

ME EN 2550

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Homework 8- Part A

8.2: a) Predicted birth weight = $120.07 - 1.93(\text{parity})$

b) If a child is not the first born then there is a predicted 1.93 decrease in predicted birth weight.

Predicted birth weight of firstborns = 120.07 oz.

Predicted birth weight of non-firstborns = 118.14 oz.

c) No, we fail to reject the null hypothesis that is, holding all other variables constant, parity is unproductive of birth weight. This is because the P-value = 0.1052 which is greater than $\alpha = 0.05$.

8.3: Predicted birth weight = $-80.41 + 0.44(\text{gestation}) - 3.33(\text{parity}) - 0.01(\text{age}) + 1.15(\text{height}) + 0.05(\text{weight}) - 8.40(\text{smoke})$

b) For a unit increase in gestation length, there is a predicted 0.44 oz. increase in birth weight all else held constant. For a unit increase in the age of the mother, there is a predicted 0.01oz.

Decrease in birth weight all else held constant.

c) There is a difference because we are dealing with a completely different model that has many more predictors. There is also the chance that parity might be correlated with another variable in the model.

d) Actual: 120 Predicted: 120.58 Residual: -0.58

e) $R^2 = 0.2504$ Adjusted $R^2 = 0.2468$

8.5: a) 95% CI ($-0.3212 < \text{coefficient of gender} < 0.1612$) There is a 95 % chance that the calculated interval contains the true coefficient of gender which predicts GPA when all other predictors are held constant.

b) Yes because for all other predictors the P-values are greater than $\alpha = 0.05$.

8.7 Age would be the predictor to be removed first because without it the model has the highest R^2 adjusted of any other model that had one predictor removed.

8.13: Nearly Normal Residuals: The probability plot appears linear and thus overall normally distributed.

Constant Variability: The scatterplots show no major patterns other than from the discrete domains of some of the predictors.

Independent: The residuals all appear randomly distributed.

Linearly Related: It appears that there are no major patterns in the residual plots thus a linear model appears to work decently well for this data.

Overall it appears that the assumptions for regression are met.

8.14: Nearly Normal Residuals: The probability plot appears approximately linear and it is reasonable to conclude the data is overall normally distributed, although possibly with some skewness.

Constant Variability: The scatterplots show no major patterns other than from the discrete domains of some of the predictors.

Independent: The residuals all appear randomly distributed.

Linearly Related: It appears that there are no major patterns in the residual plots thus a linear model appears to work decently well for this data.

Overall it appears that the assumptions for regression are met.

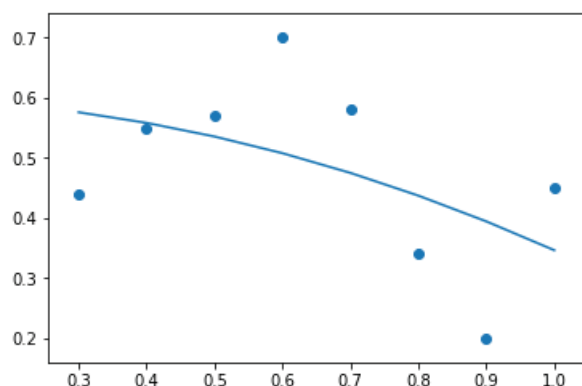
Python 3.6.5 |Anaconda, Inc.| (default, Mar 29 2018, 13:32:41) [MSC v.1900 64 bit (AMD64)]
Type "copyright", "credits" or "license" for more information.

IPython 6.4.0 -- An enhanced Interactive Python.

```
In [1]: runfile('C:/Users/hoops/OneDrive/Documents/School/ME EN 2550 Statistics and Probability/HW8/HW8.py', wdir='C:/Users/hoops/OneDrive/Documents/School/ME EN 2550 Statistics and Probability/HW8')
```

B1

b)



a)

OLS Regression Results

```
=====
Dep. Variable:          viscosity    R-squared:                0.269
Model:                  OLS          Adj. R-squared:            0.147
Method:                 Least Squares  F-statistic:              2.210
Date:                   Tue, 16 Apr 2019  Prob (F-statistic):      0.188
Time:                   15:39:10       Log-Likelihood:           5.2642
No. Observations:       8             AIC:                     -6.528
Df Residuals:           6             BIC:                     -6.370
Df Model:                1
Covariance Type:        nonrobust
=====
```

	coef	std err	t	P> t	[0.025	0.975]
Intercept	0.5986	0.095	6.269	0.001	0.365	0.832
np.power(ratio, 2)	-0.2523	0.170	-1.487	0.188	-0.668	0.163

```
=====
Omnibus:                 0.731    Durbin-Watson:              1.510
Prob(Omnibus):           0.694    Jarque-Bera (JB):          0.528
Skew:                    -0.085    Prob(JB):                  0.768
Kurtosis:                1.753    Cond. No.                  4.13
=====
```

Warnings:

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

B2

a)

OLS Regression Results

```

=====
Dep. Variable:      satisfaction    R-squared:      0.904
Model:              OLS           Adj. R-squared:  0.884
Method:             Least Squares  F-statistic:    46.87
Date:               Tue, 16 Apr 2019  Prob (F-statistic): 6.95e-10
Time:               15:39:10       Log-Likelihood: -82.062
No. Observations:   25            AIC:             174.1
Df Residuals:       20            BIC:             180.2
Df Model:           4
Covariance Type:    nonrobust
=====

```

```

=====
              coef    std err          t      P>|t|      [0.025      0.975]
-----
Intercept    143.8672     6.044     23.804     0.000     131.260     156.474
age          -1.1172     0.138     -8.075     0.000     -1.406     -0.829
severity     -0.5862     0.136     -4.324     0.000     -0.869     -0.303
surgmed       0.4149     3.008      0.138     0.892     -5.859      6.689
anxiety       1.3064     1.084      1.205     0.242     -0.955      3.568
=====

```

```

=====
Omnibus:         4.082    Durbin-Watson:      2.102
Prob(Omnibus):   0.130    Jarque-Bera (JB):    2.355
Skew:            -0.665    Prob(JB):            0.308
Kurtosis:        3.701    Cond. No.            297.
=====

```

Warnings:

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

b)

Standard error of regression coefficients:

```

Intercept    6.043698
age          0.138342
severity     0.135556
surgmed      3.007787
anxiety      1.084055

```

dtype: float64

c) Not all the model parameters are estimated with the same precision. This is because all parameters are fit to a single model and thus the predictors will have varying standard error values/precision

B3

a)

OLS Regression Results

```

=====
Dep. Variable:      y    R-squared:      0.852
Model:              OLS  Adj. R-squared:  0.768
Method:             Least Squares  F-statistic:    10.08
Date:               Tue, 16 Apr 2019  Prob (F-statistic): 0.00496
Time:               15:39:10       Log-Likelihood: -43.397
No. Observations:   12            AIC:             96.79
Df Residuals:       7            BIC:             99.22
Df Model:           4
Covariance Type:    nonrobust
=====

```

```
=====
              coef      std err          t      P>|t|      [0.025      0.975]
-----
Intercept    -123.1312    157.256     -0.783     0.459    -494.983    248.720
x1             0.7573      0.279      2.713     0.030      0.097      1.417
x2             7.5188      4.010      1.875     0.103     -1.964     17.001
x3             2.4831      1.809      1.372     0.212     -1.795      6.762
x4            -0.4811      0.555     -0.867     0.415     -1.794      0.832
=====
Omnibus:                2.436   Durbin-Watson:           1.808
Prob(Omnibus):           0.296   Jarque-Bera (JB):           1.069
Skew:                   -0.288   Prob(JB):                 0.586
Kurtosis:                1.656   Cond. No.                  6.82e+03
=====
```

Warnings:

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

[2] The condition number is large, 6.82e+03. This might indicate that there are strong multicollinearity or other numerical problems.

b)

Standard error of regression coefficients:

```
Intercept    157.256058
x1           0.279090
x2           4.010121
x3           1.809386
x4           0.555174
```

dtype: float64

Not all the model parameters are estimated with the same precision. This is because all parameters are fit to a single model and thus the predictors will have varying standard error values/precision

c)

The predicted power consumption for a month with the given values is : 290.442068

dtype: float6

C:\Users\hoops\Anaconda3\lib\site-packages\scipy\stats\stats.py:1394: UserWarning: kurtosistest only valid for n>=20 ... continuing anyway, n=8

"anyway, n=%i" % int(n))

C:\Users\hoops\Anaconda3\lib\site-packages\scipy\stats\stats.py:1394: UserWarning: kurtosistest only valid for n>=20 ... continuing anyway, n=12

"anyway, n=%i" % int(n))

In [2]:

```
# -*- coding: utf-8 -*-
```

```
"""
```

```
Created on Mon Apr 15 19:49:07 2019
```

```
ME EN 2550
```

```
Homework 8
```

```
@author: Ryan Dalby
```

```
"""
```

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import statsmodels.api as sm
```

```
#B1
```

```
print("B1")
b1data = pd.DataFrame({"viscosity": [0.45, 0.20, 0.34, 0.58, 0.70, 0.57, 0.55, 0.44], "ratio":
plt.scatter(b1data['ratio'], b1data['viscosity'])
print("b")
b1model = sm.OLS.from_formula(formula="viscosity ~ np.power(ratio,2)", data=b1data).fit()
b1predictions = b1model.predict(b1data['ratio'])
plt.plot(b1data['ratio'], b1predictions)
plt.show()
print("a")
print(b1model.summary())
print()
```

```
#B2
```

```
print("\n\nB2")
age = [55,46,30,35,59,61,74,38,27,51,53,41,37,24,42,50,58,60,62,68,70,79,63,39,49]
severity = [50,24,46,48,58,60,65,42,42,50,38,30,31,34,30,48,61,71,62,38,41,66,31,42,40]
surg = [0,1,1,1,0,0,1,1,0,1,1,0,0,0,0,1,1,1,0,0,1,1,1,0,1]
anx = [2.1,2.8,3.3,4.5,2.0,5.1,5.5,3.2,3.1,2.4,2.2,2.1,1.9,3.1,3.0,4.2,4.6,5.3,7.2,7.8,7.0,6.2
sat = [68,77,96,80,43,44,26,88,75,57,56,88,88,102,88,70,52,43,46,56,59,26,52,83,75]
b2data = pd.DataFrame({"age": age, "severity":severity, "surgmed":surg, "anxiety":anx, "satisf
b2model = sm.OLS.from_formula(formula="satisfaction ~ age + severity + surgmed + anxiety", dat
print("a")
print(b2model.summary())
print("b")
print("Standard error of regression coefficients: \n{}".format(b2model.bse))
print("c) Not all the model parameters are estimated with the same precision. This is because
```

```
#B3
```

```
print("\n\nB3")
y = [240,236,270,274,301,316,300,296,267,276,288,261]
x1 = [25,31,45,60,65,72,80,84,75,60,50,38]
x2 = [24,21,24,25,25,26,25,25,24,25,25,23]
x3 = [91,90,88,87,91,94,87,86,88,91,90,89]
x4 = [100,95,110,88,94,99,97,96,110,105,100,98]
b3data = pd.DataFrame({"y":y,"x1":x1,"x2":x2,"x3":x3,"x4":x4})
b3model = sm.OLS.from_formula(formula="y ~ x1 + x2 + x3 + x4", data=b3data).fit()
print("a")
print(b3model.summary())
print("b")
print("Standard error of regression coefficients: \n{}".format(b3model.bse))
print("Not all the model parameters are estimated with the same precision. This is because al
```

```
print("c")
b3predict = b3model.predict(exog = dict(x1 = 75, x2 = 24, x3 = 90, x4 = 98))
print("The predicted power consumption for a month with the given values is : {}".format(b3predict))
```