MULTIPLE LINEAR REGRESSION

Build a model to understand what features of players are influencing their Sold Price or Predict the players auction prices in future

In [6]:

```
# Importing all required libraries for building the regression model

import pandas as pd
import numpy as np
import statsmodels.api as sm
from sklearn.model_selection import train_test_split
```

In [7]:

```
# Load the dataset into dataframe

ipl_auction_df=pd.read_csv("IPL.csv")
```

In [8]:

```
ipl_auction_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 130 entries, 0 to 129
Data columns (total 26 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   Sl.NO.          130 non-null    int64  
 1   PLAYER NAME     130 non-null    object 
 2   AGE             130 non-null    int64  
 3   COUNTRY         130 non-null    object 
 4   TEAM            130 non-null    object 
 5   PLAYING ROLE    130 non-null    object 
 6   T-RUNS          130 non-null    int64  
 7   T-WKTS          130 non-null    int64  
 8   ODI-RUNS-S      130 non-null    int64  
 9   ODI-SR-B        130 non-null    float64
 10  ODI-WKTS        130 non-null    int64  
 11  ODI-SR-BL       130 non-null    float64
 12  CAPTAINCY EXP   130 non-null    int64  
 13  RUNS-S          130 non-null    int64  
 14  HS              130 non-null    int64  
 15  AVE             130 non-null    float64
 16  SR-B            130 non-null    float64
 17  SIXERS          130 non-null    int64  
 18  RUNS-C          130 non-null    int64  
 19  WKTS            130 non-null    int64  
 20  AVE-BL          130 non-null    float64
 21  ECON            130 non-null    float64
 22  SR-BL           130 non-null    float64
 23  AUCTION YEAR    130 non-null    int64  
 24  BASE PRICE      130 non-null    int64  
 25  SOLD PRICE      130 non-null    int64  
dtypes: float64(7), int64(15), object(4)
memory usage: 26.5+ KB
```

There are 130 observations and 26 columns in the data and there are no missing values

In [9]:

```
# iloc() is used to display the subset of the dataset

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

Out[9]:

	SI.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

We will create a variable X_features which will contain the list of features that we will finally use for building the model and ignore rest of the columns of the dataframe

In [10]:

```
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']
```

Encoding Categorical Features

There are 4 categorical features - Age, country , Playing role, Captaincy exp

In [11]:

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

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

Out[11]:

	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

In [12]:

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

In [13]:

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

We can reassign the new features to the variable X_features which we created earlier to keep track of all features that will be used to build the model finally

In [14]:

```
X_features=ipl_auction_encoded_df.columns
```

In [15]:

```
# Add constant term of 1 to the  dataset

X=sm.add_constant(ipl_auction_encoded_df)
```

In [16]:

```
Y=ipl_auction_df["SOLD PRICE"]
```

In [17]:

```
# Split dataset into train and test set into 80:20 respectively

train_X,test_X,train_Y,test_Y=train_test_split(X,Y,train_size=0.8,random_state=42)

# Fit the model

ipl_model_1=sm.OLS(train_Y,train_X).fit()
```

In [18]:

```
ipl_model_1.summary2()
```

Out[18]:

Model:	OLS	Adj. R-squared:	0.362
Dependent Variable:	SOLD PRICE	AIC:	2965.2841
Date:	2020-08-27 17:39	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	832031.1978
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	752467.3801
COUNTRY_ENG	672410.7654	238386.2220	2.8207	0.0062	197196.5172	1147625.0135
COUNTRY_IND	155306.4011	126316.3449	1.2295	0.2229	-96500.6302	407113.4325
COUNTRY_NZ	194218.9120	173491.9293	1.1195	0.2667	-151630.9280	540068.7521
COUNTRY_PAK	75921.7670	193463.5545	0.3924	0.6959	-309740.7804	461584.3143
COUNTRY_SA	64283.3894	144587.6773	0.4446	0.6579	-223946.8775	352513.6563
COUNTRY_SL	17360.1530	176333.7497	0.0985	0.9218	-334154.7526	368875.0586

COUNTRY_WI	10607.7792	230686.7892	0.0460	0.9635	-449257.9303	470473.4887
COUNTRY_ZIM	-145494.4793	401505.2815	-0.3624	0.7181	-945880.6296	654891.6710
PLAYING ROLE_Batsman	75724.7643	150250.0240	0.5040	0.6158	-223793.1844	375242.7130
PLAYING ROLE_Bowler	15395.8752	126308.1272	0.1219	0.9033	-236394.7744	267186.5249
PLAYING ROLE_W. Keeper	-71358.6280	213585.7444	-0.3341	0.7393	-497134.0278	354416.7718
CAPTAINCY EXP_1	164113.3972	123430.6353	1.3296	0.1878	-81941.0772	410167.8716

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

As per the p-value , only the features HS,AGE_2,AVE and COUNTRY_ENG have come out significant. The model says that none of the other features are influencing SOLD PRICE. This is not very intuitive and could be a result of multi-collinearity effect of variables

Handling Multi-Collinearity

In [19]:

```
from statsmodels.stats.outliers_influence import variance_inflation_factor
```

In [20]:

```
def get_vif_factors( X ):
    X_matrix = X.to_numpy()
    vif = [ variance_inflation_factor( X_matrix, i ) for i in range( X_matrix.shape[1] ) ]
    vif_factors = pd.DataFrame()
    vif_factors['column'] = X.columns
    vif_factors['vif'] = vif
    return vif_factors
```

In [21]:

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

Out[21]:

	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	[illegible]

	column	vif
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

VIF value greater than 4 requires further investigation to assess the impact of multi-collinearity

In [22]:

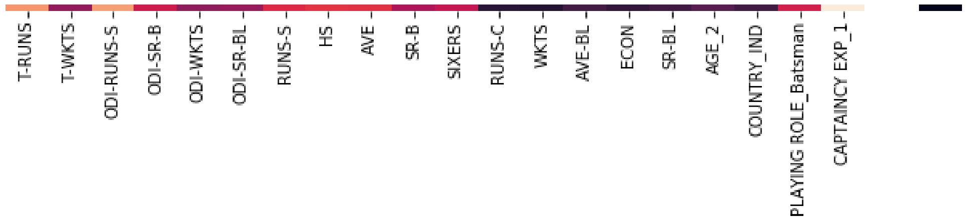
```
columns_with_large_vif=vif_factors[vif_factors.vif>4].column
```

In [23]:

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

In [24]:

```
plt.figure(figsize=(12,10))
sn.heatmap(X[columns_with_large_vif].corr(),annot=True);
```



In [25]:

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

In [26]:

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

In [27]:

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

Out[27]:

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

Building a new model after removing multi-collinearity

In [28]:

```
train_X=train_X[X_new_features]
ipl_model_2=sm.OLS(train_Y,train_X).fit()
```

In [29]:

```
ipl_model_2.summary2()
```

Out[29]:

Adj. R-squared

Model:	OLS	Adj. R-squared (uncentered):	0.728
Dependent Variable:	SOLD PRICE	AIC:	2965.1080
Date:	2020-08-27 17:39	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 (uncentered):	0.775	Scale:	1.2071e+11

	Coef.	Std.Err.	t	P>|t|	[0.025	0.975]
PLAYING ROLE_Batsman	121382.0570	106685.0356	1.1378	0.2584	-90700.7746	333464.8886
SIXERS	7862.1259	2086.6101	3.7679	0.0003	3714.0824	12010.1694
AGE_3	-8950.6659	98041.9325	-0.0913	0.9275	-203851.5772	185950.2453
COUNTRY_WI	-22234.9315	213050.5847	-0.1044	0.9171	-445765.4766	401295.6135
CAPTAINCY EXP_1	208376.6957	98128.0284	2.1235	0.0366	13304.6315	403448.7600
COUNTRY_ZIM	-67977.6781	390859.9289	-0.1739	0.8623	-844981.5006	709026.1444
WKTS	2431.8988	2105.3524	1.1551	0.2512	-1753.4033	6617.2008
COUNTRY_NZ	142968.8843	151841.7382	0.9416	0.3491	-158882.5009	444820.2695
COUNTRY_ENG	682934.7166	216150.8279	3.1595	0.0022	253241.0920	1112628.3411
ODI-SR-BL	909.0021	1267.4969	0.7172	0.4752	-1610.6983	3428.7026
PLAYING ROLE_Bowler	-18315.4968	106035.9664	-0.1727	0.8633	-229108.0215	192477.0279
COUNTRY_SL	55912.3398	142277.1829	0.3930	0.6953	-226925.3388	338750.0184
ODI-WKTS	772.4088	470.6354	1.6412	0.1044	-163.1834	1708.0009
COUNTRY_PAK	122810.2480	159600.8063	0.7695	0.4437	-194465.6541	440086.1502
COUNTRY_IND	282829.8091	96188.0292	2.9404	0.0042	91614.3356	474045.2827
COUNTRY_SA	108735.9086	115092.9596	0.9448	0.3474	-120061.3227	337533.1399
COUNTRY_BAN	-108758.6040	369274.1916	-0.2945	0.7691	-842851.4010	625334.1930
PLAYING ROLE_W. Keeper	-55121.9240	169922.5271	-0.3244	0.7464	-392916.7280	282672.8801

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

Based on the p-values onlly the variables COUNTRY_IND,COUNTRY_ENG,SIXERS and CAPTAINCY EXP_1 have came out statistically significant.

In [30]:

```
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()
```

Out[30]:

Model:	OLS	Adj. R-squared (uncentered):	0.704
Dependent Variable:	SOLD PRICE	AIC:	2961.8089
Date:	2020-08-27 17:39	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 (uncentered):	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

Residula Analysis in MLR

Test for Normality of Residuals(P-P Plot)

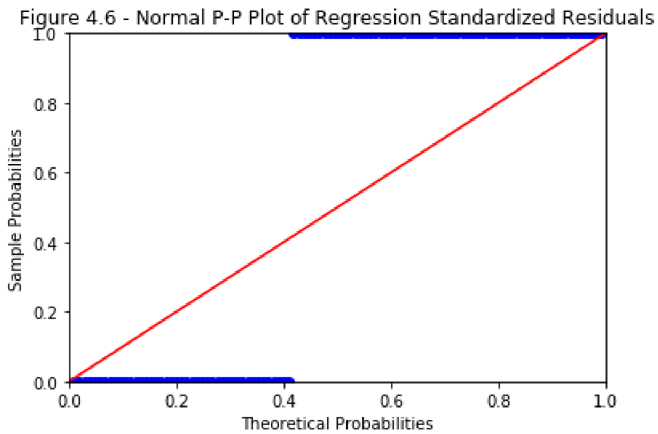
In [31]:

```
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();
```

In [32]:

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

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



Residual Plot for Homoscedasticity and Model Specification

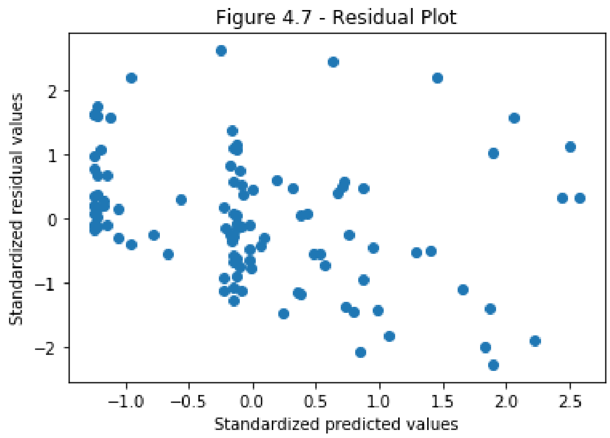
In [33]:

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

In [34]:

```
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")
```



Detecting influencers

In [35]:

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

In [36]:

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

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

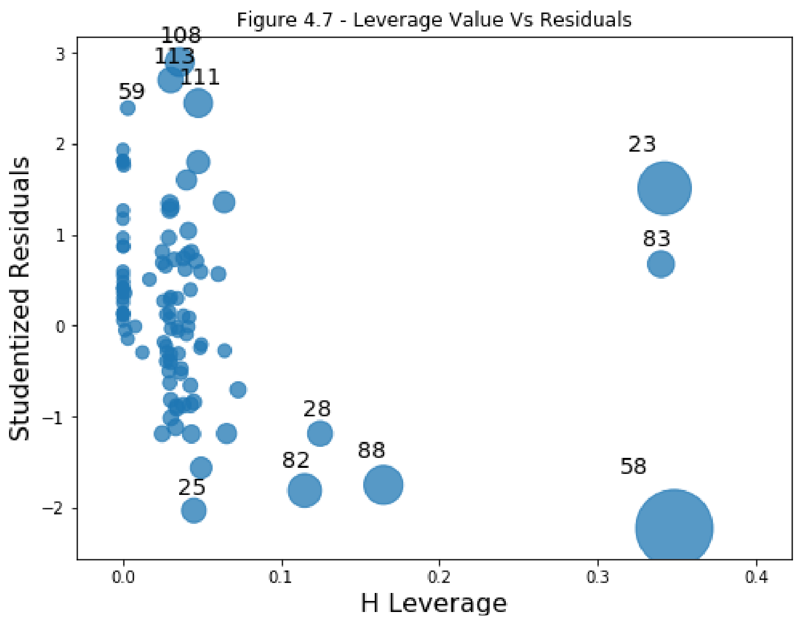
In [37]:

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

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

In [38]:

```
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()
```



Three Observations 23,58,83 have high leverage with residuals.

In [39]:

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

Out[39]:

	Sl.NO.	PLAYER NAME	AGE	COUNTRY	TEAM	PLAYING ROLE	T-RUNS	T-WKTS	ODI-RUNS-S	ODI-SR-B	...	SR-B	SIXERS	RUNS-C	WKTS	AVE-BL
23	24	Flintoff, A	2	ENG	CSK	Allrounder	3845	226	3394	88.82	...	116.98	2	105	2	52.50
58	59	Mascarenhas, AD	2	ENG	RR+	Allrounder	0	0	245	95.33	...	101.37	1	331	19	17.42
83	84	Pietersen, KP	2	ENG	RCB+	Batsman	6654	5	4184	86.76	...	141.20	30	215	7	30.71

3 rows × 26 columns

In [40]:

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

In [41]:

```
ipl_model_4 = sm.OLS(train_Y_new, train_X_new).fit()
ipl_model_4.summary2()
```

Out[41]:

Model:	OLS	Adj. R-squared (uncentered):	0.689
Dependent Variable:	SOLD PRICE	AIC:	2872.3664
Date:	2020-08-27 17:39	BIC:	2880.2117
No. Observations:	101	Log-Likelihood:	-1433.2
Df Model:	3	F-statistic:	75.50
Df Residuals:	98	Prob (F-statistic):	2.22e-25
R-squared (uncentered):	0.698	Scale:	1.2760e+11

	Coef.	Std.Err.	t	P>|t|	[0.025	0.975]
COUNTRY_IND	390069.6377	62096.7593	6.2816	0.0000	266840.6399	513298.6355
COUNTRY_ENG	0.0000	0.0000	6.4881	0.0000	0.0000	0.0000
SIXERS	8790.0052	1656.5116	5.3063	0.0000	5502.7118	12077.2986
CAPTAINCY EXP_1	334569.0056	74599.3795	4.4849	0.0000	186528.9648	482609.0464

Omnibus:	1.880	Durbin-Watson:	2.251
Prob(Omnibus):	0.391	Jarque-Bera (JB):	1.497
Skew:	0.294	Prob(JB):	0.473
Kurtosis:	3.104	Condition No.:	165576019774456896

Transforming Response Variable

In [49]:

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

In [50]:

```
ipl_model_5 = sm.OLS(train_y, train_X).fit()
ipl_model_5.summary2()
```

Out[50]:

Model:	OLS	Adj. R-squared (uncentered):	0.741
Dependent Variable:	SOLD PRICE	AIC:	1527.9999
Date:	2020-08-27 17:42	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 (uncentered):	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

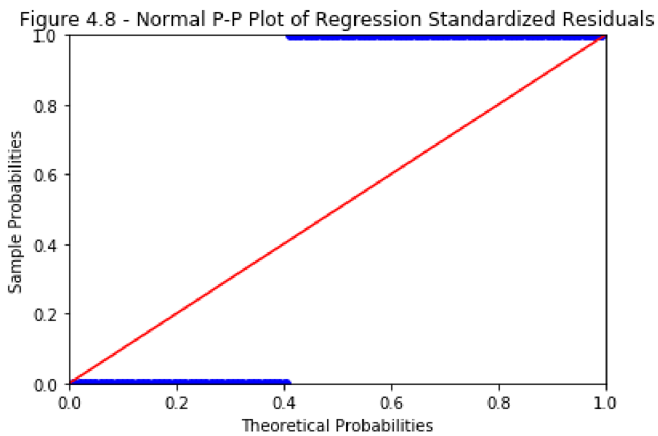
Omnibus:	0.017	Durbin-Watson:	1.879
Prob(Omnibus):	0.992	Jarque-Bera (JB):	0.145
Skew:	0.005	Prob(JB):	0.930
Kurtosis:	2.817	Condition No.:	165

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.

In [42]:

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

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



Making predictions on validation set

In [51]:

```
pred_y = np.power( ipl_model_5.predict( test_X[train_X.columns] ), 2)
```

In [52]:

```python
from sklearn import metrics
np.sqrt(metrics.mean_squared_error(pred_y, test_Y))
```

Out[52]:

```
496151.1812255808
```

In [53]:

```python
np.round( metrics.r2_score(pred_y, test_Y), 2 )
```

Out[53]:

```
0.44
```

The accuracy "R-squared" value on validation set is very low compared to the accuracy reported by the model on training dataset. this could be a sign of model overfitting