MSPA PREDICT 411

Bonus Problem: Chapter 1

```
In [1]: #!pip install sas7bdat
   import numpy as np
   import pandas as pd
   import statsmodels.api as sm

from patsy import dmatrices
   from sas7bdat import SAS7BDAT

   import seaborn as sns
   import matplotlib.pyplot as plt
   import matplotlib.pylab as pylab

sns.set_style('darkgrid')
%matplotlib inline
```

Introduction

This document presents the results of first set of bonus problems for the Masters of Science in Predictive Analytics course: PREDICT 411. This assessment required the student to w ork through the problem set of Chapters 1 & 2 of Hoffmann (2004), Generalized Linear Models, An Applied Approach.

Question 1

Loading the Data

```
In [2]: with SAS7BDAT('data/gpa.sas7bdat') as f:
    df_gpa = f.to_data_frame()
```

In [3]: df_gpa.head(5)

Out[3]:

		GPA	SAT_QUAN	SAT_VERB	HS_MATH	HS_ENGL
-	0	1.97	3.21	2.47	2.30	2.63
	1	2.74	7.18	4.36	3.80	3.57
[:	2	2.19	3.58	5.78	2.98	2.57
Ţ,	3	2.60	4.03	4.47	3.58	2.21
Ŀ	4	2.98	6.40	5.63	3.38	3.48

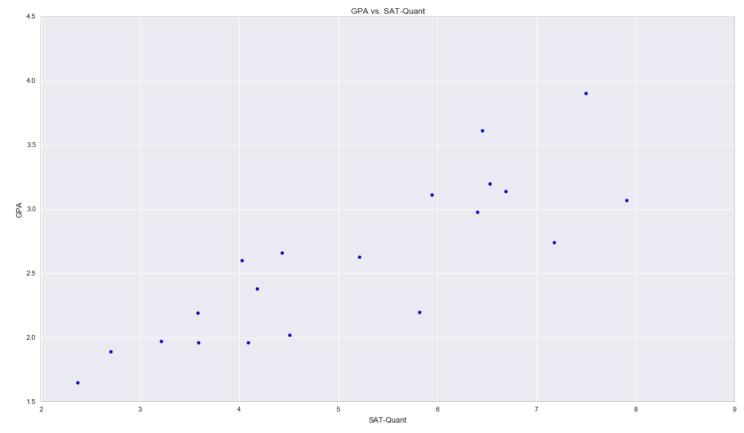
Part A

Construct a scatterplot with GPA on the y-axis and SAT-Quant. on the x-axis. Fit by hand the estimated linear regression line. Comment on the relationship between these two variables.

```
In [4]: fig, ax = plt.subplots()
    fig.set_size_inches(18, 10)

plt.scatter(df_gpa['SAT_QUAN'], df_gpa['GPA'])
    plt.title('GPA vs. SAT-Quant')
    plt.ylabel('GPA')
    plt.xlabel('SAT-Quant')

plot = ax.get_figure()
    plot.savefig('figures/q1_scatter.png')
```



Part B

Using the formulas for a two-variable OLS regression model, compute the slope and intercept for the follwoing model: $GPA = \alpha + \beta_1(\mathrm{SAT-Quant})$

0.239175919707

We will also compute the intercept using the formula:

$$\hat{lpha} = ar{Y} - \hat{eta_1}ar{X}$$

```
In [6]: alpha_hat = y_mean - beta_hat * x_mean
        print(alpha hat)
```

1.29396628773

Part C

Compute the predicted values, the residuals, the Sum of Square Errors (SSE), and the \mathbb{R}^2 for the model.

We will compute the predicted values by using our regression equation and computed parameters above, in the equation:

```
GPA = 1.2939 + 0.2391(SAT-Quant)
```

```
In [7]: y_hat = []
        for a in x:
           y_hat.append(1.2939 + 0.2391 * a)
        #for a in y_hat:
        # print(a)
```

We will compute residuals using the formula:

$$R_i = Y_i - \hat{Y}$$

```
In [8]: res = []
        for a, b in zip(y, y_hat):
           res.append(a-b)
        #for a in res:
        # print(a)
```

We will compute the Sum of Square Errors (SSE) using the formula:

$$SSE = \sum_{i=1}^n (Y_i - \hat{Y_i})^2$$

```
In [9]: sse = []
        for a, b in zip(y, y_hat):
            sse.append(np.square(a - b))
        sse = sum(sse)
        print(sse)
```

0.279123802811

We will compute the ${\cal R}^2$ using the formula:

$$R^2 = 1 - \frac{SSE}{SST}$$

where SSE is enumerated above and SST is:

$$R^2 = 1 - rac{SSE}{SST}$$
 $SST = \sum_i^n (Y_i - ar{Y})^2$

```
In [10]: sst = []
         for a in y:
            sst.append(np.square(a - y mean))
         sst = sum(sst)
         r_square = 1 - sse / sst
         print(r_square)
```

0.809341664747

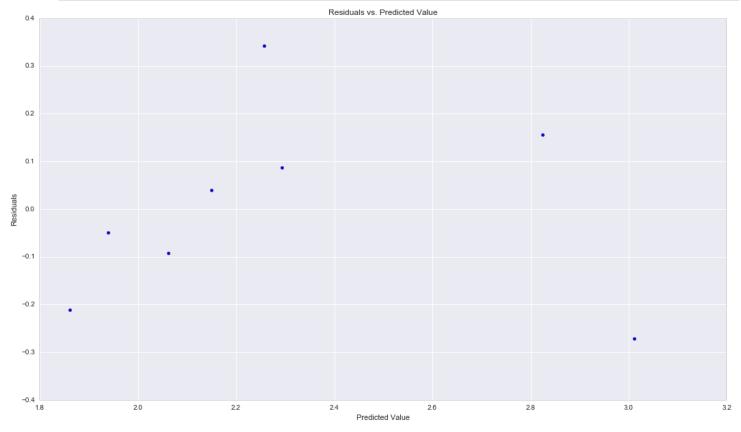
Part D

Plot the residuals (y-axis) by the predicted values (x-axis) and comment about w hat you see.

```
In [11]: fig, ax = plt.subplots()
    fig.set_size_inches(18, 10)

plt.scatter(y_hat, res)
    plt.title('Residuals vs. Predicted Value')
    plt.xlabel('Predicted Value')
    plt.ylabel('Residuals')

plot = ax.get_figure()
    plot.savefig('figures/q1_resid.png')
```



Question 2

The data set GPA is available in SPSS, Stata, and SAS formats. It contains all 20 observations from the sample of college students. We'll use it to conduct the remaining excercises.

Part A

Estimate an OLS regression model with GPA as the dependent variable and SAT-Quant. as the independent variable. Compare this model to the model you estimated in Excercise 1. In what ways are they similar or different?

Out[12]: OLS Regression Results

Dep. Variable:	GPA	R-squared:	0.722
Model:	OLS	Adj. R-squared:	0.706
Method:	Least Squares	F-statistic:	46.68
Date:	Mon, 20 Jun 2016	Prob (F-statistic):	2.15e-06
Time:	14:49:50	Log-Likelihood:	-5.5719
No. Observations:	20	AIC:	15.14
Df Residuals:	18	BIC:	17.14
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[95.0% Conf. Int.]
Intercept	0.9670	0.250	3.874	0.001	0.443 1.491
SAT_QUAN	0.3178	0.047	6.832	0.000	0.220 0.416

Om nibus:	0.075	Durbin-Watson:	2.807
Prob(Omnibus):	0.963	Jarque-Bera (JB):	0.279
Skew:	-0.092	Prob(JB):	0.870
Kurtosis:	2.452	Cond. No.	18.3

Question 3

Estimate the following three OLS regression models, all of which use GPA as the dependent variable.

Part A

Use only HS_ENGL as the independent variable.

Out[13]: OLS Regression Results

Dep. Variable:	GPA	R-squared:	0.368
Model:	OLS	Adj. R-squared:	0.333
Method:	Least Squares	F-statistic:	10.47
Date:	Mon, 20 Jun 2016	Prob (F-statistic):	0.00458
Time:	14:49:50	Log-Likelihood:	-13.777
No. Observations:	20	AIC:	31.55
Df Residuals:	18	BIC:	33.55
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[95.0% Conf. Int.]
Intercept	0.2487	0.733	0.339	0.738	-1.292 1.789
HS_ENGL	0.7790	0.241	3.236	0.005	0.273 1.285

Omnibus:	0.077	Durbin-Watson:	2.488
Prob(Omnibus):	0.962	Jarque-Bera (JB):	0.273
Skew:	0.102	Prob(JB):	0.872
Kurtosis:	2.466	Cond. No.	21.7

Part B

Use HS_ENGL and SAT_VERB as the independent variables.

Out[14]: OLS Regression Results

Dep. Variable:	GPA	R-squared:	0.562
Model:	OLS	Adj. R-squared:	0.510
Method:	Least Squares	F-statistic:	10.90
Date:	Mon, 20 Jun 2016	Prob (F-statistic):	0.000898
Time:	14:49:50	Log-Likelihood:	-10.109
No. Observations:	20	AIC:	26.22
Df Residuals:	17	BIC:	29.20
Df Model:	2		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[95.0% Conf. Int.]
Intercept	-0.0572	0.638	-0.090	0.930	-1.403 1.289
HS_ENGL	0.5195	0.227	2.290	0.035	0.041 0.998
SAT_VERB	0.2273	0.083	2.745	0.014	0.053 0.402

Omnibus:	0.371	Durbin-Watson:	2.507
Prob(Omnibus):	0.831	Jarque-Bera (JB):	0.487
Skew:	0.255	Prob(JB):	0.784
Kurtosis:	2.431	Cond. No.	40.1

Part C

Use HS_ENGL, SAT_VERB, and SAT_QUAN as the independent variables

Out[15]: OLS Regression Results

Dep. Variable:	GPA	R-squared:	0.811
Model:	OLS	Adj. R-squared:	0.776
Method:	Least Squares	F-statistic:	22.89
Date:	Mon, 20 Jun 2016	Prob (F-statistic):	4.95e-06
Time:	14:49:50	Log-Likelihood:	-1.7007
No. Observations:	20	AIC:	11.40
Df Residuals:	16	BIC:	15.38
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[95.0% Conf. Int.]
Intercept	0.4863	0.448	1.086	0.294	-0.463 1.436
HS_ENGL	0.0111	0.189	0.059	0.954	-0.390 0.412
SAT_VERB	0.1568	0.058	2.699	0.016	0.034 0.280
SAT_QUAN	0.2586	0.056	4.593	0.000	0.139 0.378

Om nibus:	0.803	Durbin-Watson:	2.332
Prob(Omnibus):	0.669	Jarque-Bera (JB):	0.736
Skew:	0.186	Prob(JB):	0.692
Kurtosis:	2.137	Cond. No.	56.7

Question 4

Part A

Interpret the unstandardized coefficient associated with HS ENGL from model 3(a):

$$GPA = 0.2487 + 0.7790(HS_ENGL)$$

Expect a one unit increase in HS_ENGL to be associated with a 0.7790 increase in GPA.

Part B

Interpret the unstandardized coefficient associated with SAT_QUAN from model 3(c):

$$GPA = 0.4863 + 0.0111 (HS_ENGL + 0.1568 (SAT_VERB) + 0.2586 (SAT_QUAN)$$

Expect a one unit increase in SAT_QUAN to be associated with a 0.2586 increase in GAP.

Part C

Interperate the \mathbb{R}^2 from model 3(c):

The R^2 shows the proportion of variability in the dependent variable that is explained by the model. In the case of model 3, the R^2 suggests that 81% of the variability in GPA is explained by the model.

Question 5

Something happened to the association between HS_ENGL and GPA as we moved from model (a) to model (c). Please describe what might have happened. Remember to provide statistical evidence to support your answer. Speculate in a conceptual way why this may have happened.

Question 6

Using model 3(c), check the following regression diagnostics and comment about any problems with the model.

Part A

A normal probability plot of the residuals.

```
In [16]:
            res = results.resid
            fig = sm.qqplot(res, fit=True, line='45')
            fig.set_size_inches(18, 10)
            fig.savefig('figures/q6_qqplot.png')
     2.0
     1.5
     1.0
     0.5
  Sample Quantiles
     0.0
    -1.0
    -1.5
    -2.0
                        -1.5
                                         -1.0
                                                           -0.5
                                                                            0.0
                                                                                              0.5
                                                                                                               1.0
                                                                                                                                 1.5
                                                                                                                                                  2.0
       -2.0
                                                                      Theoretical Quantiles
```

Part B

A Plot of the residuals by the predicted values. You may wish to use studentized residuals and standardized predicted values in the plot.

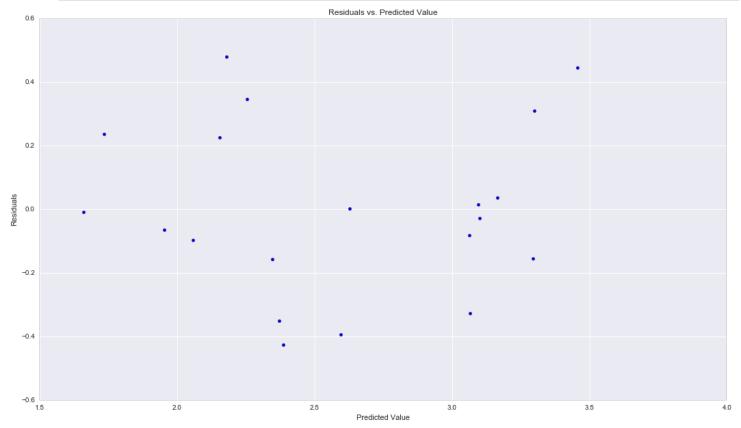
```
In [17]: engl = df_gpa['HS_ENGL'].tolist()
    verb = df_gpa['SAT_VERB'].tolist()
    quan = df_gpa['SAT_QUAN'].tolist()

y_hat = []
    for a, b, c in zip(engl, verb, quan):
        y_hat.append(0.4863 + 0.0111 * a + 0.1568 * b + 0.2586 * c)
```

```
In [18]: fig, ax = plt.subplots()
    fig.set_size_inches(18, 10)

plt.scatter(y_hat, res)
    plt.title('Residuals vs. Predicted Value')
    plt.xlabel('Predicted Value')
    plt.ylabel('Residuals')

plot = ax.get_figure()
    plot.savefig('figures/q6_resid.png')
```



Part C

A distribution of the standardized (or studentized) residuals, the leverage values, and the Cook's D values.

```
In [19]: res = results.resid
fig = sm.graphics.influence_plot(results, criterion='cooks')

fig.set_size_inches(18, 10)
fig.savefig('figures/q6_cooks.png')
```

