Chapter 4: Linear Regression

4.3 Building Simple Linear Regression Model

```
import warnings
warnings.filterwarnings('ignore')

import pandas as pd
import numpy as np

np.set_printoptions(precision=4, linewidth=100)
```

```
mba_salary_df = pd.read_csv( 'MBA Salary.csv' )
mba_salary_df.head( 10 )
```

	S. No.	Percentage in Grade 10	Salary
0	1	62.00	270000
1	2	76.33	200000
2	3	72.00	240000
3	4	60.00	250000
4	5	61.00	180000
5	6	55.00	300000
6	7	70.00	260000
7	8	68.00	235000
8	9	82.80	425000
9	10	59.00	240000

More information about the dataset

```
mba_salary_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50 entries, 0 to 49
Data columns (total 3 columns):
S. No.                    50 non-null int64
Percentage in Grade 10    50 non-null float64
Salary                    50 non-null int64
dtypes: float64(1), int64(2)
memory usage: 1.2 KB
```

4.3.1 Creating Feature Set(X) and Outcome Variable(Y)

```
import statsmodels.api as sm

X = sm.add_constant( mba_salary_df['Percentage in Grade 10'] )
X.head(5)
```

	const	Percentage in Grade 10
0	1.0	62.00
1	1.0	76.33
2	1.0	72.00
3	1.0	60.00
4	1.0	61.00

```
Y = mba_salary_df['Salary']
```

4.3.2 Splitting the dataset into training and validation sets

```
from sklearn.model_selection import train_test_split
```

```
train_X, test_X, train_y, test_y = train_test_split( X ,
                                                     Y,
                                                    train_size = 0.8,
                                                    random_state = 100 )
```

4.3.3 Fitting the Model

```
mba_salary_lm = sm.OLS( train_y, train_X ).fit()
```

4.3.3.1 Printing Estimated Parameters and interpreting them

```
print( mba_salary_lm.params )
```

```
const                      30587.285652
Percentage in Grade 10      3560.587383
dtype: float64
```

4.4 Model Diagnostics

```
mba_salary_lm.summary2()
```

Model:	OLS	Adj. R-squared:	0.190
Dependent Variable:	Salary	AIC:	1008.8680
Date:	2019-04-23 18:26	BIC:	1012.2458
No. Observations:	40	Log-Likelihood:	-502.43
Df Model:	1	F-statistic:	10.16
Df Residuals:	38	Prob (F-statistic):	0.00287
R-squared:	0.211	Scale:	5.0121e+09

	Coef.	**Std.Err.**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	30587.2857	71869.4497	0.4256	0.6728	-114904.8089	176079.3802
Percentage in Grade 10	3560.5874	1116.9258	3.1878	0.0029	1299.4892	5821.6855

Omnibus:	2.048	Durbin-Watson:	2.611
Prob(Omnibus):	0.359	Jarque-Bera (JB):	1.724
Skew:	0.369	Prob(JB):	0.422
Kurtosis:	2.300	Condition No.:	413

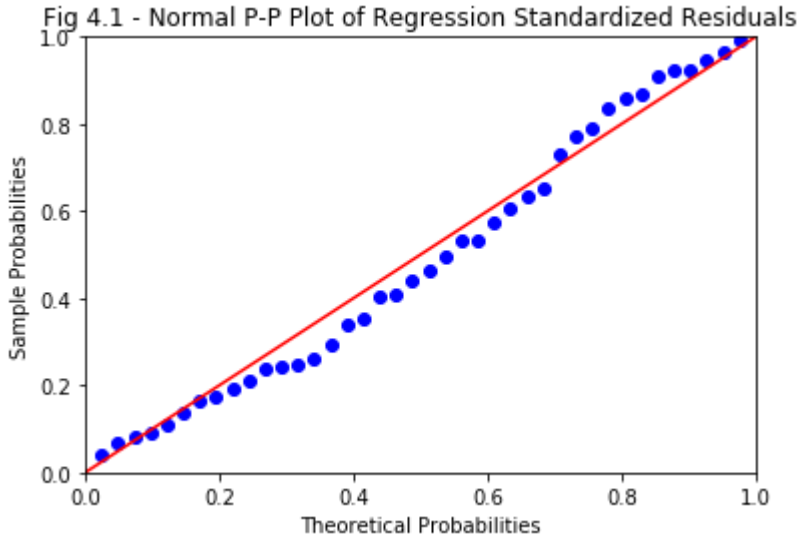
4.4.5 Residual Anlalysis

4.4.5.1 Checking Normality

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

```
mba_salary_resid = mba_salary_lm.resid
probplot = sm.ProbPlot( mba_salary_resid )
plt.figure( figsize = (8, 6) )
probplot.ppplot( line='45' )
plt.title( "Fig 4.1 - Normal P-P Plot of Regression Standardized Residuals" )
plt.show()
```

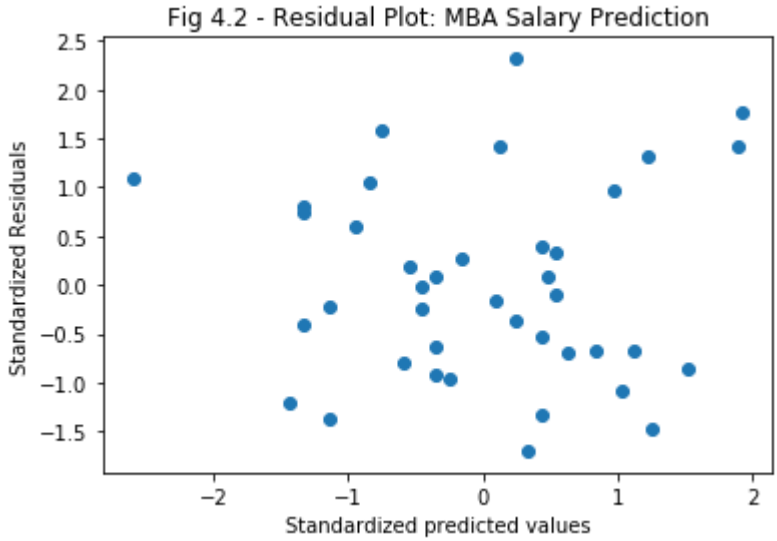
```
<Figure size 576x432 with 0 Axes>
```



4.4.5.2 Test of Homoscedasticity

```
def get_standardized_values( vals ):
    return (vals - vals.mean())/vals.std()
```

```
plt.scatter( get_standardized_values( mba_salary_lm.fittedvalues ),
             get_standardized_values( mba_salary_resid ) )
plt.title( "Fig 4.2 - Residual Plot: MBA Salary Prediction" );
plt.xlabel( "Standardized predicted values")
plt.ylabel( "Standardized Residuals");
```



4.4.6 Outlier Analysis

4.4.6.1 Z-Score

```
from scipy.stats import zscore
```

```
mba_salary_df['z_score_salary'] = zscore( mba_salary_df.Salary )
```

```
mba_salary_df[ (mba_salary_df.z_score_salary > 3.0) | (mba_salary_df.z_score_sal
ary < -3.0) ]
```

	S. No.	Percentage in Grade 10	Salary	z_score_salary

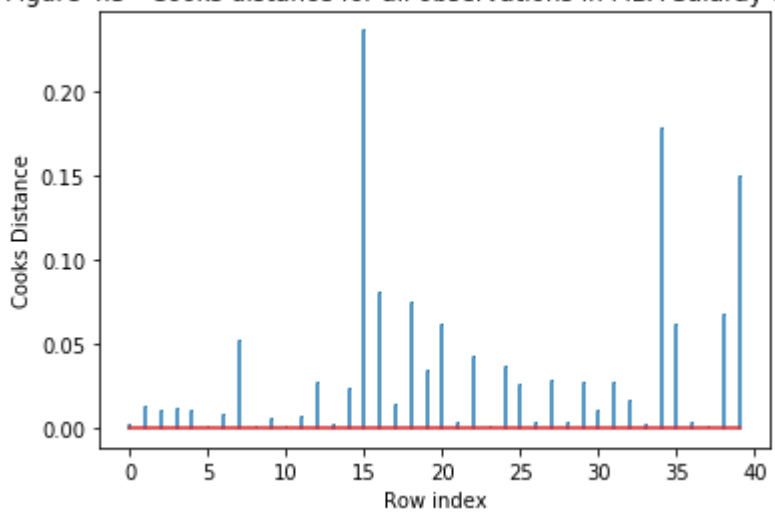
4.4.6.2 Cook's Distance

```
import numpy as np

mba_influence = mba_salary_lm.get_influence()
(c, p) = mba_influence.cooks_distance

plt.stem( np.arange( len( train_X) ),
         np.round( c, 3 ),
         markerfmt="," );
plt.title( "Figure 4.3 - Cooks distance for all observations in MBA Salaray data
set" );
plt.xlabel( "Row index")
plt.ylabel( "Cooks Distance");
```

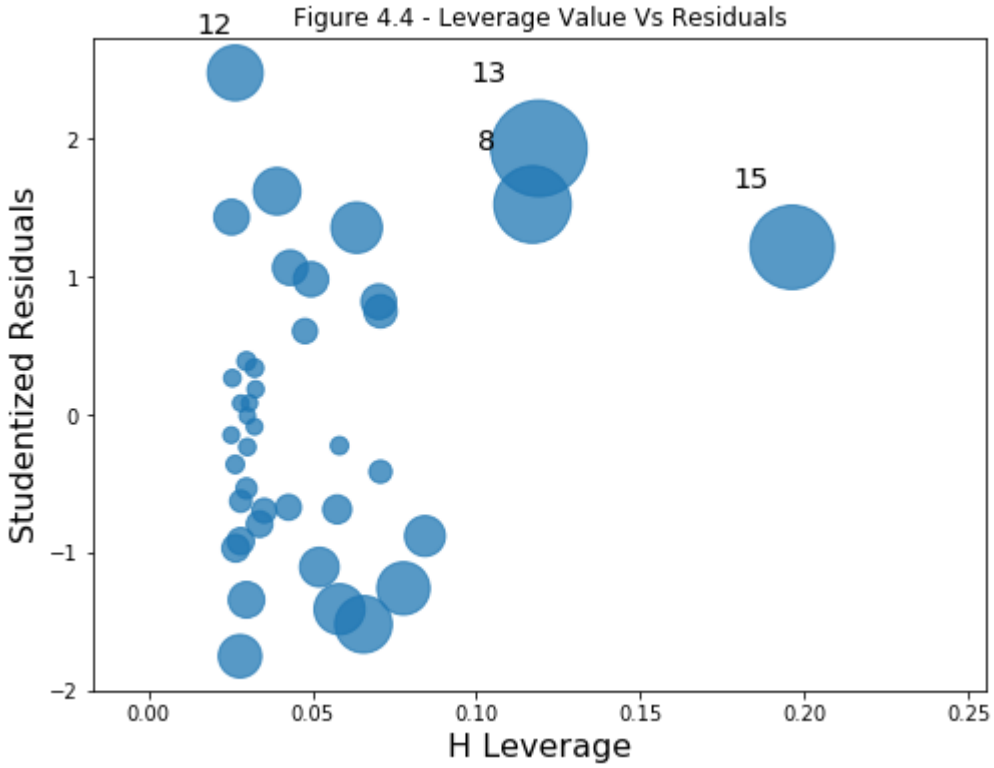
Figure 4.3 - Cooks distance for all observations in MBA Salaray dataset



4.4.6.3 Leverage Values

```
from statsmodels.graphics.regressionplots import influence_plot

fig, ax = plt.subplots( figsize=(8,6) )
influence_plot( mba_salary_lm, ax = ax )
plt.title( "Figure 4.4 - Leverage Value Vs Residuals")
plt.show();
```



4.4.7 Making prediction using the model

4.4.7.1 Predicting on validation set

```
pred_y = mba_salary_lm.predict( test_X )
```

4.4.7.2 Finding R-Square and RMSE

```
from sklearn.metrics import r2_score, mean_squared_error
```

```
np.abs(r2_score(test_y, pred_y))
```

```
0.15664584974230378
```

```
import numpy
```

```
np.sqrt(mean_squared_error(test_y, pred_y))
```

```
73458.04348346894
```

4.4.7.3 Calculating prediction intervals

```
from statsmodels.sandbox.regression.predstd import wls_prediction_std

# Predict the y values
pred_y = mba_salary_lm.predict( test_X )

# Predict the low and high interval values for y
_, pred_y_low, pred_y_high = wls_prediction_std( mba_salary_lm,
                    test_X,
                    alpha = 0.1)

# Store all the values in a dataframe
pred_y_df = pd.DataFrame( { 'grade_10_perc': test_X['Percentage in Grade 10'],
                            'pred_y': pred_y,
                            'pred_y_left': pred_y_low,
                            'pred_y_right': pred_y_high } )
```

```
pred_y_df[0:10]
```

	grade_10_perc	pred_y	pred_y_left	pred_y_right
6	70.0	279828.402452	158379.832044	401276.972860
36	68.0	272707.227686	151576.715020	393837.740352
37	52.0	215737.829560	92950.942395	338524.716726
28	58.0	237101.353858	115806.869618	358395.838097
43	74.5	295851.045675	173266.083342	418436.008008
49	60.8	247070.998530	126117.560983	368024.436076
5	55.0	226419.591709	104507.444388	348331.739030
33	78.0	308313.101515	184450.060488	432176.142542
20	63.0	254904.290772	134057.999258	375750.582286
42	74.4	295494.986937	172941.528691	418048.445182

4.5 Multiple Linear Regression

4.5.2.1 Loading the dataset

```
ipl_auction_df = pd.read_csv( 'IPL IMB381IPL2013.csv' )
```

```
ipl_auction_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 130 entries, 0 to 129
Data columns (total 26 columns):
Sl.NO.           130 non-null int64
PLAYER NAME      130 non-null object
AGE              130 non-null int64
COUNTRY          130 non-null object
TEAM             130 non-null object
PLAYING ROLE     130 non-null object
T-RUNS           130 non-null int64
T-WKTS           130 non-null int64
ODI-RUNS-S       130 non-null int64
ODI-SR-B         130 non-null float64
ODI-WKTS         130 non-null int64
ODI-SR-BL        130 non-null float64
CAPTAINCY EXP    130 non-null int64
RUNS-S           130 non-null int64
HS               130 non-null int64
AVE              130 non-null float64
SR-B             130 non-null float64
SIXERS           130 non-null int64
RUNS-C           130 non-null int64
WKTS             130 non-null int64
AVE-BL           130 non-null float64
ECON             130 non-null float64
SR-BL            130 non-null float64
AUCTION YEAR     130 non-null int64
BASE PRICE       130 non-null int64
SOLD PRICE       130 non-null int64
dtypes: float64(7), int64(15), object(4)
memory usage: 26.5+ KB
```

```
ipl_auction_df.iloc[0:5, 0:10]
```

	Sl.NO.	PLAYER NAME	AGE	COUNTRY	TEAM	PLAYING ROLE	T-RUNS	T-WKTS	ODI-RUNS-S	ODI-SR-B
0	1	Abdulla, YA	2	SA	KXIP	Allrounder	0	0	0	0.00
1	2	Abdur Razzak	2	BAN	RCB	Bowler	214	18	657	71.41
2	3	Agarkar, AB	2	IND	KKR	Bowler	571	58	1269	80.62
3	4	Ashwin, R	1	IND	CSK	Bowler	284	31	241	84.56
4	5	Badrinath, S	2	IND	CSK	Batsman	63	0	79	45.93

```
ipl_auction_df.iloc[0:5, 13:]
```

	RUNS-S	HS	AVE	SR-B	SIXERS	RUNS-C	WKTS	AVE-BL	ECON	SR-BL	AUCTION YEAR	
0	0	0	0.00	0.00	0	307	15	20.47	8.90	13.93	2009	5
1	0	0	0.00	0.00	0	29	0	0.00	14.50	0.00	2008	5
2	167	39	18.56	121.01	5	1059	29	36.52	8.81	24.90	2008	2
3	58	11	5.80	76.32	0	1125	49	22.96	6.23	22.14	2011	1
4	1317	71	32.93	120.71	28	0	0	0.00	0.00	0.00	2011	1

```
X_features = ipl_auction_df.columns
```

```
X_features = ['AGE', 'COUNTRY', 'PLAYING ROLE',
              'T-RUNS', 'T-WKTS', 'ODI-RUNS-S', 'ODI-SR-B',
              'ODI-WKTS', 'ODI-SR-BL', 'CAPTAINCY EXP', 'RUNS-S',
              'HS', 'AVE', 'SR-B', 'SIXERS', 'RUNS-C', 'WKTS',
              'AVE-BL', 'ECON', 'SR-BL']
```

4.5.3 Encoding Categorical Features

```
ipl_auction_df['PLAYING ROLE'].unique()
```

```
array(['Allrounder', 'Bowler', 'Batsman', 'W. Keeper'], dtype=objec
t)
```

```
pd.get_dummies(ipl_auction_df['PLAYING ROLE'])[0:5]
```

	Allrounder	Batsman	Bowler	W. Keeper
0	1	0	0	0
1	0	0	1	0
2	0	0	1	0
3	0	0	1	0
4	0	1	0	0

```
categorical_features = ['AGE', 'COUNTRY', 'PLAYING ROLE', 'CAPTAINCY EXP']
```

```
ipl_auction_encoded_df = pd.get_dummies( ipl_auction_df[X_features],
                                         columns = categorical_features,
                                         drop_first = True )
```

```
ipl_auction_encoded_df.columns
```

```
Index(['T-RUNS', 'T-WKTS', 'ODI-RUNS-S', 'ODI-SR-B', 'ODI-WKTS', 'OD
I-SR-BL',
       'RUNS-S', 'HS', 'AVE', 'SR-B', 'SIXERS', 'RUNS-C', 'WKTS', 'A
VE-BL',
       'ECON', 'SR-BL', 'AGE_2', 'AGE_3', 'COUNTRY_BAN', 'COUNTRY_EN
G',
       'COUNTRY_IND', 'COUNTRY_NZ', 'COUNTRY_PAK', 'COUNTRY_SA', 'CO
UNTRY_SL',
       'COUNTRY_WI', 'COUNTRY_ZIM', 'PLAYING ROLE_Batsman',
       'PLAYING ROLE_Bowler', 'PLAYING ROLE_W. Keeper', 'CAPTAINCY E
XP_1'],
      dtype='object')
```

```
X_features = ipl_auction_encoded_df.columns
```

```
X = sm.add_constant( ipl_auction_encoded_df )
Y = ipl_auction_df['SOLD PRICE']

train_X, test_X, train_y, test_y = train_test_split( X ,
                                                     Y,
                                                    train_size = 0.8,
                                                    random_state = 42 )
```

4.5.5 Building the model on training dataset

```
ipl_model_1 = sm.OLS(train_y, train_X).fit()
ipl_model_1.summary2()
```

Model:	OLS	Adj. R-squared:	0.362
Dependent Variable:	SOLD PRICE	AIC:	2965.2841
Date:	2019-04-23 18:26	BIC:	3049.9046
No. Observations:	104	Log-Likelihood:	-1450.6
Df Model:	31	F-statistic:	2.883
Df Residuals:	72	Prob (F-statistic):	0.000114
R-squared:	0.554	Scale:	1.1034e+11

	Coef.	**Std.Err.**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	375827.1991	228849.9306	1.6422	0.1049	-80376.7996	832031.197
T-RUNS	-53.7890	32.7172	-1.6441	0.1045	-119.0096	11.4316
T-WKTS	-132.5967	609.7525	-0.2175	0.8285	-1348.1162	1082.9228
ODI-RUNS-S	57.9600	31.5071	1.8396	0.0700	-4.8482	120.7681
ODI-SR-B	-524.1450	1576.6368	-0.3324	0.7405	-3667.1130	2618.8231
ODI-WKTS	815.3944	832.3883	0.9796	0.3306	-843.9413	2474.7301
ODI-SR-BL	-773.3092	1536.3334	-0.5033	0.6163	-3835.9338	2289.3154
RUNS-S	114.7205	173.3088	0.6619	0.5101	-230.7643	460.2054
HS	-5516.3354	2586.3277	-2.1329	0.0363	-10672.0855	-360.5853
AVE	21560.2760	7774.2419	2.7733	0.0071	6062.6080	37057.9439
SR-B	-1324.7218	1373.1303	-0.9647	0.3379	-4062.0071	1412.5635
SIXERS	4264.1001	4089.6000	1.0427	0.3006	-3888.3685	12416.5687
RUNS-C	69.8250	297.6697	0.2346	0.8152	-523.5687	663.2187
WKTS	3075.2422	7262.4452	0.4234	0.6732	-11402.1778	17552.6622
AVE-BL	5182.9335	10230.1581	0.5066	0.6140	-15210.5140	25576.3810
ECON	-6820.7781	13109.3693	-0.5203	0.6045	-32953.8282	19312.2721
SR-BL	-7658.8094	14041.8735	-0.5454	0.5871	-35650.7726	20333.1539
AGE_2	-230767.6463	114117.2005	-2.0222	0.0469	-458256.1279	-3279.1648
AGE_3	-216827.0808	152246.6232	-1.4242	0.1587	-520325.1772	86671.0155
COUNTRY_BAN	-122103.5196	438719.2796	-0.2783	0.7816	-996674.4194	752467.380
COUNTRY_ENG	672410.7654	238386.2220	2.8207	0.0062	197196.5172	1147625.01
COUNTRY_IND	155306.4011	126316.3449	1.2295	0.2229	-96500.6302	407113.432
COUNTRY_NZ	194218.9120	173491.9293	1.1195	0.2667	-151630.9280	540068.752
COUNTRY_PAK	75921.7670	193463.5545	0.3924	0.6959	-309740.7804	461584.314
COUNTRY_SA	64283.3894	144587.6773	0.4446	0.6579	-223946.8775	352513.656
COUNTRY_SL	17360.1530	176333.7497	0.0985	0.9218	-334154.7526	368875.058
COUNTRY_WI	10607.7792	230686.7892	0.0460	0.9635	-449257.9303	470473.488

COUNTRY_ZIM	-145494.4793	401505.2815	-0.3624	0.7181	-945880.6296	654891.671
PLAYING ROLE_Batsman	75724.7643	150250.0240	0.5040	0.6158	-223793.1844	375242.713
PLAYING ROLE_Bowler	15395.8752	126308.1272	0.1219	0.9033	-236394.7744	267186.524
PLAYING ROLE_W. Keeper	-71358.6280	213585.7444	-0.3341	0.7393	-497134.0278	354416.771
CAPTAINCY EXP_1	164113.3972	123430.6353	1.3296	0.1878	-81941.0772	410167.871

Omnibus:	0.891	Durbin-Watson:	2.244
Prob(Omnibus):	0.640	Jarque-Bera (JB):	0.638
Skew:	0.190	Prob(JB):	0.727
Kurtosis:	3.059	Condition No.:	84116

4.5.6 Multi-Collinearity

4.5.6.1 VIF

```
from statsmodels.stats.outliers_influence import variance_inflation_factor

def get_vif_factors( X ):
    X_matrix = X.as_matrix()
    vif = [ variance_inflation_factor( X_matrix, i ) for i in range( X_matrix.sh
ape[1] ) ]
    vif_factors = pd.DataFrame()
    vif_factors['column'] = X.columns
    vif_factors['vif'] = vif

    return vif_factors
```

Now, calling the above method with the X features will return the VIF for the corresponding columns.

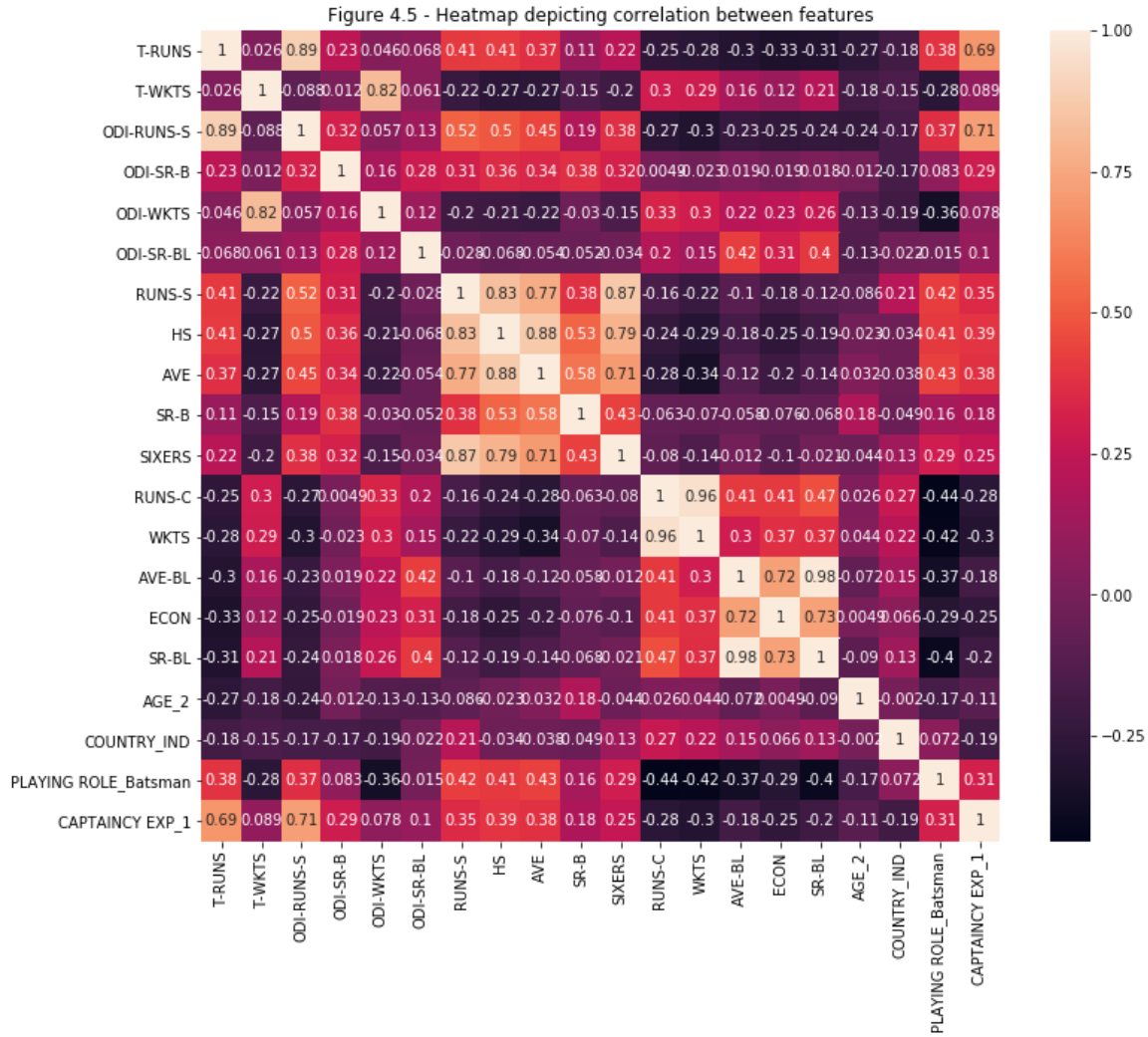
```
vif_factors = get_vif_factors( X[X_features] )
vif_factors
```

	column	vif
0	T-RUNS	12.612694
1	T-WKTS	7.679284
2	ODI-RUNS-S	16.426209
3	ODI-SR-B	13.829376
4	ODI-WKTS	9.951800
5	ODI-SR-BL	4.426818
6	RUNS-S	16.135407
7	HS	22.781017
8	AVE	25.226566
9	SR-B	21.576204
10	SIXERS	9.547268
11	RUNS-C	38.229691
12	WKTS	33.366067
13	AVE-BL	100.198105
14	ECON	7.650140
15	SR-BL	103.723846
16	AGE_2	6.996226
17	AGE_3	3.855003
18	COUNTRY_BAN	1.469017
19	COUNTRY_ENG	1.391524
20	COUNTRY_IND	4.568898
21	COUNTRY_NZ	1.497856
22	COUNTRY_PAK	1.796355
23	COUNTRY_SA	1.886555
24	COUNTRY_SL	1.984902
25	COUNTRY_WI	1.531847
26	COUNTRY_ZIM	1.312168
27	PLAYING ROLE_Batsman	4.843136
28	PLAYING ROLE_Bowler	3.795864
29	PLAYING ROLE_W. Keeper	3.132044
30	CAPTAINCY EXP_1	4.245128

4.5.6.2 Checking correlation of columns with large VIFs

```
columns_with_large_vif = vif_factors[vif_factors.vif > 4].column
```

```
plt.figure( figsize = (12,10) )
sn.heatmap( X[columns_with_large_vif].corr(), annot = True );
plt.title( "Figure 4.5 - Heatmap depicting correlation between features");
```




```
columns_to_be_removed = ['T-RUNS', 'T-WKTS', 'RUNS-S', 'HS',
                         'AVE', 'RUNS-C', 'SR-B', 'AVE-BL',
                         'ECON', 'ODI-SR-B', 'ODI-RUNS-S', 'AGE_2', 'SR-BL']
```

```
X_new_features = list( set(X_features) - set(columns_to_be_removed) )
```

```
get_vif_factors( X[X_new_features] )
```

	column	vif
0	COUNTRY_SL	1.519752
1	SIXERS	2.397409
2	COUNTRY_BAN	1.094293
3	COUNTRY_NZ	1.173418
4	AGE_3	1.779861
5	COUNTRY_ENG	1.131869
6	COUNTRY_PAK	1.334773
7	ODI-WKTS	2.742889
8	CAPTAINCY EXP_1	2.458745
9	PLAYING ROLE_W. Keeper	1.900941
10	WKTS	2.883101
11	PLAYING ROLE_Bowler	3.060168
12	COUNTRY_ZIM	1.205305
13	PLAYING ROLE_Batsman	2.680207
14	COUNTRY_WI	1.194093
15	COUNTRY_IND	3.144668
16	ODI-SR-BL	2.822148
17	COUNTRY_SA	1.416657

4.5.6.3 Building a new model after removing multicollinearity

```
train_X = train_X[X_new_features]

ipl_model_2 = sm.OLS(train_y, train_X).fit()
ipl_model_2.summary2()
```

Model:	OLS	Adj. R-squared:	0.728
Dependent Variable:	SOLD PRICE	AIC:	2965.1080
Date:	2019-04-23 18:26	BIC:	3012.7070
No. Observations:	104	Log-Likelihood:	-1464.6
Df Model:	18	F-statistic:	16.49
Df Residuals:	86	Prob (F-statistic):	1.13e-20
R-squared:	0.775	Scale:	1.2071e+11

	Coef.	**Std.Err.**	**t**	**P>|t|**	**[0.025**	**0.975]**
COUNTRY_SL	55912.3398	142277.1829	0.3930	0.6953	-226925.3388	338750.018
SIXERS	7862.1259	2086.6101	3.7679	0.0003	3714.0824	12010.169
COUNTRY_BAN	-108758.6040	369274.1916	-0.2945	0.7691	-842851.4010	625334.193
COUNTRY_NZ	142968.8843	151841.7382	0.9416	0.3491	-158882.5009	444820.269
AGE_3	-8950.6659	98041.9325	-0.0913	0.9275	-203851.5772	185950.245
COUNTRY_ENG	682934.7166	216150.8279	3.1595	0.0022	253241.0920	1112628.34
COUNTRY_PAK	122810.2480	159600.8063	0.7695	0.4437	-194465.6541	440086.150
ODI-WKTS	772.4088	470.6354	1.6412	0.1044	-163.1834	1708.0009
CAPTAINCY EXP_1	208376.6957	98128.0284	2.1235	0.0366	13304.6315	403448.760
PLAYING ROLE_W. Keeper	-55121.9240	169922.5271	-0.3244	0.7464	-392916.7280	282672.880
WKTS	2431.8988	2105.3524	1.1551	0.2512	-1753.4033	6617.2008
PLAYING ROLE_Bowler	-18315.4968	106035.9664	-0.1727	0.8633	-229108.0215	192477.027
COUNTRY_ZIM	-67977.6781	390859.9289	-0.1739	0.8623	-844981.5006	709026.144
PLAYING ROLE_Batsman	121382.0570	106685.0356	1.1378	0.2584	-90700.7746	333464.888
COUNTRY_WI	-22234.9315	213050.5847	-0.1044	0.9171	-445765.4766	401295.613
COUNTRY_IND	282829.8091	96188.0292	2.9404	0.0042	91614.3356	474045.282
ODI-SR-BL	909.0021	1267.4969	0.7172	0.4752	-1610.6983	3428.7026
COUNTRY_SA	108735.9086	115092.9596	0.9448	0.3474	-120061.3227	337533.139

Omnibus:	8.635	Durbin-Watson:	2.252
Prob(Omnibus):	0.013	Jarque-Bera (JB):	8.345
Skew:	0.623	Prob(JB):	0.015
Kurtosis:	3.609	Condition No.:	1492

```
significant_vars = ['COUNTRY_IND', 'COUNTRY_ENG', 'SIXERS', 'CAPTAINCY EXP_1']

train_X = train_X[significant_vars]

ipl_model_3 = sm.OLS(train_y, train_X).fit()
ipl_model_3.summary2()
```

Model:	OLS	Adj. R-squared:	0.704
Dependent Variable:	SOLD PRICE	AIC:	2961.8089
Date:	2019-04-23 18:26	BIC:	2972.3864
No. Observations:	104	Log-Likelihood:	-1476.9
Df Model:	4	F-statistic:	62.77
Df Residuals:	100	Prob (F-statistic):	1.97e-26
R-squared:	0.715	Scale:	1.3164e+11

	Coef.	**Std.Err.**	**t**	**P>|t|**	**[0.025**	**0.975]**
COUNTRY_IND	387890.2538	63007.1511	6.1563	0.0000	262885.8606	512894.6471
COUNTRY_ENG	731833.6386	214164.4988	3.4172	0.0009	306937.3727	1156729.9045
SIXERS	8637.8344	1675.1313	5.1565	0.0000	5314.4216	11961.2472
CAPTAINCY EXP_1	359725.2741	74930.3460	4.8008	0.0000	211065.6018	508384.9463

Omnibus:	1.130	Durbin-Watson:	2.238
Prob(Omnibus):	0.568	Jarque-Bera (JB):	0.874
Skew:	0.223	Prob(JB):	0.646
Kurtosis:	3.046	Condition No.:	165

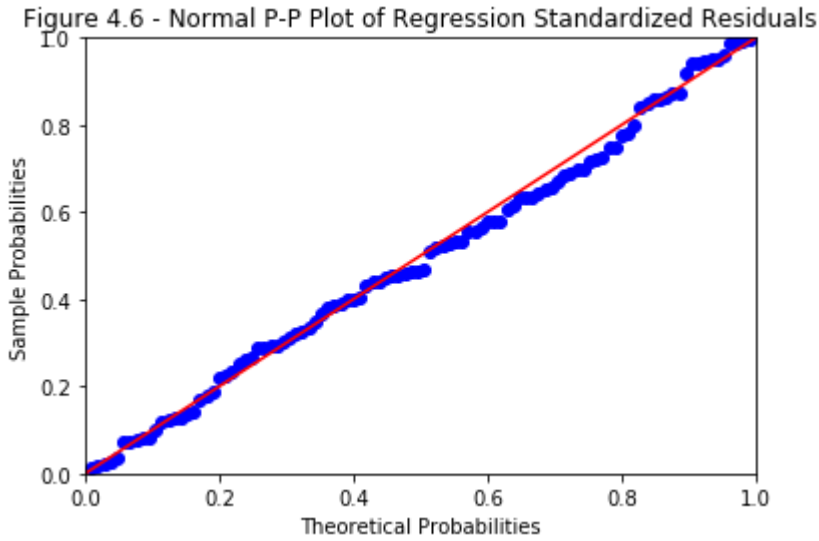
4.5.7 Residual Analysis

4.5.7.1 P-P Plot

```
def draw_pp_plot( model, title ):
    probplot = sm.ProbPlot( model.resid );
    plt.figure( figsize = (8, 6) );
    probplot.ppplot( line='45' );
    plt.title( title );
    plt.show();
```

```
draw_pp_plot( ipl_model_3,
              "Figure 4.6 - Normal P-P Plot of Regression Standardized Residuals"
);
```

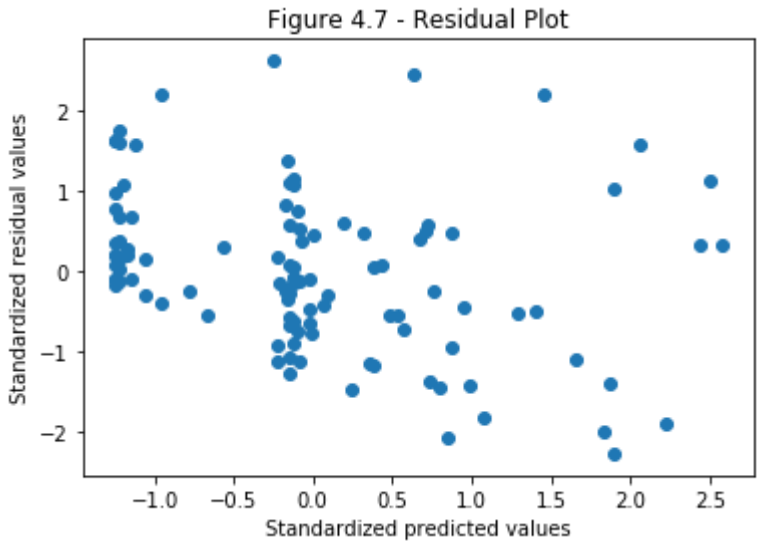
```
<Figure size 576x432 with 0 Axes>
```



4.5.7.2 Residual Plot

```
def plot_resid_fitted( fitted, resid, title):
    plt.scatter( get_standardized_values( fitted ),
             get_standardized_values( resid ) )
    plt.title( title )
    plt.xlabel( "Standardized predicted values")
    plt.ylabel( "Standardized residual values")
    plt.show()
```

```
plot_resid_fitted( ipl_model_3.fittedvalues,
                   ipl_model_3.resid,
                   "Figure 4.7 - Residual Plot")
```



4.5.8 Detecting Influencers

```
k = train_X.shape[1]
n = train_X.shape[0]
```

```
print( "Number of variables:", k, " and number of observations:", n)
```

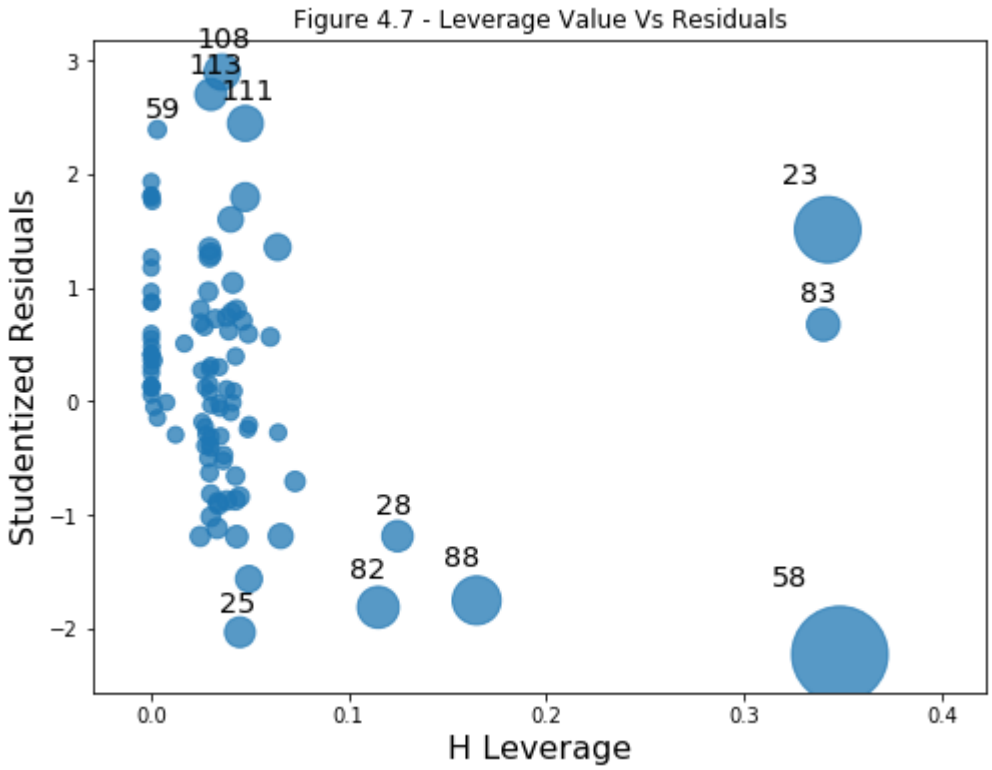
```
Number of variables: 4  and number of observations: 104
```

```
leverage_cutoff = 3*((k + 1)/n)
print( "Cutoff for leverage value: ", round(leverage_cutoff, 3) )
```

```
Cutoff for leverage value:  0.144
```

```
from statsmodels.graphics.regressionplots import influence_plot

fig, ax = plt.subplots( figsize=(8,6) )
influence_plot( ipl_model_3, ax = ax )
plt.title( "Figure 4.7 - Leverage Value Vs Residuals")
plt.show()
```



```
ipl_auction_df[ipl_auction_df.index.isin( [23, 58, 83] )]
```

	Sl.NO.	PLAYER NAME	AGE	COUNTRY	TEAM	PLAYING ROLE	T-RUNS	T-WKTS	ODI-RUNS-S	O SI
23	24	Flintoff, A	2	ENG	CSK	Allrounder	3845	226	3394	88
58	59	Mascarenhas, AD	2	ENG	RR+	Allrounder	0	0	245	95
83	84	Pietersen, KP	2	ENG	RCB+	Batsman	6654	5	4184	86

3 rows × 26 columns

```
train_X_new = train_X.drop( [23, 58, 83], axis = 0)
train_y_new = train_y.drop( [23, 58, 83], axis = 0)
```

4.5.9 Transforming Response Variable

```
train_y = np.sqrt( train_y )
```

```
ipl_model_4 = sm.OLS(train_y, train_X).fit()
ipl_model_4.summary2()
```

Model:	OLS	Adj. R-squared:	0.741
Dependent Variable:	SOLD PRICE	AIC:	1527.9999
Date:	2019-04-23 18:27	BIC:	1538.5775
No. Observations:	104	Log-Likelihood:	-760.00
Df Model:	4	F-statistic:	75.29
Df Residuals:	100	Prob (F-statistic):	2.63e-29
R-squared:	0.751	Scale:	1.3550e+05

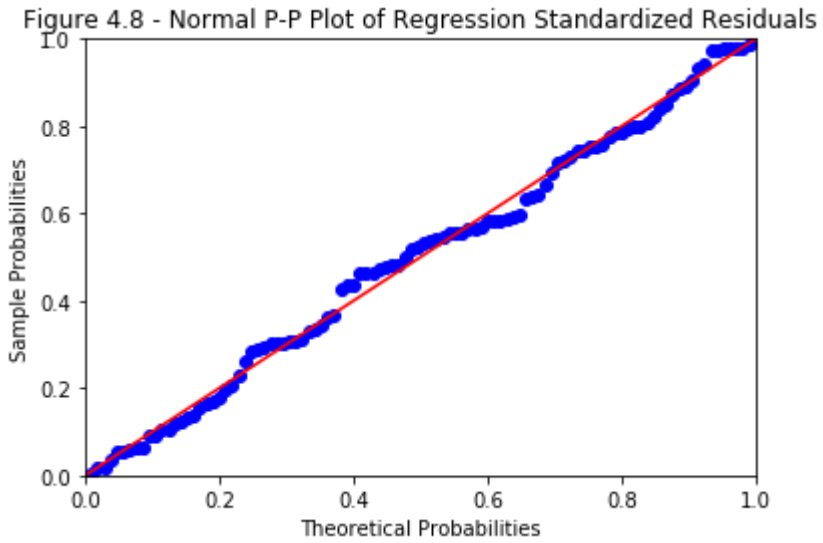
	Coef.	**Std.Err.**	**t**	**P>|t|**	**[0.025**	**0.975]**
COUNTRY_IND	490.7089	63.9238	7.6765	0.0000	363.8860	617.5318
COUNTRY_ENG	563.0261	217.2801	2.5912	0.0110	131.9486	994.1036
SIXERS	8.5338	1.6995	5.0213	0.0000	5.1620	11.9055
CAPTAINCY EXP_1	417.7575	76.0204	5.4953	0.0000	266.9352	568.5799

Omnibus:	0.017	Durbin-Watson:	1.879
Prob(Omnibus):	0.992	Jarque-Bera (JB):	0.145
Skew:	0.005	Prob(JB):	0.930
Kurtosis:	2.817	Condition No.:	165

The r-squard value of the model has increased to 0.751. And the following P-P plot also shows that the residuals follow a normal distribution.

```
draw_pp_plot( ipl_model_4,
              "Figure 4.8 - Normal P-P Plot of Regression Standardized Residuals"
);
```

```
<Figure size 576x432 with 0 Axes>
```



4.5.10 Making predictions on validation set

```
pred_y = np.power( ipl_model_4.predict( test_X[train_X.columns] ), 2)
```

Measuring RMSE

```
from sklearn import metrics

np.sqrt(metrics.mean_squared_error(pred_y, test_y))
```

```
496151.18122558104
```

Measuring R-squared value

```
np.round( metrics.r2_score(pred_y, test_y), 2 )
```

```
0.44
```