

```
In [1]: import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from sklearn.linear_model import LinearRegression
from statsmodels.formula.api import ols
miami = pd.read_csv('C:/Users/samik/Documents/econometrics/miami-housing.csv')#
miami
```

```
Out[1]:
```

	LATITUDE	LONGITUDE	PARCELNO	SALE_PRC	LND_SQFOOT	TOT_LVG_AREA	SPEC_FEA
0	25.891031	-80.160561	622280070620	440000.0	9375	1753	
1	25.891324	-80.153968	622280100460	349000.0	9375	1715	
2	25.891334	-80.153740	622280100470	800000.0	9375	2276	
3	25.891765	-80.152657	622280100530	988000.0	12450	2058	
4	25.891825	-80.154639	622280100200	755000.0	12800	1684	
...
13927	25.783130	-80.259795	131320040990	275000.0	6780	967	
13928	25.783585	-80.260354	131320040910	340000.0	7500	1854	
13929	25.783793	-80.256126	131320040420	287500.0	8460	1271	
13930	25.784007	-80.257542	131320040330	315000.0	7500	1613	
13931	25.784387	-80.258901	131320040700	250000.0	8833	1867	

13932 rows × 7 columns

```
In [2]: #very simple regression using python
simple = ols("SALE_PRC ~ CNTR_DIST", data = miami).fit()
print(simple.summary())
```

OLS Regression Results

=====						
Dep. Variable:	SALE_PRC		R-squared:	0.074		
Model:	OLS		Adj. R-squared:	0.074		
Method:	Least Squares		F-statistic:	1108.		
Date:	Wed, 22 Feb 2023		Prob (F-statistic):	8.20e-234		
Time:	22:55:28		Log-Likelihood:	-1.9572e+05		
No. Observations:	13932		AIC:	3.914e+05		
Df Residuals:	13930		BIC:	3.915e+05		
Df Model:	1					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]

Intercept	5.842e+05	6109.678	95.615	0.000	5.72e+05	5.96e+05
CNTR_DIST	-2.6899	0.081	-33.285	0.000	-2.848	-2.532
=====						
Omnibus:	8857.556		Durbin-Watson:	0.655		
Prob(Omnibus):	0.000		Jarque-Bera (JB):	109677.981		
Skew:	2.923		Prob(JB):	0.00		
Kurtosis:	15.440		Cond. No.	1.79e+05		
=====						

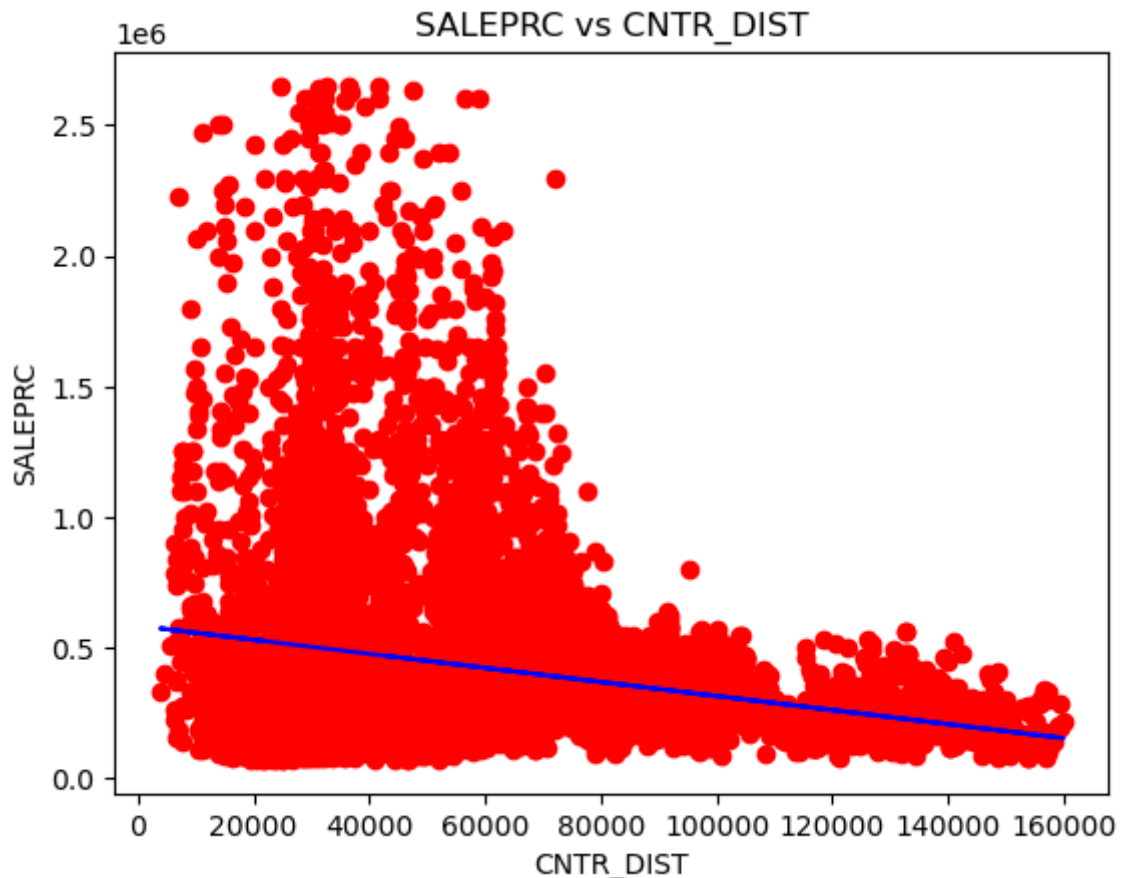
Notes:

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

[2] The condition number is large, 1.79e+05. This might indicate that there are strong multicollinearity or other numerical problems.

```
In [3]: X=miami[['CNTR_DIST']]
        Y=miami[['SALE_PRC']]

        regressor = LinearRegression()
        regressor.fit(X,Y)
        y_pred = regressor.predict(X)
        plt.scatter(X, Y, color = 'red')
        plt.plot(X, regressor.predict(X), color = 'blue')
        plt.title('SALEPRC vs CNTR_DIST')
        plt.xlabel('CNTR_DIST')
        plt.ylabel('SALEPRC')
        plt.show()
```



```
In [4]: #very simple regression using python
simple = ols("SALE_PRC ~ CNTR_DIST + HWY_DIST + RAIL_DIST", data = miami).fit()
print(simple.summary())
```

OLS Regression Results

```
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Dep. Variable:          SALE_PRC    R-squared:                0.145
Model:                  OLS         Adj. R-squared:           0.145
Method:                 Least Squares   F-statistic:             788.5
Date:                  Wed, 22 Feb 2023   Prob (F-statistic):      0.00
Time:                  22:55:28         Log-Likelihood:          -1.9516e+05
No. Observations:      13932          AIC:                    3.903e+05
Df Residuals:          13928          BIC:                    3.904e+05
Df Model:               3
Covariance Type:       nonrobust
=====
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	coef	std err	t	P> t	[0.025	0.975]
Intercept	4.782e+05	6662.856	71.775	0.000	4.65e+05	4.91e+05
CNTR_DIST	-3.3164	0.087	-37.929	0.000	-3.488	-3.145
HWY_DIST	13.9236	0.415	33.562	0.000	13.110	14.737
RAIL_DIST	4.9484	0.454	10.909	0.000	4.059	5.838

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Omnibus:                8720.077    Durbin-Watson:           0.685
Prob(Omnibus):           0.000      Jarque-Bera (JB):        104813.028
Skew:                    2.872      Prob(JB):                0.00
Kurtosis:                15.148     Cond. No.                2.05e+05
=====
```

Notes:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 2.05e+05. This might indicate that there are strong multicollinearity or other numerical problems.

In []: