```
# Import neccessary packages
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
# Import dataset
house=pd.read_csv(r"D:\Full Stack Data Science\4 Sep (Multiple
Regression)\MLR\House_data.csv")
house
# Splitting data dependent and independent
x=house.iloc[:,3:]
Χ
y=house.iloc[:,2]
У
# Splitting data into train and test
from sklearn.model selection import train test split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,random_state=0)
# Fit Multiple linear regression for training data
from sklearn.linear_model import LinearRegression
model=LinearRegression()
model.fit(x_train,y_train)
# Predicting the Test set
y_pred=model.predict(x_test)
# Building model using Backward Elimination
import statsmodels.formula.api as sm
x=np.append(arr=np.ones((21613,1)).astype(int),values=x,axis=1)
import statsmodels.api as sm
x_opt=x[:,[0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18]]
# Ordinal Least Square
OLS=sm.OLS(endog=y,exog=x_opt).fit()
OLS.summary()
```

OLS Regression Results

=============		===============	
Dep. Variable:	price	R-squared:	0.700
Model:	OLS	Adj. R-squared:	0.700
Method:	Least Squares	F-statistic:	2960.
Date:	Mon, 04 Sep 2023	Prob (F-statistic):	0.00
Time:	22:14:47	Log-Likelihood:	-2.9460e+05
No. Observations:	21613	AIC:	5.892e+05
Df Residuals:	21595	BIC:	5.894e+05
Df Model:	17		

Covariance Type: nonrobust

x2 x3 x4	6.69e+06 3.577e+04 4.114e+04 110.4417 0.1286 6689.5501	2.93e+06 1891.843 3253.678 2.270 0.048	2.282 -18.906 12.645 48.661 2.683	0.022 0.000 0.000 0.000	9.44e+05 -3.95e+04 3.48e+04 105.993	1.24e+07 -3.21e+04 4.75e+04 114.890
x2 x3 x4	4.114e+04 110.4417 0.1286	3253.678 2.270	12.645 48.661	0.000 0.000	3.48e+04	4.75e+04
x3 x4	110.4417 0.1286	2.270	48.661	0.000		
×4	0.1286				105.993	114.890
		0.048	2 683			
x5	6689 5501		2.005	0.007	0.035	0.223
	0000.0001	3595.859	1.860	0.063	-358.599	1.37e+04
х6	5.83e+05	1.74e+04	33.580	0.000	5.49e+05	6.17e+05
x7	5.287e+04	2140.055	24.705	0.000	4.87e+04	5.71e+04
x8	2.639e+04	2351.461	11.221	0.000	2.18e+04	3.1e+04
x9	9.589e+04	2152.789	44.542	0.000	9.17e+04	1e+05
x10	70.7864	2.253	31.413	0.000	66.370	75.203
x11	39.6588	2.647	14.985	0.000	34.471	44.846
x12 -:	2620.2232	72.659	-36.062	0.000	-2762.640	-2477.806
x13	19.8126	3.656	5.420	0.000	12.647	26.978
x14	-582.4199	32.986	-17.657	0.000	-647.074	-517.765
x15	6.027e+05	1.07e+04	56.149	0.000	5.82e+05	6.24e+05
x16 -:	2.147e+05	1.31e+04	-16.349	0.000	-2.4e+05	-1.89e+05
x17	21.6814	3.448	6.289	0.000	14.924	28.439
x18	-0.3826	0.073	-5.222	0.000	-0.526	-0.239

Omnibus:	18384.201	Durbin-Watson:	1.990
Prob(Omnibus):	0.000	Jarque-Bera (JB):	1868224.491
Skew:	3.566	Prob(JB):	0.00
Kurtosis:	47.985	Cond. No.	3.34e+17

Notes:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The smallest eigenvalue is 1.97e-21. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

Removing x5 whose p-value is greater than 0.05 x_opt=x[:,[0,1,2,3,4,6,7,8,9,10,11,12,13,14,15,16,17,18]]

Ordinal Least Square
OLS=sm.OLS(endog=y,exog=x_opt).fit()
OLS.summary()

				======			
Dep. Varial	ble:	**************************************	ice	R-squa			0.700
Model:					-squared:		0.699
Method:		Least Squa		F-stat			3145.
Date:	Mo	on, 04 Sep 2					0.00
Time:		22:21			kelihood:		-2.9460e+05
No. Observ				AIC:			5.892e+05
Df Residua	15:	21	596	BIC:			5.894e+05
Df Model:	_		16				
Covariance	Type:	nonrob					
	coef			t	P> t	[0.025	0.975]
const	5.741e+06	2.89e+06	1	.989	0.047	8.28e+04	1.14e+07
x1	-3.586e+04	1891.248	-18	.962	0.000	-3.96e+04	-3.22e+04
x2	4.272e+04	3141.958	13	.596	0.000	3.66e+04	4.89e+04
x 3	109.9751	2.256	48	.752	0.000	105.554	114.397
x4	0.1266	0.048	2	.643	0.008	0.033	0.221
x5	5.831e+05	1.74e+04	33	.585	0.000	5.49e+05	6.17e+05
хб	5.297e+04	2139.565	24	.756	0.000	4.88e+04	5.72e+04
x7	2.614e+04	2347.831	11	.133	0.000	2.15e+04	
x8	9.624e+04	2144.551	44	.878	0.000	9.2e+04	1e+05
x9	72.3464	2.092	34	.590	0.000	68.247	76.446
x10	37.6292	2.412	15	.604	0.000	32.902	42.356
x11	-2590.7927	70.920	-36	.531	0.000	-2729.801	-2451.784
x12	20.1729	3.651	5	.526	0.000	13.017	27.328
x13	-576.6895	32.844	-17	.559	0.000	-641.065	-512.314
×14	6.044e+05	1.07e+04	56	.494	0.000	5.83e+05	6.25e+05
x15	-2.168e+05	1.31e+04	-16	.568	0.000	-2.42e+05	-1.91e+05
x16	20.9673	3.426	6	.119	0.000	14.251	27.683
x17	-0.3874	0.073	-5	.291	0.000	-0.531	-0.244

Find intercept value and replace constant as intercept.

```
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from sklearn.model selection import train test split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,random_state=0)
```

Multiple linear regression from sklearn.linear_model import LinearRegression model=LinearRegression() model.fit(x_train,y_train)

y_pred=model.predict(x_test)
c=model.intercept_
c

Building model using Backward Elimination import statsmodels.formula.api as sm

x=np.append(arr= np.full((21613, 1),4166134.8),values=x,axis=1)

import statsmodels.api as sm

 $x_{opt}=x[:,[0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18]]$

Ordinal Least Square

OLS=sm.OLS(endog=y,exog=x_opt).fit()

OLS.summary()

OLS Regression Results

Dep. Variable:	price	R-squared:	0.700
Model:	OLS	Adj. R-squared:	0.700
Method:	Least Squares	F-statistic:	2960.
Date:	Tue, 05 Sep 2023	Prob (F-statistic):	0.00
Time:	10:48:33	Log-Likelihood:	-2.9460e+05
No. Observations:	21613	AIC:	5.892e+05
Df Residuals:	21595	BIC:	5.894e+05
Df Model:	17		

D+ Model: 1/ Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025	0.975]
const	1.6059	0.704	2.282	0.022	0.227	2.985
x1	-3.577e+04	1891.843	-18.906	0.000	-3.95e+04	-3.21e+04
x2	4.114e+04	3253.678	12.645	0.000	3.48e+04	4.75e+04
x3	110.4429	2.270	48.661	0.000	105.994	114.891
x4	0.1286	0.048	2.683	0.007	0.035	0.223
x5	6689.5501	3595.859	1.860	0.063	-358.599	1.37e+04
x6	5.83e+05	1.74e+04	33.580	0.000	5.49e+05	6.17e+05
x7	5.287e+04	2140.055	24.705	0.000	4.87e+04	5.71e+04
x8	2.639e+04	2351.461	11.221	0.000	2.18e+04	3.1e+04
x9	9.589e+04	2152.789	44.542	0.000	9.17e+04	1e+05
x10	70.7852	2.253	31.412	0.000	66.368	75.202
x11	39.6576	2.646	14.985	0.000	34.470	44.845
x12	-2620.2232	72.659	-36.062	0.000	-2762.640	-2477.806
x13	19.8126	3.656	5.420	0.000	12.647	26.978
x14	-582.4199	32.986	-17.657	0.000	-647.074	-517.765
x15	6.027e+05	1.07e+04	56.149	0.000	5.82e+05	6.24e+05
x16	-2.147e+05	1.31e+04	-16.349	0.000	-2.4e+05	-1.89e+05
x17	21.6814	3.448	6.289	0.000	14.924	28.439
x18	-0.3826	0.073	-5.222	0.000	-0.526	-0.239

Removing x5 whose p-value is greater than 0.05
x_opt=x[:,[0,1,2,3,4,6,7,8,9,10,11,12,13,14,15,16,17,18]]
Ordinal Least Square
OLS=sm.OLS(endog=y,exog=x_opt).fit()
OLS.summary()

OLS Regression Results

Dep. Var	iable:	pr	ice	R-squa	ared:		0.700	
Model:		OLS Adj. R-squared:				0.699		
Method:		Least Squares		F-statistic:			3145.	
Date:	Tu	ue, 05 Sep 2	023	Prob ((F-statisti	c):	0.00	
Time:		10:48			ikelihood:		-2.9460e+05	
No. Observations:		21613		AIC:			5.892e+05	
Df Residuals:		21	596	BIC:			5.894e+05	
Df Model	:		16					
Covarian	ice Type:	nonrob	ust					
=======	coef	std err		=====	P> t	[0.025	 0.9751	
const	1.3781	0.693	1.	989	0.047	0.020	2.736	
x1	-3.586e+04	1891.248	-18.	962	0.000	-3.96e+04	-3.22e+04	
x2	4.272e+04	3141.958	13.	596	0.000	3.66e+04	4.89e+04	
x3	109.9753	2.256	48.	753	0.000	105.554	114.397	
x4	0.1266	0.048	2.	643	0.008	0.033	0.221	
x5	5.831e+05	1.74e+04	33.	585	0.000	5.49e+05	6.17e+05	
x6	5.297e+04	2139.565	24.	756	0.000	4.88e+04	5.72e+04	
x7	2.614e+04	2347.831	11.	133	0.000	2.15e+04	3.07e+04	
x8	9.624e+04	2144.551	44.	878	0.000	9.2e+04	1e+05	
x9	72.3462	2.092	34.	590	0.000	68.247	76.446	
x10	37.6290	2.412	15.	604	0.000	32.902	42.356	
x11	-2590.7927	70.920	-36.	531	0.000	-2729.801	-2451.784	
x12	20.1729	3.651	5.	526	0.000	13.017	27.328	
x13	-576.6895	32.844	-17.	559	0.000	-641.065	-512.314	
x14	6.044e+05	1.07e+04	56.	494	0.000	5.83e+05	6.25e+05	
x15	-2.168e+05	1.31e+04	-16.	568	0.000	-2.42e+05	-1.91e+05	
x16	20.9673	3.426	6.	119	0.000	14.251	27.683	
x17	-0.3874	0.073	-5.	291	0.000	-0.531	-0.244	

Interpretation:

When we use constant as **1 or Intercept** value the model will give same result.

When we set the constant value manually (like 0 or any other constant) Then model will be change. It does not gives accurate result.