XUV 300 Case study for Thane Circle

Problem Statement: For period of Feb19 to Sept.19, XUV300 market share in Thane circle is low which is around 20% against the target of 40%. Through this study wanted to analyse which are those significant factors driving the growth of MF XUV retail in Thane circle.

Based on the domain knowledge, Project team has identified key factors driving the growth of XUV300 MF retail in Thane circle such as 'No.of_Counter', 'No.of_Executives', 'Years of Experience_In months','D_Payout_Count', 'S_Payout_count ', 'TA_Avg', 'IFTA_days_Regular',.

Importing and Understanding Data

In [63]:

```
#importing essential libraries
import pandas as pd
import numpy as np
```

In [64]:

```
# Importing XUV300.csv
XUV300 = pd.read_csv(r"C:\Users\23166622\Desktop\Auto-XUV 300\Machine Learning\MLR -2\XUV300.csv")
```

In [65]:

```
# Looking at the first five rows
XUV300.head()
```

Out[65]:

	DEALERSHIPS_NAME	Year_of_Association	No.of_Counter	No.of_Executives	Years of Experience_In months	D_Payout_Count	S_Payo
0	AAKASH AUTOMOTIVES - DHULE (A010871)	19	2	2	88	12	11
1	ACCORD MOTORS	14	3	3	36	13	12
2	AHUJA AUTO ABHIKARAN	2	2	2	18	0	0
3	AMBER AUTOMOBILES -AS	6	4	4	19	11	11
4	AMBER AUTOMOTIVES	1	3	2	18	13	9

In [66]:

```
XUV300.describe()
```

Out[66]:

	Year_of_Association	No.of_Counter	No.of_Executives	Years of Experience_In months	D_Payout_Count	S_Payout_count	TA
count	74.000000	74.000000	74.000000	74.000000	74.000000	74.000000	7.400000
mean	10.581081	2.864865	3.364865	30.567568	8.662162	7.837838	2.856858
std	8.011989	2.141081	2.524262	20.820223	8.206708	8.962673	1.935294

	Year_of_Association	No.of_Counter	No.of_Executives	Years of Experience_In months	D_Payout_Count	S_Payout_count	TA
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	3.000000	1.000000	1.250000	17.250000	2.250000	0.250000	1.648186
50%	10.000000	3.000000	3.000000	24.000000	7.000000	6.500000	2.554375
75%	16.000000	4.000000	4.000000	40.750000	13.000000	11.000000	3.709478
max	30.000000	11.000000	12.000000	88.000000	42.000000	52.000000	1.137500

In [67]:

```
# What type of values are stored in the columns?
XUV300.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 74 entries, 0 to 73
Data columns (total 10 columns):
DEALERSHIPS_NAME                 74 non-null object
Year_of_Association              74 non-null int64
No.of_Counter                    74 non-null int64
No.of_Executives                 74 non-null int64
Years of Experience_In months    74 non-null int64
D_Payout_Count                   74 non-null int64
S_Payout_count                   74 non-null int64
TA_Avg                           74 non-null float64
IFTA_days_Regular                74 non-null int64
MF_Retail                        74 non-null int64
dtypes: float64(1), int64(8), object(1)
memory usage: 5.9+ KB
```

Data Visualisation

In [68]:

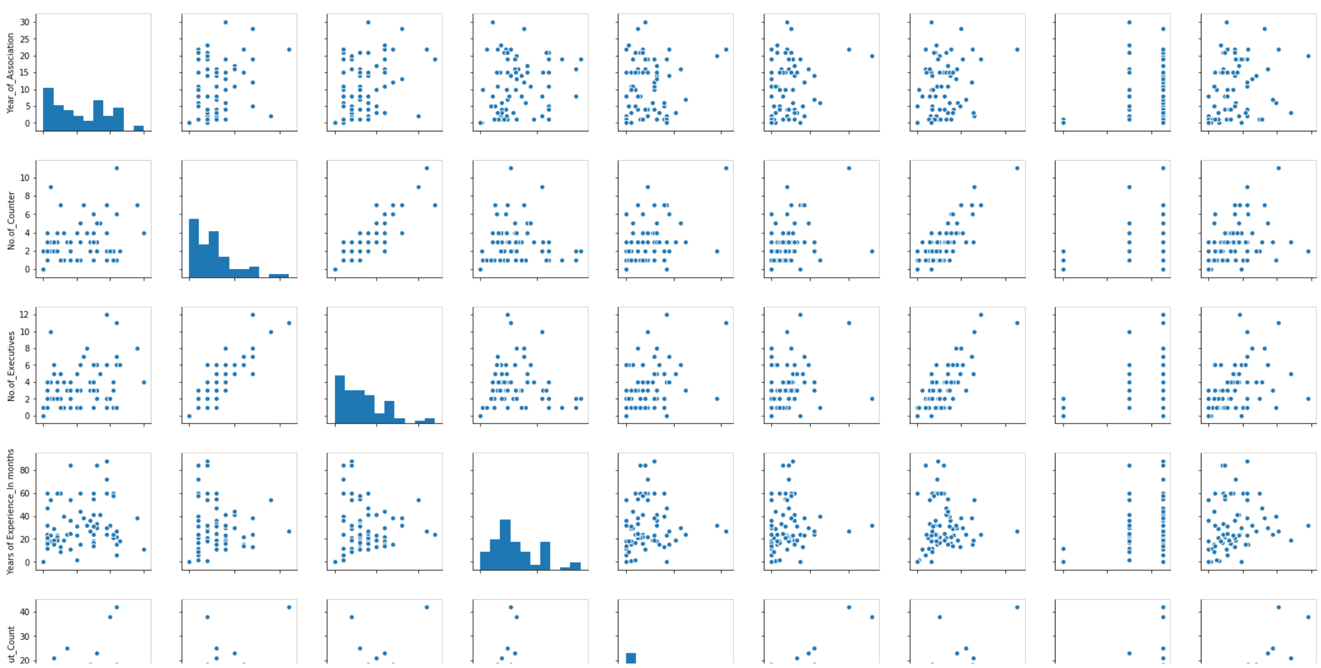
```
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

In [69]:

```
sns.pairplot(XUV300)
```

Out[69]:

```
<seaborn.axisgrid.PairGrid at 0x14fa38fd828>
```



In [70]:

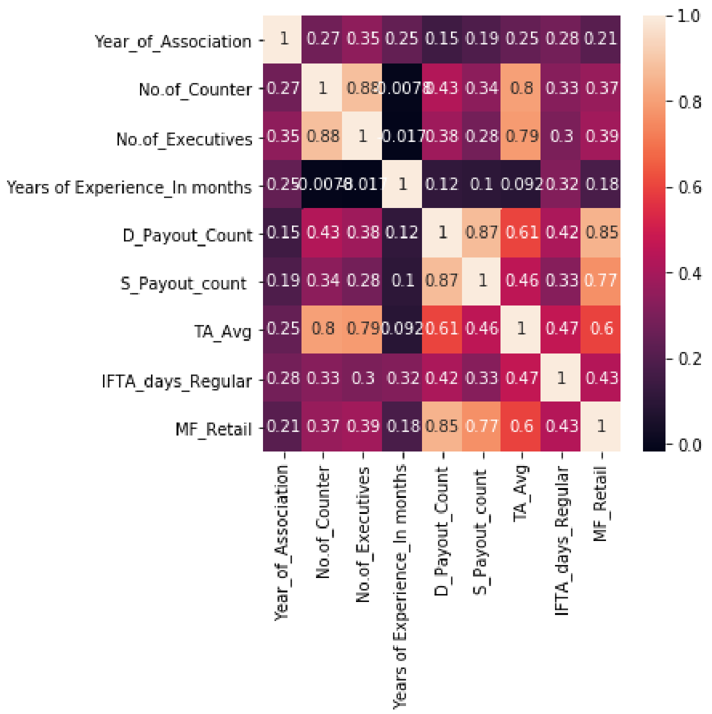
```
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

In [71]:

```
plt.figure(figsize = (5,5))
sns.heatmap(XUV300.corr(),annot = True)
```

Out[71]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x14fa67cff28>
```

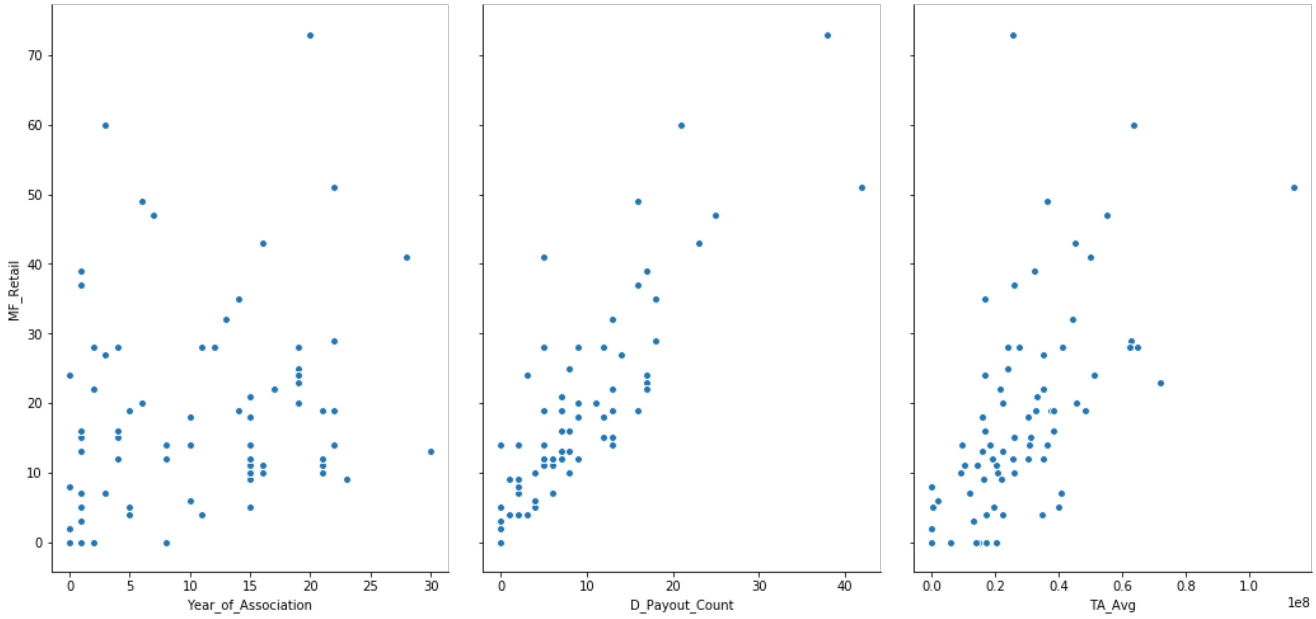


In [72]:

```
sns.pairplot(XUV300, x_vars=['Year_of_Association','D_Payout_Count','TA_Avg'], y_vars='MF_Retail',s
ize=7, aspect=0.7, kind='scatter')
```

Out[72]:

```
<seaborn.axisgrid.PairGrid at 0x14fa36a42b0>
```



In [73]:

```
XUV300.drop(['DEALERSHIPS_NAME'],axis =1, inplace =True)
```

Data Preparation

In [74]:

```
XUV300.head()
```

Out[74]:

	Year_of_Association	No.of_Counter	No.of_Executives	Years of Experience_In months	D_Payout_Count	S_Payout_count	TA_Avg	I
0	19	2	2	88	12	11	23704125.0	4
1	14	3	3	36	13	12	37313875.0	4
2	2	2	2	18	0	0	14814250.0	4
3	6	4	4	19	11	11	45612500.0	4
4	1	3	2	18	13	9	25712500.0	4

Rescaling the Features

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

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

In [75]:

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


# applying normalize ( ) to all columns
XUV300 = XUV300.apply(normalize)
```

Splitting Data into Training and Testing Sets

In [76]:

```
XUV300.columns
```

Out[76]:

```
Index(['Year_of_Association', 'No.of_Counter', 'No.of_Executives',
       'Years of Experience_In months', 'D_Payout_Count', 'S_Payout_count ',
       'TA_Avg', 'IFTA_days_Regular', 'MF_Retail'],
      dtype='object')
```

In [77]:

```
# Putting feature variable to X
X = XUV300[['Year_of_Association','No.of_Counter', 'No.of_Executives', 'Years of Experience_In mont
hs',
       'D_Payout_Count', 'S_Payout_count ', 'TA_Avg', 'IFTA_days_Regular']]

# Putting response variable to y
y = XUV300['MF_Retail']
```

In [78]:

```
#random_state is the seed used by the random number generator, it can be any integer.
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)
```

Building a linear model

Checking VIF

In [79]:

```
# UDF for calculating vif value
def vif_cal(input_data, dependent_col):
    vif_df = pd.DataFrame( columns = ['Var', 'Vif'])
    x_vars=input_data.drop([dependent_col], axis=1)
    xvar_names=x_vars.columns
    for i in range(0,xvar_names.shape[0]):
        y=x_vars[xvar_names[i]]
        x=x_vars[xvar_names.drop(xvar_names[i])]
        rsq=sm.OLS(y,x).fit().rsquared
        vif=round(1/(1-rsq),2)
        vif_df.loc[i] = [xvar_names[i], vif]
    return vif_df.sort_values(by = 'Vif', axis=0, ascending=False, inplace=False)
```

In [80]:

```
# Calculating Vif value|
#vif_cal(input_data=XUV300, dependent_col="MF_Retail")
```

In [81]:

```
#RFE
# Importing RFE and LinearRegression
from sklearn.feature_selection import RFE
from sklearn.linear_model import LinearRegression
```

In [82]:

```
# 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_)
```

```
[ True  True False False  True  True  True False]
[1 1 2 3 1 1 1 4]
```

In [83]:

```
col = X_train.columns[rfe.support_]
```

In [84]:

```
print(col)
```

```
Index(['Year_of_Association', 'No.of_Counter', 'D_Payout_Count',
       'S_Payout_count ', 'TA_Avg'],
      dtype='object')
```

In [85]:

```
#Building model using sklearn
# Creating X_test dataframe with RFE selected variables
X_train_rfe = X_train[col]
```

In [86]:

```
# Adding a constant variable
import statsmodels.api as sm
X_train_rfe = sm.add_constant(X_train_rfe)
```

In [87]:

```
lm = sm.OLS(y_train,X_train_rfe).fit()   # Running the linear model
```

In [88]:

```
#Let's see the summary of our linear model
print(lm.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              MF_Retail   R-squared:                       0.791
Model:                            OLS   Adj. R-squared:                  0.768
Method:                 Least Squares   F-statistic:                     34.16
Date:                Tue, 12 Nov 2019   Prob (F-statistic):           2.98e-14
Time:                        10:05:57   Log-Likelihood:                 49.515
No. Observations:                  51   AIC:                            -87.03
Df Residuals:                      45   BIC:                            -75.44
Df Model:                           5
Covariance Type:            nonrobust
=======================================================================================
                          coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------------
const                  -0.0078      0.030     -0.254      0.800      -0.069       0.054
Year_of_Association     0.0892      0.053      1.677      0.100      -0.018       0.196
No.of_Counter          -0.1329      0.124     -1.076      0.288      -0.382       0.116
D_Payout_Count          0.6650      0.160      4.151      0.000       0.342       0.988
S_Payout_count          0.2377      0.153      1.551      0.128      -0.071       0.546
TA_Avg                  0.3363      0.167      2.016      0.050       0.000       0.672
==============================================================================
Omnibus:                        7.231   Durbin-Watson:                   2.022
Prob(Omnibus):                  0.027   Jarque-Bera (JB):                6.464
Skew:                           0.668   Prob(JB):                       0.0395
Kurtosis:                       4.121   Cond. No.                         19.7
==============================================================================

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

In [89]:

```
vif_cal(input_data=XUV300, dependent_col="MF_Retail")
```

Out[89]:

	Var	Vif
2	No.of_Executives	15.60
1	No.of_Counter	15.08
6	TA_Avg	14.84
4	D_Payout_Count	12.33
5	S_Payout_count	8.16
7	IFTA_days_Regular	7.92
3	Years of Experience_In months	3.70
0	Year_of_Association	3.63

In [90]:

```
# 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 [91]:

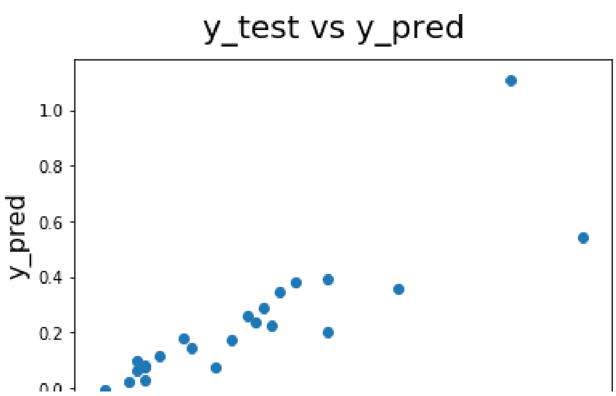
```
# Now let's check how well our model is able to make predictions.

# Importing the required libraries for plots.
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

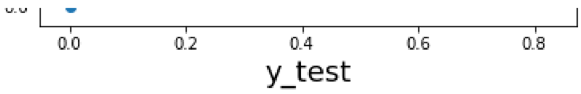
In [92]:

```
# 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[92]:

```
Text(0,0.5,'y_pred')
```





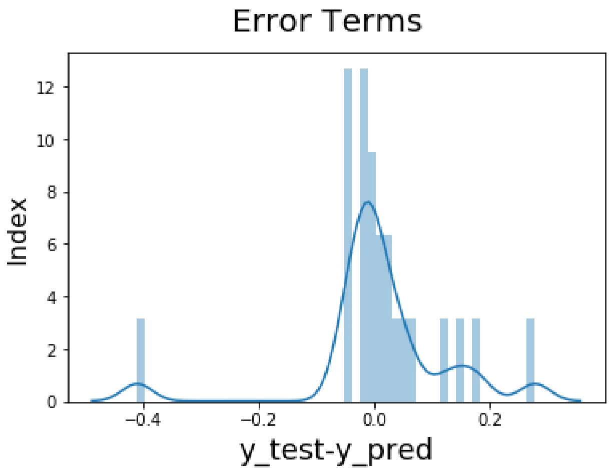
In [93]:

```
# Plotting the error terms to understand the distribution.
fig = plt.figure()
sns.distplot((y_test-y_pred),bins=50)
fig.suptitle('Error Terms', fontsize=20)                  # Plot heading
plt.xlabel('y_test-y_pred', fontsize=18)                  # X-label
plt.ylabel('Index', fontsize=16)                          # Y-label
```

```
C:\Users\23166622\Python\lib\site-packages\matplotlib\axes\_axes.py:6462: UserWarning: The
'normed' kwarg is deprecated, and has been replaced by the 'density' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```

Out[93]:

```
Text(0,0.5,'Index')
```



In [94]:

```
# 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 : 0.12022919881992057
```

Building Model with 2 significant variable

In [95]:

```
# Running RFE with the output number of the variable equal to 9
lm = LinearRegression()
rfe = RFE(lm, 3)             # running RFE
rfe = rfe.fit(X_train, y_train)
print(rfe.support_)            # Printing the boolean results
print(rfe.ranking_)
```

```
[False False False False  True  True  True False]
[3 2 4 5 1 1 1 6]
```

In [96]:

```
col = X_train.columns[rfe.support_]
```

In [97]:

```
print(col)
```

```
Index(['D_Payout_Count', 'S_Payout_count ', 'TA_Avg'], dtype='object')
```

In [98]:

```
#Building model using sklearn
# Creating X_test dataframe with RFE selected variables
X_train_rfe = X_train[col]
```

In [99]:

```
# Adding a constant variable
import statsmodels.api as sm
X_train_rfe = sm.add_constant(X_train_rfe)
```

In [100]:

```
lm = sm.OLS(y_train,X_train_rfe).fit()    # Running the linear model
```

In [101]:

```
#Let's see the summary of our linear model
print(lm.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              MF_Retail   R-squared:                       0.774
Model:                            OLS   Adj. R-squared:                  0.760
Method:                 Least Squares   F-statistic:                     53.70
Date:                Tue, 12 Nov 2019   Prob (F-statistic):           3.22e-15
Time:                        10:05:59   Log-Likelihood:                 47.475
No. Observations:                  51   AIC:                            -86.95
Df Residuals:                      47   BIC:                            -79.22
Df Model:                           3
Covariance Type:            nonrobust
==================================================================================
                     coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------
const              0.0107      0.028      0.380      0.706      -0.046       0.067
D_Payout_Count     0.6682      0.162      4.125      0.000       0.342       0.994
S_Payout_count     0.2531      0.155      1.633      0.109      -0.059       0.565
TA_Avg             0.2427      0.112      2.171      0.035       0.018       0.468
==============================================================================
Omnibus:                        8.041   Durbin-Watson:                   2.129
Prob(Omnibus):                  0.018   Jarque-Bera (JB):                7.637
Skew:                           0.693   Prob(JB):                       0.0220
Kurtosis:                       4.294   Cond. No.                         16.9
==============================================================================

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

In [102]:

```
# 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 [103]:

```
# Now let's check how well our model is able to make predictions.

# Importing the required libraries for plots.
```

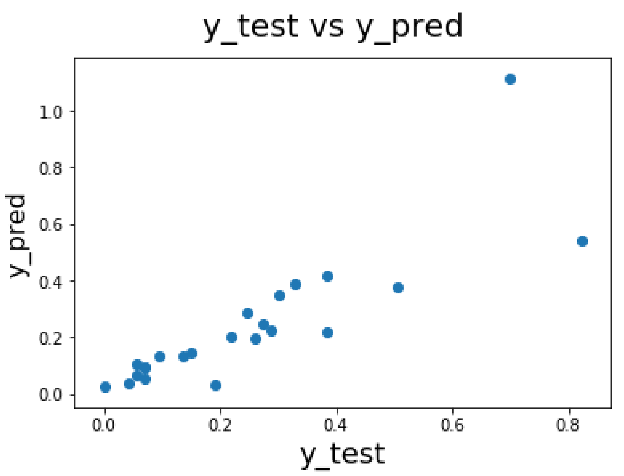
```
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

In [104]:

```
# 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[104]:

```
Text(0,0.5,'y_pred')
```



In [105]:

```
# 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 : 0.12289632713083959
```