	0.87	1
4	0.37	0.52	1
…	…	…	…
14994	0.40	0.57	1
14995	0.37	0.48	1
14996	0.37	0.53	1
14997	0.11	0.96	1
14998	0.37	0.52	1

[14999 rows x 3 columns]

[48]:
```
from sklearn.cluster import KMeans
```

[49]:
```
km=dfclus.iloc[:,:].values
kmeans = KMeans(n_clusters=3, random_state=0)
label = kmeans.fit_predict(dfclus)
labelarr = kmeans.fit_predict(km)
```

```
/voc/work/.local/lib/python3.10/site-packages/sklearn/cluster/_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/voc/work/.local/lib/python3.10/site-packages/sklearn/cluster/_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
```

[50]:
```
label
```

[50]:
```
array([1, 1, 1, …, 1, 1, 1], dtype=int32)
```

[51]:
```
dfclus[label==0].describe()
```

[51]:

	satisfaction_level	last_evaluation	left
count	6720.000000	6720.000000	6720.0
mean	0.813112	0.739728	0.0
std	0.108167	0.154900	0.0
min	0.590000	0.360000	0.0
25%	0.720000	0.610000	0.0
50%	0.810000	0.740000	0.0
75%	0.910000	0.870000	0.0
max	1.000000	1.000000	0.0

[52]:
```
dfclus[label==1].describe()
```

[52]:

	satisfaction_level	last_evaluation	left
count	3571.000000	3571.000000	3571.0
mean	0.440098	0.718113	1.0
std	0.263933	0.197673	0.0
min	0.090000	0.450000	1.0
25%	0.130000	0.520000	1.0
50%	0.410000	0.790000	1.0
75%	0.730000	0.900000	1.0
max	0.920000	1.000000	1.0

[53]:
```
dfclus[label==2].describe()
```

[53]:

	satisfaction_level	last_evaluation	left
count	4708.000000	4708.000000	4708.0

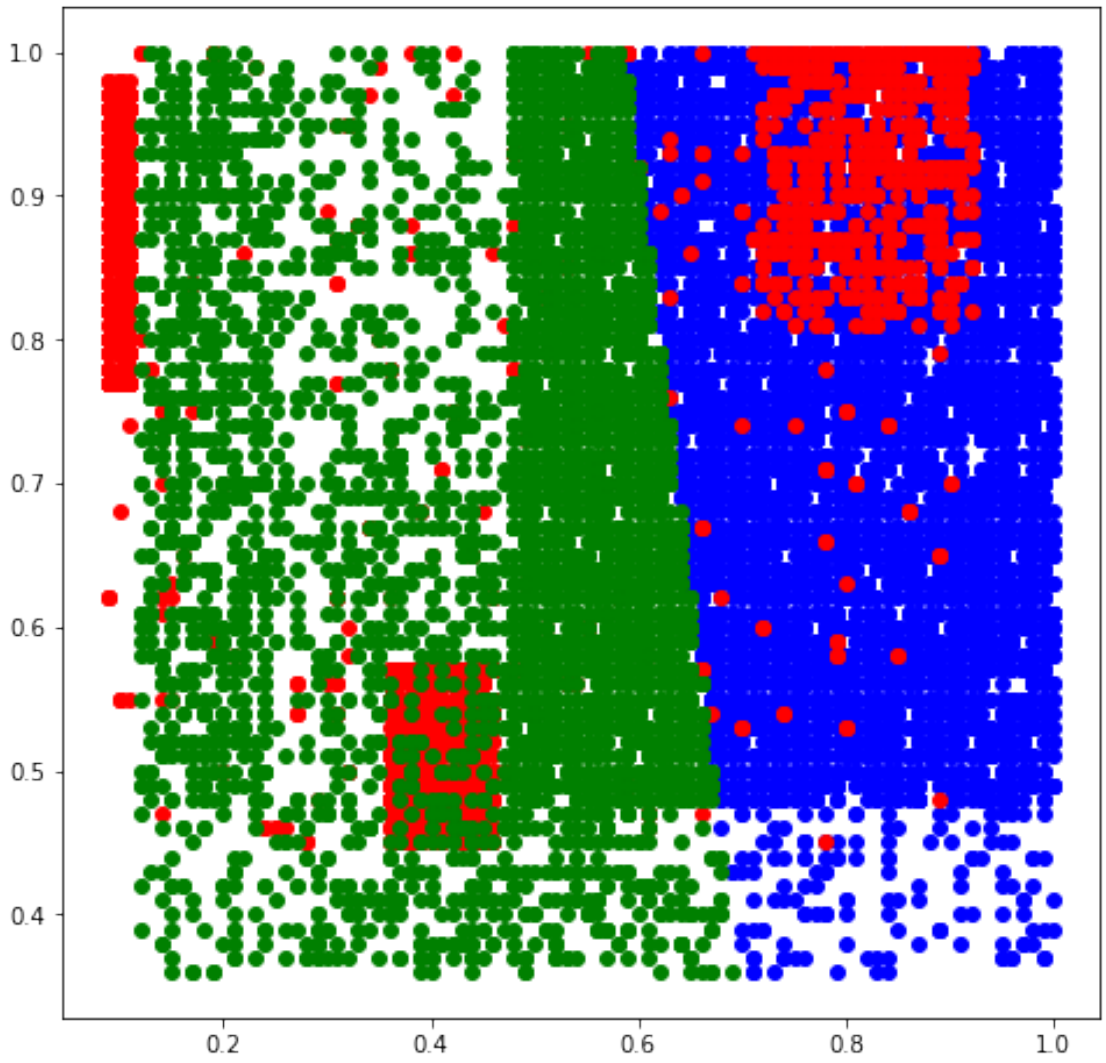
```
mean        0.457984    0.680854    0.0
std         0.153456    0.165609    0.0
min         0.120000    0.360000    0.0
25%         0.350000    0.550000    0.0
50%         0.510000    0.670000    0.0
75%         0.570000    0.810000    0.0
max         0.690000    1.000000    0.0
```

[54]:
```
km[label==0,1]
```

[54]:
```
array([0.67, 0.82, 0.91, …, 0.55, 0.95, 0.54])
```

[55]:
```
plt.figure(figsize=(8,8))
plt.scatter(km[label==0,0],km[label==0,1],color="blue")
plt.scatter(km[label==1,0],km[label==1,1],color="red")
plt.scatter(km[label==2,0],km[label==2,1],color="green")
```

[55]:
```
<matplotlib.collections.PathCollection at 0x7ff7810fff10>
```



The Blue cluster denotes people with best satisfaction levels and scored high in the last evaluation.

The Red cluster denotes people with medium satisfaction levels and scored average to high in the last evaluation

The green cluster denotes people with lower satisfaction levels and scored fairly than the above mentioned clusters.

[56]:
```
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_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   sales                  14999 non-null  object
 9   salary                 14999 non-null  object
dtypes: float64(2), int64(6), object(2)
memory usage: 1.1+ MB
```

[57]:
```
df_numerical=df.select_dtypes(include=['int64','float64'])
df_categorical=df.select_dtypes(include=['object'])
```

Converting the categorical data into numerical using one hot encoding

[58]:
```
df = pd.get_dummies(data=df,columns=['sales','salary'])
df_converted = pd.get_dummies(data=df_categorical)
```

[59]:
```
df_converted.head()
```

[59]:

	sales_IT	sales_RandD	sales_accounting	sales_hr	sales_management	\
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	0	0	0	
3	0	0	0	0	0	
4	0	0	0	0	0	

	sales_marketing	sales_product_mng	sales_sales	sales_support	\
0	0	0	1	0	
1	0	0	1	0	
2	0	0	1	0	
3	0	0	1	0	
4	0	0	1	0	

	sales_technical	salary_high	salary_low	salary_medium
0	0	0	1	0
1	0	0	0	1
2	0	0	0	1
3	0	0	1	0
4	0	0	1	0

[60]:
```
dfn = pd.concat([df_numerical, df_converted], axis=1, join="inner")
```

[61]:
```
dfn.shape
```

[61]: (14999, 21)

[62]:
```
dfn.head()
```

[62]:

	satisfaction_level	last_evaluation	number_project	average_montly_hours	\
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	

	time_spend_company	Work_accident	left	promotion_last_5years	sales_IT	\
0	3	0	1	0	0	
1	6	0	1	0	0	
2	4	0	1	0	0	
3	5	0	1	0	0	
4	3	0	1	0	0	

	sales_RandD	…	sales_hr	sales_management	sales_marketing	\
0	0	…	0	0	0	
1	0	…	0	0	0	
2	0	…	0	0	0	
3	0	…	0	0	0	
4	0	…	0	0	0	

	sales_product_mng	sales_sales	sales_support	sales_technical	\
0	0	1	0	0	
1	0	1	0	0	
2	0	1	0	0	
3	0	1	0	0	
4	0	1	0	0	

	salary_high	salary_low	salary_medium
0	0	1	0
1	0	0	1
2	0	0	1
3	0	1	0
4	0	1	0

[5 rows x 21 columns]

Splitting the dataset into training and testing in the ratio of 80:20 with random state = 123.

[63]:
```
x =dfn.drop("left",axis=1)
y = dfn["left"]
```

[64]:
```
from sklearn.model_selection import train_test_split
xtrain,xtest,ytrain,ytest = train_test_split(x,y,test_size=0.2,random_state=123)
```

[65]:
```
xtrain.shape,ytrain.shape,xtest.shape,ytest.shape
```

[65]:
```
((11999, 20), (11999,), (3000, 20), (3000,))
```

[66]:
```
ytrain.value_counts()
```

[66]:
```
0    9137
1    2862
Name: left, dtype: int64
```

Data is highly imbalanced for the training dataset as the record of people who left is very low in comparision to the record of people who didn't leave.

Using SMOTE to handle the imbalance for the left category

[ ]:
```
```

[67]:
```
pip install scikit-learn==1.2.2 imblearn==0.9.1
```

```
Defaulting to user installation because normal site-packages is not writeable
Requirement already satisfied: scikit-learn==1.2.2 in
/voc/work/.local/lib/python3.10/site-packages (1.2.2)
ERROR: Could not find a version that satisfies the requirement

imblearn==0.9.1 (from versions: 0.0)

ERROR: No matching distribution found for imblearn==0.9.1

Note: you may need to restart the kernel to use updated packages.
```

[68]:
```
pip install -- upgrade pip
```

```
Defaulting to user installation because normal site-packages is not writeable
ERROR: Could not find a version that satisfies the requirement upgrade

(from versions: none)

ERROR: No matching distribution found for upgrade

Note: you may need to restart the kernel to use updated packages.
```

[69]:
```
pip install --upgrade pip
```

```
Defaulting to user installation because normal site-packages is not writeable
Requirement already satisfied: pip in /voc/work/.local/lib/python3.10/site-
packages (24.1)
Note: you may need to restart the kernel to use updated packages.
```

[70]:
```
pip install scikit-learn==1.2.2 imbalanced-learn==0.10.1
```

```
Defaulting to user installation because normal site-packages is not writeable
Requirement already satisfied: scikit-learn==1.2.2 in
/voc/work/.local/lib/python3.10/site-packages (1.2.2)
Requirement already satisfied: imbalanced-learn==0.10.1 in
/voc/work/.local/lib/python3.10/site-packages (0.10.1)
Requirement already satisfied: numpy>=1.17.3 in /usr/local/lib/python3.10/site-
packages (from scikit-learn==1.2.2) (1.23.5)
Requirement already satisfied: scipy>=1.3.2 in /usr/local/lib/python3.10/site-
packages (from scikit-learn==1.2.2) (1.9.3)
Requirement already satisfied: joblib>=1.1.1 in /usr/local/lib/python3.10/site-
packages (from scikit-learn==1.2.2) (1.2.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.10/site-packages (from scikit-learn==1.2.2) (3.1.0)
Note: you may need to restart the kernel to use updated packages.
```

[71]:
```
pip install scikit-learn imbalanced-learn
```

```
Defaulting to user installation because normal site-packages is not writeable
Requirement already satisfied: scikit-learn in
/voc/work/.local/lib/python3.10/site-packages (1.2.2)
Requirement already satisfied: imbalanced-learn in
/voc/work/.local/lib/python3.10/site-packages (0.10.1)
Requirement already satisfied: numpy>=1.17.3 in /usr/local/lib/python3.10/site-
packages (from scikit-learn) (1.23.5)
Requirement already satisfied: scipy>=1.3.2 in /usr/local/lib/python3.10/site-
packages (from scikit-learn) (1.9.3)
Requirement already satisfied: joblib>=1.1.1 in /usr/local/lib/python3.10/site-
packages (from scikit-learn) (1.2.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.10/site-packages (from scikit-learn) (3.1.0)
Note: you may need to restart the kernel to use updated packages.
```

[ ]:
```
pip uninstall scikit-learn imbalanced-learn
```

```
Found existing installation: scikit-learn 1.2.2
Uninstalling scikit-learn-1.2.2:
  Would remove:
    /voc/work/.local/lib/python3.10/site-packages/scikit_learn-1.2.2.dist-info/*
    /voc/work/.local/lib/python3.10/site-
packages/scikit_learn.libs/libgomp-a34b3233.so.1.0.0
    /voc/work/.local/lib/python3.10/site-packages/sklearn/*
Proceed (Y/n)?
```

[ ]:
```
Y
```

[ ]:
```
pip install --upgrade pip
```

[ ]:
```
pip install scikit-learn==1.2.2 imbalanced-learn==0.10.1
```

[ ]:
```
pip install scikit-learn imbalanced-learn
```

[ ]:
```
import sklearn
import imblearn
print(f"scikit-learn version: {sklearn.__version__}")
print(f"imblearn version: {imblearn.__version__}")

from imblearn.over_sampling import SMOTE
```

[ ]:
```
sm = SMOTE(random_state = 2)
xtrainres, ytrainres = sm.fit_resample(xtrain, ytrain)
```

[ ]:
```
ytrainres.value_counts()
```

[ ]:
```
from sklearn.model_selection import cross_val_score
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import roc_auc_score
import sklearn.metrics as metrics
```

[ ]:
```
logreg = LogisticRegression(solver='lbfgs', max_iter=10000)
```

[ ]:
```
print(cross_val_score(logreg, xtrainres, ytrainres, cv=5).mean())
```

[ ]:
```
logreg.fit(xtrainres,ytrainres)
ypred = logreg.predict(xtest)
```

[ ]:
```
from sklearn.metrics import classification_report
```

Logistic regression report

[ ]:
```
metrics.confusion_matrix(ytest,ypred)
```

[ ]:
```
print(classification_report(ytest,ypred))
```

[ ]:
```
roc_auc_score(ytest,ypred)
```

[ ]:
```
fpr, tpr, threshold = metrics.roc_curve(ytest, ypred)
print(fpr)
```

```
print(tpr)
print(threshold)
roc_auc = metrics.auc(fpr, tpr)
print(roc_auc)

# method I: plt
plt.title('Receiver Operating Characteristic for Logistic Regression')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```

[ ]:
```
randm=RandomForestClassifier(max_depth=5)
```

[ ]:
```
print(cross_val_score(randm, xtrainres, ytrainres, cv=5).mean())
```

[ ]:
```
randm.fit(xtrainres,ytrainres)
ypred1=randm.predict(xtest)
```

Random Forest Classification report

[ ]:
```
metrics.confusion_matrix(ytest,ypred1)
```

[ ]:
```
print(classification_report(ytest,ypred1))
```

[ ]:
```
roc_auc_score(ytest,ypred1)
```

[ ]:
```
fpr, tpr, threshold = metrics.roc_curve(ytest, ypred1)
print(fpr)
print(tpr)
print(threshold)
roc_auc = metrics.auc(fpr, tpr)
print(roc_auc)

# method I: plt
plt.title('Receiver Operating Characteristic for Random Forest')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
```

```
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```

[ ]:
```
from sklearn.ensemble import GradientBoostingClassifier
```

[ ]:
```
gb = GradientBoostingClassifier(n_estimators=100, learning_rate=1.
↪0,max_depth=1, random_state=0)
```

[ ]:
```
print(cross_val_score(gb, xtrainres, ytrainres, cv=5).mean())
```

[ ]:
```
gb.fit(xtrainres,ytrainres)
```

[ ]:
```
ypred2 = gb.predict(xtest)
```

Gradient boosting Classification Report

[ ]:
```
metrics.confusion_matrix(ytest,ypred2)
```

[ ]:
```
print(classification_report(ytest,ypred2))
```

[ ]:
```
roc_auc_score(ytest,ypred2)
```

[ ]:
```
fpr, tpr, threshold = metrics.roc_curve(ytest, ypred2)
print(fpr)
print(tpr)
print(threshold)
roc_auc = metrics.auc(fpr, tpr)
print(roc_auc)

# method I: plt
plt.title('Receiver Operating Characteristic for Gradient Boosting')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```

Based on the confusion matrix, the false negatives should be low because if an employee who might leave the organisation is misclassified as someone who won't leave then proper strategies to retain that person will not be implemented on him or her. Hence Recall is better metric to be used

[ ]:
```
col = xtrainres.columns
```

[ ]:
```
col
```

[ ]:
```
feature_labels = np.array(col)
```

[ ]:
```
importance = randm.feature_importances_
feature_indexes_by_importance = importance.argsort()
for index in feature_indexes_by_importance:
    print('{}-{:.2f}%'.format(feature_labels[index], (importance[index] *100.
 ↪0)))
```

[ ]:
```
predict_probability = randm.predict_proba(xtest)
```

[ ]:
```
predict_probability[:,1]
```

[ ]:
```
zone=[]
prob=[]

for i in predict_probability[:,1]:
  prob.append(i)
  if (i<=0.2):
    zone.append("Safe Zone")
  elif (i>0.2 and i<=0.6):
    zone.append("Low Risk Zone")
  elif (i>0.6 and i<=0.9):
    zone.append("Medium Risk Zone ")
  else:
    zone.append("High Risk Zone ")
```

[ ]:
```
categories = ["Safe Zone","Low Risk Zone","Medium Risk Zone ","High Risk Zone "]
color = ["Green","Yellow","Orange","Red"]
```

[ ]:
```
colordict = dict(zip(categories, color))
```

[ ]:
```
clr = pd.DataFrame({"zone":zone,"probability":prob})
```

[ ]:
```
clr["zone"].unique()
```

[ ]:
```
clr["Color"] = clr["zone"].apply(lambda x: colordict[x])
```

[ ]:
```
clr.head(10)
```

[ ]:
```
color= clr["Color"].tolist()
```

[ ]:
```
c = ["Green","Red","Orange","Yellow"]
```

[ ]:
```
plt.figure(figsize=(7,7))
sns.countplot(zone,palette=c)
```

[ ]:
```

```