Juan Carlos Apitz

STAT510 Homework 4

Imports

In [1]:
```
#PANDAS
import pandas as pd
from pandas import DataFrame, Series

#NUMPY
import numpy as np

#SCIPY t and F distributions
from scipy.stats import t
from scipy.stats import f
from scipy.stats import norm
from scipy.stats import chi2

#STATMODELS
import statsmodels.api as sm
from statsmodels.formula.api import ols

#SEABORN plotting
import seaborn as sns

#MATPLOTLIB plotting
import matplotlib.pyplot as plt
%matplotlib inline
```

Problem 6.16

In [2]:
```
filename = '~/Documents/LinearRegression/STAT510/Kutner/CH6DS/CH06PR15.txt
'

patient = pd.read_table(filename, delim_whitespace=True, names=['satisfact
ion','age','severity', 'anxiety'])
patient.head()
```

Out[2]:

	satisfaction	age	severity	anxiety
0	48	50	51	2.3
1	57	36	46	2.3
2	66	40	48	2.2
3	70	41	44	1.8
4	89	28	43	1.8

a.

Test the following hypothesis:

$$H_o : \beta_1 = \beta_2 = \beta_3 = 0$$
$$H_a : \text{at least one } \beta_i = 0$$

To test the above hypothesis we fit the model and conduct an F test.

In [3]:
```
model = ols(formula="satisfaction ~ age + severity + anxiety", data=patien
t).fit()
```

In [4]:
```
dfn = model.df_model
dfd = model.df_resid
fcrit = f.ppf(0.9, dfn, dfd)
print 'The 10 percent critical F-value with 3 and 42 degrees of freedom is
 %.2f and the model F-statistic is %.2f' %(fcrit,model.fvalue)
print 'Therefore since the F-statistic is greater than the critical F-valu
e we reject the null hypothesis at the 10 percent level. We can conclude t
hat there exist a regression relation.'
print 'The p-value of the test is %.11f.' %model.f_pvalue
```

```
The 10 percent critical F-value with 3 and 42 degrees of freedom is 2.22 a
nd the model F-statistic is 30.05
Therefore since the F-statistic is greater than the critical F-value we re
ject the null hypothesis at the 10 percent level. We can conclude that the
re exist a regression relation.
The p-value of the test is 0.00000000015.
```

In [5]:
```
model.summary()
```

Out[5]:

OLS Regression Results

Dep. Variable:	satisfaction	**R-squared:**	0.682
Model:	OLS	**Adj. R-squared:**	0.659
Method:	Least Squares	**F-statistic:**	30.05
Date:	Thu, 29 Oct 2015	**Prob (F-statistic):**	1.54e-10
Time:	09:26:42	**Log-Likelihood:**	-169.36
No. Observations:	46	**AIC:**	346.7
Df Residuals:	42	**BIC:**	354.0
Df Model:	3		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[95.0% Conf. Int.]**
Intercept	158.4913	18.126	8.744	0.000	121.912 195.071
age	-1.1416	0.215	-5.315	0.000	-1.575 -0.708
severity	-0.4420	0.492	-0.898	0.374	-1.435 0.551
anxiety	-13.4702	7.100	-1.897	0.065	-27.798 0.858

Omnibus:	5.219	**Durbin-Watson:**	2.183
Prob(Omnibus):	0.074	**Jarque-Bera (JB):**	2.074
Skew:	-0.098	**Prob(JB):**	0.354
Kurtosis:	1.978	**Cond. No.**	782.

b.

In [6]:
```
g = 3; p = len(model.params); n = model.nobs; adj_alpha = 1-0.1/(2*g)
tcrit = t.ppf(adj_alpha, n-p)

b1 = model.params[1]; b1low = b1 - tcrit * model.bse[1]; b1high = b1 + tcr
it * model.bse[1]
b2 = model.params[2]; b2low = b2 - tcrit * model.bse[2]; b2high = b2 + tcr
it * model.bse[2]
b3 = model.params[3]; b3low = b3 - tcrit * model.bse[3]; b3high = b3 + tcr
it * model.bse[3]

print 'The 90 percent joint CI for beta 1 is: (%.2f, %.2f)' %(b1low, b1hig
h)
print 'The 90 percent joint CI for beta 2 is: (%.2f, %.2f)' %(b2low, b2hig
h)
print 'The 90 percent joint CI for beta 3 is: (%.2f, %.2f)' %(b3low, b3hig
h)
```

```
The 90 percent joint CI for beta 1 is: (-1.61, -0.67)
The 90 percent joint CI for beta 2 is: (-1.52, 0.64)
The 90 percent joint CI for beta 3 is: (-29.09, 2.15)
```

c.

In [7]:
```
print 'The coefficient of multiple determination is: %.2f' %model.rsquared
print 'This coefficient measures the proportinate reduction of total varia
tion associated with the model.'
```

```
The coefficient of multiple determination is: 0.68
This coefficient measures the proportinate reduction of total variation as
sociated with the model.
```

Problem 6.19

In [8]:
```
filename = '~/Documents/LinearRegression/STAT510/Kutner/CH6DS/CH06PR18.txt
'

rental = pd.read_table(filename, delim_whitespace=True, names=['rate','age
','opex', 'vacancy', 'sqf',])
rental.head()
```

Out[8]:

	rate	age	opex	vacancy	sqf
0	13.5	1	5.02	0.14	123000
1	12.0	14	8.19	0.27	104079
2	10.5	16	3.00	0.00	39998
3	15.0	4	10.70	0.05	57112
4	14.0	11	8.97	0.07	60000

a.

Test the following hypothesis:

$$H_o : \beta_1 = \beta_2 = \beta_3 = 0$$
$$H_a : \text{at least one } \beta_i = 0$$

To test the above hypothesis we fit the model and conduct an F test.

In [9]:
```
model = ols(formula="rate ~ age + opex + vacancy + sqf", data=rental).fit(
)
```

In [10]:
```
dfn = model.df_model
dfd = model.df_resid
fcrit = f.ppf(0.95, dfn, dfd)
print 'The 5 percent critical F-value with %.0f and %.0f degrees of freedo
m is %.2f and the model F-statistic is %.2f' %(dfn,dfd,fcrit,model.fvalue)
print 'Therefore since the F-statistic is greater than the critical F-valu
e we reject the null hypothesis at the 5  percent level. We can conclude t
hat there exist a regression relation.'
print 'The p-value of the test is %.15f.' %model.f_pvalue
print ''
print 'The results of the test imply that at least one of the beta paramet
ers is non-zero, which is an indication that at   least one of the explana
tory variables influences the rental rate.'
```

```
The 5 percent critical F-value with 4 and 76 degrees of freedom is 2.49 an
d the model F-statistic is 26.76
Therefore since the F-statistic is greater than the critical F-value we re
ject the null hypothesis at the 5  percent level. We can conclude that the
re exist a regression relation.
The p-value of the test is 0.000000000000073.

The results of the test imply that at least one of the beta parameters is
non-zero, which is an indication that at   least one of the explanatory va
riables influences the rental rate.
```

In [11]:
```
model.summary()
```

Out[11]:

OLS Regression Results

Dep. Variable:	rate	**R-squared:**	0.585
Model:	OLS	**Adj. R-squared:**	0.563
Method:	Least Squares	**F-statistic:**	26.76
Date:	Thu, 29 Oct 2015	**Prob (F-statistic):**	7.27e-14
Time:	09:26:43	**Log-Likelihood:**	-122.75
No. Observations:	81	**AIC:**	255.5
Df Residuals:	76	**BIC:**	267.5
Df Model:	4		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[95.0% Conf. Int.]**
Intercept	12.2006	0.578	21.110	0.000	11.049 13.352
age	-0.1420	0.021	-6.655	0.000	-0.185 -0.100
opex	0.2820	0.063	4.464	0.000	0.156 0.408
vacancy	0.6193	1.087	0.570	0.570	-1.545 2.784
sqf	7.924e-06	1.38e-06	5.722	0.000	5.17e-06 1.07e-05

Omnibus:	1.922	**Durbin-Watson:**	1.580
Prob(Omnibus):	0.383	**Jarque-Bera (JB):**	1.301
Skew:	0.148	**Prob(JB):**	0.522
Kurtosis:	3.545	**Cond. No.**	1.74e+06

b.

In [12]:
```
g = 4; p = len(model.params); n = model.nobs; adj_alpha = 1-0.05/(2*g)
tcrit = t.ppf(adj_alpha, n-p)

b1 = model.params[1]; b1low = b1 - tcrit * model.bse[1]; b1high = b1 + tcr
it * model.bse[1]
b2 = model.params[2]; b2low = b2 - tcrit * model.bse[2]; b2high = b2 + tcr
it * model.bse[2]
b3 = model.params[3]; b3low = b3 - tcrit * model.bse[3]; b3high = b3 + tcr
it * model.bse[3]
b4 = model.params[4]; b4low = b4 - tcrit * model.bse[4]; b4high = b4 + tcr
it * model.bse[4]

print 'The 90 percent joint CI for beta 1 is: (%.2f, %.2f)' %(b1low, b1hig
h)
print 'The 90 percent joint CI for beta 2 is: (%.2f, %.2f)' %(b2low, b2hig
h)
print 'The 90 percent joint CI for beta 3 is: (%.2f, %.2f)' %(b3low, b3hig
h)
print 'The 90 percent joint CI for beta 4 is: (%.7f, %.7f)' %(b4low, b4hig
h)
print ''
print 'The above results indicate that with the exception of beta 3 (since
 its confidence interval contains 0), all the coefficients are significant
. This means that there exist a linear relation between rental rates and t
he variables age, operating expense, and square footage.'
```

```
The 90 percent joint CI for beta 1 is: (-0.20, -0.09)
The 90 percent joint CI for beta 2 is: (0.12, 0.44)
The 90 percent joint CI for beta 3 is: (-2.16, 3.40)
The 90 percent joint CI for beta 4 is: (0.0000044, 0.0000115)

The above results indicate that with the exception of beta 3 (since its co
nfidence interval contains 0), all the coefficients are significant. This
means that there exist a linear relation between rental rates and the vari
ables age, operating expense, and square footage.
```

c.

In [13]:
```
print 'The R-squared of the model is: %.2f' %model.rsquared
print 'This coefficient measures the proportinate reduction of total varia
tion associated with the model. Therefore, our model "explains" approximat
le 58 percent of the variation in the data.'
```

```
The R-squared of the model is: 0.58
This coefficient measures the proportinate reduction of total variation as
sociated with the model. Therefore, our model "explains" approximatle 58 p
ercent of the variation in the data.
```

Problem 7.5

a.

Fit the full and partial models:

In [14]:
```
model1 = ols(formula="satisfaction ~ age ", data=patient).fit()
model2 = ols(formula="satisfaction ~ age + severity", data=patient).fit()
modelf = ols(formula="satisfaction ~ age + severity + anxiety", data=patie
nt).fit()
```

Calculate the appropriate sum of squares:

In [15]:
```
SSRF = modelf.ess
SSRX1 = model1.ess
SSRX2GX1 = model2.ess - model1.ess
SSRX3GX1X2 = modelf.ess - model2.ess
SSE = modelf.ssr
SST = modelf.centered_tss
```

Create the ANOVA table dataframe:

In [16]:
```
SS = Series([SSRF, SSRX1, SSRX2GX1, SSRX3GX1X2, SSE, SST])
DF = Series([modelf.df_model, 1, 1, 1, modelf.df_resid, modelf.df_model +
modelf.df_resid ])

aovtbl = DataFrame()
aovtbl['SS'] = SS
aovtbl['df'] = DF
aovtbl['MS'] = SS/DF

aovtbl.index = ['Full Model', 'X1', 'X2 given X1', 'X3 given X2, X1', 'Err
or', 'Total']

aovtbl['F'] = aovtbl['MS']/aovtbl.loc['Error','MS']

aovtbl.loc['Total',['MS','F']] = 'NA'
aovtbl.loc['Error','F'] = 'NA'
#aovtbl['MS'] = aovtbl
#/aovtbl.loc['Error','MS']
```

The ANOVA table that decomposes the regression sum of squares:

In [17]:
```
aovtbl
```

Out[17]:

	SS	df	MS	F
Full Model	9120.463666	3	3040.155	30.05208
X1	8275.388851	1	8275.389	81.80263
X2 given X1	480.915294	1	480.9153	4.753871
X3 given X2, X1	364.159521	1	364.1595	3.599735
Error	4248.840682	42	101.1629	NA
Total	13369.304348	45	NA	NA

b.

Test the following hypothesis:

$$H_o : \beta_3 = 0$$
$$H_a : \beta_3 \neq 0$$

To test the above hypothesis we calculate the F-value and compare it with $F_{0.975,1,42}$

In [18]:
```
fcrit = f.ppf(0.975,aovtbl.loc['X3 given X2, X1','df'],aovtbl.loc['Error',
'df'])
print 'The F-critical value is: %.2f' %fcrit
```

```
The F-critical value is: 5.40
```

In [19]:
```
fvalue = aovtbl.loc['X3 given X2, X1','MS']/aovtbl.loc['Error','MS']
pvalue = 1 - f.cdf(fvalue,aovtbl.loc['X3 given X2, X1','df'],aovtbl.loc['E
rror','df'])

print 'The calculated F-value for the test is: %.2f.' %fvalue
print ''
print 'Since the F-value is smaller than the F-critical value we fail to r
eject the null hypothesis. We conclude that the   variable anxiety can be
dropped from the model'
print ''
print 'The pvalue of the test is: %.4f' %pvalue
```

```
The calculated F-value for the test is: 3.60.

Since the F-value is smaller than the F-critical value we fail to reject t
he null hypothesis. We conclude that the   variable anxiety can be dropped
 from the model

The pvalue of the test is: 0.0647
```

Problem 7.6

Test the following hypothesis:

$$H_o : \beta_2 = \beta_3 = 0$$
$$H_a : \beta_2 \neq 0 \text{ or } \beta_3 \neq 0 \text{ or both.}$$

To test the above hypothesis we calculate the F-value and compare it with $F_{0.975,2,42}$

In [20]:
```
fcrit = f.ppf(0.975,aovtbl.loc['X3 given X2, X1','df'] + aovtbl.loc['X2 gi
ven X1','df'], aovtbl.loc['Error','df'])
print 'The F-critical value is: %.2f' %fcrit
```

```
The F-critical value is: 4.03
```

In [21]:
```
fvalue = ((aovtbl.loc['X3 given X2, X1','SS'] + aovtbl.loc['X2 given X1','
SS'])/2)/aovtbl.loc['Error','MS']
pvalue = 1 - f.cdf(fvalue,aovtbl.loc['X3 given X2, X1','df'] + aovtbl.loc[
'X2 given X1','df'],aovtbl.loc['Error','df'])

print 'The calculated F-value for the test is: %.2f.' %fvalue
print ''
print 'Since the F-value is greater than the F-critical value we reject th
e null hypothesis. We conclude that one or both of the variables anxiety o
r severity cannot be dropped from the model'
print ''
print 'The pvalue of the test is: %.4f' %pvalue
```

```
The calculated F-value for the test is: 4.18.

Since the F-value is greater than the F-critical value we reject the null
hypothesis. We conclude that one or both of the variables anxiety or sever
ity cannot be dropped from the model

The pvalue of the test is: 0.0222
```

Problem 7.10

Test the following hypothesis:

$$H_o : \beta_1 = -0.1, \ \ \beta_2 = 0.4$$
$$H_a : \text{not both equalities in } H_o \text{ hold}$$

To test the above hypothesis we calculate the F-value and compare it with $F_{0.99,2,76}$

In [22]:
```
rental['mod_dep'] = rental['rate'] + 0.1*rental['age'] - 0.4*rental['opex'
]
rental.head()
```

Out[22]:

	rate	age	opex	vacancy	sqf	mod_dep
0	13.5	1	5.02	0.14	123000	11.592
1	12.0	14	8.19	0.27	104079	10.124
2	10.5	16	3.00	0.00	39998	10.900
3	15.0	4	10.70	0.05	57112	11.120
4	14.0	11	8.97	0.07	60000	11.512

Fit the full and reduced model

In [23]:
```
modelf = ols(formula="rate ~ age + opex + vacancy + sqf", data=rental).fit
()
modelr = ols(formula="mod_dep ~ vacancy + sqf ", data=rental).fit()
```

In [24]:
```
fcrit = f.ppf(0.99, modelr.df_resid - modelf.df_resid, modelf.df_resid)
print 'The F-critical value is: %.2f' %fcrit
```

```
The F-critical value is: 4.90
```

In [25]:
```
fvalue = ((modelr.ssr - modelf.ssr)/(modelr.df_resid - modelf.df_resid))/m
odelf.mse_resid
pvalue = 1 - f.cdf(fvalue, modelr.df_resid - modelf.df_resid, modelf.df_re
sid)

print 'The calculated F-value for the test is: %.2f.' %fvalue
print ''
print 'Since the F-value is smaller than the F-critical value we fail to r
eject the null hypothesis. We conclude that one or both of the equalities
in the null hypothesis do not hold.'
print ''
print 'The pvalue of the test is: %.4f' %pvalue
```

```
The calculated F-value for the test is: 4.61.

Since the F-value is smaller than the F-critical value we fail to reject t
he null hypothesis. We conclude that one or both of the equalities in the
null hypothesis do not hold.

The pvalue of the test is: 0.0129
```

Problem 14.4

a.

Create the mean response function:

In [26]:
```
def mrf(beta, X):
    prob = np.exp(np.dot(X,beta))/(1 + np.exp(np.dot(X,beta)))
    return prob
```

Set up the design matrix and the coefficients vector:

In [27]:
```
X = np.hstack((np.ones(1000).reshape(1000,1),np.linspace(90,160,1000).resh
ape(1000,1)))

beta = np.array([[-25],[0.2]])
```

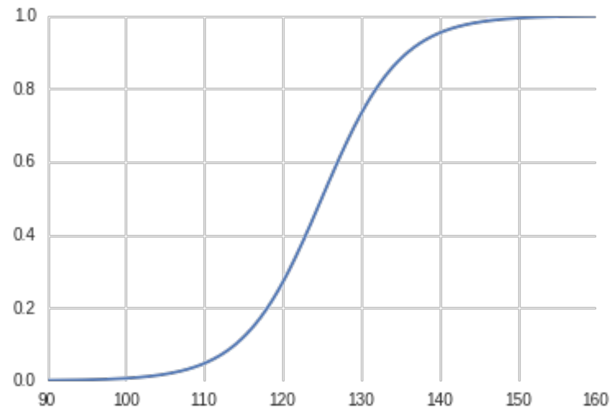
Calculate the values for the mean response function:

In [28]:
```
Y = mrf(beta,X)
```

Plot the function:

In [29]:
```
plt.plot(X[:,1],Y)
```

Out[29]:
```
[<matplotlib.lines.Line2D at 0x7eff1dd52bd0>]
```



b.

Solving the equation below for X_i:

$$\frac{e^{-25+0.2X_i}}{1+e^{-25+0.2X_i}} = 0.5$$

We obtain the solution $X_i = 125$

c.

Odds when X = 150:

In [30]:
```
odds1 = mrf(beta,np.array([[1,150]]))[0][0]/(1-mrf(beta,np.array([[1,150]]
))[0][0])

print 'The odds when X = 150 are: %.2f' %odds1
```

```
The odds when X = 150 are: 148.41
```

Odds when X = 151

In [31]:
```
odds2 = mrf(beta,np.array([[1,151]]))[0][0]/(1-mrf(beta,np.array([[1,151]]
))[0][0])

print 'The odds when X = 151 are: %.2f' %odds2
```

```
The odds when X = 151 are: 181.27
```

Ratio of the odds:

In [32]:
```
oddsratio = odds2/odds1

print 'The ratio of the odds is: %.3f' %oddsratio
```

```
The ratio of the odds is: 1.221
```

Calculate:

$e^{0.2}$

In [33]:
```
print 'The result is %.3f, which means the two quantities match as they sh
ould.' %np.exp(beta[1])[0]
```

```
The result is 1.221, which means the two quantities match as they should.
```

Problem 14.9

In [34]:
```
filename = '~/Documents/LinearRegression/STAT510/Kutner/CH14DS/CH14PR09.tx
t'

performance = pd.read_table(filename, delim_whitespace=True, names=['perfo
rm','stability',])
performance.insert(1,'intercept',1)
performance.head()
```

Out[34]:

	perform	intercept	stability
0	0	1	474
1	0	1	432
2	0	1	453
3	1	1	481
4	1	1	619

a.

Fit the model to obtain MLEs for β_0 and β_1.

In [35]:
```
model = sm.Logit(performance['perform'], performance[['intercept','stabili
ty']]).fit()
```

```
Optimization terminated successfully.
         Current function value: 0.541514
         Iterations 6
```

The MLEs are given below:

In [36]:
```
DataFrame(model.params, columns = ['MLEs'])
```

Out[36]:

	MLEs
intercept	-10.308925
stability	0.018920

The response function is given by:

$$\pi_i = \frac{e^{-10.309+0.019X_i}}{1 + e^{-10.309+0.019X_i}}$$

c.

In [37]:
```
ans1 = np.exp(model.params[1])

print 'The value of exp(b1) is %.3f.' %ans1
print ''
print 'This value means that the chance of performance increases by about 1.9 percent given a unit change in the stability  score.'
```

```
The value of exp(b1) is 1.019.

This value means that the chance of performance increases by about 1.9 per
cent given a unit change in the stability  score.
```

d.

In [38]:
```
ans2 = model.predict(exog=np.array([1,550]))[0]

print 'The estimated probability of performance given a stability score of 550 is %.3f.' %ans2
```

```
The estimated probability of performance given a stability score of 550 is
 0.524.
```

e.

Solving the equation below for X_i:

$$\frac{e^{-10.309+0.019X_i}}{1 + e^{-10.309+0.019X_i}} = 0.7$$

We obtain the solution $X_i = \left.\frac{\ln\left(\frac{7}{3}\right) - b_0}{b_1}\right|_{b_0=-10.309, b_1=0.019} = 582$

In [39]:
```
ans3 = (np.log(7/3)-model.params[0])/model.params[1]

print 'We verify this numerically and obtain %.2f.' %ans3
```

```
We verify this numerically and obtain 581.51.
```

Problem 14.20

In [40]:
```
filename = '~/Documents/LinearRegression/STAT510/Kutner/CH14DS/CH14PR14.tx
t'

flu = pd.read_table(filename, delim_whitespace=True, names=['received','ag
e','awareness','gender'])
flu.insert(1,'intercept',1)

flu.head()
```

Out[40]:

	received	intercept	age	awareness	gender
0	0	1	59	52	0
1	0	1	61	55	1
2	1	1	82	51	0
3	0	1	51	70	0
4	0	1	53	70	0

b.

Test the following hypothesis:

$$H_o : \beta_3 = 0$$
$$H_a : \beta_3 \neq 0$$

To test the above hypothesis we fit the model and conduct an F test.

Fit the model to obtain MLEs for β_3.

In [41]:
```
modelf = sm.Logit(flu['received'], flu[['intercept','age','awareness','gen
der']]).fit()
```

```
Optimization terminated successfully.
         Current function value: 0.330482
         Iterations 7
```

In [42]:
```
modelf.summary()
```

Out[42]:

Logit Regression Results

Dep. Variable:	received	**No. Observations:**	159
Model:	Logit	**Df Residuals:**	155
Method:	MLE	**Df Model:**	3
Date:	Thu, 29 Oct 2015	**Pseudo R-squ.:**	0.2212
Time:	09:26:46	**Log-Likelihood:**	-52.547
converged:	True	**LL-Null:**	-67.470
		LLR p-value:	1.486e-06

	coef	std err	z	P>|z|	[95.0% Conf. Int.]
intercept	-1.1772	2.982	-0.395	0.693	-7.023 4.668
age	0.0728	0.030	2.396	0.017	0.013 0.132
awareness	-0.0990	0.033	-2.957	0.003	-0.165 -0.033
gender	0.4340	0.522	0.832	0.406	-0.589 1.457

In [43]:
```
b3 = modelf.params[3]
se3 = modelf.bse[3]

zstat = b3/se3

print 'The calculated Z-statistic is: %.3f.' %zstat
```

```
The calculated Z-statistic is: 0.832.
```

In [44]:
```
zcrit = norm.ppf(0.975)

print 'The Z-critical value is: %.3f.' %zcrit
print ''
print 'Since the calculated Z-statistic is less than the Z-critical, we fa
il to reject the null hypothesis and conclude that we can drop gender from
 the model.'
```

```
The Z-critical value is: 1.960.

Since the calculated Z-statistic is less than the Z-critical, we fail to r
eject the null hypothesis and conclude that we can drop gender from the mo
del.
```

c.

Now we calculate the reduced model

In [45]:
```
modelr = sm.Logit(flu['received'], flu[['intercept','age','awareness']]).f
it()
```

```
Optimization terminated successfully.
         Current function value: 0.332690
         Iterations 7
```

In [46]:
```
modelr.summary()
```

Out[46]:

Logit Regression Results

Dep. Variable:	received	**No. Observations:**	159
Model:	Logit	**Df Residuals:**	156
Method:	MLE	**Df Model:**	2
Date:	Thu, 29 Oct 2015	**Pseudo R-squ.:**	0.2160
Time:	09:26:47	**Log-Likelihood:**	-52.898
converged:	True	**LL-Null:**	-67.470
		LLR p-value:	4.690e-07

	coef	std err	z	P>|z|	[95.0% Conf. Int.]
intercept	-1.4578	2.915	-0.500	0.617	-7.172 4.256
age	0.0779	0.030	2.622	0.009	0.020 0.136
awareness	-0.0955	0.032	-2.946	0.003	-0.159 -0.032

Calculate:

$$G^2 = -2\left[\log L(R) - \log L(F)\right]$$

In [47]:
```
Gsq = -2*(modelr.llf - modelf.llf)
G_pval = 1 - chi2.cdf(Gsq,1)

print 'The G squared statistic is: %.3f' %Gsq
print ''
print 'The approximate p-value is: %.3f' %G_pval
```

```
The G squared statistic is: 0.702

The approximate p-value is: 0.402
```

In [48]:
```
Chicrit = chi2.ppf(0.95,1)

print 'The chi squared critical value with 1 degree of freedom is: %.3f' % Chicrit
print ''
print 'Since the G squared statistic is less than the Chi Squared critical value, we fail to reject the null hypothesis and conclude that gender can be dropped from the model.'
print ''
print 'This indicates that Wald test conducted in part b. agrees with the likelihood ratio test conducted in c.'
```

```
The chi squared critical value with 1 degree of freedom is: 3.841

Since the G squared statistic is less than the Chi Squared critical value,
 we fail to reject the null hypothesis and conclude that gender can be dro
pped from the model.

This indicates that Wald test conducted in part b. agrees with the likelih
ood ratio test conducted in c.
```