Assignment-05-Multiple Linear Regression-1

Q1.Consider only the below columns and prepare a prediction model for predicting Price.

Corolla<-Corolla[c("Price","Age_08_04","KM","HP","cc","Doors","Gears","Quarterly_Tax","Weight")]

In [1]:

```
# Import libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import statsmodels.formula.api as smf
import statsmodels.api as sm
from statsmodels.graphics.regressionplots import influence_plot
```

In [2]:

```
# Import dataset
toyo=pd.read_csv("C:/Users/LENOVO/Documents/Custom Office Templates/ToyotaCorolla.csv",enco
toyo
```

Out[2]:

	Id	Model	Price	Age_08_04	Mfg_Month	Mfg_Year	KM	Fuel_Type	HP	Met_
0	1	TOYOTA Corolla 2.0 D4D HATCHB TERRA 2/3-Doors	13500	23	10	2002	46986	Diesel	90	
1	2	TOYOTA Corolla 2.0 D4D HATCHB TERRA 2/3-Doors	13750	23	10	2002	72937	Diesel	90	
2	3	TOYOTA Corolla 2.0 D4D HATCHB TERRA 2/3-Doors	13950	24	9	2002	41711	Diesel	90	
3	4	TOYOTA Corolla 2.0 D4D HATCHB TERRA 2/3-Doors	14950	26	7	2002	48000	Diesel	90	
4	5	TOYOTA Corolla 2.0 D4D HATCHB SOL 2/3-Doors	13750	30	3	2002	38500	Diesel	90	
...	...	...	...	...	...	...	...	...	...	
1431	1438	TOYOTA Corolla 1.3 16V HATCHB G6 2/3-Doors	7500	69	12	1998	20544	Petrol	86	
1432	1439	TOYOTA Corolla 1.3 16V HATCHB LINEA TERRA 2/3-...	10845	72	9	1998	19000	Petrol	86	

	Id	Model	Price	Age_08_04	Mfg_Month	Mfg_Year	KM	Fuel_Type	HP	Met_
1433	1440	TOYOTA Corolla 1.3 16V HATCHB LINEA TERRA 2/3-...	8500	71	10	1998	17016	Petrol	86	
1434	1441	TOYOTA Corolla 1.3 16V HATCHB LINEA TERRA 2/3-...	7250	70	11	1998	16916	Petrol	86	
1435	1442	TOYOTA Corolla 1.6 LB LINEA TERRA 4/5-Doors	6950	76	5	1998	1	Petrol	110	

1436 rows × 38 columns

EDA

In [3]:

```
toyo.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1436 entries, 0 to 1435
Data columns (total 38 columns):
 #   Column            Non-Null Count  Dtype 
---  ------            --------------  ----- 
 0   Id                1436 non-null   int64 
 1   Model             1436 non-null   object
 2   Price             1436 non-null   int64 
 3   Age_08_04         1436 non-null   int64 
 4   Mfg_Month         1436 non-null   int64 
 5   Mfg_Year          1436 non-null   int64 
 6   KM                1436 non-null   int64 
 7   Fuel_Type         1436 non-null   object
 8   HP                1436 non-null   int64 
 9   Met_Color         1436 non-null   int64 
 10  Color             1436 non-null   object
 11  Automatic         1436 non-null   int64 
 12  cc                1436 non-null   int64 
 13  Doors             1436 non-null   int64 
 14  Cylinders         1436 non-null   int64 
 15  Gears             1436 non-null   int64 
 16  Quarterly_Tax     1436 non-null   int64 
 17  Weight            1436 non-null   int64 
 18  Mfr_Guarantee     1436 non-null   int64 
 19  BOVAG_Guarantee   1436 non-null   int64 
 20  Guarantee_Period  1436 non-null   int64 
 21  ABS               1436 non-null   int64 
 22  Airbag_1          1436 non-null   int64 
 23  Airbag_2          1436 non-null   int64 
 24  Airco             1436 non-null   int64 
 25  Automatic_airco   1436 non-null   int64 
 26  Boardcomputer     1436 non-null   int64 
 27  CD_Player         1436 non-null   int64 
 28  Central_Lock      1436 non-null   int64 
 29  Powered_Windows   1436 non-null   int64 
 30  Power_Steering    1436 non-null   int64 
 31  Radio             1436 non-null   int64 
 32  Mistlamps         1436 non-null   int64 
 33  Sport_Model       1436 non-null   int64 
 34  Backseat_Divider  1436 non-null   int64 
 35  Metallic_Rim      1436 non-null   int64 
 36  Radio_cassette    1436 non-null   int64 
 37  Tow_Bar           1436 non-null   int64 
dtypes: int64(35), object(3)
memory usage: 426.4+ KB
```

In [4]:

```
toyo.isnull().sum()
```

Out[4]:

```
Id                  0
Model               0
Price               0
Age_08_04           0
Mfg_Month           0
Mfg_Year            0
KM                  0
Fuel_Type           0
HP                  0
Met_Color           0
Color               0
Automatic           0
cc                  0
Doors               0
Cylinders           0
Gears               0
Quarterly_Tax       0
Weight              0
Mfr_Guarantee       0
BOVAG_Guarantee     0
Guarantee_Period    0
ABS                 0
Airbag_1            0
Airbag_2            0
Airco               0
Automatic_airco     0
Boardcomputer       0
CD_Player           0
Central_Lock        0
Powered_Windows     0
Power_Steering      0
Radio               0
Mistlamps           0
Sport_Model         0
Backseat_Divider    0
Metallic_Rim        0
Radio_cassette      0
Tow_Bar             0
dtype: int64
```

Inference:

No NA values

In [5]:

```
toyo2=pd.concat([toyo.iloc[:,2:4],toyo.iloc[:,6:7],toyo.iloc[:,8:9],toyo.iloc[:,12:14],toyo
toyo2
```

Out[5]:

	Price	Age_08_04	KM	HP	cc	Doors	Gears	Quarterly_Tax	Weight
0	13500	23	46986	90	2000	3	5	210	1165
1	13750	23	72937	90	2000	3	5	210	1165
2	13950	24	41711	90	2000	3	5	210	1165
3	14950	26	48000	90	2000	3	5	210	1165
4	13750	30	38500	90	2000	3	5	210	1170
...	...	...	...	...	...	...	...	...	...
1431	7500	69	20544	86	1300	3	5	69	1025
1432	10845	72	19000	86	1300	3	5	69	1015
1433	8500	71	17016	86	1300	3	5	69	1015
1434	7250	70	16916	86	1300	3	5	69	1015
1435	6950	76	1	110	1600	5	5	19	1114

1436 rows × 9 columns

In [6]:

```
# rename columns
toyo3=toyo2.rename({'Age_08_04':'Age','cc':'CC','Quarterly_Tax':'QT'},axis=1)
toyo3
```

Out[6]:

	Price	Age	KM	HP	CC	Doors	Gears	QT	Weight
0	13500	23	46986	90	2000	3	5	210	1165
1	13750	23	72937	90	2000	3	5	210	1165
2	13950	24	41711	90	2000	3	5	210	1165
3	14950	26	48000	90	2000	3	5	210	1165
4	13750	30	38500	90	2000	3	5	210	1170
...	...	...	...	...	...	...	...	...	...
1431	7500	69	20544	86	1300	3	5	69	1025
1432	10845	72	19000	86	1300	3	5	69	1015
1433	8500	71	17016	86	1300	3	5	69	1015
1434	7250	70	16916	86	1300	3	5	69	1015
1435	6950	76	1	110	1600	5	5	19	1114

1436 rows × 9 columns

In [7]:

```
toyo3[toyo3.duplicated()]
```

Out[7]:

	Price	Age	KM	HP	CC	Doors	Gears	QT	Weight
113	24950	8	13253	116	2000	5	5	234	1320

In [8]:

```
toyo4=toyo3.drop_duplicates().reset_index(drop=True)
toyo4
```

Out[8]:

	Price	Age	KM	HP	CC	Doors	Gears	QT	Weight
0	13500	23	46986	90	2000	3	5	210	1165
1	13750	23	72937	90	2000	3	5	210	1165
2	13950	24	41711	90	2000	3	5	210	1165
3	14950	26	48000	90	2000	3	5	210	1165
4	13750	30	38500	90	2000	3	5	210	1170
...	...	...	...	...	...	...	...	...	...
1430	7500	69	20544	86	1300	3	5	69	1025
1431	10845	72	19000	86	1300	3	5	69	1015
1432	8500	71	17016	86	1300	3	5	69	1015
1433	7250	70	16916	86	1300	3	5	69	1015
1434	6950	76	1	110	1600	5	5	19	1114

1435 rows × 9 columns

In [9]:

```
toyo4.describe()
```

Out[9]:

	Price	Age	KM	HP	CC	Doors	
count	1435.000000	1435.000000	1435.000000	1435.000000	1435.000000	1435.000000	1435
mean	10720.915679	55.980488	68571.782578	101.491986	1576.560976	4.032753	5
std	3608.732978	18.563312	37491.094553	14.981408	424.387533	0.952667	0
min	4350.000000	1.000000	1.000000	69.000000	1300.000000	2.000000	3
25%	8450.000000	44.000000	43000.000000	90.000000	1400.000000	3.000000	5
50%	9900.000000	61.000000	63451.000000	110.000000	1600.000000	4.000000	5
75%	11950.000000	70.000000	87041.500000	110.000000	1600.000000	5.000000	5
max	32500.000000	80.000000	243000.000000	192.000000	16000.000000	5.000000	6

Correlation Analysis

In [10]:

```
toyo4.corr()
```

Out[10]:

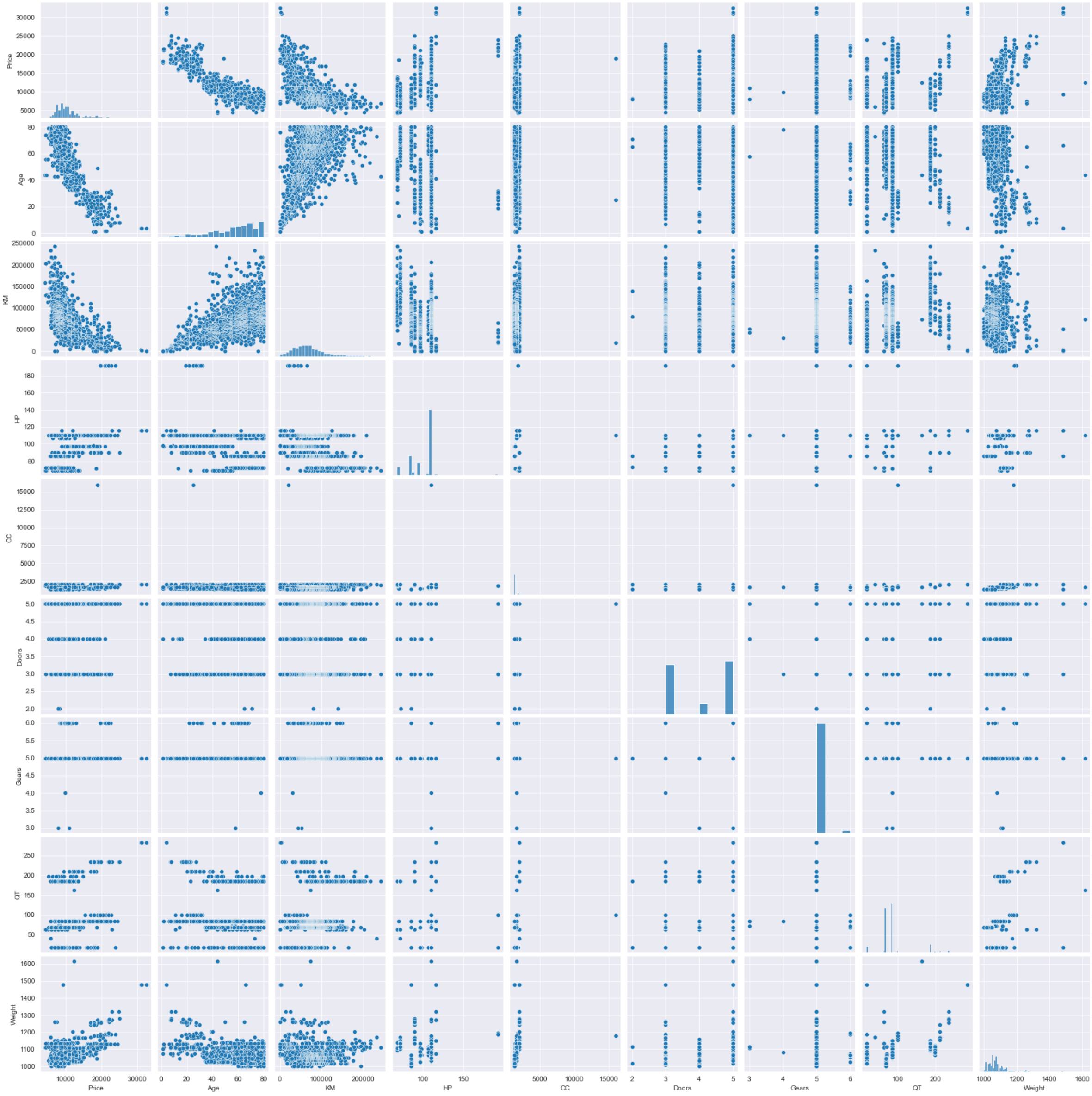
	Price	Age	KM	HP	CC	Doors	Gears	QT	
Price	1.000000	-0.876273	-0.569420	0.314134	0.124375	0.183604	0.063831	0.211508	
Age	-0.876273	1.000000	0.504575	-0.155293	-0.096549	-0.146929	-0.005629	-0.193319	-
KM	-0.569420	0.504575	1.000000	-0.332904	0.103822	-0.035193	0.014890	0.283312	-
HP	0.314134	-0.155293	-0.332904	1.000000	0.035207	0.091803	0.209642	-0.302287	
CC	0.124375	-0.096549	0.103822	0.035207	1.000000	0.079254	0.014732	0.305982	
Doors	0.183604	-0.146929	-0.035193	0.091803	0.079254	1.000000	-0.160101	0.107353	
Gears	0.063831	-0.005629	0.014890	0.209642	0.014732	-0.160101	1.000000	-0.005125	
QT	0.211508	-0.193319	0.283312	-0.302287	0.305982	0.107353	-0.005125	1.000000	
Weight	0.575869	-0.466484	-0.023969	0.087143	0.335077	0.301734	0.021238	0.621988	

In [11]:

```
sns.set_style(style='darkgrid')
sns.pairplot(toyo4)
```

Out[11]:

```
<seaborn.axisgrid.PairGrid at 0x74dd8e9760>
```



Model Building

In [12]:

```
model=smf.ols("Price~Age+KM+HP+CC+Doors+Gears+QT+Weight",data=toyo4).fit()
```

In [13]:

```
# Finding coefficient parameters
model.params
```

Out[13]:

```
Intercept   -5472.540368
Age          -121.713891
KM             -0.020737
HP             31.584612
CC             -0.118558
Doors          -0.920189
Gears         597.715894
QT              3.858805
Weight         16.855470
dtype: float64
```

In [14]:

```
# Finding tvalues and pvalues
model.tvalues , np.round(model.pvalues,5)
```

Out[14]:

```
(Intercept    -3.875273
 Age         -46.551876
 KM          -16.552424
 HP           11.209719
 CC           -1.316436
 Doors        -0.023012
 Gears         3.034563
 QT            2.944198
 Weight       15.760663
 dtype: float64,
 Intercept    0.00011
 Age          0.00000
 KM           0.00000
 HP           0.00000
 CC           0.18824
 Doors        0.98164
 Gears        0.00245
 QT           0.00329
 Weight       0.00000
 dtype: float64)
```

Inference:

CC and Doors are insignificant

In [15]:

```
# Finding  rsquared values
model.rsquared ,model.rsquared_adj
```

Out[15]:

```
(0.8625200256947, 0.8617487495415146)
```

Inference:

R_Squared value is 0.86 model is a Good model

In [16]:

```
# Build SLR and MLR for insignificant variables 'CC' and 'Doors'
# Also find their tvalues and pvalues
```

In [17]:

```
slr_c=smf.ols("Price~CC",data=toyo4).fit()
slr_c.tvalues, slr_c.pvalues  # CC has significant pvalue
```

Out[17]:

```
(Intercept    24.879592
 CC            4.745039
 dtype: float64,
 Intercept    7.236022e-114
 CC            2.292856e-06
 dtype: float64)
```

In [18]:

```
slr_d=smf.ols("Price~Doors",data=toyo4).fit()
slr_d.tvalues, slr_d.pvalues # Doors has significant value
```

Out[18]:

```
(Intercept    19.421546
 Doors         7.070520
 dtype: float64,
 Intercept    8.976407e-75
 Doors        2.404166e-12
 dtype: float64)
```

In [19]:

```
mlr_cd=smf.ols("Price~CC+Doors",data=toyo4).fit()
mlr_cd.tvalues, mlr_cd.pvalues  # CC and Doors have significant pvalue
```

Out[19]:

```
(Intercept    12.786341
 CC            4.268006
 Doors         6.752236
 dtype: float64,
 Intercept    1.580945e-35
 CC           2.101878e-05
 Doors        2.109558e-11
 dtype: float64)
```

Model Validation Techniques

Two Techniques:1. Collinearity Check & 2. Residual Analysis

In [20]:

```
# 1) Collinearity problem Check
# Calculate VIF = 1/(1-Rsquare) For all independent variables

rsq_age=smf.ols("Age~KM+HP+CC+Doors+Gears+QT+Weight",data=toyo4).fit().rsquared
vif_age=1/(1-rsq_age)

rsq_km=smf.ols("KM~Age+HP+CC+Doors+Gears+QT+Weight",data=toyo4).fit().rsquared
vif_km=1/(1-rsq_km)

rsq_hp=smf.ols("HP~Age+KM+CC+Doors+Gears+QT+Weight",data=toyo4).fit().rsquared
vif_hp=1/(1-rsq_hp)

rsq_cc=smf.ols("CC~Age+KM+HP+Doors+Gears+QT+Weight",data=toyo4).fit().rsquared
vif_cc=1/(1-rsq_cc)

rsq_dr=smf.ols("Doors~Age+KM+HP+CC+Gears+QT+Weight",data=toyo4).fit().rsquared
vif_dr=1/(1-rsq_dr)

rsq_gr=smf.ols("Gears~Age+KM+HP+CC+Doors+QT+Weight",data=toyo4).fit().rsquared
vif_gr=1/(1-rsq_gr)

rsq_qt=smf.ols("QT~Age+KM+HP+CC+Doors+Gears+Weight",data=toyo4).fit().rsquared
vif_qt=1/(1-rsq_qt)

rsq_wt=smf.ols("Weight~Age+KM+HP+CC+Doors+Gears+QT",data=toyo4).fit().rsquared
vif_wt=1/(1-rsq_wt)

# Putting the values in DataFrame
d1={'Vriables':['Age','KM','HP','CC','Doors','Gears','QT','Weight'],
    'VIF':[vif_age ,vif_km,vif_hp,vif_cc,vif_dr,vif_gr,vif_qt,vif_wt]}
Vif_df=pd.DataFrame(d1)
Vif_df
```

Out[20]:

	Vriables	VIF
0	Age	1.876236
1	KM	1.757178
2	HP	1.419180
3	CC	1.163470
4	Doors	1.155890
5	Gears	1.098843
6	QT	2.295375
7	Weight	2.487180

None variable has VIF>20, No Collinearity,so consider all variables in Regression

equation

In [21]:

```
# 2) Residual Analysis
# Test for normality of residuals (Q-Q Plot) using residual model (model.resid)
sm.qqplot(model.resid,line='q')  # 'q' - A  line is fit through the quartiles # line= '45'-
plt.title("Normal Q-Q plot of residuals")
plt.show()
```

In [22]:

```
list(np.where(model.resid>6000)) # oulier detection from above Q-Q plot of residual
```

Out[22]:

```
[array([109, 146, 522], dtype=int64)]
```

In [23]:

```
list(np.where(model.resid<-6000))
```

Out[23]:

```
[array([220, 600, 959], dtype=int64)]
```

In [24]:

```
# Test for Homoscedasticity or heteroscedasticity (plotting model's standardized fitted val
def standard_values(vals) : return (vals-vals.mean())/vals.std()  # user defined z= (x-mu)/
```

In [25]:

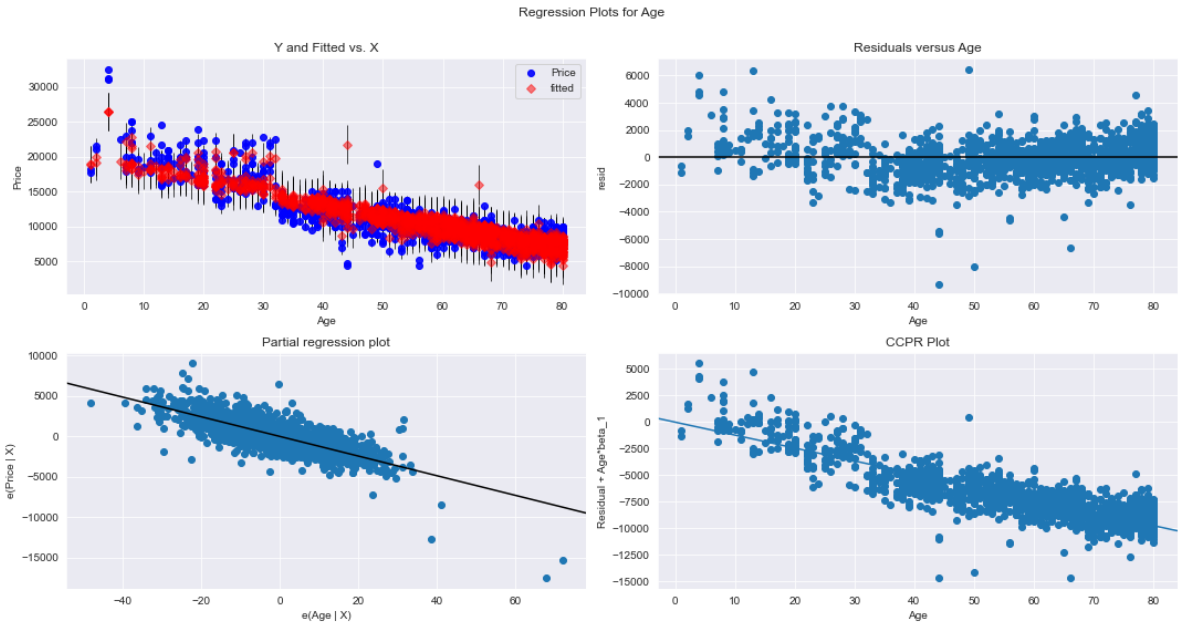
```
plt.scatter(standard_values(model.fittedvalues),standard_values(model.resid))
plt.title('Residual Plot')
plt.xlabel('standardized fitted values')
plt.ylabel('standardized residual values')
plt.show()
```

In [26]:

```
# Test for error or Residuals Vs Regressors or Independent 'x'vaiables or predictors
# Using Residual Regression plot code graphics.plot_regress_exog(model,'x',fig) # exog = x-
```

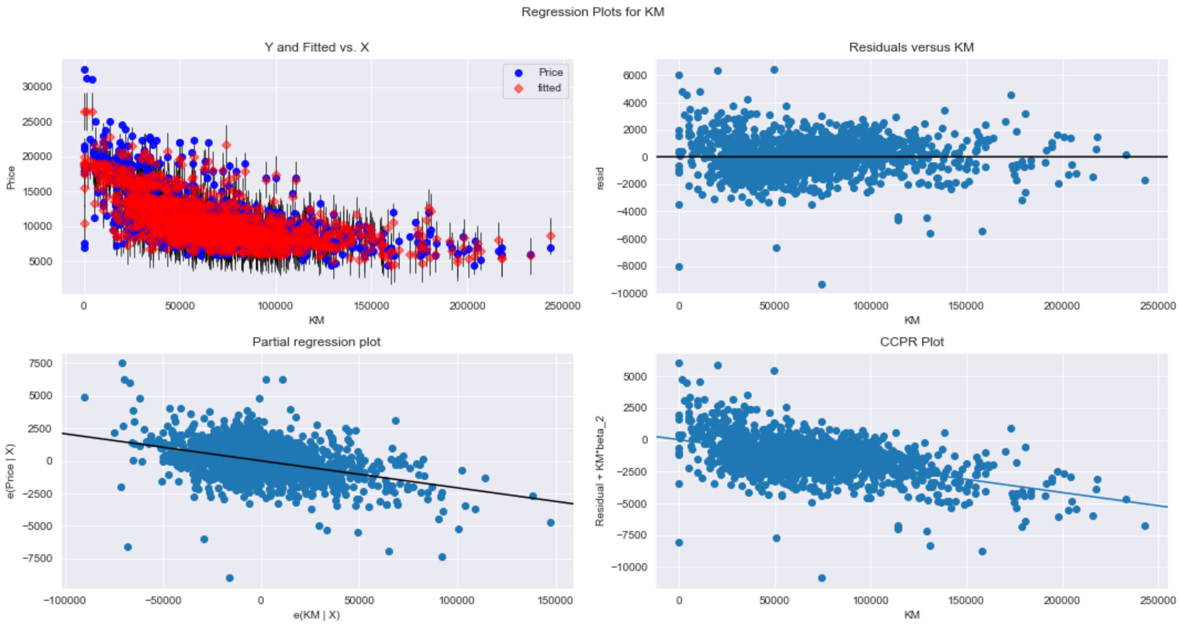
In [27]:

```
fig=plt.figure(figsize=(15,8))
sm.graphics.plot_regress_exog(model,'Age',fig=fig)
plt.show()
```



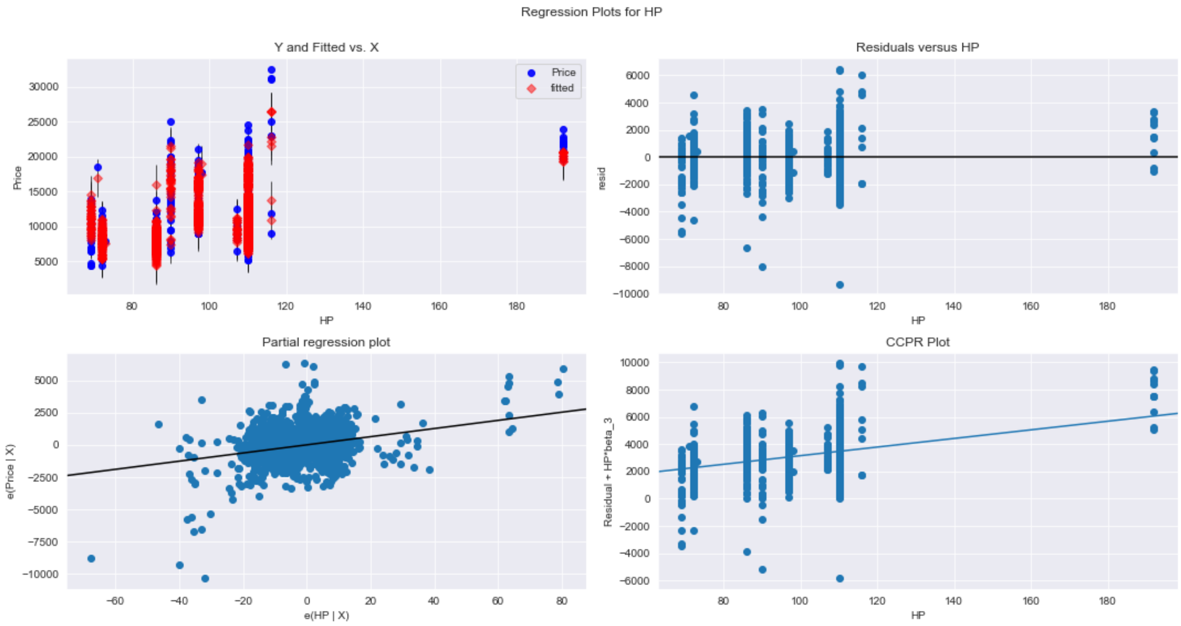
In [28]:

```
fig=plt.figure(figsize=(15,8))
sm.graphics.plot_regress_exog(model,'KM',fig=fig)
plt.show()
```



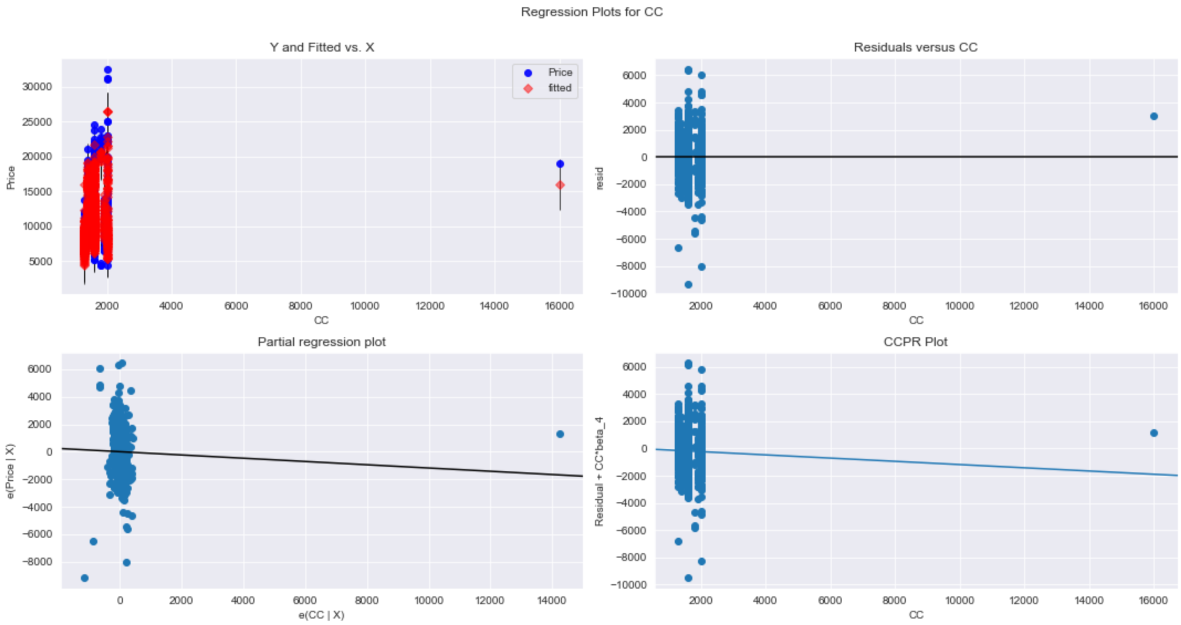
In [29]:

```
fig=plt.figure(figsize=(15,8))
sm.graphics.plot_regress_exog(model,'HP',fig=fig)
plt.show()
```



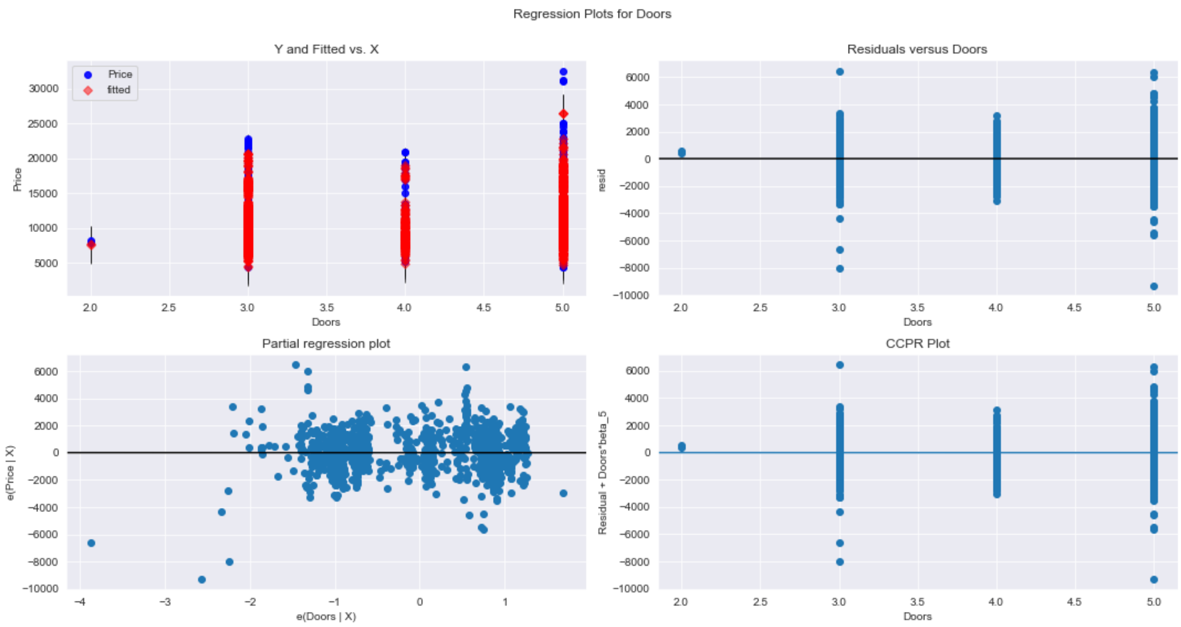
In [30]:

```
fig=plt.figure(figsize=(15,8))
sm.graphics.plot_regress_exog(model,'CC',fig=fig)
plt.show()
```



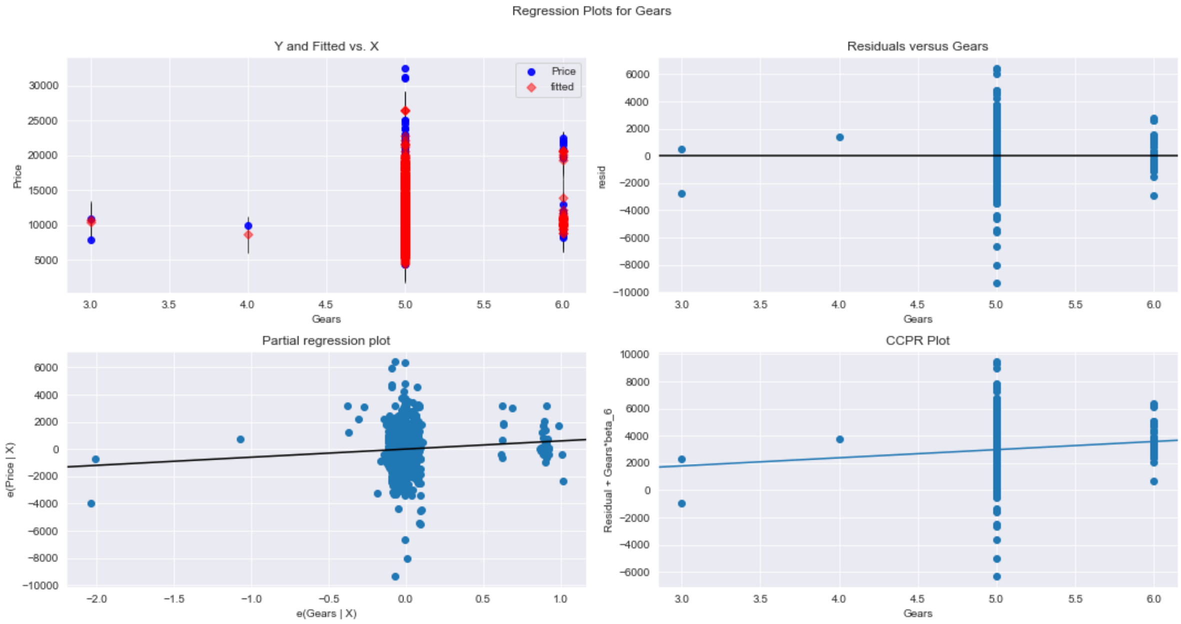
In [31]:

```
fig=plt.figure(figsize=(15,8))
sm.graphics.plot_regress_exog(model,'Doors',fig=fig)
plt.show()
```



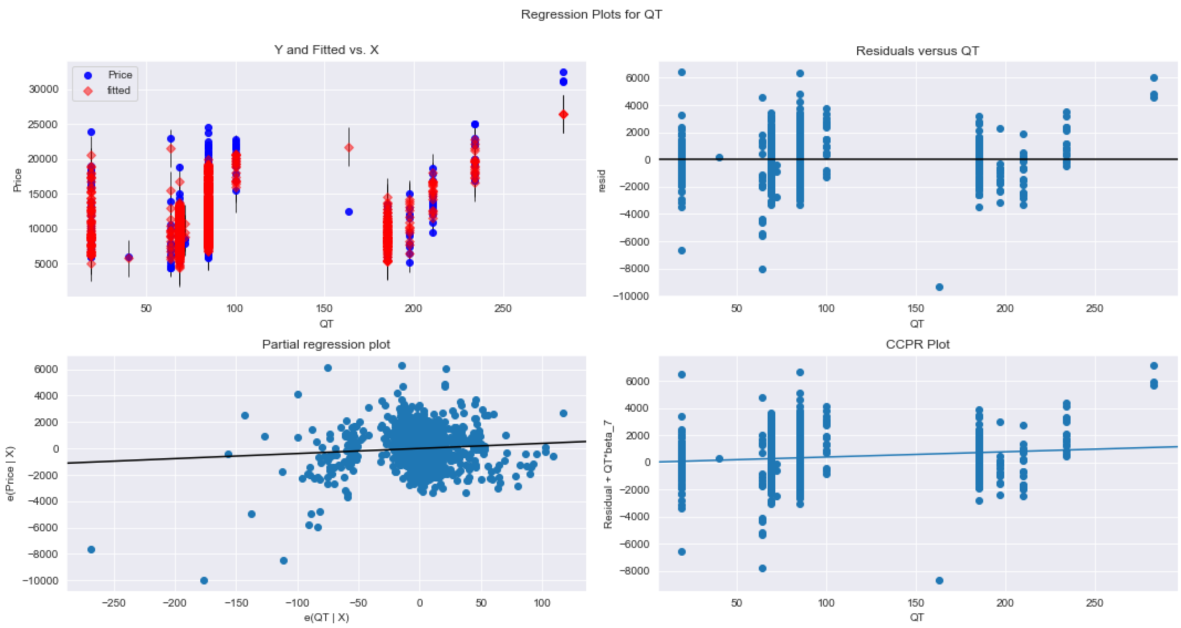
In [32]:

```
fig=plt.figure(figsize=(15,8))
sm.graphics.plot_regress_exog(model,'Gears',fig=fig)
plt.show()
```



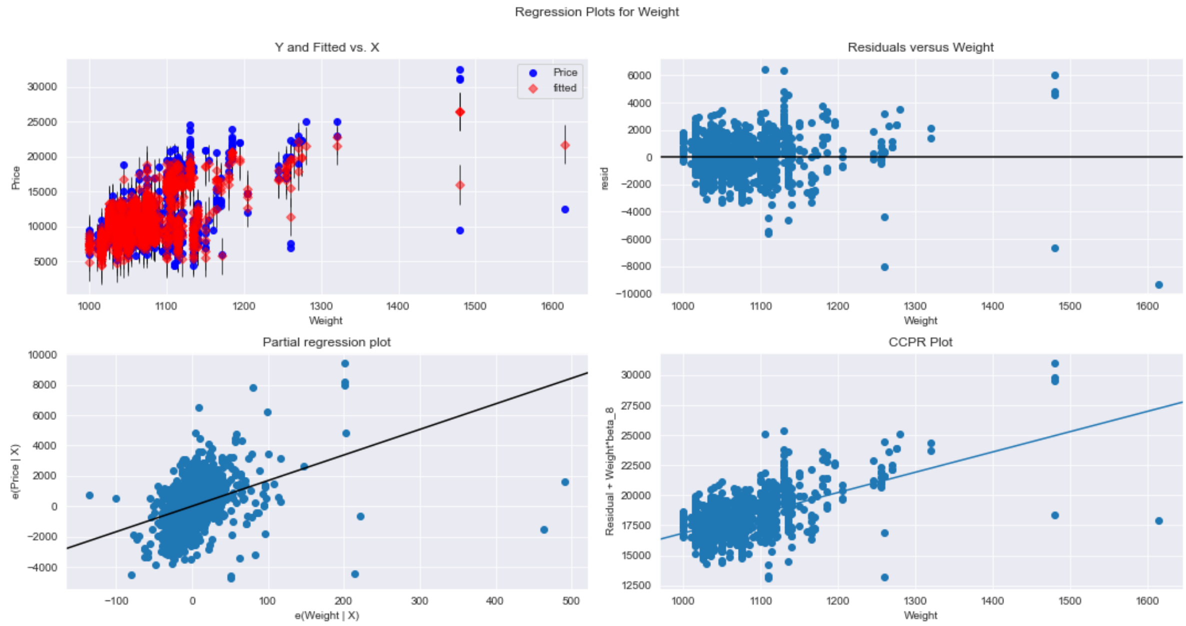
In [33]:

```
fig=plt.figure(figsize=(15,8))
sm.graphics.plot_regress_exog(model,'QT',fig=fig)
plt.show()
```



In [34]:

```
fig=plt.figure(figsize=(15,8))
sm.graphics.plot_regress_exog(model,'Weight',fig=fig)
plt.show()
```



Model Deletion Diagnostics (checking outliers or influencers)

Two Techniques: 1.Cook's Distance & 2. Leverage value

In [35]:

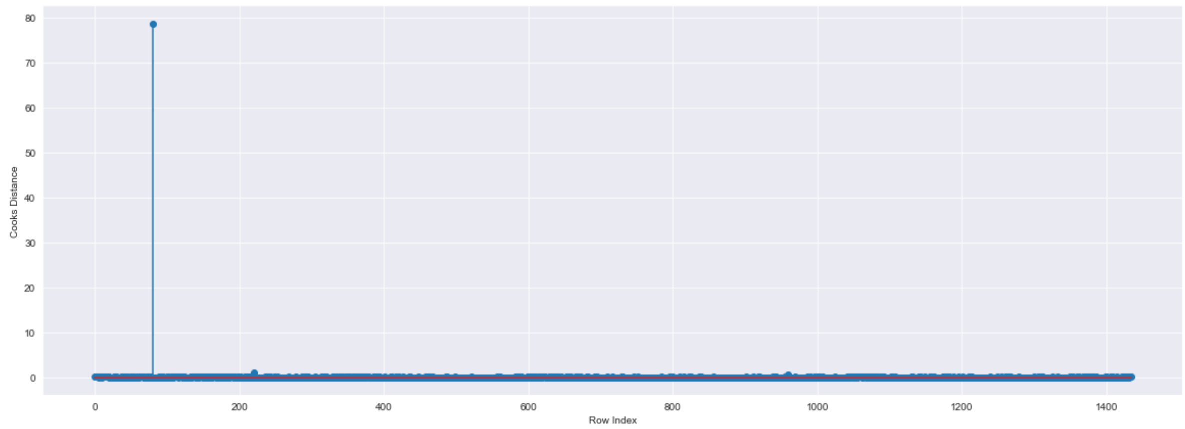
```
# Cook's Distance: If Cook's distance > 1, Then it's an outlier
# Get influencers using cook's distance
(c,_)=model.get_influence().cooks_distance
c
```

Out[35]:

```
array([7.22221054e-03, 3.94547973e-03, 5.44224039e-03, ...,
       8.04110550e-07, 6.99854767e-04, 1.08408002e-02])
```

In [36]:

```
# Plot the influencer using the stem plot
fig=plt.figure(figsize=(20,7))
plt.stem(np.arange(len(toyo4)),np.round(c,3))
plt.xlabel('Row Index')
plt.ylabel('Cooks Distance')
plt.show()
```



In [37]:

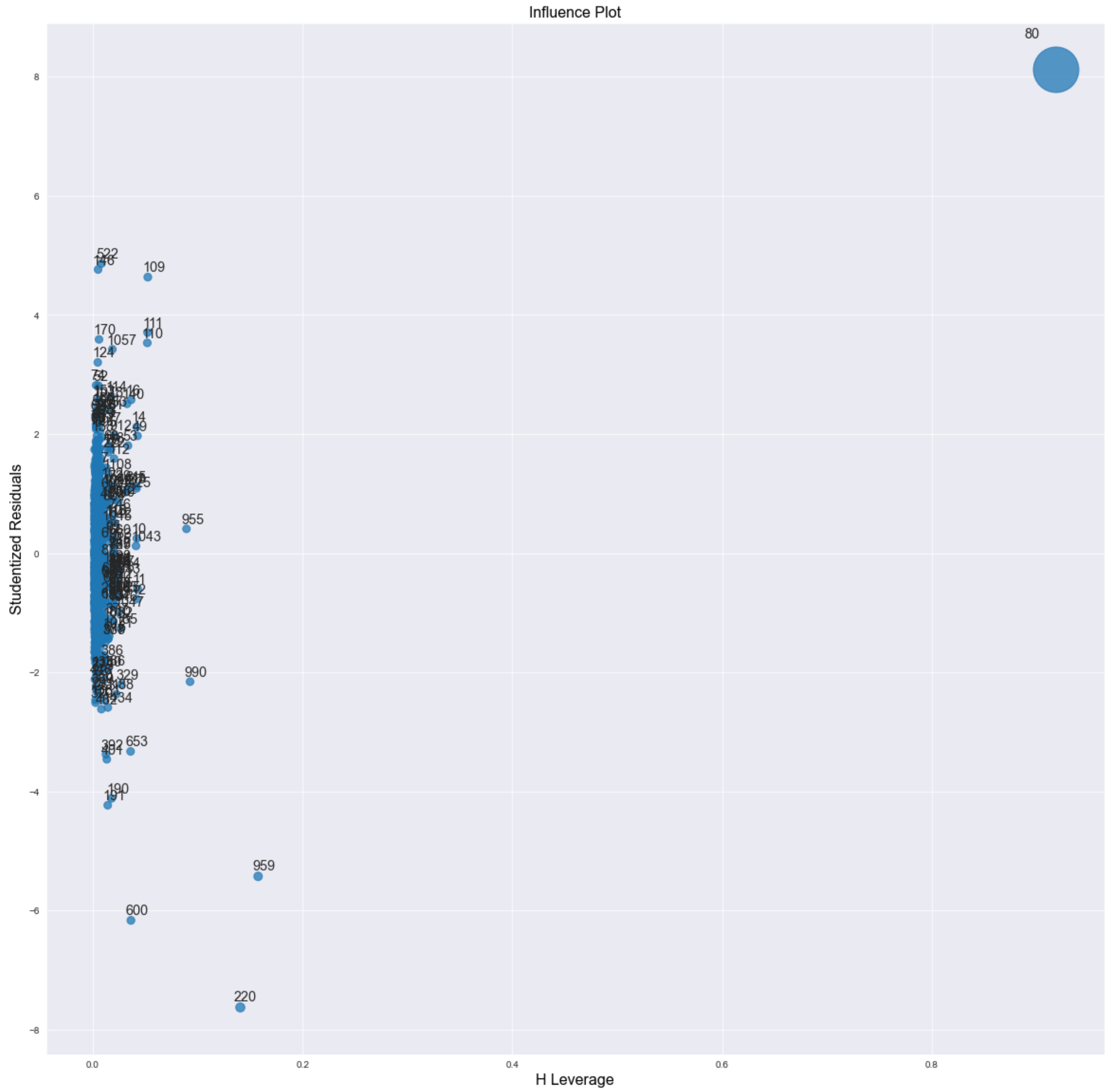
```
# Index and value of influncer where C>0.5
np.argmax(c),np.max(c)
```

Out[37]:

```
(80, 78.7295058224916)
```

In [38]:

```
# 2.Leverage Value using High Influncer Points: Points beyond Leverage_cutoff value are inf
fig,ax=plt.subplots(figsize=(20,20))
fig=influence_plot(model,ax = ax)
```



In [39]:

```
# Levarge Cutoff value = 3*(k+1)/n; k= no.of features/columns & n=no.of datapoints
k=toyo4.shape[1]
n=toyo4.shape[0]
leverage_cutoff=(3*(k+1))/n
leverage_cutoff
```

Out[39]:

```
0.020905923344947737
```

In [40]:

```
toyo4[toyo4.index.isin([80])]
```

Out[40]:

	Price	Age	KM	HP	CC	Doors	Gears	QT	Weight
80	18950	25	20019	110	16000	5	5	100	1180

improving the model

In [41]:

```
# Creating a copy lof data so that original dataset is not affected
toyo_new=toyo4.copy()
toyo_new
```

Out[41]:

	Price	Age	KM	HP	CC	Doors	Gears	QT	Weight
0	13500	23	46986	90	2000	3	5	210	1165
1	13750	23	72937	90	2000	3	5	210	1165
2	13950	24	41711	90	2000	3	5	210	1165
3	14950	26	48000	90	2000	3	5	210	1165
4	13750	30	38500	90	2000	3	5	210	1170
...	...	...	...	...	...	...	...	...	...
1430	7500	69	20544	86	1300	3	5	69	1025
1431	10845	72	19000	86	1300	3	5	69	1015
1432	8500	71	17016	86	1300	3	5	69	1015
1433	7250	70	16916	86	1300	3	5	69	1015
1434	6950	76	1	110	1600	5	5	19	1114

1435 rows × 9 columns

In [42]:

```
# Discard the data points which are influencers and reassign the row number (reset_index(dr
toyo5=toyo_new.drop(toyo_new.index[[80]],axis=0).reset_index(drop=True)
toyo5
```

Out[42]:

	Price	Age	KM	HP	CC	Doors	Gears	QT	Weight
0	13500	23	46986	90	2000	3	5	210	1165
1	13750	23	72937	90	2000	3	5	210	1165
2	13950	24	41711	90	2000	3	5	210	1165
3	14950	26	48000	90	2000	3	5	210	1165
4	13750	30	38500	90	2000	3	5	210	1170
...	...	...	...	...	...	...	...	...	...
1429	7500	69	20544	86	1300	3	5	69	1025
1430	10845	72	19000	86	1300	3	5	69	1015
1431	8500	71	17016	86	1300	3	5	69	1015
1432	7250	70	16916	86	1300	3	5	69	1015
1433	6950	76	1	110	1600	5	5	19	1114

1434 rows × 9 columns

Model Deletion Diagnostics and Final Model

In [43]:

```
while np.max(c)>0.5:
    model=smf.ols("Price~Age+KM+HP+CC+Doors+Gears+QT+Weight",data=toyo5).fit()
    (c,_)=model.get_influence().cooks_distance
    c
    np.argmax(c),np.max(c)
    toyo5=toyo5.drop(toyo5.index[[np.argmax(c)]],axis=0).reset_index(drop=True)
    toyo5
else:
    final_model=smf.ols("Price~Age+KM+HP+CC+Doors+Gears+QT+Weight",data=toyo5).fit()
    final_model.rsquared, final_model.aic
    print("Thus model accuracy is improved to",final_model.rsquared)
```

```
Thus model accuracy is improved to 0.8882395145171204
```

In [44]:

```
if np.max(c)>0.5:
    model=smf.ols("Price~Age+KM_HP+CC+Doors+Gears+QT+Weight",data=toyo5).fit()
    (c,_)=model.get_influence().cooks_distance
    c

    np.argmax(c),np.max(c)
    toyo5=toyo5.drop(toyo5.index[[np.argmax(c)]],axis=0).reset_index(drop=True)
    toyo5
else:
    final_model=smf.ols("Price~Age+KM+HP+CC+Doors+Gears+QT+Weight",data=toyo5).fit()
    final_model.rsquared, final_model.aic
    print("Thus model accuracy is improved to",final_model.rsquared)
```

```
Thus model accuracy is improved to 0.8882395145171204
```

In [45]:

```
final_model.rsquared
```

Out[45]:

```
0.8882395145171204
```

Creation of model using Lasso

In [46]:

```
x=toyo5[['Age','Weight','KM','HP','CC','Doors','QT','Weight']]
y=toyo5['Price']

from sklearn.model_selection import train_test_split
from sklearn.linear_model import Lasso
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.25,random_state=10)
reg=Lasso(alpha=0.5)
reg.fit(x_train, y_train)

print('Lasso Regression: R^2 score on training set',reg.score(x_train, y_train)*100)
print('Lasso Regression: R^2 score on test set',reg.score(x_test, y_test)*100)

lambdas=(0.001,0.01,0.1,0.5,1,2,10)
l_num=7
pred_num=x.shape[1]

# prepare data for enumerate
coeff_a = np.zeros((l_num, pred_num))
train_r_squared =np.zeros(l_num)
test_r_squared =np.zeros(l_num)

# enumerate through lambdas with index and i
for ind, i in enumerate(lambdas):
    reg = Lasso(alpha =1)
    reg.fit(x_train, y_train)

    coeff_a[ind,:]=reg.coef_
    train_r_squared[ind] = reg.score(x_train, y_train)
    test_r_squared[ind] = reg.score(x_test, y_test)
```

```
Lasso Regression: R^2 score on training set 88.74698071262482
Lasso Regression: R^2 score on test set 88.77836439214997
```

Creation of model using Ridge

In [47]:

```
from sklearn.linear_model import Ridge
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.25,random_state=10)
reg=Ridge(alpha=0.5)
reg.fit(x_train, y_train)

print('Ridge Regression: R^2 score on training set',reg.score(x_train, y_train)*100)
print('Ridge Regression: R^2 score on test set',reg.score(x_test, y_test)*100)

lambdas=(0.001,0.01,0.1,0.5,1,2,10)
l_num=7
pred_num=x.shape[1]

# prepare data for enumerate
coeff_a = np.zeros((l_num, pred_num))
train_r_squared =np.zeros(l_num)
test_r_squared =np.zeros(l_num)

# enumerate through lambdas with index and i
for ind, i in enumerate(lambdas):
    reg = Ridge(alpha =1)
    reg.fit(x_train, y_train)

    coeff_a[ind,:]=reg.coef_
    train_r_squared[ind] = reg.score(x_train, y_train)
    test_r_squared[ind] = reg.score(x_test, y_test)
```

```
Ridge Regression: R^2 score on training set 88.74698328222092
Ridge Regression: R^2 score on test set 88.77884476539593
```

Model Predictions

In [48]:

```
# say New data for prediction is
new_data=pd.DataFrame({"Age":12,"KM":40000,"HP":80,"CC":1300,"Doors":4,"Gears":5,"QT":69,"W
new_data
```

Out[48]:

	Age	KM	HP	CC	Doors	Gears	QT	Weight
0	12	40000	80	1300	4	5	69	1012

In [49]:

```
# Manual prediction of price
final_model.predict(new_data)
```

Out[49]:

```
0    14341.570181
dtype: float64
```

In [50]:

```
# Auotamatioc precdiction of price with 90.02% accuracy
pred_y=final_model.predict(toyo5)
pred_y
```

Out[50]:

```
0       16345.352610
1       15886.635544
2       16328.224968
3       15996.318854
4       15883.424182
            ...
1426     9161.230587
1427     8536.091326
1428     8681.531063
1429     8793.668694
1430    10860.695492
Length: 1431, dtype: float64
```

Table Containig R^2 value for each prepared model

In [51]:

```
d2={'Prep_Models':['Model','Final_Model'],'Rsquared':[model.rsquared,final_model.rsquared]}
table=pd.DataFrame(d2)
table
```

Out[51]:

	Prep_Models	Rsquared
0	Model	0.883968
1	Final_Model	0.888240

In [ ]:

```

```

Assignment-05-Multiple Linear Regression-2

In [52]:

```
#Import dataset
data=pd.read_csv("C:/Users/LENOVO/Documents/Custom Office Templates/50_Startups.csv")
data
```

Out[52]:

	R&D Spend	Administration	Marketing Spend	State	Profit
0	165349.20	136897.80	471784.10	New York	192261.83
1	162597.70	151377.59	443898.53	California	191792.06
2	153441.51	101145.55	407934.54	Florida	191050.39
3	144372.41	118671.85	383199.62	New York	182901.99
4	142107.34	91391.77	366168.42	Florida	166187.94
5	131876.90	99814.71	362861.36	New York	156991.12
6	134615.46	147198.87	127716.82	California	156122.51
7	130298.13	145530.06	323876.68	Florida	155752.60
8	120542.52	148718.95	311613.29	New York	152211.77
9	123334.88	108679.17	304981.62	California	149759.96
10	101913.08	110594.11	229160.95	Florida	146121.95
11	100671.96	91790.61	249744.55	California	144259.40
12	93863.75	127320.38	249839.44	Florida	141585.52
13	91992.39	135495.07	252664.93	California	134307.35
14	119943.24	156547.42	256512.92	Florida	132602.65
15	114523.61	122616.84	261776.23	New York	129917.04
16	78013.11	121597.55	264346.06	California	126992.93
17	94657.16	145077.58	282574.31	New York	125370.37
18	91749.16	114175.79	294919.57	Florida	124266.90
19	86419.70	153514.11	0.00	New York	122776.86
20	76253.86	113867.30	298664.47	California	118474.03
21	78389.47	153773.43	299737.29	New York	111313.02
22	73994.56	122782.75	303319.26	Florida	110352.25
23	67532.53	105751.03	304768.73	Florida	108733.99
24	77044.01	99281.34	140574.81	New York	108552.04
25	64664.71	139553.16	137962.62	California	107404.34
26	75328.87	144135.98	134050.07	Florida	105733.54
27	72107.60	127864.55	353183.81	New York	105008.31
28	66051.52	182645.56	118148.20	Florida	103282.38
29	65605.48	153032.06	107138.38	New York	101004.64
30	61994.48	115641.28	91131.24	Florida	99937.59
31	61136.38	152701.92	88218.23	New York	97483.56
32	63408.86	129219.61	46085.25	California	97427.84

	R&D Spend	Administration	Marketing Spend	State	Profit
33	55493.95	103057.49	214634.81	Florida	96778.92
34	46426.07	157693.92	210797.67	California	96712.80
35	46014.02	85047.44	205517.64	New York	96479.51
36	28663.76	127056.21	201126.82	Florida	90708.19
37	44069.95	51283.14	197029.42	California	89949.14
38	20229.59	65947.93	185265.10	New York	81229.06
39	38558.51	82982.09	174999.30	California	81005.76
40	28754.33	118546.05	172795.67	California	78239.91
41	27892.92	84710.77	164470.71	Florida	77798.83
42	23640.93	96189.63	148001.11	California	71498.49
43	15505.73	127382.30	35534.17	New York	69758.98
44	22177.74	154806.14	28334.72	California	65200.33
45	1000.23	124153.04	1903.93	New York	64926.08
46	1315.46	115816.21	297114.46	Florida	49490.75
47	0.00	135426.92	0.00	California	42559.73
48	542.05	51743.15	0.00	New York	35673.41
49	0.00	116983.80	45173.06	California	14681.40

In [53]:

```
# EDA
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50 entries, 0 to 49
Data columns (total 5 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   R&D Spend        50 non-null     float64
 1   Administration   50 non-null     float64
 2   Marketing Spend  50 non-null     float64
 3   State            50 non-null     object 
 4   Profit           50 non-null     float64
dtypes: float64(4), object(1)
memory usage: 2.1+ KB
```

In [54]:

```
data.isnull().sum()
```

Out[54]:

```
R&D Spend          0
Administration     0
Marketing Spend    0
State              0
Profit             0
dtype: int64
```

Inference:

No NA values

In [55]:

```
data1=data.rename({'R&D Spend':'RDS','Administration':'ADMS','Marketing Spend':'MKTS'},axis
data1
```

Out[55]:

	RDS	ADMS	MKTS	State	Profit
0	165349.20	136897.80	471784.10	New York	192261.83
1	162597.70	151377.59	443898.53	California	191792.06
2	153441.51	101145.55	407934.54	Florida	191050.39
3	144372.41	118671.85	383199.62	New York	182901.99
4	142107.34	91391.77	366168.42	Florida	166187.94
5	131876.90	99814.71	362861.36	New York	156991.12
6	134615.46	147198.87	127716.82	California	156122.51
7	130298.13	145530.06	323876.68	Florida	155752.60
8	120542.52	148718.95	311613.29	New York	152211.77
9	123334.88	108679.17	304981.62	California	149759.96
10	101913.08	110594.11	229160.95	Florida	146121.95
11	100671.96	91790.61	249744.55	California	144259.40
12	93863.75	127320.38	249839.44	Florida	141585.52
13	91992.39	135495.07	252664.93	California	134307.35
14	119943.24	156547.42	256512.92	Florida	132602.65
15	114523.61	122616.84	261776.23	New York	129917.04
16	78013.11	121597.55	264346.06	California	126992.93
17	94657.16	145077.58	282574.31	New York	125370.37
18	91749.16	114175.79	294919.57	Florida	124266.90
19	86419.70	153514.11	0.00	New York	122776.86
20	76253.86	113867.30	298664.47	California	118474.03
21	78389.47	153773.43	299737.29	New York	111313.02
22	73994.56	122782.75	303319.26	Florida	110352.25
23	67532.53	105751.03	304768.73	Florida	108733.99
24	77044.01	99281.34	140574.81	New York	108552.04
25	64664.71	139553.16	137962.62	California	107404.34
26	75328.87	144135.98	134050.07	Florida	105733.54
27	72107.60	127864.55	353183.81	New York	105008.31
28	66051.52	182645.56	118148.20	Florida	103282.38
29	65605.48	153032.06	107138.38	New York	101004.64
30	61994.48	115641.28	91131.24	Florida	99937.59
31	61136.38	152701.92	88218.23	New York	97483.56
32	63408.86	129219.61	46085.25	California	97427.84
33	55493.95	103057.49	214634.81	Florida	96778.92

	RDS	ADMS	MKTS	State	Profit
34	46426.07	157693.92	210797.67	California	96712.80
35	46014.02	85047.44	205517.64	New York	96479.51
36	28663.76	127056.21	201126.82	Florida	90708.19
37	44069.95	51283.14	197029.42	California	89949.14
38	20229.59	65947.93	185265.10	New York	81229.06
39	38558.51	82982.09	174999.30	California	81005.76
40	28754.33	118546.05	172795.67	California	78239.91
41	27892.92	84710.77	164470.71	Florida	77798.83
42	23640.93	96189.63	148001.11	California	71498.49
43	15505.73	127382.30	35534.17	New York	69758.98
44	22177.74	154806.14	28334.72	California	65200.33
45	1000.23	124153.04	1903.93	New York	64926.08
46	1315.46	115816.21	297114.46	Florida	49490.75
47	0.00	135426.92	0.00	California	42559.73
48	542.05	51743.15	0.00	New York	35673.41
49	0.00	116983.80	45173.06	California	14681.40

In [56]:

```
data1[data1.duplicated()]    # No duplicated data
```

Out[56]:

RDS	ADMS	MKTS	State	Profit

In [57]:

```
data1.describe()
```

Out[57]:

	RDS	ADMS	MKTS	Profit
count	50.000000	50.000000	50.000000	50.000000
mean	73721.615600	121344.639600	211025.097800	112012.639200
std	45902.256482	28017.802755	122290.310726	40306.180338
min	0.000000	51283.140000	0.000000	14681.400000
25%	39936.370000	103730.875000	129300.132500	90138.902500
50%	73051.080000	122699.795000	212716.240000	107978.190000
75%	101602.800000	144842.180000	299469.085000	139765.977500
max	165349.200000	182645.560000	471784.100000	192261.830000

Correlation Analysis

In [58]:

```
data1.corr()
```

Out[58]:

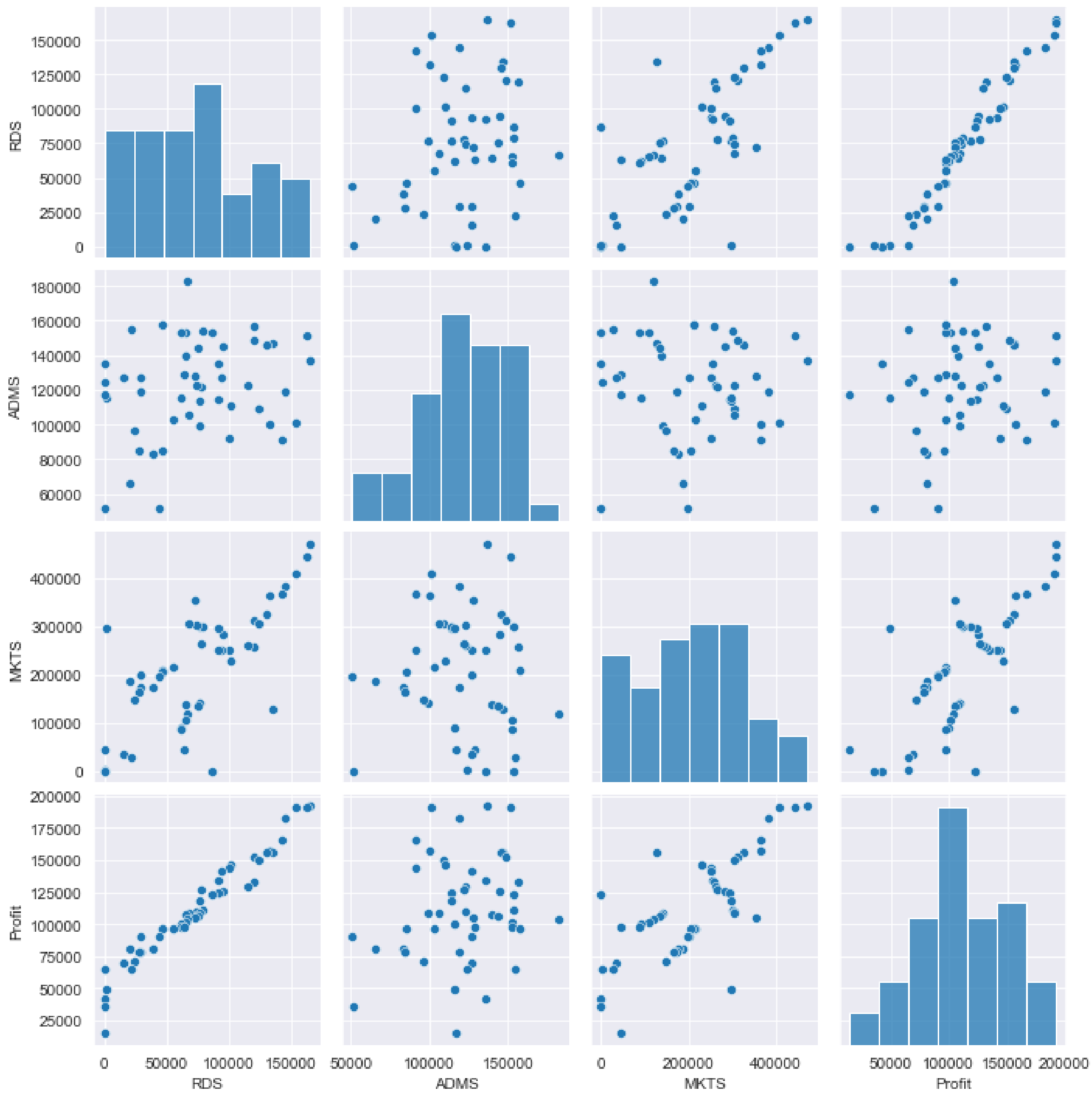
	RDS	ADMS	MKTS	Profit
RDS	1.000000	0.241955	0.724248	0.972900
ADMS	0.241955	1.000000	-0.032154	0.200717
MKTS	0.724248	-0.032154	1.000000	0.747766
Profit	0.972900	0.200717	0.747766	1.000000

In [59]:

```
sns.set_style(style='darkgrid')
sns.pairplot(data1)
```

Out[59]:

```
<seaborn.axisgrid.PairGrid at 0x74e7940310>
```



Model Building

In [60]:

```
model=smf.ols("Profit~RDS+ADMS+MKTS",data=data1).fit()
```

In [61]:

```
# Model Testing
# finding coefficient parameters
model.params
```

Out[61]:

```
Intercept    50122.192990
RDS              0.805715
ADMS            -0.026816
MKTS             0.027228
dtype: float64
```

In [62]:

```
# finding tvalues and pvalues
model.tvalues, np.round(model.pvalues,5)
```

Out[62]:

```
(Intercept     7.626218
 RDS          17.846374
 ADMS         -0.525507
 MKTS          1.655077
 dtype: float64,
 Intercept    0.00000
 RDS          0.00000
 ADMS         0.60176
 MKTS         0.10472
 dtype: float64)
```

Inference:

ADMS and MKTS has insignificant values

In [63]:

```
# Finding rquared values
model.rsquared, model.rsquared_adj  # Model accuracy is 94.75%
```

Out[63]:

```
(0.9507459940683246, 0.9475337762901719)
```

In [64]:

```
# Build SLR and MLR models for insignificant variables 'ADMS' and 'MKTS'
# Also find their tvalues and pvalues
```

In [65]:

```
slr_a=smf.ols("Profit~ADMS", data=data1).fit()
slr_a.tvalues,  slr_a.pvalues   # ADMS has insignificant pvalue
```

Out[65]:

```
(Intercept    3.040044
 ADMS         1.419493
 dtype: float64,
 Intercept    0.003824
 ADMS         0.162217
 dtype: float64)
```

In [66]:

```
slr_m=smf.ols("Profit~MKTS", data=data1).fit()
slr_m.tvalues,  slr_m.pvalues   #MKTS has significant pvalue
```

Out[66]:

```
(Intercept    7.808356
 MKTS         7.802657
 dtype: float64,
 Intercept    4.294735e-10
 MKTS         4.381073e-10
 dtype: float64)
```

In [67]:

```
mlr_am=smf.ols("Profit~ADMS+MKTS", data=data1).fit()
mlr_am.tvalues,  mlr_am.pvalues  # variables have significant pvalues
```

Out[67]:

```
(Intercept    1.142741
 ADMS         2.467779
 MKTS         8.281039
 dtype: float64,
 Intercept    2.589341e-01
 ADMS         1.729198e-02
 MKTS         9.727245e-11
 dtype: float64)
```

Model Validation

Two Techniques: 1. Collinearity Check & 2. Residual Analysis

In [68]:

```
# 1) Collinearity Problem Check
# Calculate VIF =1/(1-Rsquare) for all independent varaibles

rsq_r=smf.ols("RDS~ADMS+MKTS",data=data1).fit().rsquared
vif_r=1/(1-rsq_r)

rsq_a=smf.ols("ADMS~RDS+MKTS",data=data1).fit().rsquared
vif_a=1/(1-rsq_a)

rsq_m=smf.ols("MKTS~RDS+ADMS",data=data1).fit().rsquared
vif_m=1/(1-rsq_m)

# Putting the values in DataFrame
d1={'Variables':['RDS','ADM','MKTS'], 'VIF':[vif_r,vif_a,vif_m]}
Vif_df=pd.DataFrame(d1)
Vif_df
```

Out[68]:

	Variables	VIF
0	RDS	2.468903
1	ADM	1.175091
2	MKTS	2.326773

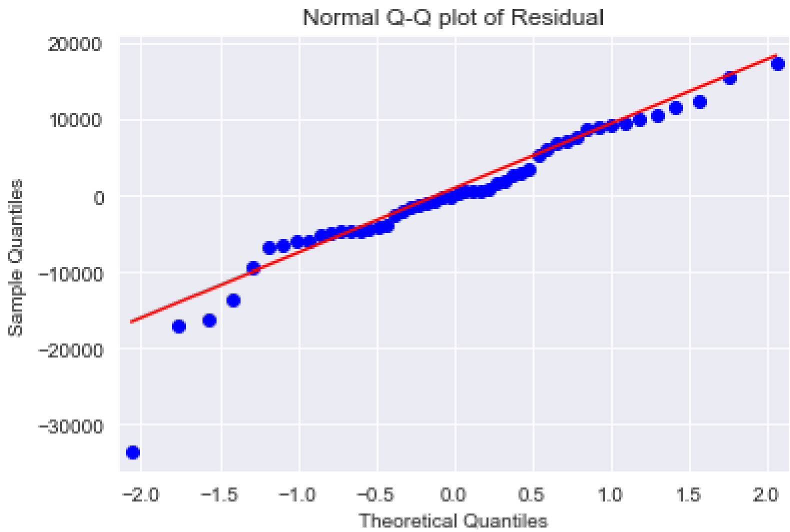
In [69]:

```
# None variable has Vif>20, No Collinearity, so cosider all variables in Regression equatio
```

In [70]:

```
# 2) Residual analysis
# Test for Normality of Residual (Q-Q Plot) using residual model(model.resid)

sm.qqplot(model.resid,line='q')
plt.title('Normal Q-Q plot of Residual')
plt.show()
```



In [71]:

```
list(np.where(model.resid<-30000))
```

Out[71]:

```
[array([49], dtype=int64)]
```

In [72]:

```
# Test for Homoscedasticity or heteroscedasticity (plotting model's standardized fitted val
def standard_values(vals) : return (vals-vals.mean())/vals.std()  # user defined z= (x-mu)/
```

In [73]:

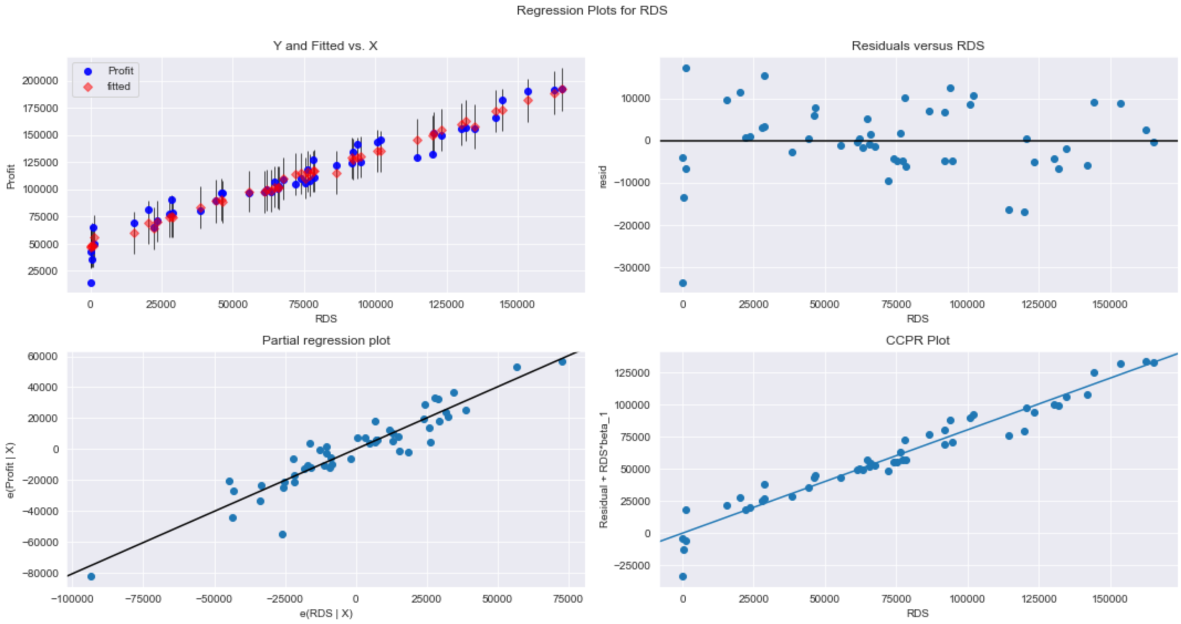
```
plt.scatter(standard_values(model.fittedvalues),standard_values(model.resid))
plt.title('Residual Plot')
plt.xlabel('standardized fitted values')
plt.ylabel('standardized residual values')
plt.show()
```

In [74]:

```
# Test for error or Residuals Vs Regressors or Independent 'x'vaiables or predictors
# Using Residual Regression plot code graphics.plot_regress_exog(model,'x',fig) # exog = x-
```

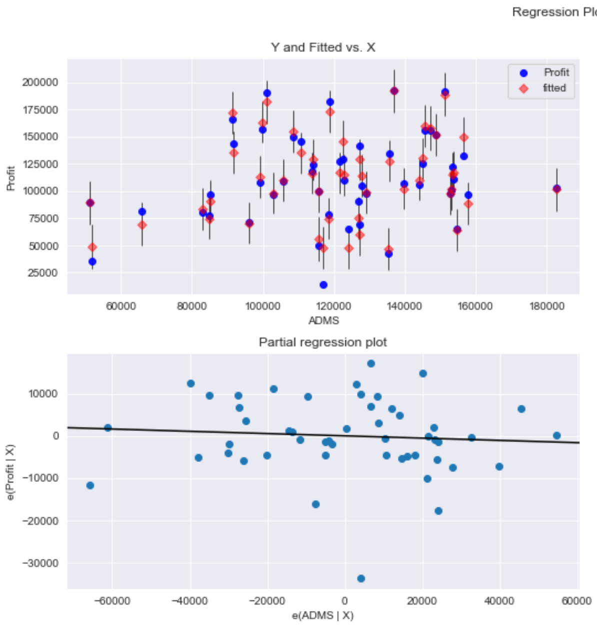
In [75]:

```
fig=plt.figure(figsize=(15,8))
sm.graphics.plot_regress_exog(model,'RDS',fig=fig)
plt.show()
```



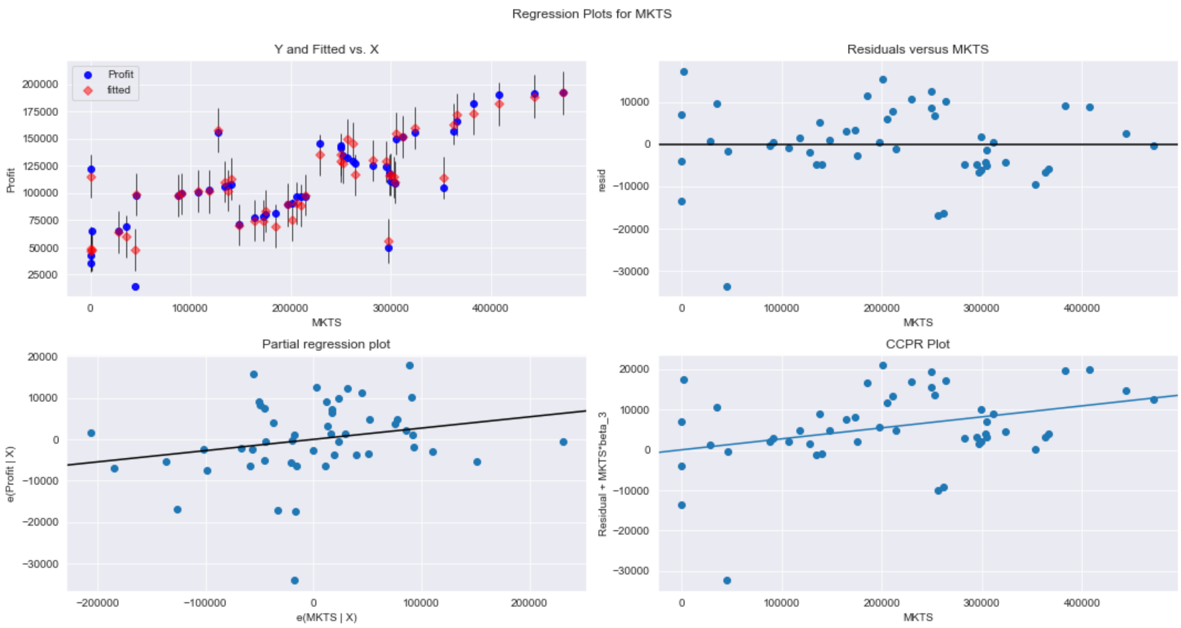
In [76]:

```
fig=plt.figure(figsize=(15,8))
sm.graphics.plot_regress_exog(model,'ADMS',fig=fig)
plt.show()
```



In [77]:

```
fig=plt.figure(figsize=(15,8))
sm.graphics.plot_regress_exog(model,'MKTS',fig=fig)
plt.show()
```



Model Deletion Diagnostics (checking outliers or influencers)

Two Techniques: 1.Cook's Distance & 2. Leverage value

In [78]:

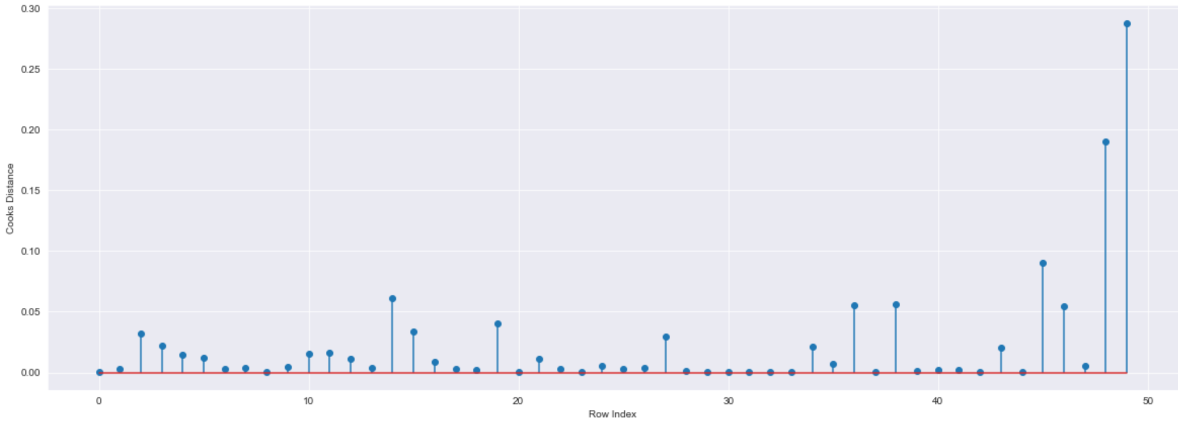
```
# Cook's Distance: If Cook's distance > 1, Then it's an outlier
# Get influencers using cook's distance
(c,_)=model.get_influence().cooks_distance
c
```

Out[78]:

```
array([3.21825244e-05, 3.27591036e-03, 3.23842699e-02, 2.17206555e-02,
       1.44833032e-02, 1.17158463e-02, 2.91766303e-03, 3.56513444e-03,
       4.04303948e-05, 4.86758017e-03, 1.51064757e-02, 1.63564959e-02,
       1.15516625e-02, 4.01422811e-03, 6.12934253e-02, 3.40013448e-02,
       8.33556413e-03, 3.30534399e-03, 2.16819303e-03, 4.07440577e-02,
       4.25137222e-04, 1.09844352e-02, 2.91768000e-03, 2.76030254e-04,
       5.04643588e-03, 3.00074623e-03, 3.41957068e-03, 2.98396413e-02,
       1.31590664e-03, 1.25992620e-04, 4.18505125e-05, 9.27434786e-06,
       7.08656521e-04, 1.28122674e-04, 2.09815032e-02, 6.69508674e-03,
       5.55314705e-02, 6.55050578e-05, 5.61547311e-02, 1.54279607e-03,
       1.84850929e-03, 1.97578066e-03, 1.36089280e-04, 2.05553171e-02,
       1.23156041e-04, 9.03234206e-02, 5.45303387e-02, 5.33885616e-03,
       1.90527441e-01, 2.88082293e-01])
```

In [79]:

```
# Plot the influencer using the stem plot
fig=plt.figure(figsize=(20,7))
plt.stem(np.arange(len(data1)),np.round(c,5))
plt.xlabel('Row Index')
plt.ylabel('Cooks Distance')
plt.show()
```



In [80]:

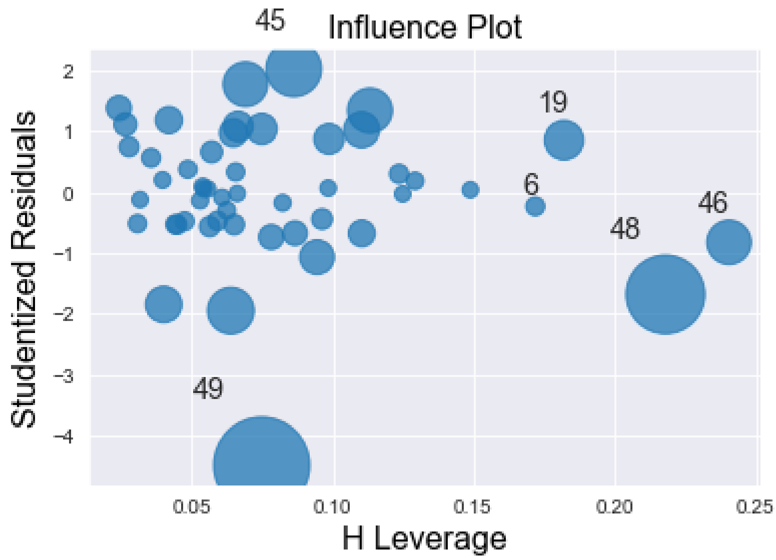
```
# Index and value of influncer where C>0.5
np.argmax(c),np.max(c)
```

Out[80]:

```
(49, 0.28808229275432634)
```

In [81]:

```
# 2. Leverage Value using High Influence Points : Points beyond Leverage_cutoff value are i
influence_plot(model)
plt.show()
```



In [82]:

```
# Levarge Cutoff value = 3*(k+1)/n; k= no.of features/columns & n=no.of datapoints
k=data1.shape[1]
n=data1.shape[0]
leverage_cutoff=(3*(k+1))/n
leverage_cutoff
```

Out[82]:

0.36

In [83]:

```
data1[data1.index.isin([49])]
```

Out[83]:

	RDS	ADMS	MKTS	State	Profit
49	0.0	116983.8	45173.06	California	14681.4

In [84]:

```
# Discard the data points which are influencers and reassign the row number (reset_index(dr
data2=data1.drop(toyo_new.index[[49]],axis=0).reset_index(drop=True)
data2
```

Out[84]:

	RDS	ADMS	MKTS	State	Profit
0	165349.20	136897.80	471784.10	New York	192261.83
1	162597.70	151377.59	443898.53	California	191792.06
2	153441.51	101145.55	407934.54	Florida	191050.39
3	144372.41	118671.85	383199.62	New York	182901.99
4	142107.34	91391.77	366168.42	Florida	166187.94
5	131876.90	99814.71	362861.36	New York	156991.12
6	134615.46	147198.87	127716.82	California	156122.51
7	130298.13	145530.06	323876.68	Florida	155752.60
8	120542.52	148718.95	311613.29	New York	152211.77
9	123334.88	108679.17	304981.62	California	149759.96
10	101913.08	110594.11	229160.95	Florida	146121.95
11	100671.96	91790.61	249744.55	California	144259.40
12	93863.75	127320.38	249839.44	Florida	141585.52
13	91992.39	135495.07	252664.93	California	134307.35
14	119943.24	156547.42	256512.92	Florida	132602.65
15	114523.61	122616.84	261776.23	New York	129917.04
16	78013.11	121597.55	264346.06	California	126992.93
17	94657.16	145077.58	282574.31	New York	125370.37
18	91749.16	114175.79	294919.57	Florida	124266.90
19	86419.70	153514.11	0.00	New York	122776.86
20	76253.86	113867.30	298664.47	California	118474.03
21	78389.47	153773.43	299737.29	New York	111313.02
22	73994.56	122782.75	303319.26	Florida	110352.25
23	67532.53	105751.03	304768.73	Florida	108733.99
24	77044.01	99281.34	140574.81	New York	108552.04
25	64664.71	139553.16	137962.62	California	107404.34
26	75328.87	144135.98	134050.07	Florida	105733.54
27	72107.60	127864.55	353183.81	New York	105008.31
28	66051.52	182645.56	118148.20	Florida	103282.38
29	65605.48	153032.06	107138.38	New York	101004.64
30	61994.48	115641.28	91131.24	Florida	99937.59
31	61136.38	152701.92	88218.23	New York	97483.56
32	63408.86	129219.61	46085.25	California	97427.84

	RDS	ADMS	MKTS	State	Profit
33	55493.95	103057.49	214634.81	Florida	96778.92
34	46426.07	157693.92	210797.67	California	96712.80
35	46014.02	85047.44	205517.64	New York	96479.51
36	28663.76	127056.21	201126.82	Florida	90708.19
37	44069.95	51283.14	197029.42	California	89949.14
38	20229.59	65947.93	185265.10	New York	81229.06
39	38558.51	82982.09	174999.30	California	81005.76
40	28754.33	118546.05	172795.67	California	78239.91
41	27892.92	84710.77	164470.71	Florida	77798.83
42	23640.93	96189.63	148001.11	California	71498.49
43	15505.73	127382.30	35534.17	New York	69758.98
44	22177.74	154806.14	28334.72	California	65200.33
45	1000.23	124153.04	1903.93	New York	64926.08
46	1315.46	115816.21	297114.46	Florida	49490.75
47	0.00	135426.92	0.00	California	42559.73
48	542.05	51743.15	0.00	New York	35673.41

Model Deletion Diagnostics and Final Model

In [85]:

```
while np.max(c)>0.5:
    model=smf.ols("Profit~RDS+ADMS+MKTS",data=data2).fit()
    (c,_)=model.get_influence().cooks_distance
    c
    np.argmax(c),np.max(c)
    data2=data2.drop(data2.index[[np.argmax(c)]],axis=0).reset_index(drop=True)
    data2
else:
    final_model=smf.ols("Profit~RDS+ADMS+MKTS",data=data2).fit()
    final_model.rsquared, final_model.aic
    print("Thus model accuracy is improved to",final_model.rsquared)
```

```
Thus model accuracy is improved to 0.9613162435129847
```

In [86]:

```
final_model.rsquared
```

Out[86]:

```
0.9613162435129847
```

Creation of model using Lasso

In [87]:

```
x=data2[['RDS','ADMS','MKTS']]
y=data2['Profit']

from sklearn.model_selection import train_test_split
from sklearn.linear_model import Lasso
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.25,random_state=10)
reg=Lasso(alpha=0.5)
reg.fit(x_train, y_train)

print('Lasso Regression: R^2 score on training set',reg.score(x_train, y_train)*100)
print('Lasso Regression: R^2 score on test set',reg.score(x_test, y_test)*100)

lambdas=(0.001,0.01,0.1,0.5,1,2,10)
l_num=7
pred_num=x.shape[1]

# prepare data for enumerate
coeff_a = np.zeros((l_num, pred_num))
train_r_squared =np.zeros(l_num)
test_r_squared =np.zeros(l_num)

# enumerate through lambdas with index and i
for ind, i in enumerate(lambdas):
    reg = Lasso(alpha =1)
    reg.fit(x_train, y_train)

    coeff_a[ind,:]=reg.coef_
    train_r_squared[ind] = reg.score(x_train, y_train)
    test_r_squared[ind] = reg.score(x_test, y_test)
```

```
Lasso Regression: R^2 score on training set 95.24694195134217
Lasso Regression: R^2 score on test set 97.33570553521325
```

Creation of model using Ridge

In [88]:

```
from sklearn.linear_model import Ridge
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.25,random_state=10)
reg=Ridge(alpha=0.5)
reg.fit(x_train, y_train)

print('Ridge Regression: R^2 score on training set',reg.score(x_train, y_train)*100)
print('Ridge Regression: R^2 score on test set',reg.score(x_test, y_test)*100)

lambdas=(0.001,0.01,0.1,0.5,1,2,10)
l_num=7
pred_num=x.shape[1]

# prepare data for enumerate
coeff_a = np.zeros((l_num, pred_num))
train_r_squared =np.zeros(l_num)
test_r_squared =np.zeros(l_num)

# enumerate through lambdas with index and i
for ind, i in enumerate(lambdas):
    reg = Ridge(alpha =1)
    reg.fit(x_train, y_train)

    coeff_a[ind,:]=reg.coef_
    train_r_squared[ind] = reg.score(x_train, y_train)
    test_r_squared[ind] = reg.score(x_test, y_test)
```

```
Ridge Regression: R^2 score on training set 95.24694195134217
Ridge Regression: R^2 score on test set 97.33570551715988
```

In [89]:

```
data2
```

Out[89]:

	RDS	ADMS	MKTS	State	Profit
0	165349.20	136897.80	471784.10	New York	192261.83
1	162597.70	151377.59	443898.53	California	191792.06
2	153441.51	101145.55	407934.54	Florida	191050.39
3	144372.41	118671.85	383199.62	New York	182901.99
4	142107.34	91391.77	366168.42	Florida	166187.94
5	131876.90	99814.71	362861.36	New York	156991.12
6	134615.46	147198.87	127716.82	California	156122.51
7	130298.13	145530.06	323876.68	Florida	155752.60
8	120542.52	148718.95	311613.29	New York	152211.77
9	123334.88	108679.17	304981.62	California	149759.96
10	101913.08	110594.11	229160.95	Florida	146121.95
11	100671.96	91790.61	249744.55	California	144259.40
12	93863.75	127320.38	249839.44	Florida	141585.52
13	91992.39	135495.07	252664.93	California	134307.35
14	119943.24	156547.42	256512.92	Florida	132602.65
15	114523.61	122616.84	261776.23	New York	129917.04
16	78013.11	121597.55	264346.06	California	126992.93
17	94657.16	145077.58	282574.31	New York	125370.37
18	91749.16	114175.79	294919.57	Florida	124266.90
19	86419.70	153514.11	0.00	New York	122776.86
20	76253.86	113867.30	298664.47	California	118474.03
21	78389.47	153773.43	299737.29	New York	111313.02
22	73994.56	122782.75	303319.26	Florida	110352.25
23	67532.53	105751.03	304768.73	Florida	108733.99
24	77044.01	99281.34	140574.81	New York	108552.04
25	64664.71	139553.16	137962.62	California	107404.34
26	75328.87	144135.98	134050.07	Florida	105733.54
27	72107.60	127864.55	353183.81	New York	105008.31
28	66051.52	182645.56	118148.20	Florida	103282.38
29	65605.48	153032.06	107138.38	New York	101004.64
30	61994.48	115641.28	91131.24	Florida	99937.59
31	61136.38	152701.92	88218.23	New York	97483.56
32	63408.86	129219.61	46085.25	California	97427.84
33	55493.95	103057.49	214634.81	Florida	96778.92

	RDS	ADMS	MKTS	State	Profit
34	46426.07	157693.92	210797.67	California	96712.80
35	46014.02	85047.44	205517.64	New York	96479.51
36	28663.76	127056.21	201126.82	Florida	90708.19
37	44069.95	51283.14	197029.42	California	89949.14
38	20229.59	65947.93	185265.10	New York	81229.06
39	38558.51	82982.09	174999.30	California	81005.76
40	28754.33	118546.05	172795.67	California	78239.91
41	27892.92	84710.77	164470.71	Florida	77798.83
42	23640.93	96189.63	148001.11	California	71498.49
43	15505.73	127382.30	35534.17	New York	69758.98
44	22177.74	154806.14	28334.72	California	65200.33
45	1000.23	124153.04	1903.93	New York	64926.08
46	1315.46	115816.21	297114.46	Florida	49490.75
47	0.00	135426.92	0.00	California	42559.73
48	542.05	51743.15	0.00	New York	35673.41

Model Predictions

In [90]:

```
# say new data for prediction is
new_data=pd.DataFrame({'RDS':70000,'ADMS':90000,'MKTS':140000},index=[0])
new_data
```

Out[90]:

	RDS	ADMS	MKTS
0	70000	90000	140000

In [91]:

```
# Manual Prediction of price
final_model.predict(new_data)
```

Out[91]:

```
0    108727.154753
dtype: float64
```

In [92]:

```
# Auotomatic prediction of price with 09.02% accuracy
pred_y=final_model.predict(data2)
pred_y
```

Out[92]:

```
0     190716.676999
1     187537.122227
2     180575.526396
3     172461.144642
4     170863.486721
5     162582.583177
6     157741.338633
7     159347.735318
8     151328.826941
9     154236.846778
10    135507.792682
11    135472.855621
12    129355.599449
13    127780.129139
14    149295.404796
15    145937.941975
16    117437.627921
17    130408.626295
18    129129.234457
19    116641.003121
20    117097.731866
21    117911.019038
22    115248.217796
23    110603.139045
24    114051.073877
25    103398.054385
26    111547.638935
27    114916.165026
28    103027.229434
29    103057.621761
30    100656.410227
31     99088.213693
32    100325.741335
33     98962.303136
34     90552.307809
35     91709.288672
36     77080.554255
37     90722.503244
38     71433.021956
39     85147.375646
40     76625.510303
41     76492.145175
42     72492.394974
43     62592.049718
44     67025.731107
45     50457.297206
46     58338.443625
47     49375.776655
48     51658.096812
dtype: float64
```

Table containig R^2 value for each prepared model

In [93]:

```
d2={'Prep_Models':['Model','Final_Model'],'Rsquared':[model.rsquared,final_model.rsquared]}
table=pd.DataFrame(d2)
table
```

Out[93]:

	Prep_Models	Rsquared
0	Model	0.950746
1	Final_Model	0.961316

In [ ]: