Assignment 2

October 17, 2018

1 Assignment 2 - Josephine Tan

2 Question 1

```
In [121]: #Import packages
          import pandas as pd
```

I chose to open the two datasets with the following labels. I labelled the variables of weight and total income from the SurveyIncome dataset differently from the BestIncome dataset to differentiate between these two variables which are from two datasets.

```
In [122]: BestIncome = pd.read_csv('BestIncome.txt', names=['labor income', 'capital income',
          BestIncome.describe()
```

```
Out[122]:        labor income  capital income        height        weight
          count  10000.000000    10000.000000  10000.000000  10000.000000
          mean   57052.925133     9985.798563     65.014021    150.006011
          std     8036.544363     2010.123691      1.999692      9.973001
          min    22917.607900     1495.191896     58.176154    114.510700
          25%    51624.339880     8611.756679     63.652971    143.341979
          50%    56968.709935     9969.840117     65.003557    149.947641
          75%    62408.232277    11339.905773     66.356915    156.724586
          max    90059.898537    19882.320069     72.802277    185.408280
```

```
In [123]: SurveyIncome = pd.read_csv('SurvIncome.txt', names=['total_income1', 'weight1', 'age
          SurveyIncome.describe()
```

```
Out[123]:        total_income1      weight1          age      female
          count    1000.000000  1000.000000  1000.000000  1000.00000
          mean    64871.210860   149.542181    44.839320     0.50000
          std      9542.444214    22.028883     5.939185     0.50025
          min     31816.281649    99.662468    25.741333     0.00000
          25%     58349.862384   130.179235    41.025231     0.00000
          50%     65281.271149   149.758434    44.955981     0.50000
          75%     71749.038000   170.147337    48.817644     1.00000
          max     92556.135462   196.503274    66.534646     1.00000
```

(a) I will use a linear regression twice to derive the coefficients of the following equations from the SurveyIncome dataset: Equations I will use: age = B0 + total income1B1 + weight1B2 and female = BO + total income1B1 + weight1B2

In [124]:
```
#For the linear regression for age:
outcome = 'age'
features = ['total_income1', 'weight1']
x, y = SurveyIncome[features], SurveyIncome[outcome]
```

In [125]:
```
#Testing if the X and Y variables are correct:
x.head()
```

Out[125]:

	total_income1	weight1
0	63642.513655	134.998269
1	49177.380692	134.392957
2	67833.339128	126.482992
3	62962.266217	128.038121
4	58716.952597	126.211980

In [126]:
```
y.head()
```

Out[126]:
```
0    46.610021
1    48.791349
2    48.429894
3    41.543926
4    41.201245
Name: age, dtype: float64
```

In [127]:
```
#Running the linear regression for age
import statsmodels.api as sm

x = sm.add_constant(x, prepend=False)
x.head()

m = sm.OLS(y, x)

res = m.fit()
print(res.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    age   R-squared:                       0.001
Model:                            OLS   Adj. R-squared:                 -0.001
Method:                 Least Squares   F-statistic:                    0.6326
Date:                Tue, 16 Oct 2018   Prob (F-statistic):              0.531
Time:                        20:10:45   Log-Likelihood:                -3199.4
No. Observations:                1000   AIC:                             6405.
Df Residuals:                     997   BIC:                             6419.
Df Model:                           2
```

```
Covariance Type:            nonrobust
================================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
total_income1  2.52e-05  2.26e-05      1.114      0.266   -1.92e-05    6.96e-05
weight1         -0.0067     0.010     -0.686      0.493      -0.026       0.013
const           44.2097     1.490     29.666      0.000      41.285      47.134
==============================================================================
Omnibus:                        2.460   Durbin-Watson:                   1.921
Prob(Omnibus):                  0.292   Jarque-Bera (JB):                2.322
Skew:                          -0.109   Prob(JB):                        0.313
Kurtosis:                       3.092   Cond. No.                     5.20e+05
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 5.2e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [128]:
```
#Saving prediction of model for age
ols_df = pd.concat([y, x], axis=1)
ols_df.head()
```

Out[128]:

	age	total_income1	weight1	const
0	46.610021	63642.513655	134.998269	1.0
1	48.791349	49177.380692	134.392957	1.0
2	48.429894	67833.339128	126.482992	1.0
3	41.543926	62962.266217	128.038121	1.0
4	41.201245	58716.952597	126.211980	1.0

In [129]:
```
#Adding model prediction of age to the SurveyIncome dataset
ols_df['age_pred'] = res.predict(x)
ols_df.head()
```

Out[129]:

	age	total_income1	weight1	const	age_pred
0	46.610021	63642.513655	134.998269	1.0	44.906121
1	48.791349	49177.380692	134.392957	1.0	44.545636
2	48.429894	67833.339128	126.482992	1.0	45.068980
3	41.543926	62962.266217	128.038121	1.0	44.935764
4	41.201245	58716.952597	126.211980	1.0	44.841048

In [130]:
```
#Running linear regression on gender (female) as gender
outcome = 'female'
features = ['total_income1', 'weight1']
X, y = SurveyIncome[features], SurveyIncome[outcome]

import statsmodels.api as sm
```

```python
X = sm.add_constant(X, prepend=False)
X.head()

m = sm.OLS(y, X)

res = m.fit()
print(res.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                 female   R-squared:                       0.834
Model:                            OLS   Adj. R-squared:                  0.834
Method:                 Least Squares   F-statistic:                     2513.
Date:                Tue, 16 Oct 2018   Prob (F-statistic):               0.00
Time:                        20:10:50   Log-Likelihood:                 173.49
No. Observations:                1000   AIC:                            -341.0
Df Residuals:                     997   BIC:                            -326.3
Df Model:                           2
Covariance Type:            nonrobust
=================================================================================
                    coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------
total_income1  -5.25e-06   7.76e-07     -6.765      0.000   -6.77e-06   -3.73e-06
weight1          -0.0195      0.000    -58.098      0.000      -0.020      -0.019
const             3.7611      0.051     73.600      0.000       3.661       3.861
==============================================================================
Omnibus:                        0.170   Durbin-Watson:                   1.634
Prob(Omnibus):                  0.918   Jarque-Bera (JB):                0.114
Skew:                          -0.022   Prob(JB):                        0.945
Kurtosis:                       3.029   Cond. No.                     5.20e+05
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 5.2e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [131]:
```python
#Saving prediction of model for gender
ols_df = pd.concat([y, x], axis=1)
ols_df.head()
```

Out[131]:

	female	total_income1	weight1	const
0	1.0	63642.513655	134.998269	1.0
1	1.0	49177.380692	134.392957	1.0
2	1.0	67833.339128	126.482992	1.0
3	1.0	62962.266217	128.038121	1.0
4	1.0	58716.952597	126.211980	1.0

In [132]:
```
#Adding model prediction for gender to the SurveyIncome dataset
ols_df['gender_pred'] = res.predict(x)
ols_df.head()
```

Out[132]:

	female	total_income1	weight1	const	gender_pred
0	1.0	63642.513655	134.998269	1.0	0.790496
1	1.0	49177.380692	134.392957	1.0	0.878254
2	1.0	67833.339128	126.482992	1.0	0.934802
3	1.0	62962.266217	128.038121	1.0	0.930001
4	1.0	58716.952597	126.211980	1.0	0.987952

(b) Imputing the variables into the BestIncome dataset

In [133]:
```
#For us to estimate age and gender (female) on the BestIncome dataset, and use the f

#age = B0 + total incomeB1 + weightB2
#female = B0 + total incomeB1 + weightB2

#We need to add labor income and capital income to equate to total income in the Bes
BestIncome['total_income'] = BestIncome['labor income'] + BestIncome['capital income
BestIncome.head()
```

Out[133]:

	labor income	capital income	height	weight	total_income
0	52655.605507	9279.509829	64.568138	152.920634	61935.115336
1	70586.979225	9451.016902	65.727648	159.534414	80037.996127
2	53738.008339	8078.132315	66.268796	152.502405	61816.140654
3	55128.180903	12692.670403	62.910559	149.218189	67820.851305
4	44482.794867	9812.975746	68.678295	152.726358	54295.770612

In [134]:
```
#Adding the equation of predicted age (age_pred) from the SurveyIncome dataset to th
def age_pred(row):

    total_income = row[0]
    weight = row[1]

    age_pred = 44.2097+(total_income*-2.52e-05)+(weight*-0.0067)
    return age_pred
age_pred([63642.513655, 134.998269])
```

Out[134]: 41.701420253594

In [135]:
```
#Adding the imputed age variable (imputed_age) into the BestIncome dataset
BestIncome['imputed_age'] = BestIncome[['total_income', 'weight']].apply(age_pred, a
BestIncome.head()
```

Out[135]:

	labor income	capital income	height	weight	total_income \
0	52655.605507	9279.509829	64.568138	152.920634	61935.115336
1	70586.979225	9451.016902	65.727648	159.534414	80037.996127
2	53738.008339	8078.132315	66.268796	152.502405	61816.140654

```
3  55128.180903    12692.670403  62.910559  149.218189  67820.851305
4  44482.794867     9812.975746  68.678295  152.726358  54295.770612

   imputed_age
0    41.624367
1    41.123862
2    41.630167
3    41.500853
4    41.818180
```

In [136]:
```
#Adding the equation of female (gender_pred) from the SurveyIncome dataset to the Be
def gender_pred(row):

    total_income = row[0]
    weight = row[1]

    gender_pred = 3.7611+(total_income*-5.25e-06)+(weight*-0.0195)
    if gender_pred < 0.5:
        return 0
    elif gender_pred >= 0.5:
        return 1

gender_pred([63642.513655, 134.998269])
```

Out[136]:
```
1
```

In [137]:
```
BestIncome['imputed_gender_pred'] = BestIncome[['total_income', 'weight']].apply(genc
BestIncome.head()
```

Out[137]:
```
   labor income  capital income     height      weight  total_income  \
0  52655.605507     9279.509829  64.568138  152.920634  61935.115336
1  70586.979225     9451.016902  65.727648  159.534414  80037.996127
2  53738.008339     8078.132315  66.268796  152.502405  61816.140654
3  55128.180903    12692.670403  62.910559  149.218189  67820.851305
4  44482.794867     9812.975746  68.678295  152.726358  54295.770612

   imputed_age  imputed_gender_pred
0    41.624367                    0
1    41.123862                    0
2    41.630167                    0
3    41.500853                    0
4    41.818180                    0
```

(c) Descriptive Statistics of age and gender

In [138]:
```
BestIncome['imputed_age'].describe()
```

Out[138]:
```
count    10000.000000
mean        41.515284
```

```
std          0.219817
min         40.683056
25%         41.365293
50%         41.515710
75%         41.664056
max         42.373440
Name: imputed_age, dtype: float64
```

The mean is 41.52, standard deviation is 0.22, maximum is 42.37, minimum is 40.68, number of observations is 10,000.

```
In [139]: BestIncome['imputed_gender_pred'].describe()
```

```
Out[139]: count    10000.000000
          mean         0.470500
          std          0.499154
          min          0.000000
          25%          0.000000
          50%          0.000000
          75%          1.000000
          max          1.000000
          Name: imputed_gender_pred, dtype: float64
```

The mean is 0.47, standard deviation is 0.50, maximum is 1.00, minimum is 0.00, number of observations is 10,000.

(d) Correlation Matrix

```
In [140]: #In matrix form
          BestIncome = BestIncome.drop(columns = ["total_income"])

          corr = BestIncome.corr()
          corr.style.background_gradient()
```

```
Out[140]: <pandas.io.formats.style.Styler at 0x1c23f8b128>
```

3 Question 2

```
In [141]: #Opening dataset
          IncomeIntel = pd.read_csv('IncomeIntel1.txt', names=['grad_year', 'gre_qnt', 'salary
          IncomeIntel.head()
```

```
Out[141]:    grad_year     gre_qnt        salary
          0     2001.0  739.737072  67400.475185
          1     2001.0  721.811673  67600.584142
          2     2001.0  736.277908  58704.880589
          3     2001.0  770.498485  64707.290345
          4     2001.0  735.002861  51737.324165
```

(a) Obtaining the coefficients of the regression of Salary on GRE quantitative scores

```
In [142]: #Linear regression on Salary on GRE quantitative scores
          outcome  = 'salary'
          features = ['gre_qnt']

          X, y = IncomeIntel[features], IncomeIntel[outcome]

          import statsmodels.api as sm

          X = sm.add_constant(X, prepend=False)
          X.head()

          m = sm.OLS(y, X)

          res = m.fit()
          print(res.summary())
```

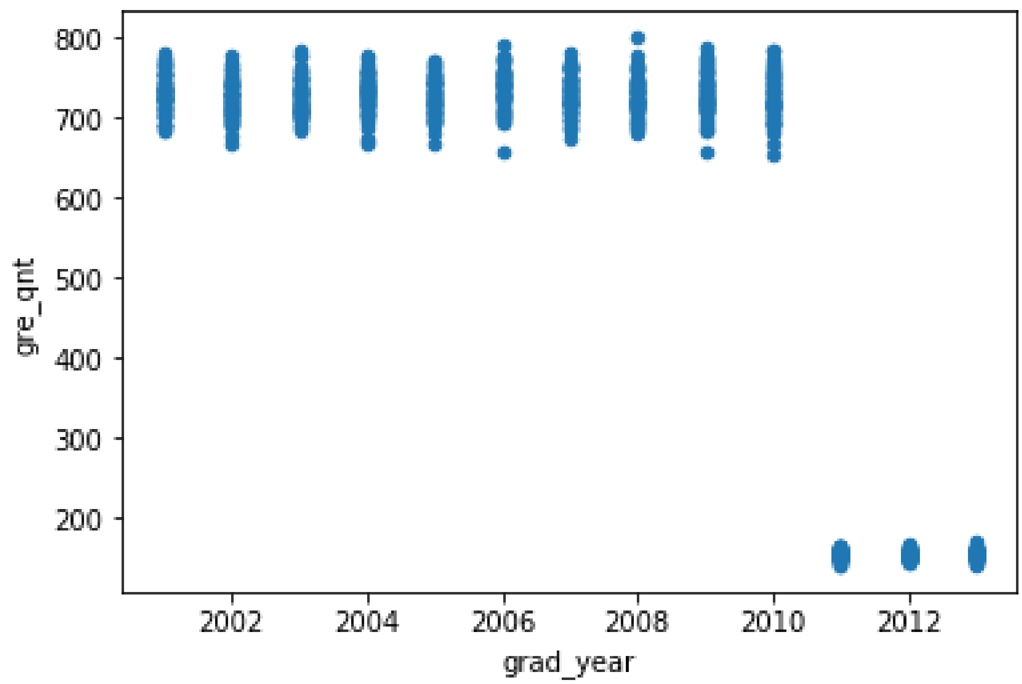
```
                            OLS Regression Results
==============================================================================
Dep. Variable:                 salary   R-squared:                       0.263
Model:                            OLS   Adj. R-squared:                  0.262
Method:                 Least Squares   F-statistic:                     356.3
Date:                Tue, 16 Oct 2018   Prob (F-statistic):           3.43e-68
Time:                        20:11:43   Log-Likelihood:                -10673.
No. Observations:                1000   AIC:                         2.135e+04
Df Residuals:                     998   BIC:                         2.136e+04
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
gre_qnt      -25.7632      1.365    -18.875      0.000     -28.442     -23.085
const       8.954e+04    878.764    101.895      0.000    8.78e+04    9.13e+04
==============================================================================
Omnibus:                        9.118   Durbin-Watson:                   1.424
Prob(Omnibus):                  0.010   Jarque-Bera (JB):                9.100
Skew:                           0.230   Prob(JB):                       0.0106
Kurtosis:                       3.077   Cond. No.                     1.71e+03
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.71e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

The coefficient for GRE quantitative score is -25.76 and the constant is 8.95e+04, and the standard error is 1.37.

(b) Scatter plot of graduation year and GRE quantitative score

In [143]:
```
#Running a simple scatter plot of the graduation year and GRE quantitative scores
import matplotlib.pyplot as plt
grad_year = IncomeIntel['grad_year']
gre_qnt = IncomeIntel['gre_qnt']
IncomeIntel.plot(x='grad_year', y='gre_qnt', kind='scatter')
plt.show()
```



As seen in the scatter plot, the three variables in 2011, 2012 and 2013 have a very low GRE quantitative score of 200, while the rest of the GRE scores are around 800. This drop in GRE scores are because the GRE tests have changed in testing format since 2011. As such, we cannot compare GRE scores for 2011 and after 2011 based on absolute numbers alone. One solution is to change all the GRE scores to Z-scores (as these scores have not changed over the years), for us to compare between all the years.

In [144]:
```
#Implementing solution proposed above
df = IncomeIntel.copy()
gre2 = df.groupby('grad_year').transform(lambda x : (x - x.mean()) / x.std())  # tra
gre2.head()
IncomeIntel['zscore'] = gre2['gre_qnt']
IncomeIntel.head
```

Out[144]:
```
<bound method NDFrame.head of      grad_year     gre_qnt          salary    zscore
0       2001.0  739.737072   67400.475185  0.406740
1       2001.0  721.811673   67600.584142 -0.356635
```

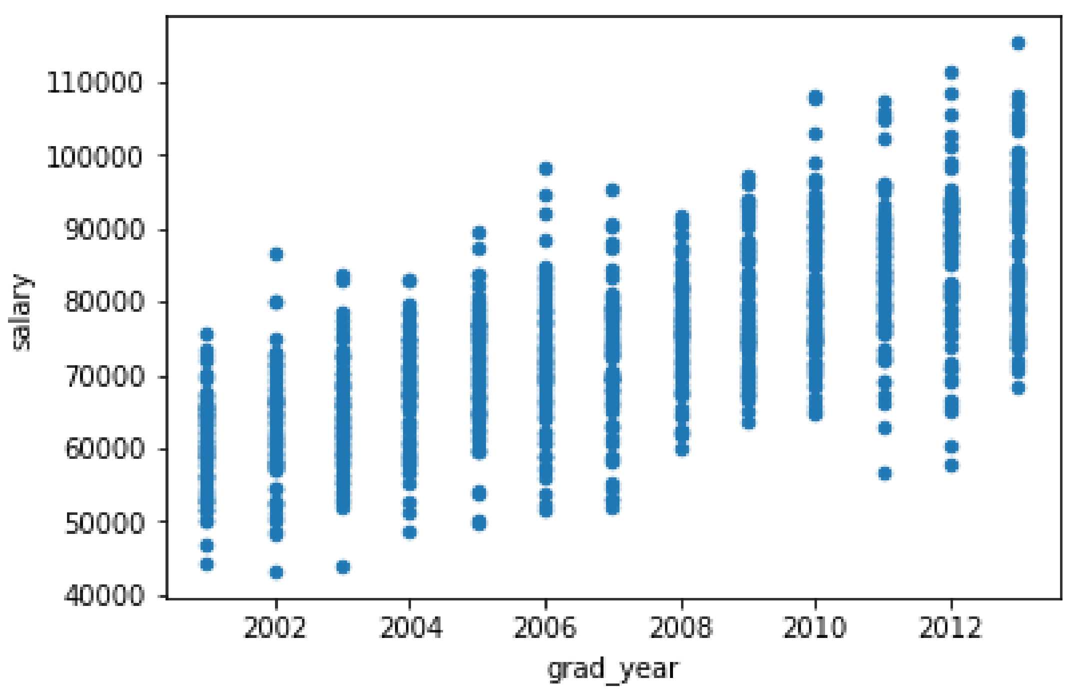
2	2001.0	736.277908	58704.880589	0.259427
3	2001.0	770.498485	64707.290345	1.716750
4	2001.0	735.002861	51737.324165	0.205128
5	2001.0	763.876037	64010.822579	1.434726
6	2001.0	738.758659	60080.107481	0.365073
7	2001.0	706.407471	56263.309815	-1.012641
8	2001.0	705.886037	62109.859243	-1.034847
9	2001.0	700.971986	50189.704747	-1.244117
10	2001.0	709.754522	58721.753127	-0.870103
11	2001.0	734.854582	65380.594586	0.198813
12	2001.0	753.384151	52857.212365	0.987916
13	2001.0	690.312090	63572.217765	-1.698081
14	2001.0	774.154371	65892.177035	1.872441
15	2001.0	726.377225	67454.545201	-0.162205
16	2001.0	702.735945	59346.670232	-1.168997
17	2001.0	723.806542	70031.012603	-0.271681
18	2001.0	758.051159	53441.672888	1.186666
19	2001.0	711.063082	61008.652046	-0.814376
20	2001.0	702.975969	50065.932451	-1.158775
21	2001.0	733.877837	75612.225369	0.157217
22	2001.0	735.918767	59580.620375	0.244133
23	2001.0	749.069115	57825.611782	0.804156
24	2001.0	732.581793	52809.225854	0.102024
25	2001.0	728.050446	57492.084316	-0.090949
26	2001.0	690.265988	64686.224351	-1.700045
27	2001.0	732.448836	53067.021394	0.096361
28	2001.0	724.755887	58902.707320	-0.231252
29	2001.0	721.739038	62094.061567	-0.359728
..	...	...	...	...
970	2013.0	158.578197	79263.470892	0.576381
971	2013.0	147.667305	104782.627567	-1.440563
972	2013.0	160.086274	94013.946074	0.855158
973	2013.0	156.289493	74032.543183	0.153300
974	2013.0	150.340044	84220.290724	-0.946491
975	2013.0	163.054596	74940.546965	1.403870
976	2013.0	157.624151	83293.343135	0.400020
977	2013.0	150.927266	78340.908128	-0.837940
978	2013.0	157.393763	91066.889575	0.357431
979	2013.0	154.449630	87169.012509	-0.186810
980	2013.0	153.756644	90033.601423	-0.314912
981	2013.0	150.796371	98650.768576	-0.862137
982	2013.0	150.691700	70455.885421	-0.881486
983	2013.0	153.639896	91133.301177	-0.336494
984	2013.0	150.374470	91796.617819	-0.940128
985	2013.0	162.350725	73780.832249	1.273755
986	2013.0	155.803279	96927.925237	0.063421
987	2013.0	159.111662	71875.246552	0.674995
988	2013.0	158.338350	103357.966587	0.532044

```
989      2013.0   162.308518   73780.472319  1.265953
990      2013.0   156.651125   79055.571295  0.220150
991      2013.0   153.836045   91529.313046 -0.300235
992      2013.0   149.542467   75940.200168 -1.093928
993      2013.0   155.349020   97688.397380 -0.020552
994      2013.0   161.767399   75260.194609  1.165924
995      2013.0   160.441025  100430.166532  0.920736
996      2013.0   160.431891   82198.200872  0.919047
997      2013.0   154.254526   84340.214218 -0.222876
998      2013.0   162.036321   87600.881985  1.215636
999      2013.0   156.946735   82854.576903  0.274795

[1000 rows x 4 columns]>
```

(c) Scatter plot of income and graduation year

In [145]:
```
#Running a simple scatter plot on the graduation year and GRE quantitative scores
grad_year = IncomeIntel['grad_year']
salary = IncomeIntel['salary']
IncomeIntel.plot(x='grad_year', y='salary', kind='scatter')
plt.show()
```



As the data spans over time, and time increases constantly, we need to stationarize the data and control for time for us to complete the regression. Because these data are not panel data, I cannot use differencing or log differencing methods to detrend them. Instead, I plan to use growth rate to stationarize the data.

In [146]:
```
#Implementing solution proposed above
#To calculate the average growth rate in salary,
avg_inc_by_year = IncomeIntel['salary'].groupby(IncomeIntel['grad_year']).mean().valu
```

In [147]:
```
#To calculate the average growth rate in salaries across all 13 years,
avg_growth_rate = ((avg_inc_by_year[1:] - avg_inc_by_year[:-1]) / avg_inc_by_year[:-
```

In [148]:
```
#Divide each salary by the growth rate
IncomeIntel['adj_salary'] = IncomeIntel['salary'] / (1 + avg_growth_rate)**(IncomeInt
```

(d) Reestimating the coefficients with updated variables

In [149]:
```
#Linear regression on revised Salary on revised GRE quantitative scores (Z scores)
outcome  = 'adj_salary'
features = ['zscore']

X, y = IncomeIntel[features], IncomeIntel[outcome]

import statsmodels.api as sm

X = sm.add_constant(X, prepend=False)
X.head()

m = sm.OLS(y, X)

res = m.fit()
print(res.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:             adj_salary   R-squared:                       0.000
Model:                            OLS   Adj. R-squared:                 -0.001
Method:                 Least Squares   F-statistic:                    0.4395
Date:                Tue, 16 Oct 2018   Prob (F-statistic):              0.508
Time:                        20:12:11   Log-Likelihood:                -10291.
No. Observations:                1000   AIC:                         2.059e+04
Df Residuals:                     998   BIC:                         2.060e+04
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
zscore      -150.6097    227.193     -0.663      0.508    -596.440     295.221
const       6.142e+04    225.711    272.117      0.000      6.1e+04    6.19e+04
==============================================================================
Omnibus:                        0.776   Durbin-Watson:                   2.025
Prob(Omnibus):                  0.678   Jarque-Bera (JB):                0.687
Skew:                           0.059   Prob(JB):                        0.709
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Kurtosis:                       3.049   Cond. No.                        1.01
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
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The estimated coefficients for Z score (for GRE quantitative score) is -150.61 and the constant is now 6.142e+04. The new estimated coefficients for zscore on revised salary is much higher than before and is no longer significant (P>0.05) as compared to the regression ran between the unrevised GRE scores and unrevised salary data. This means that after accounting for the test format changes in the GRE, and time drift in the salary data, there is no longer a significant relationship between these two variables. Thus the hypothesis that that higher intelligence, as operationalized as quantitative GRE scores, is associated with higher salary, is not supported.