Improve productivity of business executives

Problem Statement: -50% of total business executives productivity are less than the set target which impact on business performance.

1. Data Understanding and Exploration

Let's first have a look at the dataset and understand the size, attribute names etc.

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import linear_model
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso
from sklearn.model_selection import GridSearchCV
import os

# hide warnings
import warnings
warnings.filterwarnings('ignore')
sns.set_style('whitegrid')
```

In [2]:
```
# reading the dataset
df = pd.read_csv("factor analysis v11.csv")
```

Understanding the Dataset

The data dictionary contains the meaning of various attributes; some non-obvious ones are:

In [3]:
```python
# summary of the dataset: 944 rows, 16 features, no null values
print(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 767 entries, 0 to 766
Data columns (total 23 columns):
EMPCODE                              767 non-null int64
EMPNAME                              767 non-null object
Active/Inactive                      767 non-null object
Circle                               767 non-null object
Division                             767 non-null object
Category of Branch                   767 non-null object
Location Change                      767 non-null object
Seating Location                     767 non-null object
Cooling/ Non-Cooling                 767 non-null object
% Target Achieved                    767 non-null float64
Tenure in months                     767 non-null int64
Role Change Tenure                   767 non-null int64
Role Change Count                    767 non-null int64
Branches Assigned                    767 non-null int64
Leads assigned                       767 non-null int64
Age                                  767 non-null int64
Salary                               767 non-null float64
Dealers Handled                      767 non-null int64
Business through dealer              767 non-null float64
Business through others              767 non-null float64
Count of RBMI Received in Months     767 non-null int64
RBMI% Achived                        767 non-null float64
Total Business Done                  767 non-null int64
dtypes: float64(5), int64(10), object(8)
memory usage: 137.9+ KB
None
```

In [4]:
```python
# Check first 5 rows of Dataset
df.head()
```

Out[4]:

	EMPCODE	EMPNAME	Active/Inactive	Circle	Division	Category of Branch	Location Change	Seating Location	Cooling/ Non-Cooling	% Tar Achiev
0	23202947	Jegan J	A	Chennai	Trichy	Rural	No	Dindigul	Non-Cooling	
1	23207679	Sathyan K	A	Chennai	Trichy	Rural	No	Madurai	Non-Cooling	
2	23212153	Selvaprakash S	A	Chennai	Trichy	Rural	No	Karaikudi	Non-Cooling	
3	23177485	Ravindra Kumar Srivastava	A	Lucknow	Allahabad	Rural	No	Jounpur	Non-Cooling	
4	23177496	Abiral Singh	A	Lucknow	Allahabad	Rural	No	Bhadohi	Non-Cooling	

5 rows × 23 columns

In [5]:
```
#Check Statistics of Dataset
df.describe()
```

Out[5]:

	EMPCODE	% Target Achieved	Tenure in months	Role Change Tenure	Role Change Count	Branches Assigned	Leads assigned	Age	
count	7.670000e+02	767.000000	767.000000	767.000000	767.000000	767.000000	767.000000	767.000000	
mean	2.365207e+07	0.373142	32.890482	25.466754	0.331160	2.190352	9.946545	29.859192	334
std	1.199947e+06	0.257693	26.753756	19.571617	0.754348	1.470426	9.029456	4.280137	73
min	2.307143e+07	0.000000	6.000000	0.000000	0.000000	0.000000	0.000000	20.000000	170
25%	2.318465e+07	0.100000	15.000000	13.000000	0.000000	1.000000	2.000000	27.000000	286
50%	2.321819e+07	0.400000	25.000000	21.000000	0.000000	2.000000	8.000000	29.000000	329
75%	2.323724e+07	0.600000	41.000000	36.500000	0.000000	3.000000	15.000000	32.000000	367
max	2.700382e+07	1.000000	160.000000	160.000000	3.000000	9.000000	63.000000	47.000000	741

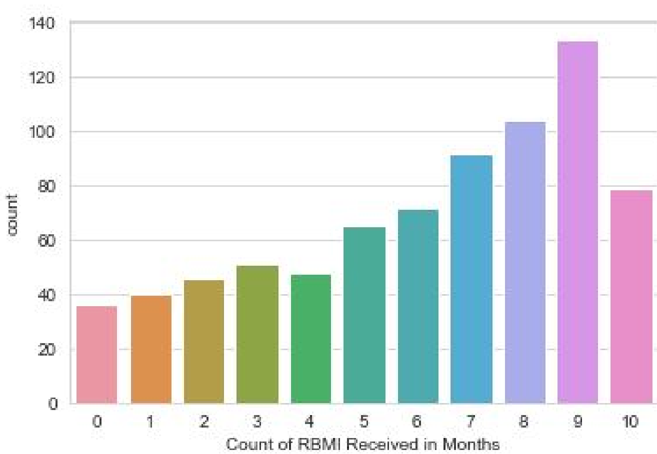
Data Cleaning¶

In [6]:
```
#Change datatype
df['EMPCODE'] = df['EMPCODE'].astype('object')
```

Explorartory Data Analysis on Categorical Variables

In [7]:
```
sns.countplot(x = 'Count of RBMI Received in Months', data = df)
```

Out[7]: <matplotlib.axes._subplots.AxesSubplot at 0x2591f3d3a20>



In [8]:
```
# Count of RBMI Achived
df['Count of RBMI Received in Months'].value_counts().T
```

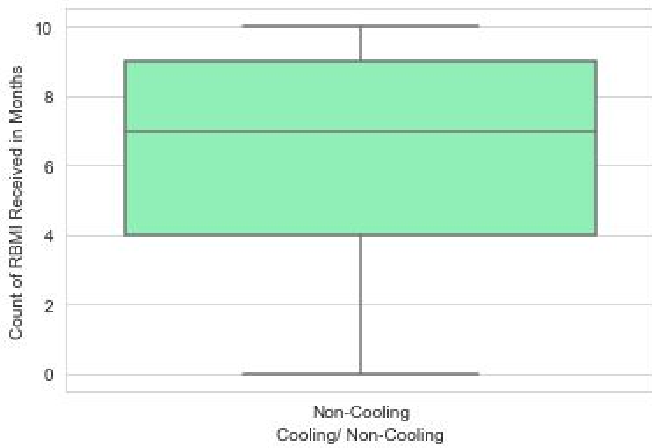
Out[8]:
```
9     134
8     104
7      92
10     79
6      72
5      65
3      51
4      48
2      46
1      40
0      36
Name: Count of RBMI Received in Months, dtype: int64
```

In [9]:
```
round(df.groupby('Cooling/ Non-Cooling').mean()['RBMI% Achived'],2)
```

Out[9]:
```
Cooling/ Non-Cooling
Non-Cooling    0.61
Name: RBMI% Achived, dtype: float64
```

In [10]:
```
# Create box plot
sns.boxplot(x = 'Cooling/ Non-Cooling', y = 'Count of RBMI Received in Months', dat
a = df, palette = 'rainbow')
```

Out[10]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x259214e9908>
```

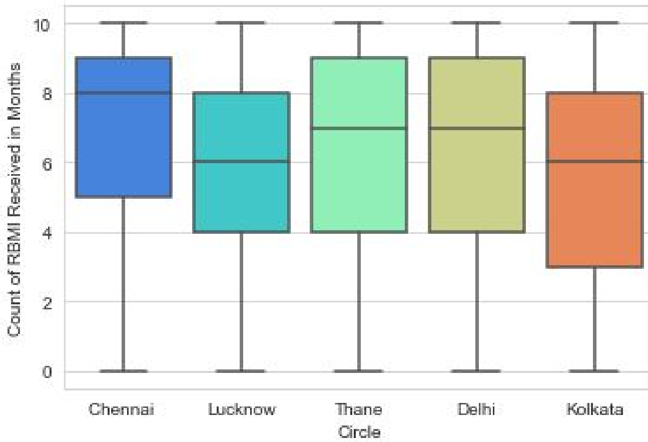


In [11]:
```
round(df.groupby('Circle').mean()['RBMI% Achived'],2)
```

Out[11]:
```
Circle
Chennai     0.66
Delhi       0.62
Kolkata     0.54
Lucknow     0.58
Thane       0.63
Name: RBMI% Achived, dtype: float64
```

In [12]:
```
# Create box plot
sns.boxplot(x = 'Circle', y = 'Count of RBMI Received in Months', data = df, palett
e = 'rainbow')
```

Out[12]: <matplotlib.axes._subplots.AxesSubplot at 0x25921572128>

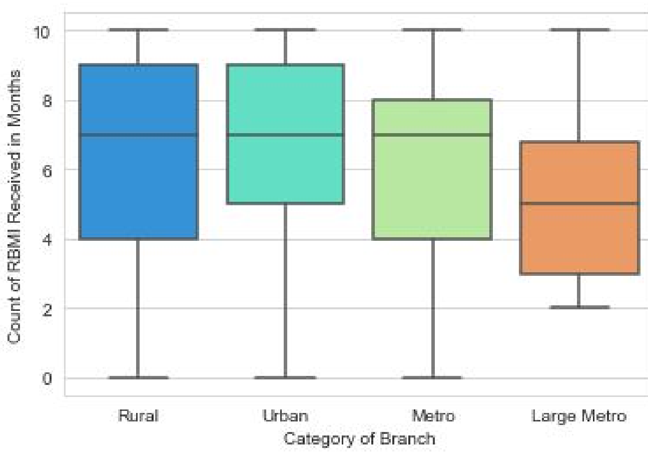


In [13]:
```
round(df.groupby('Category of Branch').mean()['RBMI% Achived'],2)
```

Out[13]:
```
Category of Branch
Large Metro    0.52
Metro          0.61
Rural          0.61
Urban          0.64
Name: RBMI% Achived, dtype: float64
```

In [14]:
```
# Create box plot
sns.boxplot(x = 'Category of Branch', y = 'Count of RBMI Received in Months', data
= df, palette = 'rainbow')
```

Out[14]: <matplotlib.axes._subplots.AxesSubplot at 0x259216175c0>

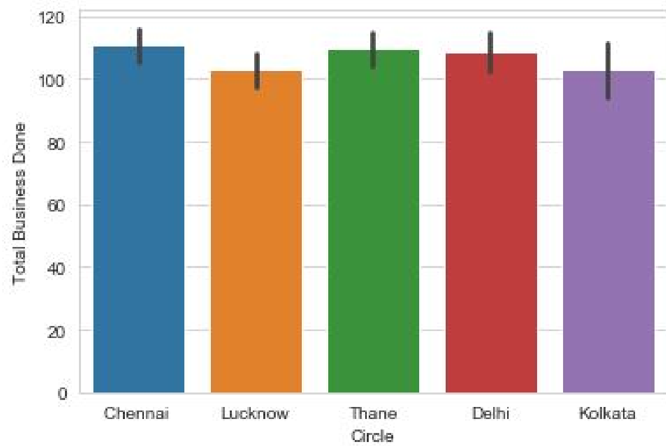


In [15]:
```
#Checking counts of object
df['Circle'].value_counts()
```

Out[15]:
```
Thane      188
Chennai    183
Lucknow    164
Delhi      145
Kolkata     87
Name: Circle, dtype: int64
```

In [16]:
```
#Create Barplot
sns.barplot(x='Circle',y='Total Business Done',data=df)
```

Out[16]: <matplotlib.axes._subplots.AxesSubplot at 0x25921556320>



In [17]:
```
# Agreegate response against the object
(df.groupby('Circle').mean()['Total Business Done'])
```

Out[17]:
```
Circle
Chennai     110.683060
Delhi       108.862069
Kolkata     103.068966
Lucknow     103.036585
Thane       109.686170
Name: Total Business Done, dtype: float64
```

In [18]:
```
#Checking counts of object
round(df.groupby('Circle').mean(),2)
```

Out[18]:

	% Target Achieved	Tenure in months	Role Change Tenure	Role Change Count	Branches Assigned	Leads assigned	Age	Salary	Dealers Handled	Business through dealer	Bu th
Circle											
Chennai	0.40	33.77	26.98	0.32	2.27	8.87	29.77	346893.54	5.97	0.38	
Delhi	0.37	35.79	28.66	0.33	1.77	10.01	30.39	341675.64	5.12	0.34	
Kolkata	0.31	28.97	21.49	0.34	3.01	10.14	29.84	313273.26	5.79	0.34	
Lucknow	0.35	30.40	24.26	0.24	1.95	8.15	29.78	324628.88	5.10	0.29	
Thane	0.39	33.79	24.43	0.42	2.27	12.41	29.62	335914.22	8.28	0.38	

In [19]:
```
#Checking counts of object
round(df.groupby('Cooling/ Non-Cooling').mean(),2)
```

Out[19]:

Cooling/ Non-Cooling	% Target Achieved	Tenure in months	Role Change Tenure	Role Change Count	Branches Assigned	Leads assigned	Age	Salary	Dealers Handled	Business through dealer	Bus thr c
Non-Cooling	0.37	32.89	25.47	0.33	2.19	9.95	29.86	334641.81	6.17	0.35	

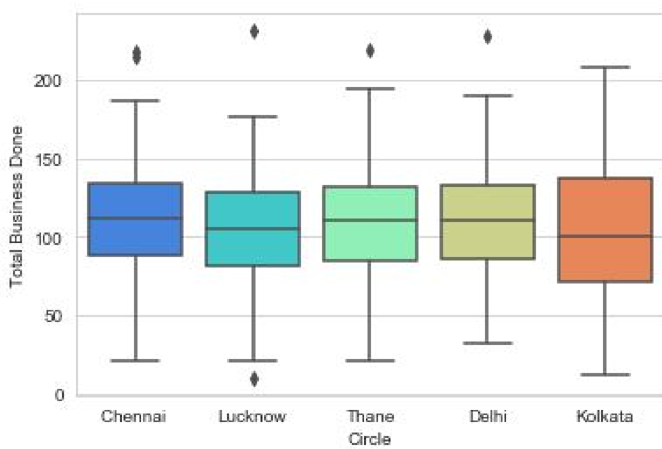
In [20]:
```
round(df.groupby('Category of Branch').mean(),2)
```

Out[20]:

Category of Branch	% Target Achieved	Tenure in months	Role Change Tenure	Role Change Count	Branches Assigned	Leads assigned	Age	Salary	Dealers Handled	Business through dealer	Bus th
Large Metro	0.29	33.50	27.00	0.33	2.61	11.89	30.67	361606.11	6.94	0.35	
Metro	0.37	27.07	22.91	0.32	2.84	9.23	30.14	338136.38	8.30	0.53	
Rural	0.37	34.07	25.90	0.35	2.14	10.35	29.78	332059.07	5.81	0.30	
Urban	0.39	29.50	24.23	0.22	2.07	7.83	30.03	342175.68	6.83	0.51	

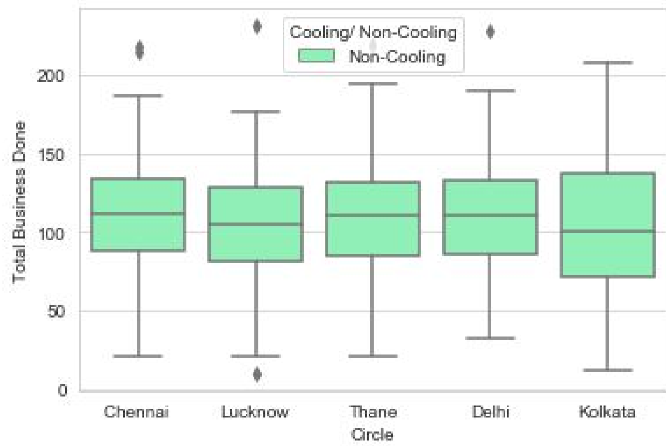
In [21]:
```
# Create box plot
sns.boxplot(x = 'Circle', y = 'Total Business Done', data = df, palette = 'rainbow
')
```

Out[21]: <matplotlib.axes._subplots.AxesSubplot at 0x2592172c208>



In [22]:
```
# Create box plot
sns.boxplot(x = 'Circle', y = 'Total Business Done', data = df, palette = 'rainbow
',hue ='Cooling/ Non-Cooling')
```

Out[22]: <matplotlib.axes._subplots.AxesSubplot at 0x259217d1358>

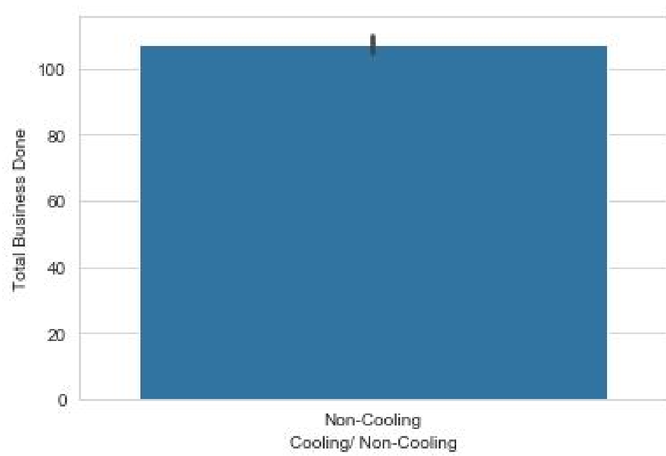


In [23]:
```
#Checking counts of object
df['Cooling/ Non-Cooling'].value_counts()
```

Out[23]:
```
Non-Cooling    767
Name: Cooling/ Non-Cooling, dtype: int64
```

In [24]:
```
sns.barplot(x='Cooling/ Non-Cooling',y='Total Business Done',data=df)
```

Out[24]: <matplotlib.axes._subplots.AxesSubplot at 0x2592187b5f8>

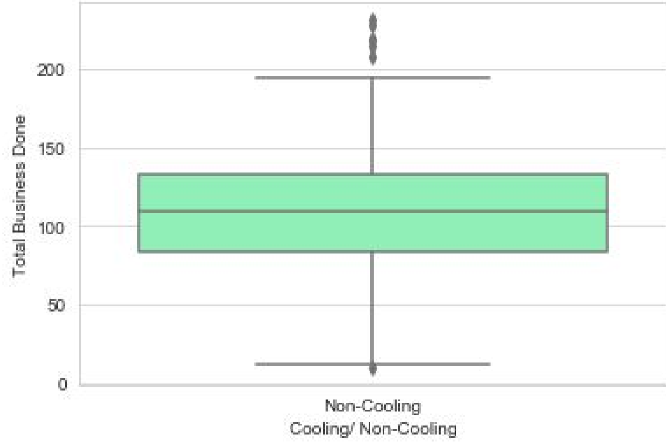


In [25]:
```
df.groupby('Cooling/ Non-Cooling').mean()['Total Business Done']
```

Out[25]:
```
Cooling/ Non-Cooling
Non-Cooling    107.595828
Name: Total Business Done, dtype: float64
```

In [26]:
```
sns.boxplot(x = 'Cooling/ Non-Cooling', y = 'Total Business Done', data = df, palet
te = 'rainbow')
```

Out[26]: <matplotlib.axes._subplots.AxesSubplot at 0x259218f8dd8>



In [27]:
```
df
```

Out[27]:

	EMPCODE	EMPNAME	Active/Inactive	Circle	Division	Category of Branch	Location Change	Seating Location	Cooling/ Non-Cooling
0	23202947	Jegan J	A	Chennai	Trichy	Rural	No	Dindigul	Non-Cooling
1	23207679	Sathyan K	A	Chennai	Trichy	Rural	No	Madurai	Non-Cooling
2	23212153	Selvaprakash S	A	Chennai	Trichy	Rural	No	Karaikudi	Non-Cooling
3	23177485	Ravindra Kumar Srivastava	A	Lucknow	Allahabad	Rural	No	Jounpur	Non-Cooling
4	23177496	Abiral Singh	A	Lucknow	Allahabad	Rural	No	Bhadohi	Non-Cooling
...	...	...	...	...	...	...	...	...	...
762	27002773	Anupal Gogoi	A	Kolkata	Guwahati	Rural	No	Sivasagar	Non-Cooling
763	23179495	Arjun Sawant	A	Thane	Thane	Rural	No	Jalna	Non-Cooling
764	23187476	Prasad Kulkarni	A	Thane	Thane	Rural	No	Parbhani	Non-Cooling
765	23224493	Yogeshwar Dabhade	A	Thane	Thane	Rural	No	Aurangabad	Non-Cooling
766	27000113	Pawan Wade	A	Thane	Thane	Rural	No	Sillod	Non-Cooling

767 rows × 23 columns

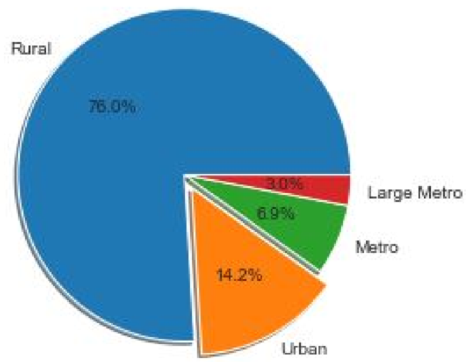
In [28]:
```
df['Role Change Tenure'].value_counts()[0]
```

Out[28]: 11

In [29]:
```
#Checking counts of object
df['Category of Branch'].value_counts()
```

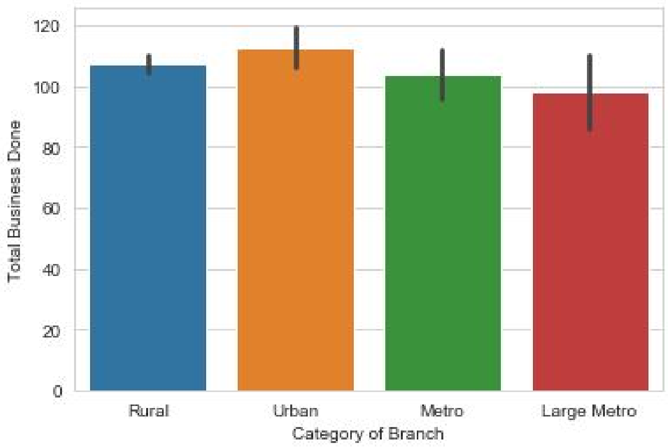
Out[29]:
```
Rural          583
Urban          109
Metro           57
Large Metro     18
Name: Category of Branch, dtype: int64
```

In [30]:
```
#Draw Pie Chart
branch_category = [717,134,65,28]
branch_category_name = ['Rural','Urban','Metro','Large Metro']
#colors = ['gold', 'yellowgreen', 'lightcoral', 'lightskyblue']
plt.pie(branch_category,labels=branch_category_name,shadow=True,autopct='%1.1f%%',radius=1.1,explode=[0,0.1,0,0])
plt.axis('equal')
plt.show()
```



In [31]:
```
sns.barplot(x='Category of Branch',y='Total Business Done',data=df)
```

Out[31]: <matplotlib.axes._subplots.AxesSubplot at 0x2592195be48>

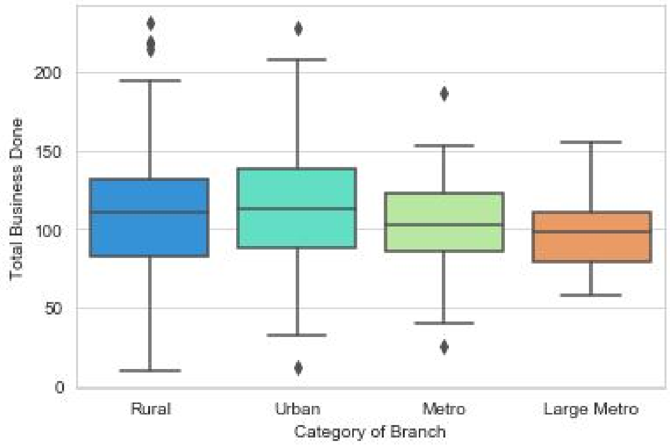


In [32]:
```
df.groupby('Category of Branch').mean()['Total Business Done']
```

Out[32]:
```
Category of Branch
Large Metro     98.000000
Metro          104.017544
Rural          107.332762
Urban          112.458716
Name: Total Business Done, dtype: float64
```

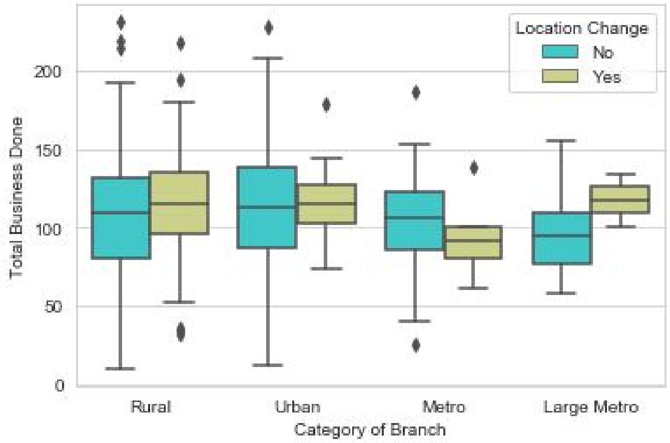
In [33]:
```
# Create box plot
sns.boxplot(x = 'Category of Branch', y = 'Total Business Done', data = df, palette
= 'rainbow')
```

Out[33]: <matplotlib.axes._subplots.AxesSubplot at 0x259229ee7f0>



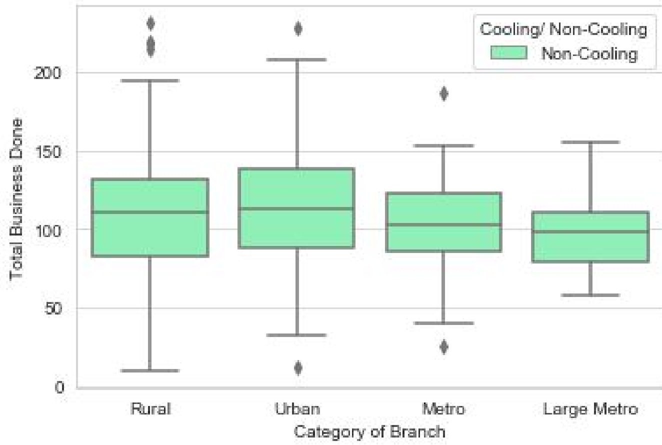
In [34]:
```
# Create box plot
sns.boxplot(x = 'Category of Branch', y = 'Total Business Done', data = df, palette
= 'rainbow',hue = 'Location Change')
```

Out[34]: <matplotlib.axes._subplots.AxesSubplot at 0x25922a93748>



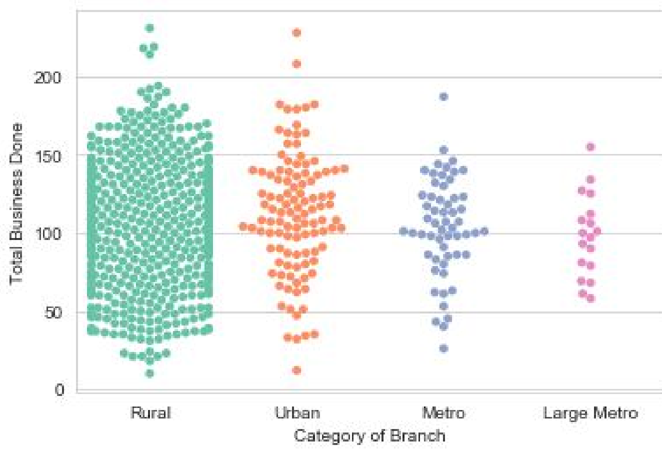
In [35]:
```
# Create box plot
sns.boxplot(x = 'Category of Branch', y = 'Total Business Done', data = df, palette
= 'rainbow',hue = 'Cooling/ Non-Cooling')
```

Out[35]: <matplotlib.axes._subplots.AxesSubplot at 0x25922b86cc0>



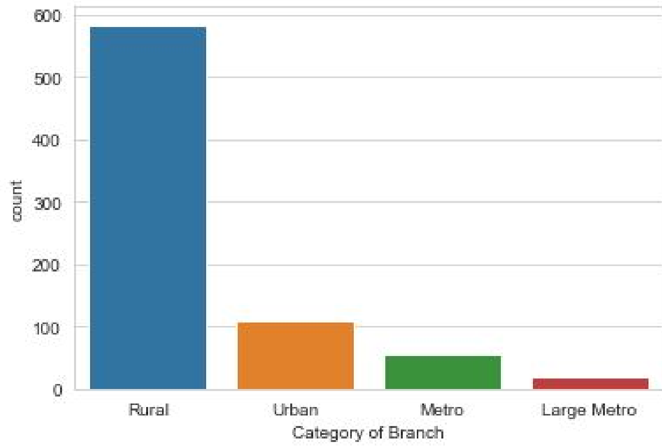
In [36]:
```
# Create swarm plot
sns.swarmplot(x = 'Category of Branch', y = 'Total Business Done', data = df, palet
te = 'Set2')
```

Out[36]: <matplotlib.axes._subplots.AxesSubplot at 0x25922c34780>



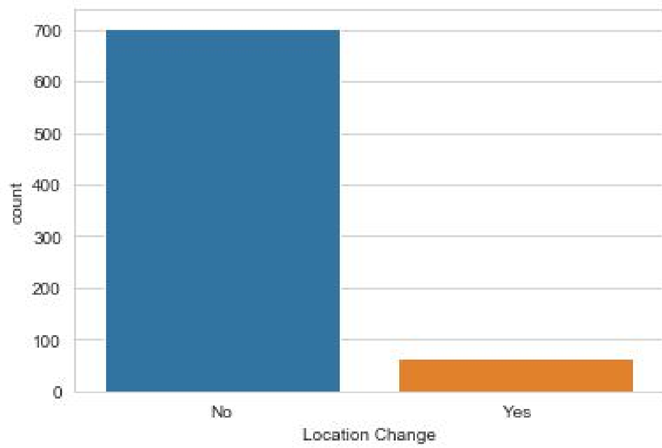
In [37]:
```
sns.countplot(x = 'Category of Branch', data = df)
```

Out[37]: <matplotlib.axes._subplots.AxesSubplot at 0x2592197db00>



In [38]:
```
sns.countplot(x = 'Location Change', data = df)
```

Out[38]: <matplotlib.axes._subplots.AxesSubplot at 0x25922c78860>

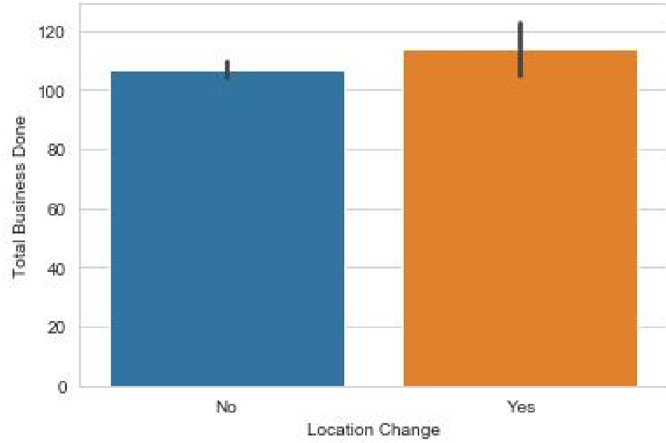


In [39]:
```
df['Location Change'].value_counts()
```

Out[39]:
```
No     703
Yes     64
Name: Location Change, dtype: int64
```

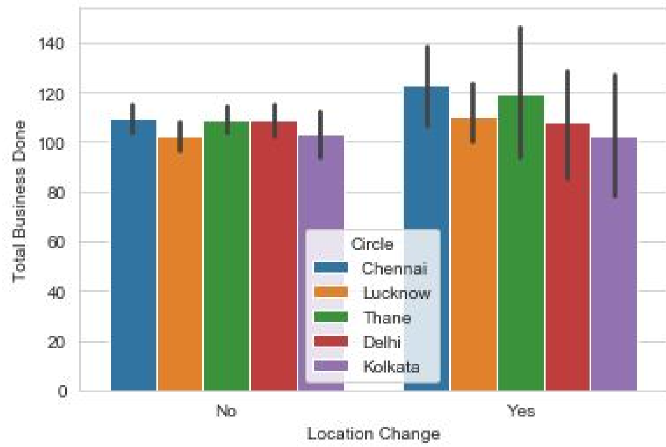
In [40]:
```
sns.barplot(x='Location Change',y='Total Business Done',data=df)
```

Out[40]: <matplotlib.axes._subplots.AxesSubplot at 0x25922cdf668>



In [41]:
```
sns.barplot(x='Location Change',y='Total Business Done',data=df, hue = 'Circle')
```

Out[41]: <matplotlib.axes._subplots.AxesSubplot at 0x25922d30198>



In [42]:
```
df.head()
```

Out[42]:

	EMPCODE	EMPNAME	Active/Inactive	Circle	Division	Category of Branch	Location Change	Seating Location	Cooling/ Non-Cooling	% Tar Achiev
0	23202947	Jegan J	A	Chennai	Trichy	Rural	No	Dindigul	Non-Cooling	
1	23207679	Sathyan K	A	Chennai	Trichy	Rural	No	Madurai	Non-Cooling	
2	23212153	Selvaprakash S	A	Chennai	Trichy	Rural	No	Karaikudi	Non-Cooling	
3	23177485	Ravindra Kumar Srivastava	A	Lucknow	Allahabad	Rural	No	Jounpur	Non-Cooling	
4	23177496	Abiral Singh	A	Lucknow	Allahabad	Rural	No	Bhadohi	Non-Cooling	

5 rows × 23 columns

In [43]:
```
df['Role Change Tenure'].value_counts()
```

Out[43]:
```
39     46
7      35
20     34
6      31
11     26
       ..
69      1
68      1
67      1
58      1
160     1
Name: Role Change Tenure, Length: 77, dtype: int64
```

In [44]:
```
#df['Target Achieved'].value_counts()
```

In [45]:
```
#sns.countplot(x = 'Target Achieved', data = df)
```

In [46]:
```
#sns.countplot(x = 'Target Achieved', data = df,hue ='Cooling/ Non-Cooling')
```

Create function and apply it on dataframe

def status(tenure):

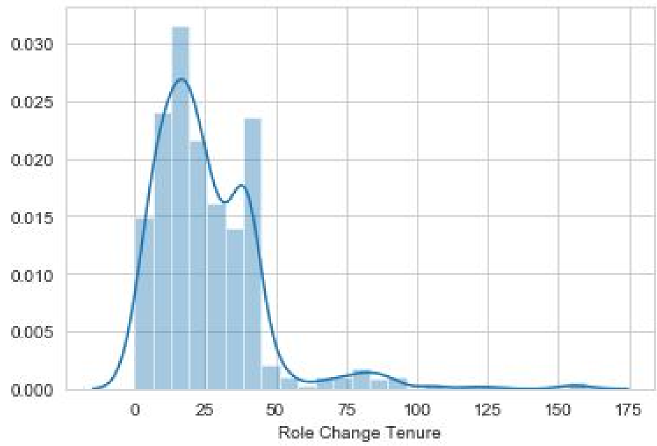
```
#if tenure>3:
    #return 'Non cooling'
#else:
    #return 'Cooling'
```

df['cstatus'] = df['Tenure in months'].apply(lambda x:status(x))

Exploratory data analysis on Numerical data

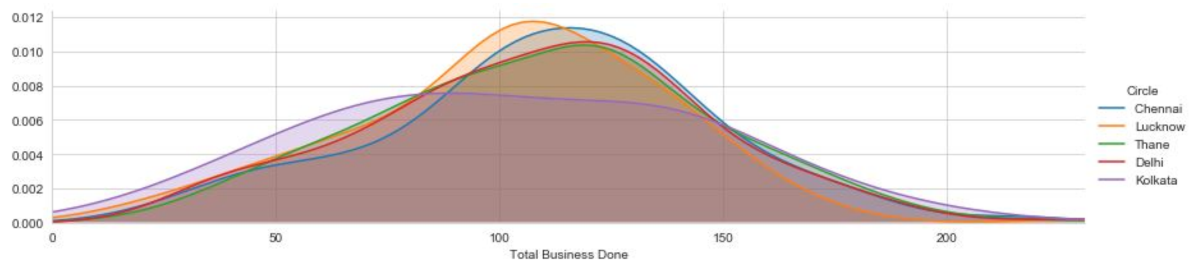
In [47]:
```
# Role Change Histogram
sns.distplot(df['Role Change Tenure'],bins=25)
```

Out[47]: <matplotlib.axes._subplots.AxesSubplot at 0x25922dc2d30>



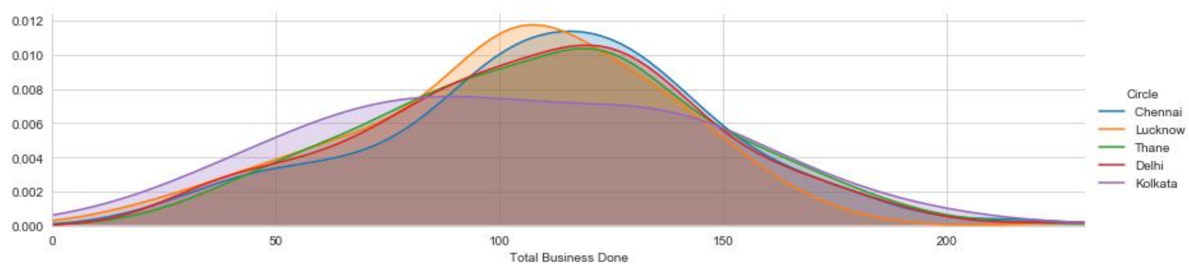
In [48]:
```
# Let's do the same for class by changing the hue argument:
fig = sns.FacetGrid(df, hue="Circle",aspect=4)
fig.map(sns.kdeplot,'Total Business Done',shade= True)
oldest = df['Total Business Done'].max()
fig.set(xlim=(0,oldest))
fig.add_legend()
```

Out[48]: <seaborn.axisgrid.FacetGrid at 0x25922e6da20>



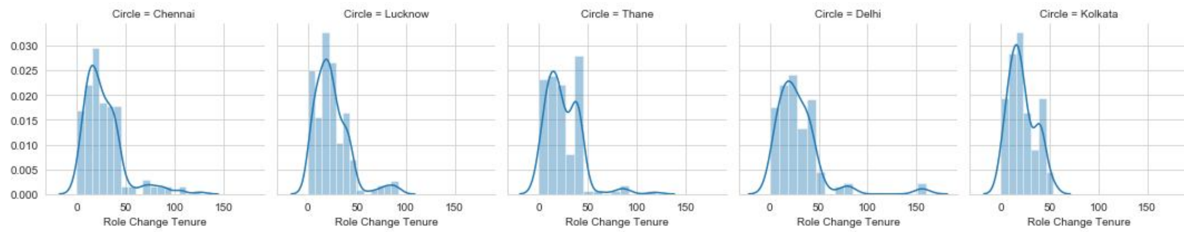
In [49]:
```
# Let's do the same for class by changing the hue argument:
fig = sns.FacetGrid(df, hue="Circle",aspect=4)
fig.map(sns.kdeplot,'Total Business Done',shade= True)
oldest = df['Total Business Done'].max()
fig.set(xlim=(0,oldest))
fig.add_legend()
```

Out[49]: <seaborn.axisgrid.FacetGrid at 0x25922e96748>



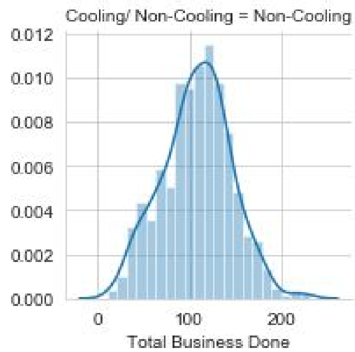
In [50]:
```
#Draw distplot
t = sns.FacetGrid(data = df, col = 'Circle')
t.map(sns.distplot, 'Role Change Tenure')
```

Out[50]: <seaborn.axisgrid.FacetGrid at 0x25922e96400>



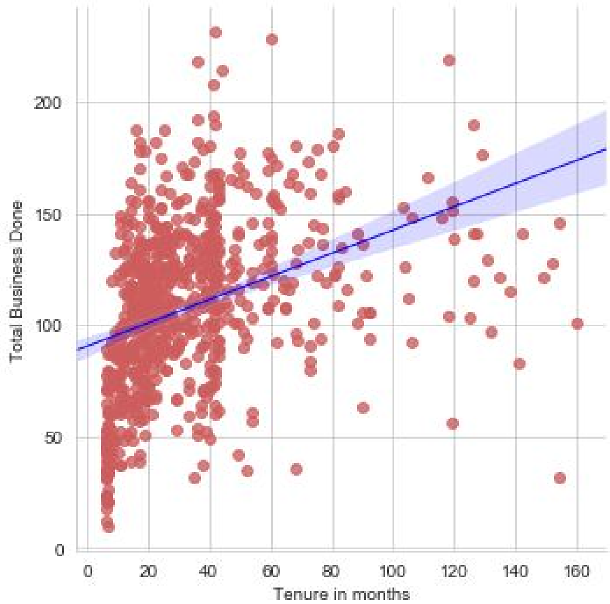
In [51]:
```
#Draw distplot
t = sns.FacetGrid(data = df, col = 'Cooling/ Non-Cooling')
t.map(sns.distplot, 'Total Business Done')
```

Out[51]: <seaborn.axisgrid.FacetGrid at 0x25923195be0>

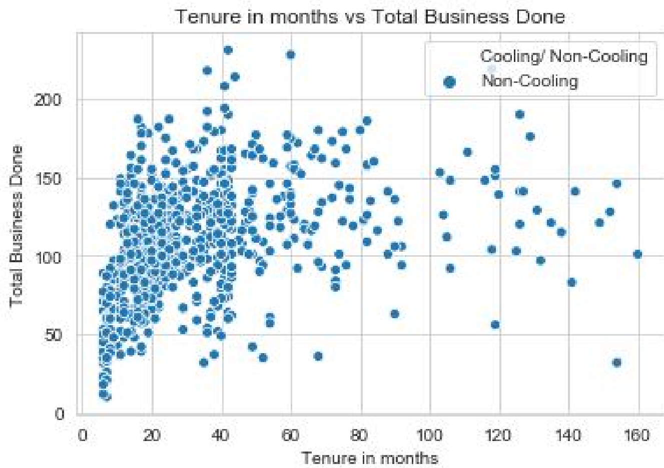


In [52]:
```
#Linear regression
sns.lmplot(x='Tenure in months',y='Total Business Done',data=df,
           scatter_kws={"marker": "o", "color": "indianred"},
           line_kws={"linewidth": 1, "color": "blue"})
```

Out[52]: <seaborn.axisgrid.FacetGrid at 0x2592326c898>

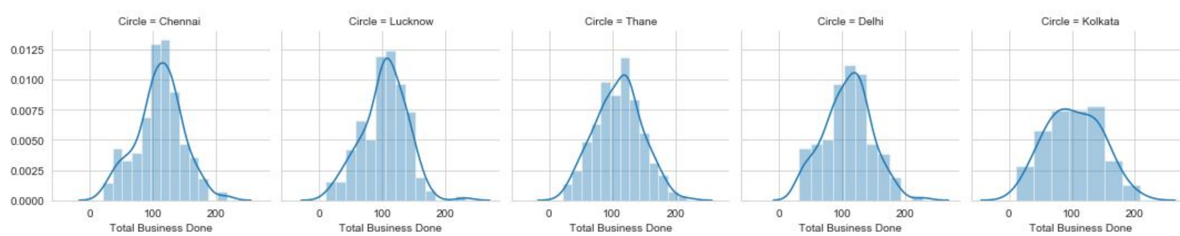


In [53]:
```
sns.scatterplot(x=df['Tenure in months'],y =df['Total Business Done'],hue =df['Cool
ing/ Non-Cooling'])
plt.title('Tenure in months vs Total Business Done')
plt.xlabel('Tenure in months')
plt.ylabel('Total Business Done')
plt.legend(loc ='upper right')
plt.show()
```



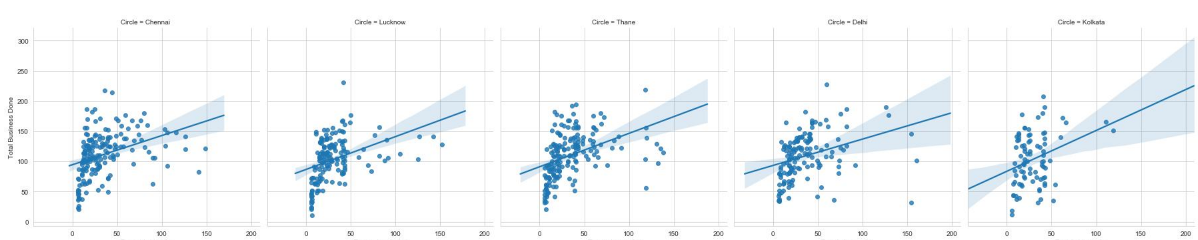
In [54]:
```
t = sns.FacetGrid(data = df, col = 'Circle')
t.map(sns.distplot, 'Total Business Done')
```

Out[54]: <seaborn.axisgrid.FacetGrid at 0x2592330fef0>



In [55]:
```
sns.lmplot(x='Tenure in months',y='Total Business Done',data=df,col='Circle')
```

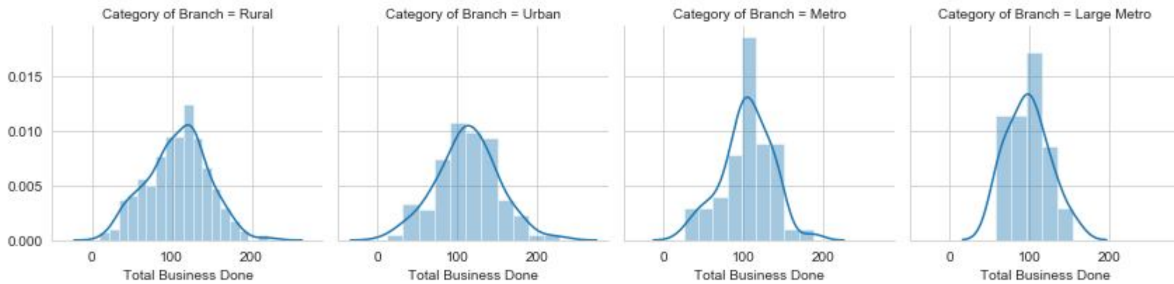
Out[55]: <seaborn.axisgrid.FacetGrid at 0x259245977f0>



In [56]:
```
# Let's do the same for class by changing the hue argument:
#fig = sns.FacetGrid(df, hue="Category of Branch",aspect=4)
#fig.map(sns.kdeplot,'Total Business Done',shade= True)
#oldest = df['Total Business Done'].max()
#fig.set(xlim=(0,oldest))
#fig.add_legend()
```

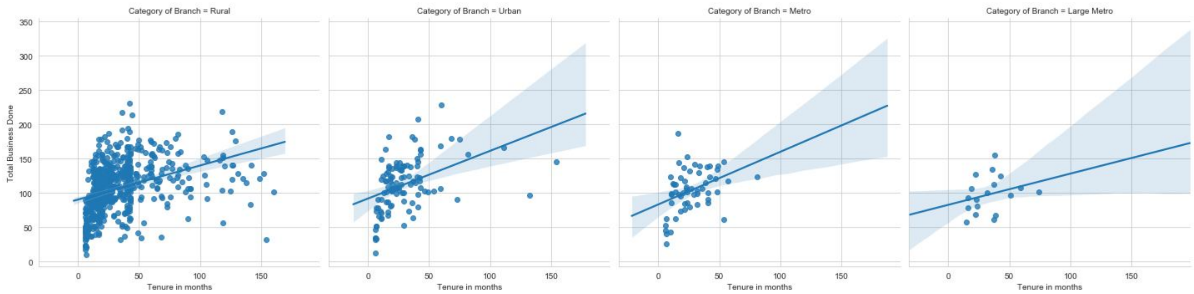
In [57]:
```
h = sns.FacetGrid(data = df, col = 'Category of Branch')
h.map(sns.distplot, 'Total Business Done')
```

Out[57]: <seaborn.axisgrid.FacetGrid at 0x259249e1ac8>



In [58]:
```
sns.lmplot(x='Tenure in months',y='Total Business Done',data=df,col='Category of Br
anch')
```

Out[58]: <seaborn.axisgrid.FacetGrid at 0x25924e05668>



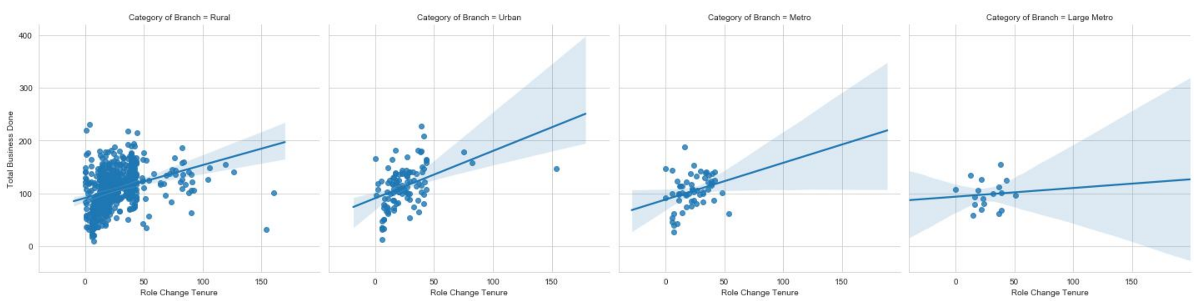
In [59]:
```
#Location change

sns.scatterplot(x=df['Tenure in months'],y =df['Total Business Done'],hue =df['Loca
tion Change'])
plt.title('Tenure in months vs Total Business Done')
plt.xlabel('Tenure in months')
plt.ylabel('Total Business Done')
plt.legend(loc ='upper right')
plt.show()
```

In [60]:
```
sns.lmplot(x='Tenure in months',y='Total Business Done',data=df,col='Location Chang
e')
```

Out[60]: <seaborn.axisgrid.FacetGrid at 0x259233024e0>

In [61]:
```
sns.lmplot(x='Role Change Tenure',y='Total Business Done',data=df,col='Category of
Branch')
```

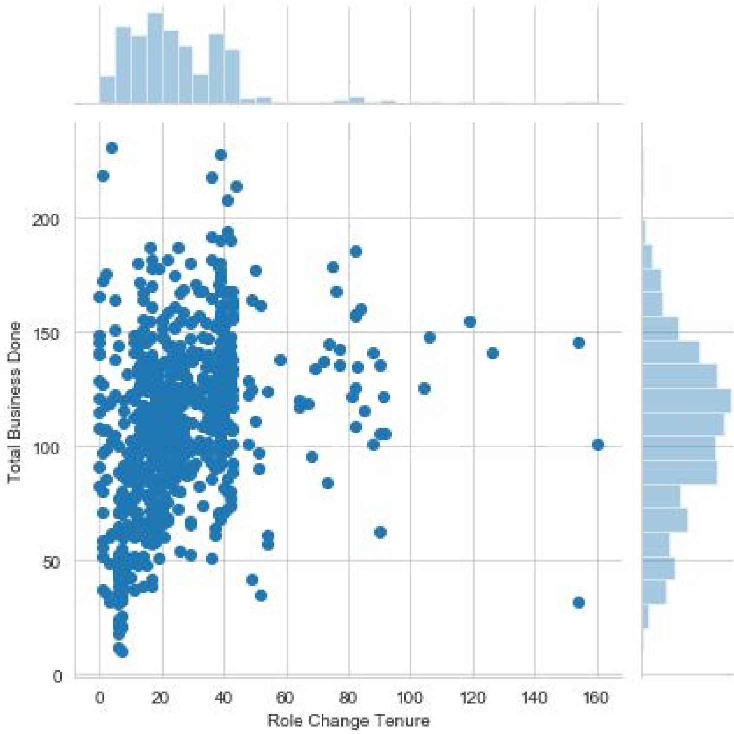
Out[61]: <seaborn.axisgrid.FacetGrid at 0x2592546da90>



In [62]:
```
# Regression
#sns.pairplot(df, x_vars=['Salary','Dealers Handled','Rle Change Tenure'], y_vars='
Total Business Done',size=7, aspect=0.5, kind='scatter')
```

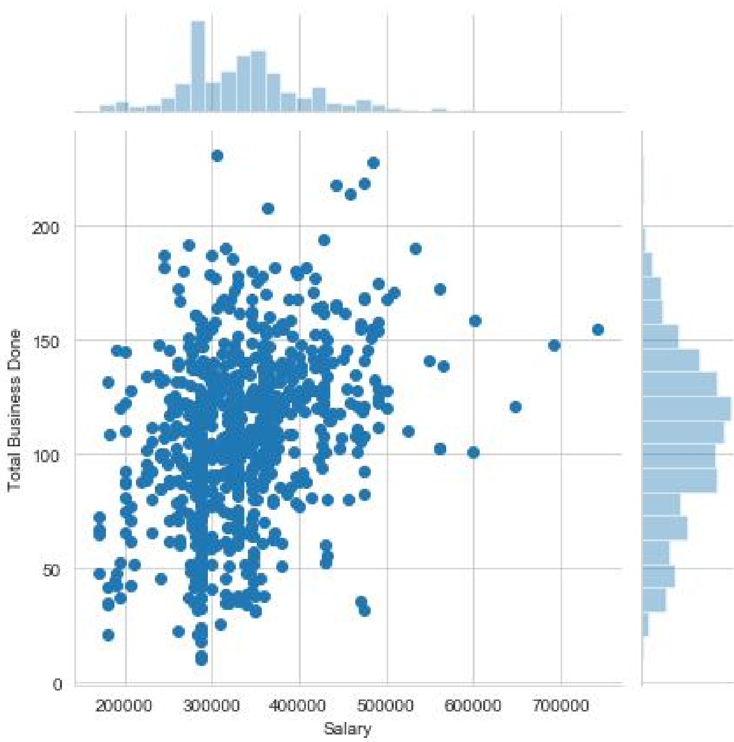
In [63]:
```
# Create joint distribution plot
sns.jointplot(x = 'Role Change Tenure', y = 'Total Business Done', data = df)
```

Out[63]: <seaborn.axisgrid.JointGrid at 0x259257f2128>



In [64]:
```
# Create joint distribution plot
sns.jointplot(x = 'Salary', y = 'Total Business Done', data = df)
```

Out[64]: <seaborn.axisgrid.JointGrid at 0x25925b70780>



In [65]:
```
# paiwise scatter plot

#plt.figure(figsize=(20, 10))
#sns.pairplot(df)
#plt.show()
```

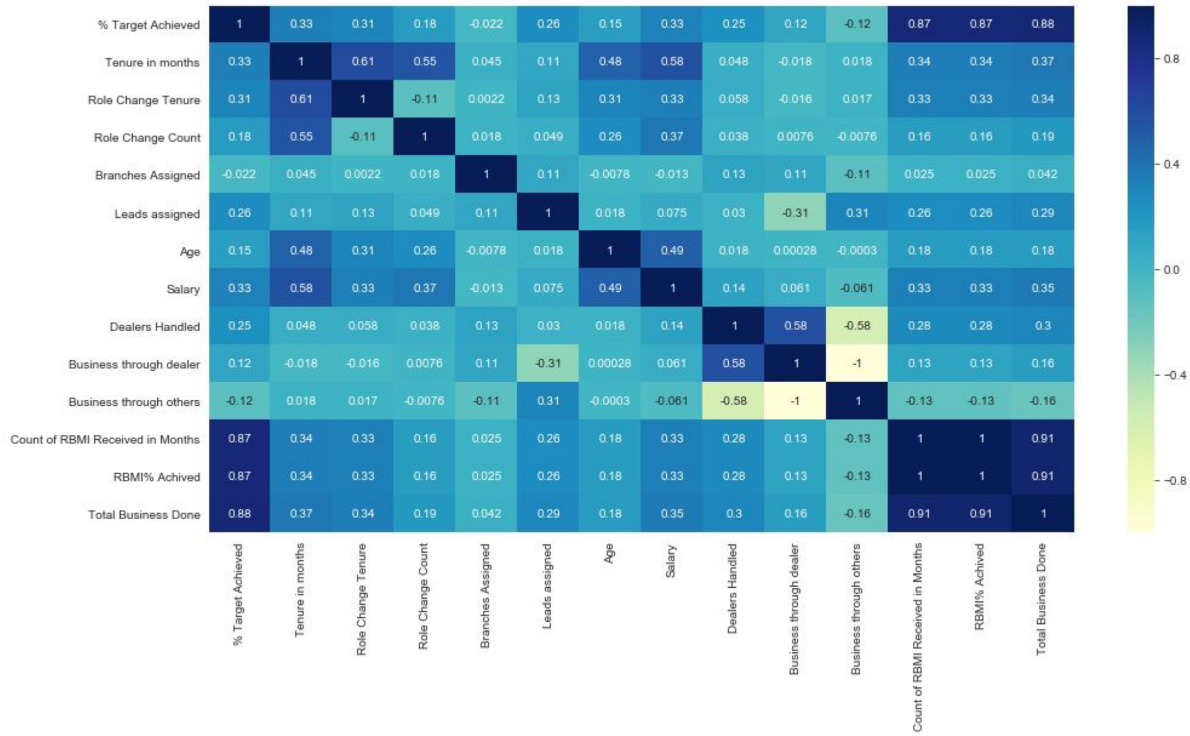
This is quite hard to read, and we can rather plot correlations between variables. Also, a heatmap is pretty useful to visualise multiple correlations in one plot.

In [66]:
```
# correlation matrix
cor = df.corr()
cor
```

Out[66]:

	% Target Achieved	Tenure in months	Role Change Tenure	Role Change Count	Branches Assigned	Leads assigned	Age	Salary	Dealers Handled	Bus th
% Target Achieved	1.000000	0.332786	0.311733	0.177444	-0.022321	0.258422	0.153633	0.325319	0.245105	0.1
Tenure in months	0.332786	1.000000	0.605700	0.552865	0.045397	0.107296	0.481622	0.576862	0.048343	-0.0
Role Change Tenure	0.311733	0.605700	1.000000	-0.108723	0.002171	0.127786	0.310227	0.334485	0.058161	-0.0
Role Change Count	0.177444	0.552865	-0.108723	1.000000	0.018420	0.049176	0.258680	0.371802	0.037742	0.0
Branches Assigned	-0.022321	0.045397	0.002171	0.018420	1.000000	0.105484	-0.007767	-0.013037	0.132191	0.1
Leads assigned	0.258422	0.107296	0.127786	0.049176	0.105484	1.000000	0.017843	0.075415	0.030165	-0.3
Age	0.153633	0.481622	0.310227	0.258680	-0.007767	0.017843	1.000000	0.489549	0.018368	0.0
Salary	0.325319	0.576862	0.334485	0.371802	-0.013037	0.075415	0.489549	1.000000	0.135288	0.0
Dealers Handled	0.245105	0.048343	0.058161	0.037742	0.132191	0.030165	0.018368	0.135288	1.000000	0.5
Business through dealer	0.116774	-0.017518	-0.016450	0.007556	0.111495	-0.311008	0.000276	0.061395	0.579768	1.0
Business through others	-0.116712	0.017610	0.016512	-0.007554	-0.111550	0.311025	-0.000299	-0.061266	-0.579791	-0.9
Count of RBMI Received in Months	0.871622	0.340628	0.333534	0.159350	0.025255	0.259041	0.178016	0.329568	0.278355	0.1
RBMI% Achived	0.871622	0.340628	0.333534	0.159350	0.025255	0.259041	0.178016	0.329568	0.278355	0.1
Total Business Done	0.878272	0.370418	0.339651	0.188762	0.041644	0.291482	0.176834	0.353401	0.303286	0.1

In [67]:
```python
# plotting correlations on a heatmap

# figure size
plt.figure(figsize=(16,8))

# heatmap
sns.heatmap(cor, cmap="YlGnBu", annot=True)
plt.show()
```



Handle Categorical data

In [68]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 767 entries, 0 to 766
Data columns (total 23 columns):
EMPCODE                            767 non-null object
EMPNAME                            767 non-null object
Active/Inactive                    767 non-null object
Circle                             767 non-null object
Division                           767 non-null object
Category of Branch                 767 non-null object
Location Change                    767 non-null object
Seating Location                   767 non-null object
Cooling/ Non-Cooling               767 non-null object
% Target Achieved                  767 non-null float64
Tenure in months                   767 non-null int64
Role Change Tenure                 767 non-null int64
Role Change Count                  767 non-null int64
Branches Assigned                  767 non-null int64
Leads assigned                     767 non-null int64
Age                                767 non-null int64
Salary                             767 non-null float64
Dealers Handled                    767 non-null int64
Business through dealer            767 non-null float64
Business through others            767 non-null float64
Count of RBMI Received in Months   767 non-null int64
RBMI% Achived                      767 non-null float64
Total Business Done                767 non-null int64
dtypes: float64(5), int64(9), object(9)
memory usage: 137.9+ KB
```

In [69]:
```
df.tail()
```

Out[69]:

	EMPCODE	EMPNAME	Active/Inactive	Circle	Division	Category of Branch	Location Change	Seating Location	Cooling/ Non-Cooling	% Ta Achi
762	27002773	Anupal Gogoi	A	Kolkata	Guwahati	Rural	No	Sivasagar	Non-Cooling	
763	23179495	Arjun Sawant	A	Thane	Thane	Rural	No	Jalna	Non-Cooling	
764	23187476	Prasad Kulkarni	A	Thane	Thane	Rural	No	Parbhani	Non-Cooling	
765	23224493	Yogeshwar Dabhade	A	Thane	Thane	Rural	No	Aurangabad	Non-Cooling	
766	27000113	Pawan Wade	A	Thane	Thane	Rural	No	Sillod	Non-Cooling	

5 rows × 23 columns

In [70]:
```
df['Cooling/ Non-Cooling']
```

Out[70]:
```
0      Non-Cooling
1      Non-Cooling
2      Non-Cooling
3      Non-Cooling
4      Non-Cooling
          ...
762    Non-Cooling
763    Non-Cooling
764    Non-Cooling
765    Non-Cooling
766    Non-Cooling
Name: Cooling/ Non-Cooling, Length: 767, dtype: object
```

In [71]:
```
#df['Cooling/ Non-Cooling']= df['Cooling/ Non-Cooling'].map({'Cooling':0,'Non-Cooli
ng':1})
```

In [72]:
```
df.drop(['Cooling/ Non-Cooling'],axis=1,inplace =True)
```

In [73]:
```
#df['Cooling/ Non-Cooling']
```

In [74]:
```
df['Location Change']= df['Location Change'].map({'No':0,'Yes':1})
```

In [75]:
```
df['Location Change']
```

Out[75]:
```
0      0
1      0
2      0
3      0
4      0
      ..
762    0
763    0
764    0
765    0
766    0
Name: Location Change, Length: 767, dtype: int64
```

In [76]:
```
df['Location Change'].value_counts()
```

Out[76]:
```
0    703
1     64
Name: Location Change, dtype: int64
```

In [77]:
```
#df['Target Achieved']= df['Target Achieved'].map({'N':0,'Y':1})
```

In [78]:
```
#df['Target Achieved'].value_counts()
```

In [79]:
```
# Creating a dummy variable for 'furnishingstatus'
dummy = pd.get_dummies(df['Category of Branch'])
```

In [80]:
```
# we don't need 4 columns.
# we can use drop_first = True to drop the first column from status df.
dummy = pd.get_dummies(df['Category of Branch'],drop_first=True)
```

In [81]:
```
#Adding the results to the master dataframe
df = pd.concat([df,dummy],axis=1)
```

In [82]:
```
df.drop(['EMPCODE'],axis =1,inplace =True)
```

In [83]:
```
df.drop(['Count of RBMI Received in Months'],axis =1,inplace =True)
```

In [84]:
```
df.drop(['Category of Branch'],axis=1,inplace =True)
```

In [85]:
```
#df.drop(['EMPCODE'],axis=1,inplace =True)
```

In [86]:
```
df.drop(['EMPNAME'],axis=1,inplace =True)
```

In [87]:
```
df.drop(['Active/Inactive'],axis=1,inplace =True)
```

In [88]:
```
df.drop(['Circle'],axis=1,inplace =True)
```

In [89]:
```
df.drop(['Division'],axis=1,inplace =True)
```

In [90]:
```
df.drop(['Seating Location'],axis=1,inplace =True)
```

In [123]:
```
df['Location Change'].value_counts()
```

Out[123]:
```
0.0    703
1.0     64
Name: Location Change, dtype: int64
```

In [126]:
```
df['Location Change']
```

Out[126]:
```
0      0.0
1      0.0
2      0.0
3      0.0
4      0.0
      ...
762    0.0
763    0.0
764    0.0
765    0.0
766    0.0
Name: Location Change, Length: 767, dtype: float64
```

In [125]:
```
df.head()
```

Out[125]:

	Location Change	% Target Achieved	Tenure in months	Role Change Tenure	Role Change Count	Branches Assigned	Leads assigned	Age	Salary	Dealers Handled	Busines throug deal
0	0.0	0.2	0.155844	0.18750	0.0	0.333333	0.206349	0.333333	0.280090	0.142857	0.6
1	0.0	0.4	0.142857	0.17500	0.0	0.444444	0.190476	0.296296	0.415588	0.190476	0.6
2	0.0	0.2	0.129870	0.16250	0.0	0.222222	0.142857	0.259259	0.305291	0.190476	0.5
3	0.0	0.7	0.240260	0.26875	0.0	0.555556	0.000000	0.370370	0.339229	0.190476	0.0
4	0.0	0.6	0.240260	0.26875	0.0	0.111111	0.142857	0.333333	0.258333	0.000000	0.0

Rescaling the Features

It is extremely important to rescale the variables so that they have a comparable scale. There are twocoon ways of rescaling

```
Normalisation (min-max scaling) and
standardisation (mean-o, sigma-1) Let's try normalisation
```

In [92]:
```
#defining a normalisation function
def normalize (x):
    return ( (x-np.min(x))/ (max(x) - min(x)))


#applying normalize ( ) to all columns
df =df.apply(normalize)
```

Splitting Data into Training and Testing Sets

In [93]:
```
df
```

Out[93]:

	Location Change	% Target Achieved	Tenure in months	Role Change Tenure	Role Change Count	Branches Assigned	Leads assigned	Age	Salary	Dealers Handled	Busir thro de
0	0.0	0.2	0.155844	0.18750	0.0	0.333333	0.206349	0.333333	0.280090	0.142857	
1	0.0	0.4	0.142857	0.17500	0.0	0.444444	0.190476	0.296296	0.415588	0.190476	
2	0.0	0.2	0.129870	0.16250	0.0	0.222222	0.142857	0.259259	0.305291	0.190476	
3	0.0	0.7	0.240260	0.26875	0.0	0.555556	0.000000	0.370370	0.339229	0.190476	
4	0.0	0.6	0.240260	0.26875	0.0	0.111111	0.142857	0.333333	0.258333	0.000000	
...	...	...	...	...	...	...	...	...	...	...	
762	0.0	0.0	0.000000	0.03750	0.0	0.111111	0.015873	0.444444	0.202774	0.000000	
763	0.0	0.6	0.233766	0.26250	0.0	0.111111	0.190476	0.333333	0.385256	0.238095	
764	0.0	0.4	0.214286	0.24375	0.0	0.111111	0.174603	0.222222	0.254927	0.190476	
765	0.0	0.2	0.090909	0.12500	0.0	0.222222	0.365079	0.296296	0.278069	0.666667	
766	0.0	0.0	0.019481	0.05625	0.0	0.111111	0.063492	0.370370	0.202767	0.285714	

767 rows × 17 columns

In [94]:
```
df.columns
```

Out[94]:
```
Index(['Location Change', '% Target Achieved', 'Tenure in months',
       'Role Change Tenure', 'Role Change Count', 'Branches Assigned',
       'Leads assigned', 'Age', 'Salary', 'Dealers Handled',
       'Business through dealer', 'Business through others', 'RBMI% Achived',
       'Total Business Done', 'Metro', 'Rural', 'Urban'],
      dtype='object')
```

In [95]:
```
# Putting feature variable to X
X = df[['Location Change','Tenure in months',
       'Role Change Tenure', 'Role Change Count', 'Branches Assigned',
       'Leads assigned', 'Age', 'Salary', 'Dealers Handled',
       'Business through dealer', 'Business through others','Metro', 'Rural', 'Urba
n','RBMI% Achived']]

# Putting response variable to y
y = df['Total Business Done']
```

In [96]:
```
#random_state is the seed used by the random number generator, it can be any intege
r.
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.7 ,test_size
= 0.3, random_state=100)
```

In [97]:
```
import statsmodels.api as sm          # Importing statsmodels
X_train_lm = sm.add_constant(X_train)    # Adding a constant column to our datafram
e
# create a first fitted model
lm_1 = sm.OLS(y_train,X_train).fit()
```

K-Fold Validation

In [98]:
```
from sklearn.model_selection import ShuffleSplit
from sklearn.model_selection import cross_val_score

cv = ShuffleSplit(n_splits=5, test_size=0.2, random_state=0)

cross_val_score(LinearRegression(), X, y, cv=cv)
```

Out[98]:
```
array([0.81861013, 0.8292798 , 0.77629196, 0.78851091, 0.79360452])
```

In [99]:
```
print(lm_1.summary())
```

```
                            OLS Regression Results
================================================================================
========
Dep. Variable:     Total Business Done   R-squared (uncentered):
0.979
Model:                             OLS   Adj. R-squared (uncentered):
0.979
Method:                  Least Squares   F-statistic:
1643.
Date:                 Thu, 26 Mar 2020   Prob (F-statistic):
0.00
Time:                         21:07:58   Log-Likelihood:
683.99
No. Observations:                  536   AIC:
-1338.
Df Residuals:                      521   BIC:
-1274.
Df Model:                           15
Covariance Type:             nonrobust
================================================================================
===========
                              coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
-----------
Location Change            -0.0011      0.011     -0.098      0.922      -0.023
0.021
Tenure in months            0.0185      0.037      0.503      0.615      -0.054
0.091
Role Change Tenure          0.0392      0.041      0.945      0.345      -0.042
0.121
Role Change Count           0.0160      0.019      0.827      0.409      -0.022
0.054
Branches Assigned          -0.0017      0.019     -0.090      0.928      -0.039
0.035
Leads assigned              0.0991      0.024      4.131      0.000       0.052
0.146
Age                        -0.0110      0.023     -0.468      0.640      -0.057
0.035
Salary                      0.0404      0.031      1.303      0.193      -0.021
0.101
Dealers Handled            -0.0001      0.023     -0.006      0.995      -0.046
0.046
Business through dealer     0.1299      0.025      5.181      0.000       0.081
0.179
Business through others     0.0845      0.022      3.804      0.000       0.041
0.128
Metro                      -0.0187      0.021     -0.872      0.384      -0.061
0.023
Rural                       0.0076      0.019      0.401      0.688      -0.030
0.045
Urban                       0.0152      0.020      0.755      0.451      -0.024
0.055
RBMI% Achived               0.4895      0.012     41.837      0.000       0.467
0.513
==============================================================================
Omnibus:                       87.101   Durbin-Watson:                   2.125
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              240.929
Skew:                           0.795   Prob(JB):                     4.82e-53
Kurtosis:                       5.874   Cond. No.                         26.4
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
```

Random Forest Regression

In [100]:
```
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import r2_score,mean_squared_error
```

In [101]:
```
rf = RandomForestRegressor(n_estimators=500,max_depth =5)
rf.fit(X_train, y_train)
y_pred_rf =rf.predict(X_test)
print(r2_score(y_pred_rf,y_test))
```

```
0.814584620148798
```

RFE (Recurssive Feature Extraction)

In [102]:
```
# Importing RFE and LinearRegression
from sklearn.feature_selection import RFE
from sklearn.linear_model import LinearRegression
```

In [103]:
```
# Running RFE with the output number of the variable equal to 9
lm = LinearRegression()
rfe = RFE(lm, 5)             # running RFE
rfe = rfe.fit(X_train, y_train)
print(rfe.support_)           # Printing the boolean results
print(rfe.ranking_)
```

```
[False False False False False  True False  True False  True  True False
 False False  True]
[10  5  2  4  9  1  6  1 11  1  1  3  8  7  1]
```

In [104]:
```
col = X_train.columns[rfe.support_]
```

In [105]:
```
col
```

Out[105]:
```
Index(['Leads assigned', 'Salary', 'Business through dealer',
       'Business through others', 'RBMI% Achived'],
      dtype='object')
```

Building model using sklearn

In [106]:
```
# Creating X_test dataframe with RFE selected variables
X_train_rfe = X_train[col]
```

In [107]:
```
# Adding a constant variable
import statsmodels.api as sm
X_train_rfe = sm.add_constant(X_train_rfe)
```

In [108]:
```
lm = sm.OLS(y_train,X_train_rfe).fit()   # Running the linear model
```

In [109]:
```
#Let's see the summary of our linear model
print(lm.summary())
```

```
                          OLS Regression Results
==============================================================================
Dep. Variable:     Total Business Done   R-squared:                       0.841
Model:                             OLS   Adj. R-squared:                  0.839
Method:                  Least Squares   F-statistic:                     559.9
Date:                 Thu, 26 Mar 2020   Prob (F-statistic):          8.09e-209
Time:                         21:08:03   Log-Likelihood:                 677.33
No. Observations:                  536   AIC:                            -1343.
Df Residuals:                      530   BIC:                            -1317.
Df Model:                            5
Covariance Type:             nonrobust
================================================================================
===========
                              coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
-----------
const                      -1.2260      3.097     -0.396      0.692      -7.311
4.859
Leads assigned              0.0981      0.023      4.268      0.000       0.053
0.143
Salary                      0.0688      0.025      2.805      0.005       0.021
0.117
Business through dealer     1.3533      3.098      0.437      0.662      -4.732
7.439
Business through others     1.3126      3.097      0.424      0.672      -4.772
7.397
RBMI% Achived               0.4973      0.011     44.256      0.000       0.475
0.519
==============================================================================
Omnibus:                       92.421   Durbin-Watson:                   2.129
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              247.462
Skew:                           0.854   Prob(JB):                     1.84e-54
Kurtosis:                       5.857   Cond. No.                     2.58e+03
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 2.58e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Making Prediction

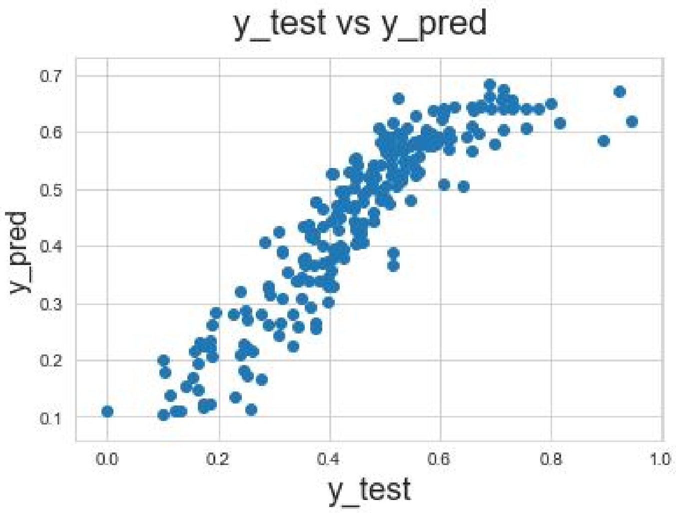
In [110]:
```
# Now let's use our model to make predictions.

# Creating X_test_6 dataframe by dropping variables from X_test
X_test_rfe = X_test[col]

# Adding a constant variable
X_test_rfe = sm.add_constant(X_test_rfe)

# Making predictions
y_pred = lm.predict(X_test_rfe)
```

In [111]:
```
X_test_rfe.shape
```

Out[111]: (231, 6)

In [112]:
```
# Plotting y_test and y_pred to understand the spread.
fig = plt.figure()
plt.scatter(y_test,y_pred)
fig.suptitle('y_test vs y_pred', fontsize=20)              # Plot heading
plt.xlabel('y_test', fontsize=18)                          # X-label
plt.ylabel('y_pred', fontsize=16)                          # Y-label
```

Out[112]: Text(0, 0.5, 'y_pred')



In [113]:
```
# Now let's check the Root Mean Square Error of our model.
import numpy as np
from sklearn import metrics
print('RMSE :', np.sqrt(metrics.mean_squared_error(y_test, y_pred)))
```

RMSE : 0.070377871787728329

In [114]:
```
df1 =pd.DataFrame(data={'predictions': y_pred, 'actual': y_test})
```

In [115]:
```
round(df1,2)*100
```

Out[115]:

	predictions	actual
173	39.0	32.0
253	44.0	45.0
207	15.0	16.0
433	32.0	24.0
191	59.0	60.0
...	...	...
259	34.0	34.0
511	52.0	53.0
111	50.0	44.0
547	54.0	51.0
724	66.0	52.0

231 rows × 2 columns

Ridge Regression

In [116]:
```
# list of alphas to tune
params = {'alpha': [0.0001, 0.001, 0.01, 0.05, 0.1,
 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 2.0, 3.0,
 4.0, 5.0, 6.0, 7.0, 8.0, 9.0, 10.0, 20, 50, 100, 500, 1000 ]}


ridge = Ridge()

# cross validation
folds = 5
model_cv = GridSearchCV(estimator = ridge,
                        param_grid = params,
                        scoring= 'neg_mean_absolute_error',
                        cv = folds,
                        return_train_score=True,
                        verbose = 1)
model_cv.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 28 candidates, totalling 140 fits

[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done 140 out of 140 | elapsed:    1.6s finished
```

Out[116]:
```
GridSearchCV(cv=5, error_score=nan,
             estimator=Ridge(alpha=1.0, copy_X=True, fit_intercept=True,
                             max_iter=None, normalize=False, random_state=None,
                             solver='auto', tol=0.001),
             iid='deprecated', n_jobs=None,
             param_grid={'alpha': [0.0001, 0.001, 0.01, 0.05, 0.1, 0.2, 0.3,
                                   0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 2.0, 3.0,
                                   4.0, 5.0, 6.0, 7.0, 8.0, 9.0, 10.0, 20, 50,
                                   100, 500, 1000]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
             scoring='neg_mean_absolute_error', verbose=1)
```

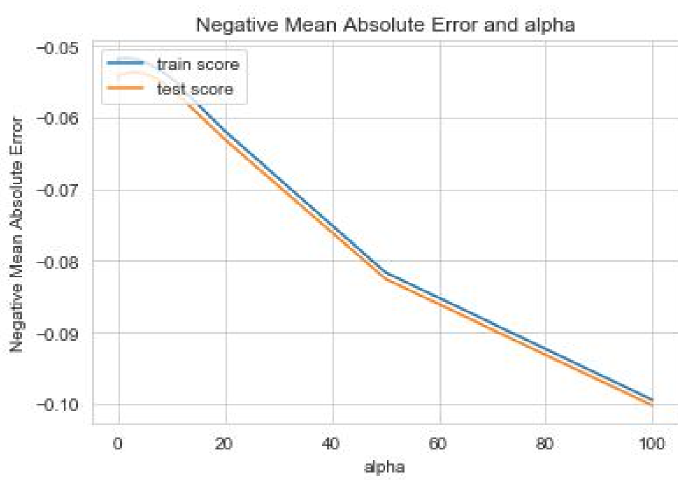
In [117]:
```
cv_results = pd.DataFrame(model_cv.cv_results_)
cv_results = cv_results[cv_results['param_alpha']<=200]
cv_results.head()
```

Out[117]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_alpha	params	split0_test_score	split
0	0.041419	0.070845	0.003198	7.540231e-04	0.0001	{'alpha': 0.0001}	-0.050153	
1	0.004801	0.001166	0.002201	4.000905e-04	0.001	{'alpha': 0.001}	-0.050102	
2	0.004202	0.000400	0.001601	4.902908e-04	0.01	{'alpha': 0.01}	-0.050066	
3	0.004402	0.001020	0.002401	4.907190e-04	0.05	{'alpha': 0.05}	-0.049972	
4	0.004002	0.000633	0.002001	4.909339e-07	0.1	{'alpha': 0.1}	-0.049859	

5 rows × 21 columns

In [118]:
```
# plotting mean test and train scoes with alpha
cv_results['param_alpha'] = cv_results['param_alpha'].astype('int32')

# plotting
plt.plot(cv_results['param_alpha'], cv_results['mean_train_score'])
plt.plot(cv_results['param_alpha'], cv_results['mean_test_score'])
plt.xlabel('alpha')
plt.ylabel('Negative Mean Absolute Error')
plt.title("Negative Mean Absolute Error and alpha")
plt.legend(['train score', 'test score'], loc='upper left')
plt.show()
```



In [119]:
```
alpha = 15
ridge = Ridge(alpha=alpha)

ridge.fit(X_train, y_train)
ridge.coef_
```

Out[119]:
```
array([-0.00082598,  0.04109402,  0.03807344,  0.01936305, -0.00136596,
        0.06773305,  0.01159477,  0.03663395,  0.03135675,  0.01963086,
       -0.01959039, -0.01454714,  0.0093065 ,  0.01979468,  0.366985  ])
```

In [120]:
```
from sklearn.model_selection import GridSearchCV

from sklearn.linear_model import Lasso
from sklearn.tree import DecisionTreeRegressor

def find_best_model_using_gridsearchcv(X,y):
    algos = {
        'linear_regression' : {
            'model': LinearRegression(),
            'params': {
                'normalize': [True, False]
            }
        },
        'lasso': {
            'model': Lasso(),
            'params': {
                'alpha': [1,2],
                'selection': ['random', 'cyclic']
            }
        },
        'decision_tree': {
            'model': DecisionTreeRegressor(),
            'params': {
                'criterion' : ['mse','friedman_mse'],
                'splitter': ['best','random']
            }
        }
    }
    scores = []
    cv = ShuffleSplit(n_splits=5, test_size=0.2, random_state=0)
    for algo_name, config in algos.items():
        gs =  GridSearchCV(config['model'], config['params'], cv=cv, return_train_
score=False)
        gs.fit(X,y)
        scores.append({
            'model': algo_name,
            'best_score': gs.best_score_,
            'best_params': gs.best_params_
        })

    return pd.DataFrame(scores,columns=['model','best_score','best_params'])

find_best_model_using_gridsearchcv(X,y)
```

Out[120]:

	model	best_score	best_params
0	linear_regression	0.801259	{'normalize': True}
1	lasso	-0.023256	{'alpha': 1, 'selection': 'random'}
2	decision_tree	0.669755	{'criterion': 'mse', 'splitter': 'random'}

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]: