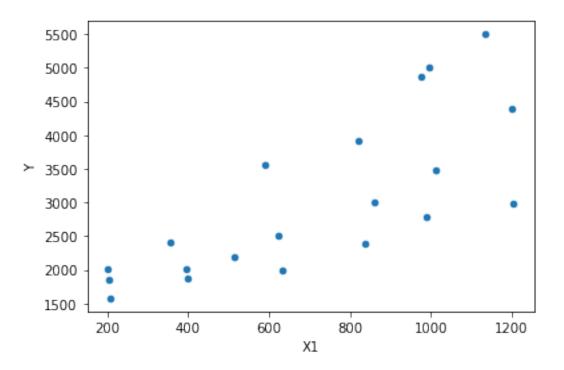
# Assignment 4

October 21, 2022

# 1 Assignment 4

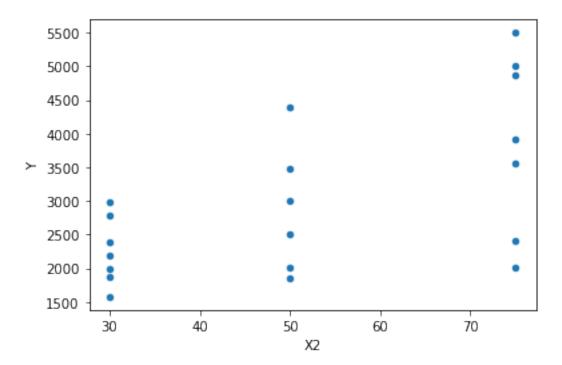
Matthias Rathbun, Mir Khan, Jay Nagabhairu, Jason Ng, Phoebe Collins  $10/21/2022\,$ 

```
[1]: import pandas as pd
     import numpy as np
     import matplotlib.pyplot as plt
     import seaborn as sns
     import statsmodels.api as sm
     import statsmodels.formula.api as smf
     import scipy.stats
[2]: df = pd.read_csv("ACT_04_Data.csv")
[3]:
    df.head()
[3]:
                   Х1
                       Х2
                             X12
                                    X1SQ
                                          X2SQ
     0
            2010
                  201
                       75
                           15075
                                   40401
                                           5625
     1
            1850
                  205
                       50
                           10250
                                   42025
                                          2500
     2
            2400
                  355
                          26625
                                  126025 5625
                       75
     3
            1575
                  208
                       30
                            6240
                                   43264
                                           900
     4
            3550
                  590
                       75 44250
                                 348100 5625
[4]: df = df.rename(columns = {" Y
                                        ":"Y"})
[5]: df.plot.scatter(x = "X1", y = "Y")
[5]: <AxesSubplot:xlabel='X1', ylabel='Y'>
```



[6]: df.plot.scatter(x = "X2", y = "Y")

[6]: <AxesSubplot:xlabel='X2', ylabel='Y'>



```
[7]: lm1 = smf.ols(formula = "Y~X1+X2", data = df).fit() lm1.summary()
```

[7]: <class 'statsmodels.iolib.summary.Summary'>

#### OLS Regression Results

Dep. Variable: Y R-squared: 0.900 Model: OLS Adj. R-squared: 0.888 Method: F-statistic: Least Squares 76.28 Date: Fri, 21 Oct 2022 Prob (F-statistic): 3.23e-09 Time: -146.2913:21:12 Log-Likelihood: No. Observations: AIC: 298.6 20 Df Residuals: BIC: 301.6 17

Df Model: 2
Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025	0.975]
Intercept X1	-566.4182 2.5509	312.265 0.267	-1.814 9.564	0.087 0.000	-1225.240 1.988	92.404 3.114
X2	34.2847	4.680	7.326	0.000	24.410	44.159
Omnibus:		3	.525 Durk	oin-Watson:		1.870
Prob(Omnibu	ıs):	0	.172 Jaro	ue-Bera (JI	3):	1.410
Skew:		0	.191 Prob	(JB):		0.494
Kurtosis:		1	.756 Cond	l. No.		2.77e+03

## Notes:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 2.77e+03. This might indicate that there are strong multicollinearity or other numerical problems.
- [8]: sm.stats.anova\_lm(lm1, typ=1)
- [8]: df sum\_sq mean\_sq F PR(>F)
   X1 1.0 1.537060e+07 1.537060e+07 98.894347 1.679621e-08
   X2 1.0 8.340715e+06 8.340715e+06 53.664106 1.185020e-06
   Residual 17.0 2.642216e+06 1.554245e+05 NaN NaN
- [9]: lm2 = smf.ols(formula = "Y~X1+X2+X12", data = df).fit()
  lm2.summary()

[9]: <class 'statsmodels.iolib.summary.Summary'>

## OLS Regression Results

Dep. Variable:		Y	R-squared:			0.978		
Model:		OLS		Adj. R-squared:			0.974	
Method:		Least Squares		F-statistic:			239.4	
Date:		Fri, 21 Oct 2022		Prob (F-statistic):		:):	1.68e-13	
Time:		13:21:12		Log-Likelihood:			-131.03	
No. Observa	ations:		20	AIC:			270.1	
Df Residuals:			16	BIC:			274.0	
Df Model:			3					
Covariance Type:		nonro	bust					
========		:	:=====		D. L. L	[0.005	0.075	
	coei	f std err		t 	P> t	[0.025	0.975]	
Intercept	1340.1506	5 292.598		4.580	0.000	719.870	1960.431	
X1	-0.173	0.381	-(	0.455	0.655	-0.981	0.634	
X2	-2.8062	5.379	-(	0.522	0.609	-14.210	8.598	
X12	0.0529	0.007	•	7.590	0.000	0.038	0.067	
========								

 Skew:
 -0.457
 Prob(JB):
 0.453

 Kurtosis:
 1.969
 Cond. No.
 3.01e+05

2.452

0.294

Durbin-Watson:

Jarque-Bera (JB):

1.397

1.582

#### Notes:

Omnibus:

Prob(Omnibus):

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 3.01e+05. This might indicate that there are strong multicollinearity or other numerical problems.

```
[10]: sm.stats.anova_lm(lm2, typ=1)
```

- [10]: df sum\_sq mean\_sq F PR(>F) Х1 1.0 1.537060e+07 1.537060e+07 428.222921 5.653519e-13 X2 1.0 8.340715e+06 8.340715e+06 232.371222 5.998742e-11 X12 1.0 2.067913e+06 2.067913e+06 57.611787 1.089461e-06 Residual 16.0 5.743028e+05 3.589392e+04 NaNNaN
- [11]: lm3 = smf.ols(formula = "Y~X1+X2+X12+X1SQ+X2SQ", data = df).fit()
  lm3.summary()
- [11]: <class 'statsmodels.iolib.summary.Summary'>

## OLS Regression Results

========	=======	=======	=====	=====	=======	========	=======
Dep. Varial	ble:		Y	R-sq	uared:		0.986
Model:			OLS	Adj.	R-squared:		0.981
Method:		Least Sq	uares	F-st	atistic:		199.4
Date:		Fri, 21 Oct	2022	Prob	(F-statisti	c):	1.71e-12
Time:		13:	21:12	Log-	Likelihood:		-126.50
No. Observa	ations:		20	AIC:			265.0
Df Residua	ls:		14	BIC:			271.0
Df Model:			5				
Covariance	Type:	nonr	obust				
========							
	coef	std err		t	P> t	[0.025	0.975]
Intercept	2405.7779	495.491		1.855	0.000	1343.055	3468.501
X1	-1.5734	0.680	-2	2.315	0.036	-3.031	-0.115
X2	-32.4259	17.270	-1	1.878	0.081	-69.466	4.614
X12	0.0542	0.006	Ş	9.092	0.000	0.041	0.067
X1SQ	0.0010	0.000	2	2.379	0.032	9.37e-05	0.002
X2SQ	0.2684	0.158	1	1.695	0.112	-0.071	0.608
Omnibus:	=======		====== 0.504	Durb:	======= in-Watson:	========	1.835
Prob(Omnibus):		0.777 Jarque-Bera (JB):			0.589		

#### Notes:

Skew:

Kurtosis:

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

0.295

2.402

Prob(JB):

Cond. No.

0.745

1.06e+07

[2] The condition number is large, 1.06e+07. This might indicate that there are strong multicollinearity or other numerical problems.

```
[12]: sm.stats.anova_lm(lm3, typ=1)
```

[12]:	df	sum_sq	mean_sq	F	PR(>F)
X1	1.0	1.537060e+07	1.537060e+07	589.561805	7.645837e-13
X2	1.0	8.340715e+06	8.340715e+06	319.920281	4.860083e-11
X12	1.0	2.067913e+06	2.067913e+06	79.317822	3.844920e-07
X1SQ	1.0	1.343881e+05	1.343881e+05	5.154650	3.950402e-02
X2SQ	1.0	7.491751e+04	7.491751e+04	2.873570	1.121613e-01
Residual	14.0	3.649972e+05	2.607123e+04	NaN	NaN

```
[13]: lm4 = smf.ols(formula = "Y~X1+X2+X12+X1SQ", data = df).fit()
lm4.summary()
```

# [13]: <class 'statsmodels.iolib.summary.Summary'>

## OLS Regression Results

============	:==========		=========
Dep. Variable:	Y	R-squared:	0.983
Model:	OLS	Adj. R-squared:	0.979
Method:	Least Squares	F-statistic:	220.9
Date:	Fri, 21 Oct 2022	Prob (F-statistic):	3.91e-13
Time:	13:21:12	Log-Likelihood:	-128.36
No. Observations:	20	AIC:	266.7
Df Residuals:	15	BIC:	271.7
Df Model:	4		
Covariance Type:	nonrobust		

Covariance Type: nonrobust

========		=========			========	=======
	coef	std err	t	P> t	[0.025	0.975]
Intercept	1746.3777	325.522	5.365	0.000	1052.544	2440.211
X1	-1.5279	0.720	-2.121	0.051	-3.063	0.008
X2	-4.2211	4.907	-0.860	0.403	-14.681	6.238
X12	0.0545	0.006	8.616	0.000	0.041	0.068
X1SQ	0.0009	0.000	2.141	0.049	3.89e-06	0.002
Omnibus:		0.4	======== 481 Durbir	======= n-Watson:		1.617
Prob(Omnibu	ıs):	0.	786 Jarque	e-Bera (JB)	:	0.590
Skew:		0.:	255 Prob(3	JB):		0.745
Kurtosis:		2.3	330 Cond.	No.		6.54e+06
========		========			========	=======

#### Notes:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 6.54e+06. This might indicate that there are strong multicollinearity or other numerical problems.

# [14]: sm.stats.anova\_lm(lm4, typ=1)

```
[14]:
                                                        F
                                                                 PR(>F)
                df
                          sum_sq
                                       mean_sq
     X1
                1.0 1.537060e+07 1.537060e+07 524.099340 4.418034e-13
     Х2
                1.0 8.340715e+06 8.340715e+06
                                                284.397677 3.675408e-11
     X12
                1.0 2.067913e+06 2.067913e+06
                                                70.510704 4.718263e-07
                                                 4.582299 4.913919e-02
     X1SQ
                1.0 1.343881e+05 1.343881e+05
     Residual 15.0 4.399147e+05 2.932765e+04
                                                      {\tt NaN}
```

```
[15]: data = [[lm1.rsquared, lm1.mse_resid],[lm2.rsquared, lm2.mse_resid],[lm3.
      →rsquared, lm3.mse_resid],[lm4.rsquared, lm4.mse_resid]]
      results = pd.DataFrame(data, columns=['R Squared', 'MSE'])
```

```
results.index.name = 'Model'
      results.index += 1
[16]: results
[16]:
             R Squared
                                   MSE
      Model
      1
              0.899740
                        155424.460740
      2
              0.978208
                          35893.923075
      3
              0.986150
                          26071.228596
      4
              0.983307
                          29327.647321
[17]: q1 = scipy.stats.norm.ppf(0.0125)
[18]: q2 = scipy.stats.norm.ppf(0.99)
[19]: q3 = scipy.stats.t.ppf(0.0125, 333)
[20]: q4 = scipy.stats.t.ppf(0.99, 345)
[21]: q5 = scipy.stats.chi2.ppf(0.025, 125)
[22]: q6 = scipy.stats.t.ppf(0.975, 245)
[23]: q7 = scipy.stats.f.ppf(0.01, 12, 250)
[24]: q8 = scipy.stats.f.ppf(0.99, 24, 500)
[25]: data = [["Normal", None, None, 0.0125, q1], ["Normal", None, None, 0.99, [
       \rightarrowq2],["Student t",333,None, 0.0125, q3],["Student t",345,None, 0.99, q4],
               ["Chi-Square",125,None, 0.025, q5],["Chi-Square",245,None, 0.975,
       \hookrightarrowq6],["F",12,250, 0.01, q7],["F",24,500, 0.99, q8]]
[26]: quantiles = pd.DataFrame(data, columns=['Distribution', 'Degrees Freedom I', |
       →'Degrees Freedom II', 'Probability', 'Quantile'])
      quantiles = quantiles.set_index("Distribution")
[27]:
      quantiles
[27]:
                    Degrees Freedom I Degrees Freedom II Probability
                                                                            Quantile
      Distribution
      Normal
                                                        NaN
                                                                  0.0125 -2.241403
                                   NaN
                                                                  0.9900
      Normal
                                   NaN
                                                        NaN
                                                                            2.326348
      Student t
                                                                  0.0125 -2.251584
                                 333.0
                                                        NaN
      Student t
                                 345.0
                                                        NaN
                                                                  0.9900
                                                                            2.337205
                                 125.0
      Chi-Square
                                                        NaN
                                                                  0.0250 95.945725
      Chi-Square
                                 245.0
                                                        NaN
                                                                  0.9750
                                                                            1.969694
                                  12.0
                                                      250.0
                                                                  0.0100
                                                                            0.293798
```

F 24.0 500.0 0.9900 1.828539