MSPA PREDICT 411

Bonus Problem: Chapter 6

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 third 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 6 of Hoffmann (2004), Generalized Linear Models, An Applied Approach.

Question 1

Loading the Data

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

In [3]:
```
df_stress.head(5)
```

Out[3]:

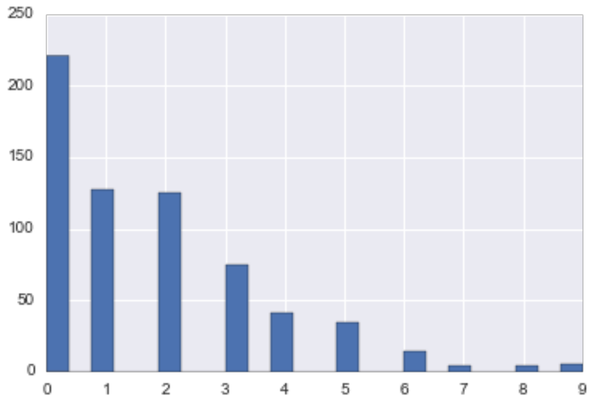
	AGE	COHES	ESTEEM	GRADES	SATTACH	STRESS	NEWID
0	11	61.256001	32	15	21	0	5
1	14	49.000000	33	17	22	0	6
2	14	35.000000	27	15	28	0	10
3	11	74.000000	34	14	33	0	15
4	14	58.000000	29	15	28	0	16

Part A

Estimate a histogram and summary statistics for the variable stress. What do you think is its most likely probability distribution?

```
In [4]: import matplotlib.pyplot as plt
        %matplotlib inline

        plt.hist(df_stress['STRESS'], 24)
        plt.show()
```



Seems to have a shape similar to that of a Beta Negative Binomial distribution. Is non-continuous in nature.

```
In [5]: print('mean:', round(df_stress['STRESS'].mean(), 2))
```

```
mean: 1.73
```

```
In [6]: import numpy as np

        print('variance:', round(np.var(df_stress['STRESS']), 2))
```

```
variance: 3.41
```

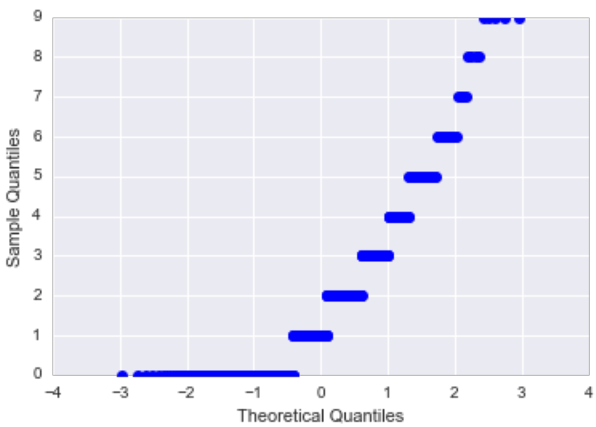
The variance is greater than the mean.

Part B

Plot a normal probability (Q-Q) plot of the variable stress. Comment about its departure from a normal distribution.

```
In [7]: import statsmodels.api as sm
        from matplotlib import pyplot as plt

        #fig = sm.qqplot(df_stress['STRESS'], line='45')
        fig = sm.qqplot(df_stress['STRESS'])
        plt.show()
```



Has a fat negative tail.

Question 2

Part A

Interpret the coefficients (from the Poisson and negative binomial models) associated w ith the variables cohes and sattach using the percent change formula w e have seen in this and earlier chapters.

In [62]:
```
import statsmodels.formula.api as smf
import statsmodels.api as sm

model_poi = smf.glm('STRESS ~ COHES + ESTEEM + GRADES + SATTACH',
                    data=df_stress,
                    family=sm.families.Poisson(link=sm.families.links.log)).fit()

model_poi.summary()
```

Out[62]:

Generalized Linear Model Regression Results

Dep. Variable:	STRESS	**No. Observations:**	651
Model:	GLM	**Df Residuals:**	646
Model Family:	Poisson	**Df Model:**	4
Link Function:	log	**Scale:**	1.0
Method:	IRLS	**Log-Likelihood:**	-1203.6
Date:	Mon, 15 Aug 2016	**Deviance:**	1245.4
Time:	09:44:34	**Pearson chi2:**	1.15e+03
No. Iterations:	8		

	coef	std err	z	P>|z|	[95.0% Conf. Int.]
Intercept	2.7345	0.234	11.683	0.000	2.276 3.193
COHES	-0.0129	0.003	-4.466	0.000	-0.019 -0.007
ESTEEM	-0.0237	0.008	-2.947	0.003	-0.039 -0.008
GRADES	-0.0235	0.010	-2.379	0.017	-0.043 -0.004
SATTACH	-0.0165	0.006	-2.850	0.004	-0.028 -0.005

In [63]:
```python
import statsmodels.formula.api as smf
import statsmodels.api as sm

model_nb = smf.glm('STRESS ~ COHES + ESTEEM + GRADES + SATTACH',
                   data=df_stress,
                   family=sm.families.NegativeBinomial()).fit()

model_nb.summary()
```

Out[63]:

Generalized Linear Model Regression Results

Dep. Variable:	STRESS	**No. Observations:**	651
Model:	GLM	**Df Residuals:**	646
Model Family:	NegativeBinomial	**Df Model:**	4
Link Function:	log	**Scale:**	0.664952252883
Method:	IRLS	**Log-Likelihood:**	-1148.4
Date:	Mon, 15 Aug 2016	**Deviance:**	576.00
Time:	09:44:37	**Pearson chi2:**	430.
No. Iterations:	7		

	coef	std err	z	P>|z|	[95.0% Conf. Int.]
Intercept	2.7623	0.334	8.272	0.000	2.108 3.417
COHES	-0.0135	0.004	-3.340	0.001	-0.021 -0.006
ESTEEM	-0.0229	0.011	-2.047	0.041	-0.045 -0.001
GRADES	-0.0244	0.014	-1.795	0.073	-0.051 0.002
SATTACH	-0.0169	0.008	-2.088	0.037	-0.033 -0.001

Part B

Based on both the Poisson and negative binomial regression models, compute the predicted count of stress for those whose levels of family cohesion are less than one standard deviation below the mean (low), between one standard deviation below and one standard deviation above the mean (medium), and more than one standard deviation above the mean (high).

In [36]:
```python
import numpy as np

mean = df_stress['COHES'].mean()
std = np.std(df_stress['COHES'])

lq = mean - std
uq = mean + std
```

In [43]:
```python
df_stress['STRESS_pred'] = model_poi.predict()

print('Poisson:')
print('low:', df_stress[df_stress['COHES'] < lq]['STRESS_pred'].sum())
print('medium:', df_stress[(df_stress['COHES'] >= lq) & (df_stress['COHES'] <= uq
)]['STRESS_pred'].sum())
print('high:', df_stress[df_stress['COHES'] > uq]['STRESS_pred'].sum())
```

```
Poisson:
low: 265.2951611150819
medium: 743.0657502689479
high: 117.63908861596572
```

```
In [44]: df_stress['STRESS_pred'] = model_nb.predict()

         print('Negative Binomial:')
         print('low:', df_stress[df_stress['COHES'] < lq]['STRESS_pred'].sum())
         print('medium:', df_stress[(df_stress['COHES'] >= lq) & (df_stress['COHES'] <= uq
         )]['STRESS_pred'].sum())
         print('high:', df_stress[df_stress['COHES'] > uq]['STRESS_pred'].sum())
```

```
Negative Binomial:
low: 268.0616134173716
medium: 742.4349950455183
high: 116.48048023141301
```

Part C

What is the expected percent difference in the number of stressful life events for those at high and low levels of family cohesion in each model?

```
In [56]: df_stress['STRESS_pred'] = model_poi.predict()

         low = df_stress[df_stress['COHES'] < lq]['STRESS_pred'].sum()
         high = df_stress[df_stress['COHES'] > uq]['STRESS_pred'].sum()

         print('Poisson:')
         print('STRESS for low COHES is', round(low / high, 2), 'times higher than high CO
         HES')
```

```
Poisson:
STRESS for low COHES is 2.26 times higher than high COHES
```

```
In [55]: df_stress['STRESS_pred'] = model_nb.predict()

         low = df_stress[df_stress['COHES'] < lq]['STRESS_pred'].sum()
         high = df_stress[df_stress['COHES'] > uq]['STRESS_pred'].sum()

         print('Negative Binomial:')
         print('STRESS for low COHES is', round(low / high, 2), 'times higher than high CO
         HES')
```

```
Negative Binomial:
STRESS for low COHES is 2.3 times higher than high COHES
```

Question 3

Compute the AICs and BICs from the Poisson, the overdispersed Poisson, and the negative binomial regression models estimated in exercise 2. Discuss w hich model you prefer and w hy.

In [64]:
```
model_poi.summary2()
```

Out[64]:

Model:	GLM	AIC:	2417.2190
Link Function:	log	BIC:	-2939.6906
Dependent Variable:	STRESS	Log-Likelihood:	-1203.6
Date:	2016-08-15 09:44	LL-Null:	-1255.8
No. Observations:	651	Deviance:	1245.4
Df Model:	4	Pearson chi2:	1.15e+03
Df Residuals:	646	Scale:	1.0000
Method:	IRLS		

	Coef.	Std.Err.	z	P>|z|	[0.025	0.975]
Intercept	2.7345	0.2341	11.6826	0.0000	2.2758	3.1933
COHES	-0.0129	0.0029	-4.4656	0.0000	-0.0186	-0.0072
ESTEEM	-0.0237	0.0080	-2.9472	0.0032	-0.0394	-0.0079
GRADES	-0.0235	0.0099	-2.3791	0.0174	-0.0428	-0.0041
SATTACH	-0.0165	0.0058	-2.8501	0.0044	-0.0278	-0.0051

In [66]:
```
#model_nb.summary2()
#no easy way to get AIC/BIC for nb using statsmodel at the moment
```

Question 4

Using the Poisson regression model estimated in exercise 2, plot the deviance residuals by the predicted values. Discuss w hat this plot indicates about the regression model.