

```
# Travel time for deliveries is dependent on distance travelled in miles, number of deliveries  
#Following is a model for analysis of the collected data:
```

```
import pandas  
import math  
import matplotlib.pyplot as plt  
from sklearn.linear_model import LinearRegression  
import statsmodels.api as sm  
from statsmodels.stats.outliers_influence import variance_inflation_factor
```

```
df = pandas.read_csv('D:\DS\Data\TravelTime.csv')
```

```
df
```

	miles	deliveries	gasPrice	traveltime
0	89	4	3.84	7.0
1	66	1	3.19	5.4
2	78	3	3.78	6.6
3	111	6	3.89	7.4
4	44	1	3.57	4.8
5	77	3	3.57	6.4
6	80	3	3.03	7.0
7	66	2	3.51	5.6
8	109	5	3.54	7.3
9	76	3	3.25	6.4

```
...  
Dependent variable = TravelTime  
Independent variables:  
    miles  
    deliveries  
    gasPrice
```

The following independent variables are compared with the dependent variable:

TravelTime vs miles
TravelTime vs deliveries
TravelTime vs gasPrice

For multicollinearity the following independent variables are considered:

miles vs deliveries
miles vs gasPrice
deliveries vs gasPrice

Dependent variable vs multiple independent variables

TravelTime vs (deliveries, gasPrice)
TravelTime vs (miles, gasPrice)
TravelTime vs (miles, deliveries)
TravelTime vs (miles, deliveries, gasPrice)

...

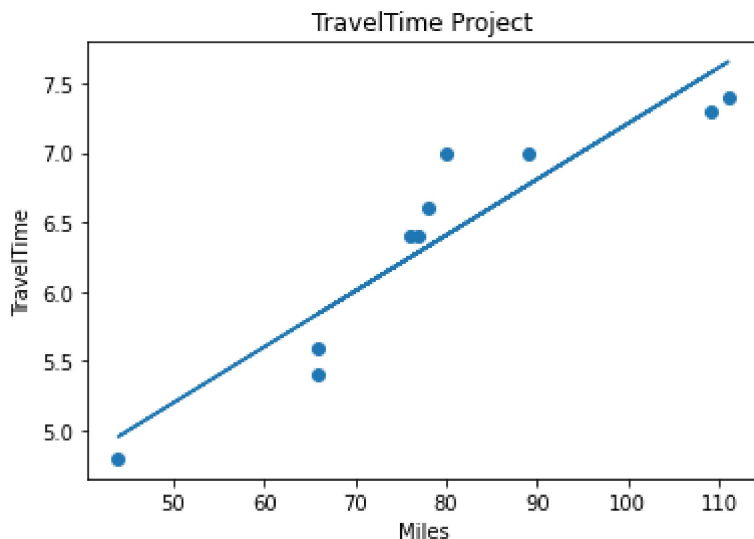
TravelTime vs miles

```
X = df[['miles']]  
y = df['traveltime']
```

```
model = LinearRegression().fit(X, y)
```

```
plt.scatter(X, y)  
plt.plot(X, model.predict(X))  
plt.title('TravelTime Project')  
plt.xlabel('Miles')  
plt.ylabel('TravelTime')  
plt.show()
```

```
print('co-efficient', model.coef_)  
print('constant', model.intercept_)
```



co-efficient [0.04025678]
constant 3.185560248999555

```
# TravelTime vs miles
```

```
X = sm.add_constant(X)
res = sm.OLS(y,X).fit()
print(res.summary())
```

```

OLS Regression Results
=====
Dep. Variable:          traveltime    R-squared:                0.862
Model:                  OLS          Adj. R-squared:           0.844
Method:                 Least Squares  F-statistic:              49.77
Date:                  Sat, 16 Apr 2022  Prob (F-statistic):      0.000107
Time:                  12:56:04       Log-Likelihood:          -2.3532
No. Observations:      10            AIC:                    8.706
Df Residuals:          8             BIC:                    9.312
Df Model:              1
Covariance Type:       nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
const	3.1856	0.467	6.822	0.000	2.109	4.262
miles	0.0403	0.006	7.055	0.000	0.027	0.053

```

=====
Omnibus:                0.542    Durbin-Watson:           2.608
Prob(Omnibus):          0.763    Jarque-Bera (JB):        0.554
Skew:                   0.370    Prob(JB):                0.758
Kurtosis:               2.115    Cond. No.                 353.
=====

```

Notes:

```
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified
C:\Users\fakhi\AppData\Local\Programs\Python\Python310\lib\site-packages\scipy\stats\_stats.py:101:
warnings.warn("kurtosistest only valid for n>=20 ... continuing ")
```

```
print('standard error of regression', math.sqrt(1-(res.rsquared_adj))*(df.std()['traveltime'])
# print(variance_inflation_factor(res.resid,1))
```

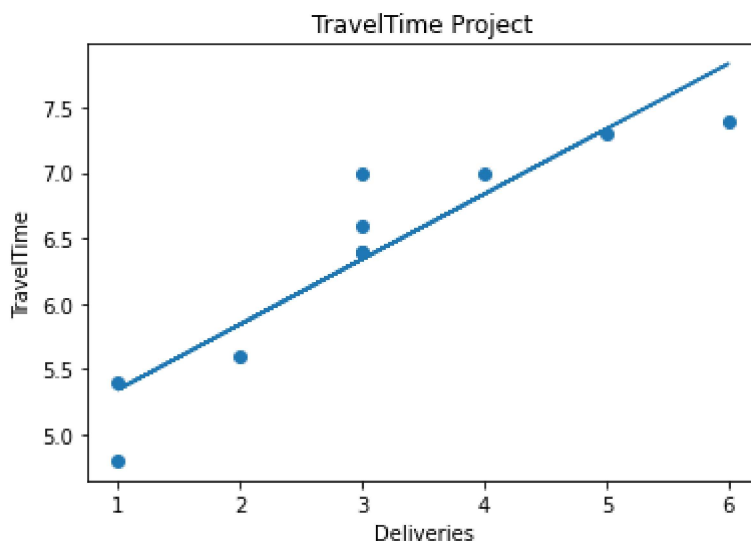
standard error of regression 0.3423088398195204

```
# TravelTime vs deliveries
```

```
X = df[['deliveries']]
y = df['traveltime']
```

```
model = LinearRegression().fit(X, y)
```

```
plt.scatter(X, y)
plt.plot(X, model.predict(X))
plt.title('TravelTime Project')
plt.xlabel('Deliveries')
plt.ylabel('TravelTime')
plt.show()
```



```
# TravelTime vs Deliveries
```

```
X = sm.add_constant(X)
res = sm.OLS(y,X).fit()
print(res.summary())
```

OLS Regression Results

=====						
Dep. Variable:	traveltime		R-squared:	0.840		
Model:	OLS		Adj. R-squared:	0.820		
Method:	Least Squares		F-statistic:	41.96		
Date:	Sat, 16 Apr 2022		Prob (F-statistic):	0.000193		
Time:	12:56:05		Log-Likelihood:	-3.0794		
No. Observations:	10		AIC:	10.16		
Df Residuals:	8		BIC:	10.76		
Df Model:	1					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]

const	4.8454	0.265	18.261	0.000	4.234	5.457
deliveries	0.4983	0.077	6.478	0.000	0.321	0.676
=====						
Omnibus:	0.391	Durbin-Watson:		1.970		
Prob(Omnibus):	0.822	Jarque-Bera (JB):		0.065		
Skew:	0.147	Prob(JB):		0.968		
Kurtosis:	2.736	Cond. No.		8.41		
=====						

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
 C:\Users\fakhi\AppData\Local\Programs\Python\Python310\lib\site-packages\scipy\stats_stats.py:447: UserWarning: kurtosistest: Sample skewness not near zero. Sample kurtosis not near 3.
 warnings.warn("kurtosistest only valid for n>=20 ... continuing ")



```
# TravelTime vs Gas Price
```

```
X = df[['gasPrice']]
y = df['traveltime']
```

```
model = LinearRegression().fit(X, y)
```

```
plt.scatter(X, y)
#plt.plot(X, model.predict(X))
plt.title('TravelTime Project')
plt.xlabel('Gas Price')
plt.ylabel('TravelTime')
plt.show()
```



```
# TravelTime vs Gas Price
X = sm.add_constant(X)
res = sm.OLS(y,X).fit()
print(res.summary())
```

OLS Regression Results

Dep. Variable:	traveltime	R-squared:	0.071
Model:	OLS	Adj. R-squared:	-0.045
Method:	Least Squares	F-statistic:	0.6151
Date:	Sat, 16 Apr 2022	Prob (F-statistic):	0.455
Time:	12:56:05	Log-Likelihood:	-11.868
No. Observations:	10	AIC:	27.74
Df Residuals:	8	BIC:	28.34
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
const	3.5365	3.649	0.969	0.361	-4.878	11.951
gasPrice	0.8113	1.034	0.784	0.455	-1.574	3.197

Omnibus:	1.232	Durbin-Watson:	2.823
Prob(Omnibus):	0.540	Jarque-Bera (JB):	0.765
Skew:	-0.619	Prob(JB):	0.682
Kurtosis:	2.451	Cond. No.	49.6

Notes:

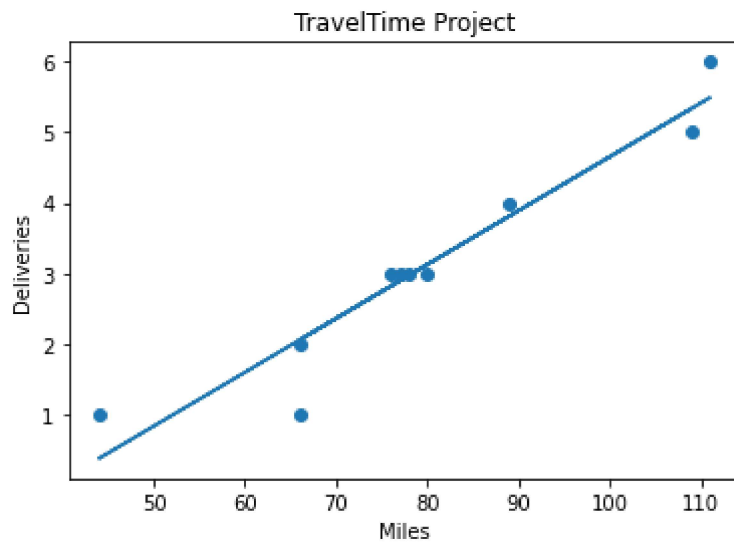
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
C:\Users\fakhi\AppData\Local\Programs\Python\Python310\lib\site-packages\scipy\stats_stats.py:447: UserWarning: kurtosistest only valid for n>=20 ... continuing "

```
# miles vs deliveries
```

```
X = df[['miles']]
y = df['deliveries']
```

```
model = LinearRegression().fit(X, y)
```

```
plt.scatter(X, y)
plt.plot(X, model.predict(X))
plt.title('TravelTime Project')
plt.xlabel('Miles')
plt.ylabel('Deliveries')
plt.show()
```

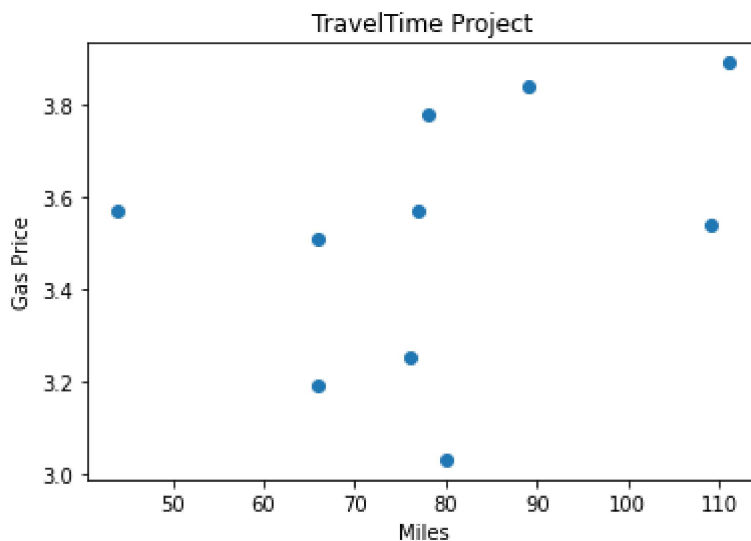


miles vs Gas Price

```
X = df[['miles']]
y = df['gasPrice']
```

```
model = LinearRegression().fit(X, y)
```

```
plt.scatter(X, y)
#plt.plot(X, model.predict(X))
plt.title('TravelTime Project')
plt.xlabel('Miles')
plt.ylabel('Gas Price')
plt.show()
```

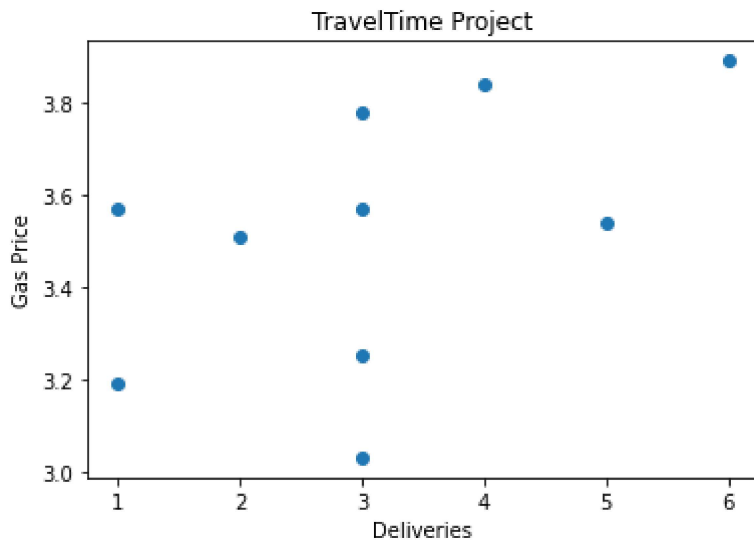


deliveries vs Gas Price

```
X = df[['deliveries']]
y = df['gasPrice']
```

```
model = LinearRegression().fit(X, y)
```

```
plt.scatter(X, y)
#plt.plot(X, model.predict(X))
plt.title('TravelTime Project')
plt.xlabel('Deliveries')
plt.ylabel('Gas Price')
plt.show()
```



```
# TravelTime vs (deliveries, gasPrice)
```

```
X = df[['deliveries', 'gasPrice']]
y = df['traveltime']
```

```
X = sm.add_constant(X)
res = sm.OLS(y,X).fit()
print(res.summary())
```

OLS Regression Results

=====						
Dep. Variable:	traveltime	R-squared:	0.888			
Model:	OLS	Adj. R-squared:	0.855			
Method:	Least Squares	F-statistic:	27.63			
Date:	Sat, 16 Apr 2022	Prob (F-statistic):	0.000476			
Time:	12:56:06	Log-Likelihood:	-1.3104			
No. Observations:	10	AIC:	8.621			
Df Residuals:	7	BIC:	9.529			
Df Model:	2					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]

const	7.3243	1.458	5.025	0.002	3.878	10.771
deliveries	0.5665	0.079	7.129	0.000	0.379	0.754


```

gasPrice      -0.7650      0.444      -1.724      0.128      -1.814      0.284
=====
Omnibus:                1.321      Durbin-Watson:                2.054
Prob(Omnibus):          0.517      Jarque-Bera (JB):          0.811
Skew:                   0.339      Prob(JB):                  0.667
Kurtosis:               1.781      Cond. No.                  71.9
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
 C:\Users\fakhi\AppData\Local\Programs\Python\Python310\lib\site-packages\scipy\stats_stats.py:117: UserWarning: kurtosistest only valid for n>=20 ... continuing "



```

# TravelTime vs (miles, gasPrice)
X = df[['miles', 'gasPrice']]
y = df['traveltime']

```

```

X = sm.add_constant(X)
res = sm.OLS(y,X).fit()
print(res.summary())

```

OLS Regression Results

```

=====
Dep. Variable:          traveltime      R-squared:                0.866
Model:                  OLS             Adj. R-squared:          0.828
Method:                 Least Squares    F-statistic:            22.63
Date:                   Sat, 16 Apr 2022  Prob (F-statistic):      0.000879
Time:                   12:56:06         Log-Likelihood:         -2.1863
No. Observations:       10              AIC:                   10.37
Df Residuals:           7                BIC:                   11.28
Df Model:               2
Covariance Type:        nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
const	3.8676	1.482	2.609	0.035	0.362	7.373
miles	0.0414	0.006	6.445	0.000	0.026	0.057
gasPrice	-0.2191	0.449	-0.488	0.641	-1.282	0.844

```

=====
Omnibus:                0.731      Durbin-Watson:                2.740
Prob(Omnibus):          0.694      Jarque-Bera (JB):          0.563
Skew:                   0.025      Prob(JB):                  0.755
Kurtosis:               1.839      Cond. No.                  1.11e+03
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
 [2] The condition number is large, 1.11e+03. This might indicate that there are strong multicollinearity or other numerical problems.
 C:\Users\fakhi\AppData\Local\Programs\Python\Python310\lib\site-packages\scipy\stats_stats.py:117: UserWarning: kurtosistest only valid for n>=20 ... continuing "



```
# TravelTime vs (miles, deliveries)
X = df[['miles', 'deliveries']]
y = df['traveltime']
```

```
X = sm.add_constant(X)
res = sm.OLS(y,X).fit()
print(res.summary())
```

C:\Users\fakhi\AppData\Local\Programs\Python\Python310\lib\site-packages\scipy\stats_st
warnings.warn("kurtosistest only valid for n>=20 ... continuing ")

OLS Regression Results

```
=====
Dep. Variable:          traveltime    R-squared:                0.871
Model:                  OLS          Adj. R-squared:            0.835
Method:                 Least Squares    F-statistic:              23.72
Date:                  Sat, 16 Apr 2022    Prob (F-statistic):       0.000763
Time:                  12:56:06          Log-Likelihood:           -1.9830
No. Observations:      10              AIC:                     9.966
Df Residuals:          7                BIC:                     10.87
Df Model:              2
Covariance Type:       nonrobust
=====
```

	coef	std err	t	P> t	[0.025	0.975]
const	3.7322	0.887	4.208	0.004	1.635	5.830
miles	0.0262	0.020	1.310	0.232	-0.021	0.074
deliveries	0.1840	0.251	0.733	0.487	-0.409	0.777

```
=====
Omnibus:                1.340    Durbin-Watson:              2.402
Prob(Omnibus):          0.512    Jarque-Bera (JB):         0.867
Skew:                   0.654    Prob(JB):                 0.648
Kurtosis:               2.393    Cond. No.                  670.
=====
```

Notes:

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



```
# VIF dataframe
vif_data = pandas.DataFrame()
vif_data["feature"] = X.columns

# calculating VIF for each feature
vif_data["VIF"] = [variance_inflation_factor(X.values, i)
                   for i in range(len(X.columns))]

print(vif_data)
```

	feature	VIF
0	const	63.263365

```
1      miles  11.593044
```

```
# TravelTime vs (miles, deliveries, gasPrice)
X = df[['miles', 'deliveries', 'gasPrice']]
y = df['traveltime']
```

```
X = sm.add_constant(X)
res = sm.OLS(y,X).fit()
print(res.summary())
```

```

                        OLS Regression Results
=====
Dep. Variable:          traveltime    R-squared:                0.895
Model:                  OLS          Adj. R-squared:            0.842
Method:                 Least Squares    F-statistic:             16.99
Date:                  Sat, 16 Apr 2022    Prob (F-statistic):       0.00245
Time:                  12:56:07          Log-Likelihood:          -0.98426
No. Observations:      10              AIC:                    9.969
Df Residuals:          6                BIC:                    11.18
Df Model:               3
Covariance Type:       nonrobust
=====
               coef      std err          t      P>|t|      [0.025      0.975]
-----
const          6.2114      2.321       2.677     0.037     0.533     11.890
miles          0.0141      0.022       0.636     0.548    -0.040     0.068
deliveries     0.3832      0.300       1.277     0.249    -0.351     1.117
gasPrice      -0.6066      0.527      -1.152     0.293    -1.895     0.682
=====
Omnibus:            2.874    Durbin-Watson:           2.406
Prob(Omnibus):      0.238    Jarque-Bera (JB):         1.204
Skew:               0.457    Prob(JB):                 0.548
Kurtosis:           1.567    Cond. No.                  1.79e+03
=====
```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
 [2] The condition number is large, 1.79e+03. This might indicate that there are strong multicollinearity or other numerical problems.

C:\Users\fakhi\AppData\Local\Programs\Python\Python310\lib\site-packages\scipy\stats_stats.py:447: RuntimeWarning: kurtosistest only valid for n>=20 ... continuing "



```
# VIF dataframe
vif_data = pandas.DataFrame()
vif_data["feature"] = X.columns

# calculating VIF for each feature
vif_data["VIF"] = [variance_inflation_factor(X.values, i)
                   for i in range(len(X.columns))]

print(vif_data)
```

	feature	VIF
0	const	453.235497
1	miles	14.936013
2	deliveries	17.353065
3	gasPrice	1.713803

```
df.corr()
```

	miles	deliveries	gasPrice	traveltime
miles	1.000000	0.955898	0.355796	0.928179
deliveries	0.955898	1.000000	0.498242	0.916443
gasPrice	0.355796	0.498242	1.000000	0.267212
traveltime	0.928179	0.916443	0.267212	1.000000

```
df2 = pandas.read_csv("D:\DS\Data\Summary.csv")
df2
```



	F	P-value	std error	RsQ(Adj)	RSQ(Pred)	miles	deliveries	gasPrice	VIF
0	49.77	< 0.001	0.34230	0.8442	0.7907	X	NaN	NaN	1.00
1	41.96	< 0.001	0.36809	0.8199	0.7027	NaN	X	NaN	1.00
2	0.62	0.455	0.88640	0.0000	0.0000	NaN	NaN	X	1.00
3	23.72	0.001	0.35264	0.8347	0.5995	X	X	NaN	11.59
4	22.63	0.001	0.35988	0.8278	0.6811	X	NaN	X	1.14
5	27.63	< 0.001	0.32970	0.8555	0.7176	NaN	X	X	1.33
6	16.99	0.002	0.34469	0.8420	0.5749	X	X	X	below
7	NaN	NaN	NaN	NaN	NaN	14.94	17.35	1.71	NaN

```
...
```

Conclusion

In terms of dependent variable TimeTravel, the following have a high correlation:

TravelTime vs Miles

TravelTime vs Number of Deliveries

Miles vs Number of Deliveries- Miles and Deliveries have multicollinearity and thus one of the variance inflation factor VIF is 11.59 and low predicted R Squared therefore one of miles or deliveries independent variables has to be dropped. Also two variab

miles and deliveries can be dropped.

Gas Price has a low correlation with Time Travel and a high standard error and can be taken out from the list of independent variables. All models with gas price can be dropped.

Miles travelled has the highest Adjusted RSquared, RSquared predicted and a low standard error. This is the best model and should be used.

...

