Assignment_2_Ken_Chen

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1 Assignment 2

MACS 30000, Instructor Dr. Evans

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```
In [1]: # Import packages
        import numpy as np
        import pandas as pd
        import statsmodels.api as sm
        import matplotlib.pyplot as plt
```

1.0.1 1. Imputing age and gender

(a) My proposed strategy for imputing *age* and *gender* into BestIncome dataset:

- Step1: Construct a **linear regression model** to predict age, a **logistic regression model** to predict gender, within SurveyIncome data (independent variables include TotalIncome and weight)

$$Age = \beta_0 + \beta_1 TotalIncome + \beta_2 Weight + \epsilon$$

$$logit\,(p) = log(\frac{Prob(Gender = Female\,|\,X)}{1 - Prob(Gender = Female\,|\,X)}) = \alpha_0 + \alpha_1 TotalIncome + \alpha_2 Weight$$

- Step2: Apply the models to the BestIncome dataset, and predict each observation's age and gender

$$Age_i = \beta_0 + \beta_1 TotalIncome_i + \beta_2 Weight_i$$

$$logit\,(p_i) = \alpha_0 + \alpha_1 TotalIncome_i + \alpha_2 Weight_i$$

(b) Import the datasets and name the variables

```
In [2]: #Import the files and rename the variables
        BestIncome = pd.read_table(
            "D:\persp-analysis_A18\Assignments\A2\BestIncome.txt", sep = ',', header = None)
        BestIncome = BestIncome.rename(
            columns = {0: 'Labor_Income', 1: 'Capital_Income', 2:'height', 3:'weight'})

        SurveyIncome = pd.read_table(
            "D:\persp-analysis_A18\Assignments\A2\SurvIncome.txt", sep = ',', header = None)
        SurveyIncome = SurveyIncome.rename(
            columns = {0: 'Total_Income', 1: 'weight', 2:'age', 3:'gender'})
```

```
In [3]: BestIncome['Total_Income'] = BestIncome['Labor_Income'] + BestIncome['Capital_Income']
        BestIncome.head()
```

Out[3]:

	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 [4]: SurveyIncome.head()
```

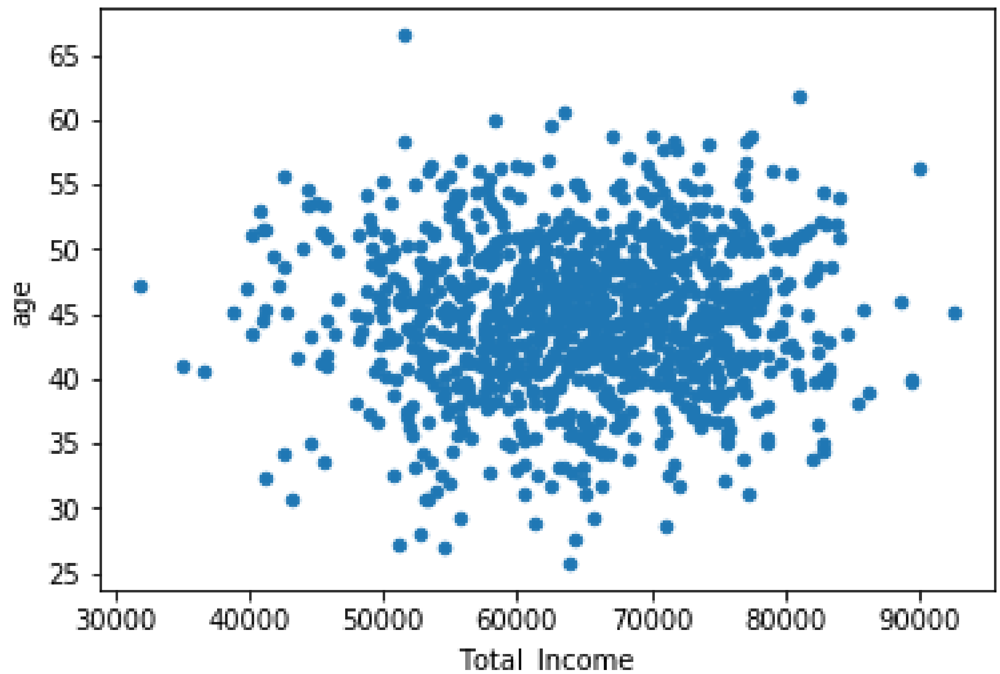
Out[4]:

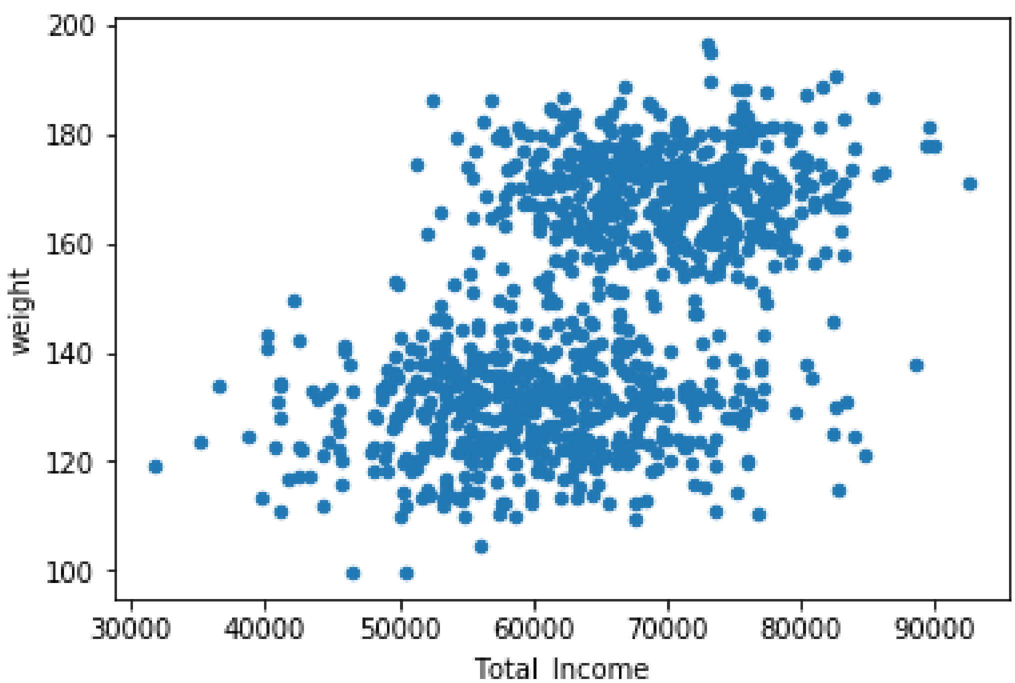
	Total_Income	weight	age	gender
0	63642.513655	134.998269	46.610021	1.0
1	49177.380692	134.392957	48.791349	1.0
2	67833.339128	126.482992	48.429894	1.0
3	62962.266217	128.038121	41.543926	1.0
4	58716.952597	126.211980	41.201245	1.0

(b) Here is where I'll use my proposed method from part (a) to impute variables.

```
In [5]: # Scatterplot before regression

        SurveyIncome.plot(x = 'Total_Income', y = 'age', kind = 'scatter')
        SurveyIncome.plot(x = 'Total_Income', y = 'weight', kind = 'scatter')
```

```
Out[5]: <matplotlib.axes._subplots.AxesSubplot at 0x1f664ddbd68>
```





In [6]:
```
# Train the linear regression model using SurveyIncome dataset
import statsmodels.api as sm
```

```python
X_vars = SurveyIncome[['Total_Income', 'weight']]
X_vars = sm.add_constant(X_vars, prepend=False)

y = SurveyIncome['age']

m = sm.OLS(y, X_vars)

res = m.fit(cov_type='HC3')
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:                    0.6042
Date:                Mon, 15 Oct 2018   Prob (F-statistic):              0.547
Time:                        22:23:15   Log-Likelihood:                -3199.4
No. Observations:                1000   AIC:                             6405.
Df Residuals:                     997   BIC:                             6419.
Df Model:                           2
Covariance Type:                  HC3
================================================================================
                   coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
Total_Income   2.52e-05   2.34e-05      1.076      0.282   -2.07e-05    7.11e-05
weight          -0.0067      0.009     -0.711      0.477      -0.025       0.012
const           44.2097      1.525     28.983      0.000      41.220      47.199
==============================================================================
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 are heteroscedasticity robust (HC3)
[2] The condition number is large, 5.2e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

The estimated model looks:

$$\widehat{Age}_i = 44.2097 + 0.0000252 \times TotalIncome_i - 0.0067 \times Weight_i$$

The estimators are not statistically significant, which implies weak linear correlation. However, I'll put up with this and go on with the following analysis.

```python
In [7]: # Impute the age variable for BestIncome dataset
```

```
def impute_age(x):
    return 44.2097 + 2.52e-05*x[4] - 0.0067*x[3]

BestIncome['age_imputed'] = BestIncome.apply(impute_age, axis = 1)
BestIncome.head()
```

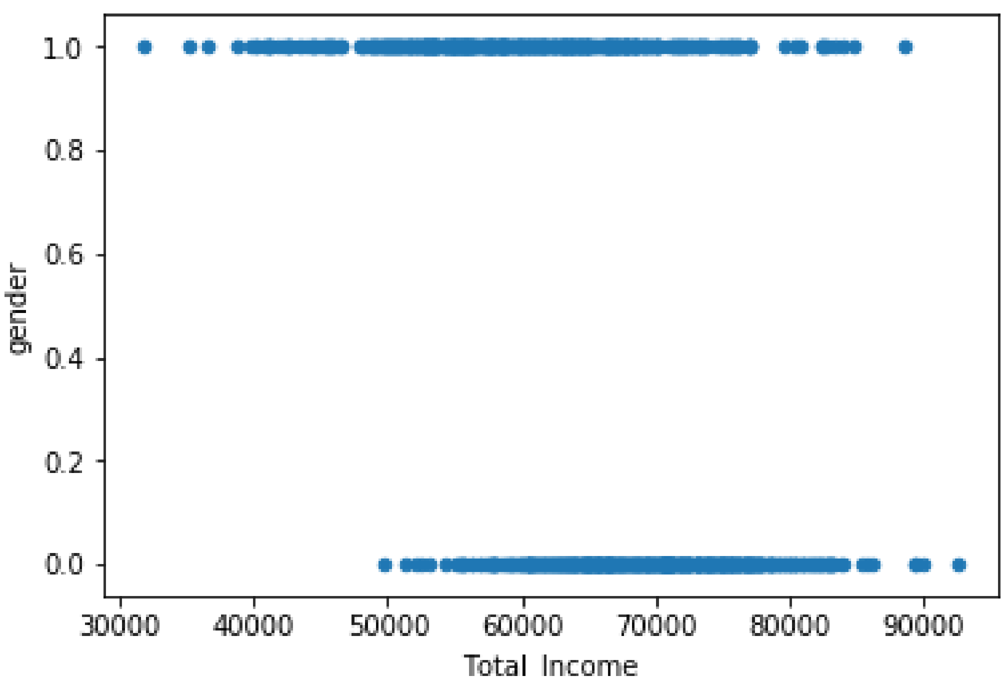
Out[7]:

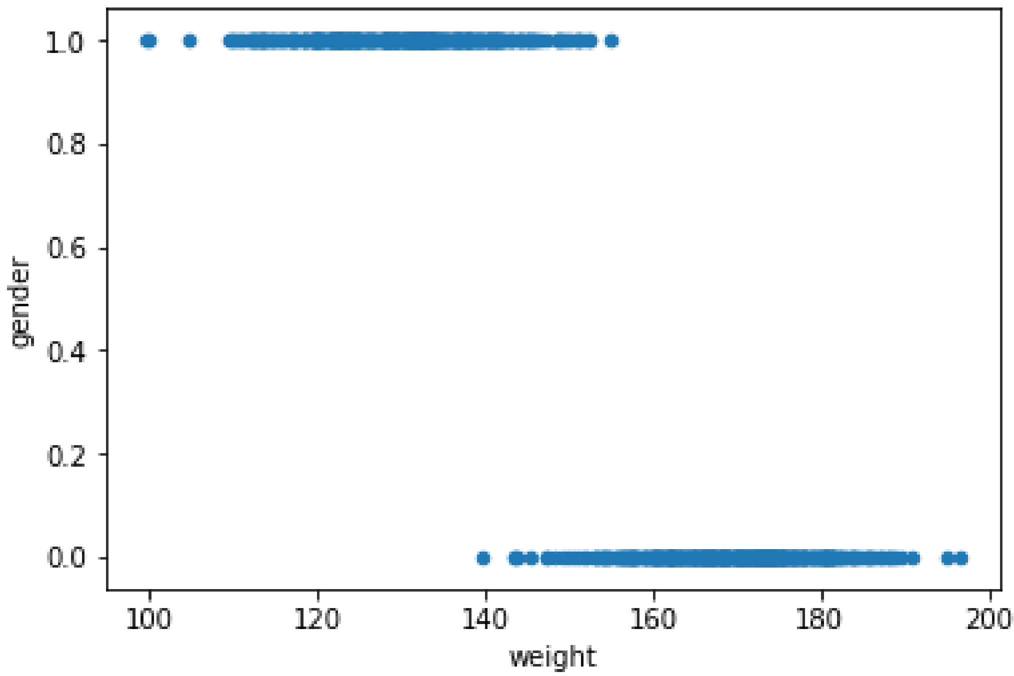
```
   Labor_Income  Capital_Income     height      weight  Total_Income  \
0  52655.605507     9279.509829  64.568138  152.920634  61935.115336
1  70586.979225     9451.016902  65.727648  159.534414  80037.996127
2  53738.008339     8078.132315  66.268796  152.502405  61816.140654
3  55128.180903    12692.670403  62.910559  149.218189  67820.851305
4  44482.794867     9812.975746  68.678295  152.726358  54295.770612

   age_imputed
0    44.745897
1    45.157777
2    44.745701
3    44.919024
4    44.554687
```

In [8]:

```
# Scatterplot before regression

SurveyIncome.plot(x = 'Total_Income', y = 'gender', kind = 'scatter')
SurveyIncome.plot(x = 'weight', y = 'gender', kind = 'scatter')
```

Out[8]: <matplotlib.axes._subplots.AxesSubplot at 0x1f6652e67b8>






```
In [9]: # Train the logistic regression model using SurveyIncome dataset

        X_vars = SurveyIncome[['Total_Income', 'weight']]
        X_vars = sm.add_constant(X_vars, prepend=False)

        y = SurveyIncome['gender']

        m = sm.Logit(y, X_vars)

        res_1 = m.fit()
        print(res_1.summary())
```

```
Optimization terminated successfully.
         Current function value: 0.036050
         Iterations 11
                           Logit Regression Results
==============================================================================
Dep. Variable:                 gender   No. Observations:                 1000
Model:                          Logit   Df Residuals:                      997
Method:                           MLE   Df Model:                            2
Date:                Mon, 15 Oct 2018   Pseudo R-squ.:                  0.9480
Time:                        22:24:38   Log-Likelihood:                -36.050
converged:                       True   LL-Null:                       -693.15
                                        LLR p-value:                 4.232e-286
================================================================================
```

```
                     coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
Total_Income      -0.0002   4.25e-05     -3.660      0.000      -0.000   -7.22e-05
weight            -0.4460      0.062     -7.219      0.000      -0.567      -0.325
const             76.7929     10.569      7.266      0.000      56.078      97.508
================================================================================

Possibly complete quasi-separation: A fraction 0.55 of observations can be
perfectly predicted. This might indicate that there is complete
quasi-separation. In this case some parameters will not be identified.
```

The estimated model looks:

$$\widehat{logit\,(p_i)} = 76.7929 - 0.0002 \times TotalIncome_i - 0.4460 \times Weight_i$$

We then impute the gender of each individaul as `female if the predicted probability is greater than 0.5`

```
In [10]: # Impute the age variable for BestIncome dataset

         predictData = sm.add_constant \
             (BestIncome[['Total_Income', 'weight']], prepend = False)

         BestIncome['gender_imputed'] = (res_1.predict(predictData)>0.5).apply(float)
         BestIncome.head()
```

```
Out[10]:    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

            age_imputed  gender_imputed
         0    44.745897             0.0
         1    45.157777             0.0
         2    44.745701             0.0
         3    44.919024             0.0
         4    44.554687             1.0
```

(c) Here is where I'll report the descriptive statistics for my new imputed variables.

```
In [11]: BestIncome[['age_imputed','gender_imputed']].describe()
```

```
Out[11]:          age_imputed  gender_imputed
         count  10000.000000    10000.000000
         mean      44.894036        0.454600
         std        0.219066        0.497959
```

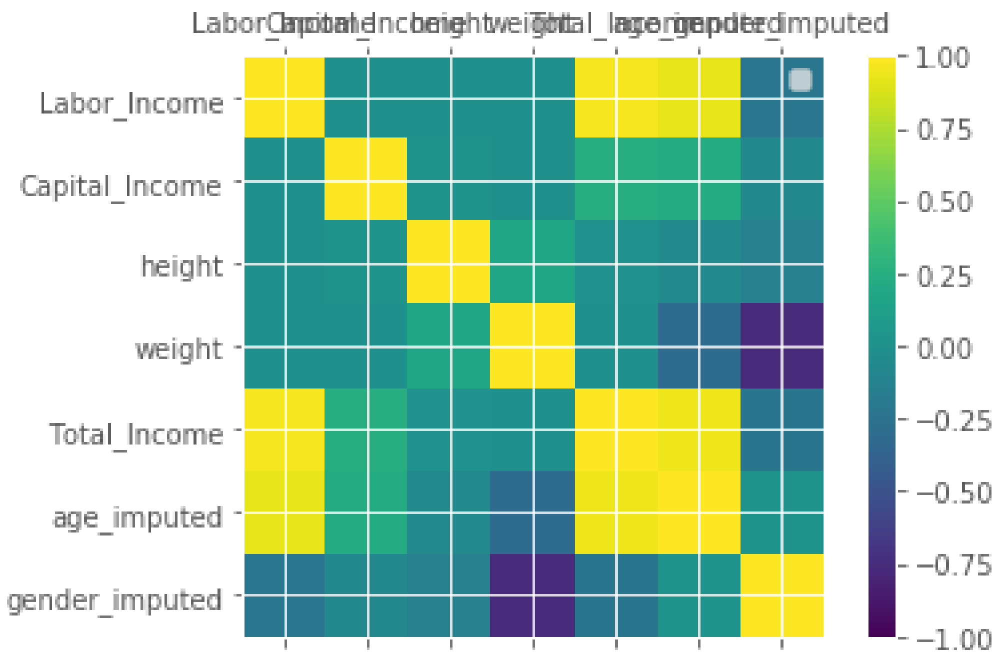
```
min      43.980016      0.000000
25%      44.747065      0.000000
50%      44.890281      0.000000
75%      45.042239      1.000000
max      45.706849      1.000000
```

(d) Correlation matrix for the now six variables

```
In [12]: # Correlation matrix: in matrix form

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

```
Out[12]: <pandas.io.formats.style.Styler at 0x1f6652f0c50>
```

```
In [13]: # Correlation matrix: in Matrix Plot
         plt.style.use('ggplot')

         names = BestIncome.columns
         N = len(names)

         correlations = BestIncome.corr()
         fig = plt.figure()
         ax = fig.add_subplot(111)
         cax = ax.matshow(correlations, vmin=-1.0, vmax=1.0)
         fig.colorbar(cax)
         ticks = np.arange(0,N,1)
         ax.set_xticks(ticks)
         ax.set_yticks(ticks)
         ax.set_xticklabels(names)
         ax.set_yticklabels(names)
         plt.legend('best')
         plt.show()
```



1.0.2 2. Stationarity and data drift

(a) Estimate by OLS and report coefficients

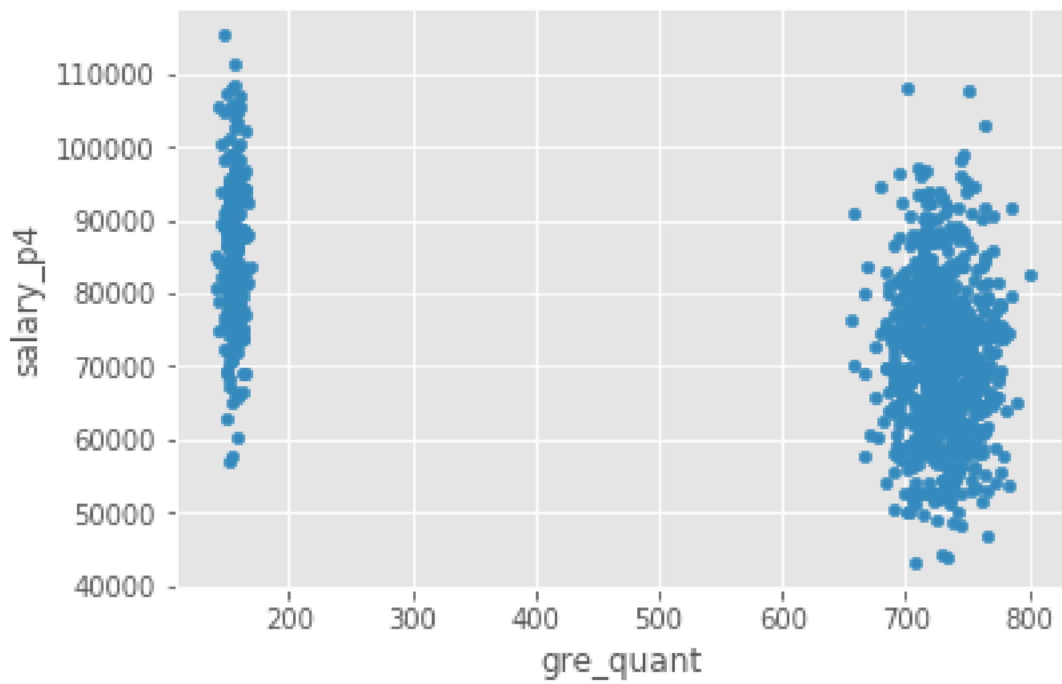
In [14]:
```
# Read in my third data set
# Name my variables

IncomeIntel = pd.read_table(
    "D:\persp-analysis_A18\Assignments\A2\IncomeIntel.txt", sep = ',', header = None)
IncomeIntel = IncomeIntel.rename(
    columns = {0:'grad_year', 1:'gre_quant', 2:'salary_p4'})
IncomeIntel.head()
```

Out[14]:

	grad_year	gre_quant	salary_p4
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

In [15]:
```
IncomeIntel.plot(x = 'gre_quant', y = 'salary_p4', kind = 'scatter')
```

Out[15]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1f6652dffd0>
```




```
In [16]: # Train the linear regression model
         # Report estimated coefficients and SE

         X_vars = IncomeIntel['gre_quant']
         X_vars = sm.add_constant(X_vars, prepend = False)

         y = IncomeIntel['salary_p4']

         m = sm.OLS(y, X_vars)
         res_2 = m.fit(cov_type = 'HC3')

         print(res_2.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              salary_p4   R-squared:                       0.263
Model:                            OLS   Adj. R-squared:                  0.262
Method:                 Least Squares   F-statistic:                     358.1
Date:                Mon, 15 Oct 2018   Prob (F-statistic):           1.74e-68
Time:                        22:24:52   Log-Likelihood:                -10673.
No. Observations:                1000   AIC:                         2.135e+04
Df Residuals:                     998   BIC:                         2.136e+04
Df Model:                           1
Covariance Type:                  HC3
```

```
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
gre_quant    -25.7632      1.361    -18.924      0.000     -28.431     -23.095
const       8.954e+04    876.015    102.214      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 are heteroscedasticity robust (HC3)
[2] The condition number is large, 1.71e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

The estimated model looks:

$$salary\_4years_i = 89540 - 25.7632 \times gre\_quant_i$$

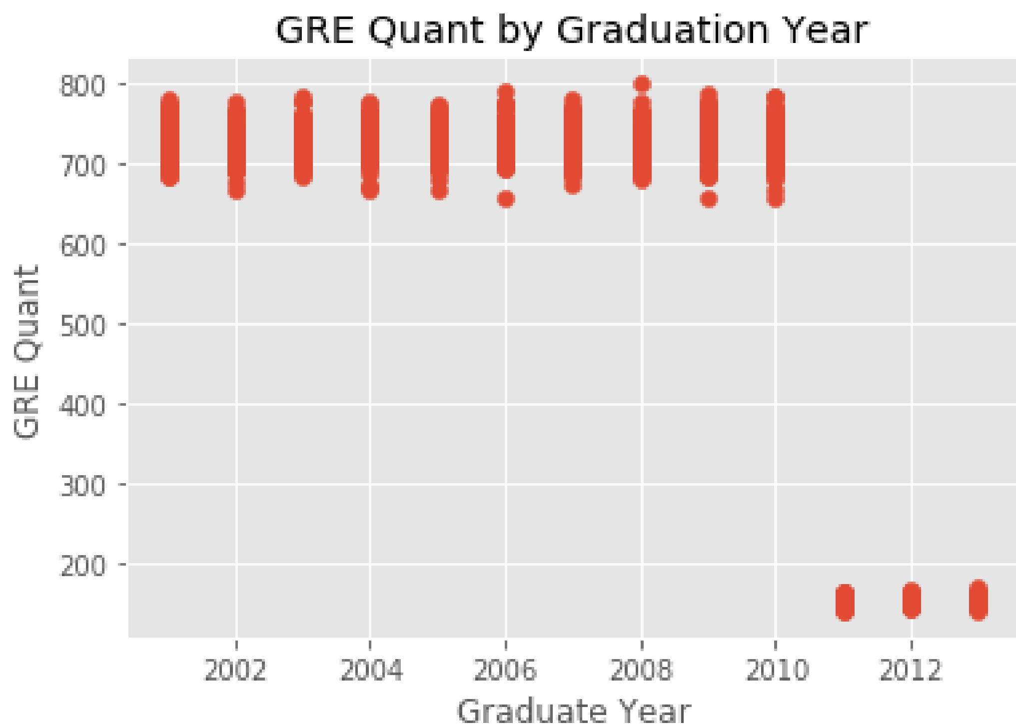
The estimated effect of gre score is a bit counter-intuitive, as we would expect higher gre score associated with better earnings. There are two contributing factors to this result:

- The data generation process didn't conform to our intuition of a positive relationship.
- The salary_p4 variable on average grows each year, but due to the change in gre score scaling, lower gre scores after 2010 are associated with higher salaries

Therefore, though strange, **my hypothesis would be that gre scores are negatively associated with salaries after four years.**

(b) Create a scatterplot of GRE score and graduation year.

```
In [17]: # Code and output of scatterplot

         plt.figure()
         x = IncomeIntel['grad_year']
         y = IncomeIntel['gre_quant']
         plt.scatter(x = x, y = y)
         plt.xlabel('Graduate Year'); plt.ylabel('GRE Quant')
         plt.title('GRE Quant by Graduation Year')
         plt.show()
```



Problem: Here we can observe clear and substantial **drift** in gre quant score, due to the change in scoring scale. Therefore, I would propose to map the gre scores before 2011 to the new gre scale by doing `gre_quant*170/800 if grad_year<2011`.

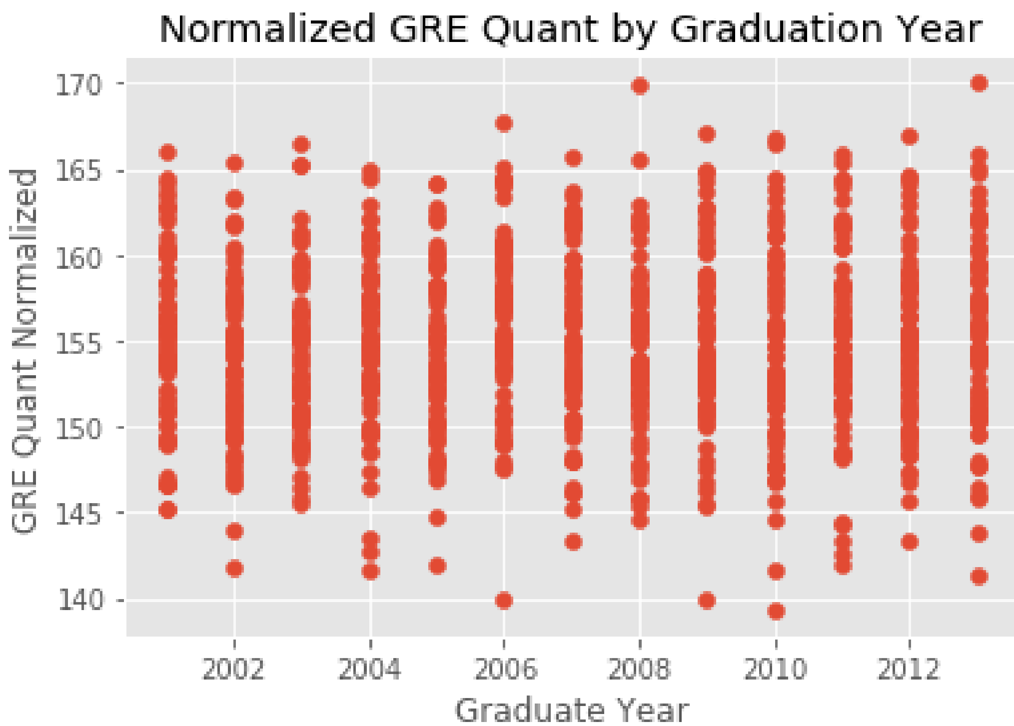
In [18]:
```
# Code to implement solution
gre_norm = IncomeIntel[['grad_year', 'gre_quant']] \
    .apply(lambda x: x['gre_quant']*170/800
           if x['grad_year']<2011 else x['gre_quant'], axis = 1)

IncomeIntel['gre_norml'] = gre_norm
IncomeIntel.head()
```

Out[18]:

	grad_year	gre_quant	salary_p4	gre_norml
0	2001.0	739.737072	67400.475185	157.194128
1	2001.0	721.811673	67600.584142	153.384980
2	2001.0	736.277908	58704.880589	156.459055
3	2001.0	770.498485	64707.290345	163.730928
4	2001.0	735.002861	51737.324165	156.188108

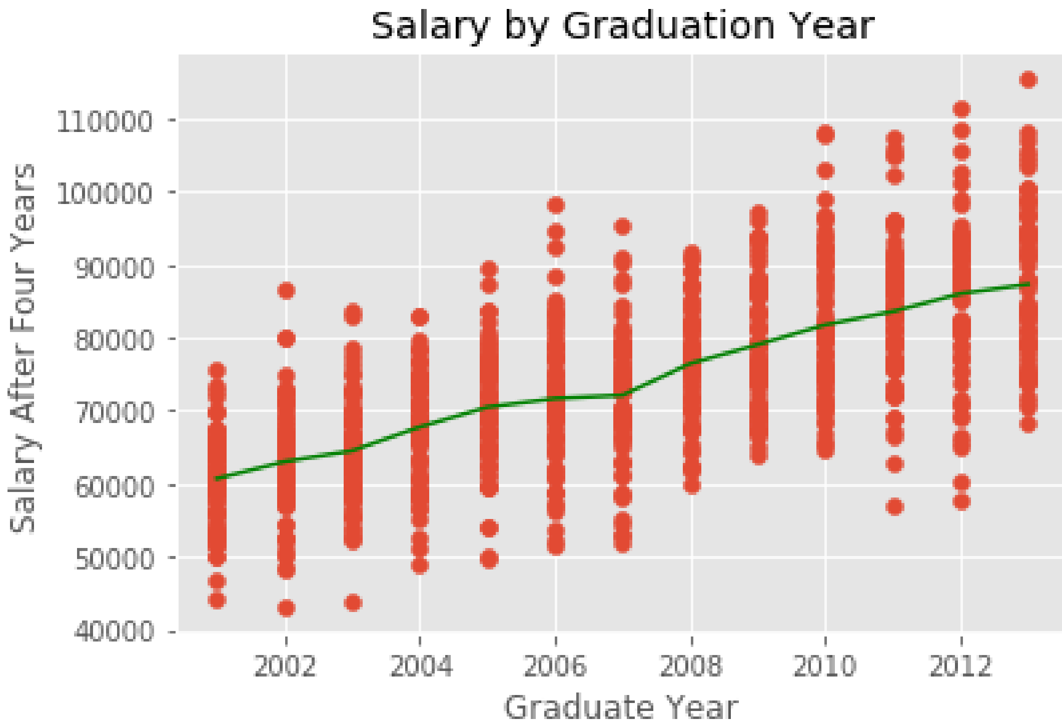
In [19]:
```
# Draw the scatterplot again and the drifting effect seems eliminated

plt.figure()
x = IncomeIntel['grad_year']
y = IncomeIntel['gre_norml']
plt.scatter(x = x, y = y)
```

```
plt.xlabel('Graduate Year'); plt.ylabel('GRE Quant Normalized')
plt.title('Normalized GRE Quant by Graduation Year')
plt.show()
```



(c) Create a scatterplot of income and graduation year

```
In [20]: # Code and output of scatterplot

         plt.figure()
         x = IncomeIntel['grad_year']
         y = IncomeIntel['salary_p4']
         plt.scatter(x = x, y = y)
         x_mean = IncomeIntel.groupby('grad_year').mean().index
         y_mean = IncomeIntel.groupby('grad_year').mean()['salary_p4']
         plt.plot(x_mean, y_mean, 'g-')
         plt.xlabel('Graduate Year'); plt.ylabel('Salary After Four Years')
         plt.title('Salary by Graduation Year')
         plt.show()
```

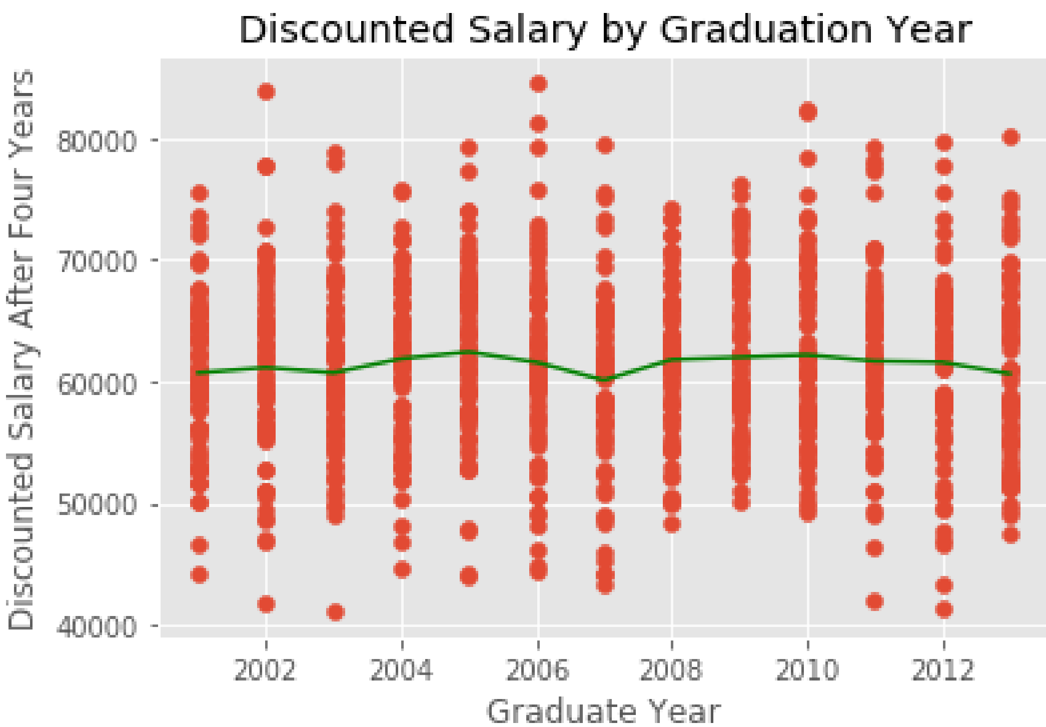


The average salary by year indicates non-stationarity: there seems to be an upward trending in these people's earnings. Therefore, we need to detrend this variable. Myt strategy is to first calculate the average grwoth rate, and then dicount their salaries `divide by (1 + avg_growth_rate) ** (grad_year - 2001)` down to the base year, so that we could eliminate the trend effects and make salaries across years comparable.

```
In [21]: # Calculate the mean salary each year
         avg_inc_by_year = IncomeIntel['salary_p4'] \
             .groupby(IncomeIntel['grad_year']).mean().values

         # 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[:-1]).mean()

         # Discount the salaries
         IncomeIntel['salary_p4_disc'] \
             = IncomeIntel.apply(
             lambda x: x['salary_p4']/((1 +avg_growth_rate)**(x['grad_year']-2001)), axis = 1)
```

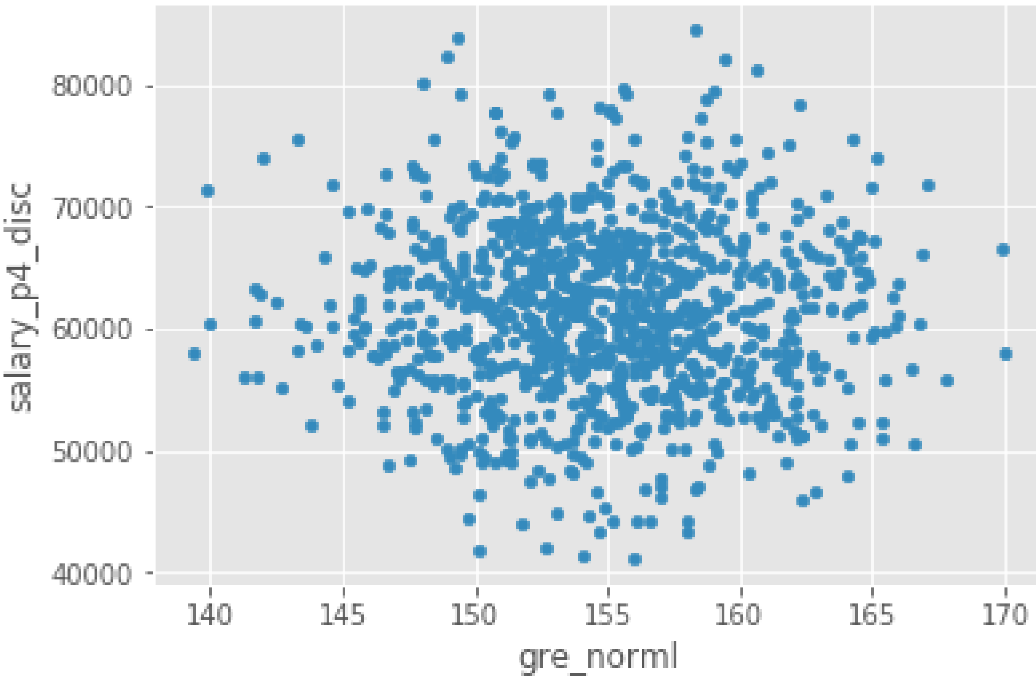
```
In [22]: # Draw the scatterplot again

         plt.figure()
         x = IncomeIntel['grad_year']
         y = IncomeIntel['salary_p4_disc']
```

```
plt.scatter(x = x, y = y)
x_mean = IncomeIntel.groupby('grad_year').mean().index
y_mean = IncomeIntel.groupby('grad_year').mean()['salary_p4_disc']
plt.plot(x_mean, y_mean, 'g-')
plt.xlabel('Graduate Year'); plt.ylabel('Discounted Salary After Four Years')
plt.title('Discounted Salary by Graduation Year')
plt.show()
```



(d) Re-estimate coefficients with updated variables.

```
In [23]: IncomeIntel.plot(x = 'gre_norml', y = 'salary_p4_disc', kind = 'scatter')

Out[23]: <matplotlib.axes._subplots.AxesSubplot at 0x1f664dd3160>
```




```
In [24]: # Train the linear regression model after data transformation
         # Report estimated coefficients and SE

         X_vars = IncomeIntel['gre_norml']
         X_vars = sm.add_constant(X_vars, prepend = False)

         y = IncomeIntel['salary_p4_disc']

         m = sm.OLS(y, X_vars)
         res_3 = m.fit(cov_type = 'HC3')

         print(res_3.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:         salary_p4_disc   R-squared:                       0.001
Model:                            OLS   Adj. R-squared:                 -0.000
Method:                 Least Squares   F-statistic:                    0.6710
Date:                Mon, 15 Oct 2018   Prob (F-statistic):              0.413
Time:                        22:25:17   Log-Likelihood:                -10291.
No. Observations:                1000   AIC:                         2.059e+04
Df Residuals:                     998   BIC:                         2.060e+04
Df Model:                           1
Covariance Type:                  HC3
```

```
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
gre_norml    -34.9747     42.698     -0.819      0.413    -118.660      48.711
const       6.683e+04   6612.635     10.107      0.000    5.39e+04    7.98e+04
==============================================================================
Omnibus:                        0.789   Durbin-Watson:                   2.025
Prob(Omnibus):                  0.674   Jarque-Bera (JB):                0.698
Skew:                           0.060   Prob(JB):                        0.705
Kurtosis:                       3.050   Cond. No.                     4.78e+03
==============================================================================

Warnings:
[1] Standard Errors are heteroscedasticity robust (HC3)
[2] The condition number is large, 4.78e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

The coefficients changed substantially after we coped with data drift and non-stationarity:

$$salary\_4years_i = 66830 - 34.9747 \times gre\_quant_i$$

Compared with the previous model:

$$salary\_4years_i = 89540 - 25.7632 \times gre\_quant_i$$

The estimated effect of gre score has dropped in value (increased in scale), and this aligns with our hypothesis **(gre scores are negatively associated with salaries after four years)**. There are two contradicting factors that cause this change:

- a) The elimination of time trends would make the coefficient less negative, since new gre scores (lower scale) are not systematically assocaited with higher salary (time trend).
- b) By mapping the old gre scores to the new scale, we would expect the marginal effects of gre score be higher, since new gre scores are based on a narrower scale.

Finally, it seems that factor b) dominates the change.

```
In [25]: # Train the linear regression model after data transformation
         # Report estimated coefficients and SE

         X_vars = IncomeIntel['gre_norml']
         X_vars = sm.add_constant(X_vars, prepend = False)

         y = IncomeIntel['salary_p4']

         m = sm.OLS(y, X_vars)
         res_3 = m.fit(cov_type = 'HC3')

         print(res_3.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              salary_p4   R-squared:                       0.000
Model:                            OLS   Adj. R-squared:                 -0.001
Method:                 Least Squares   F-statistic:                   0.06150
Date:                Mon, 15 Oct 2018   Prob (F-statistic):              0.804
Time:                        22:25:19   Log-Likelihood:                -10825.
No. Observations:                1000   AIC:                         2.165e+04
Df Residuals:                     998   BIC:                         2.166e+04
Df Model:                           1
Covariance Type:                  HC3
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
gre_norml    -18.8463     75.996     -0.248      0.804    -167.796     130.103
const       7.709e+04   1.18e+04      6.544      0.000      5.4e+04       1e+05
==============================================================================
Omnibus:                       16.601   Durbin-Watson:                   1.052
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               17.193
Skew:                           0.315   Prob(JB):                     0.000185
Kurtosis:                       2.874   Cond. No.                     4.78e+03
==============================================================================

Warnings:
[1] Standard Errors are heteroscedasticity robust (HC3)
[2] The condition number is large, 4.78e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

1.0.3 3. Assessment of Kossinets and Watts.

See attached PDF.

Question 3

How does homopholy originate within a dynamic social network? This is a broadly reserched question among social science studies. This paper states its question of interest explicitly: **How do individuals' attribute similarity and their structural constraints affect their selection to make or break some ties over others?** After comprehensive and thorough analysis, the authors conclude that pairs with higher extent of similarity do show above-average propensity to form new ties; however, that tie formation is heavily biased by triadic closure and focal closure.

The analysis was proceeded with a novel synthesized dataset. It was constructed by merging three different databases: **(1) the logs of e-mail interactions within the university over one academic year, (2) a database of individual attributes (status, gender, age, department, number of years in the community, etc.), and (3) records of course registration, in which courses were recorded separately for each semester.**

The dataset contains **30,396 selected individuals** (43,553 individuals before data cleansing), **7,156,162 messages exchanged** by these individuals **spanning 270 days of observation**. **The precise definitions of all variables are provided in appendix A**, and a note about missing data appears in appendix B. But basically they can be categorized into four domains: (1) personal characteristics (age, gender, home state, formal status, years in school); (2) organizational affiliations (primary department, school, campus, dormitory, academic field); (3) course-related variables (courses taken, courses taught); (4) and e-mail-related variables (days active, messages sent, messages received, in-degree, out-degree, reciprocated degree). The richness of the dataset enables the researchers to track individuals' social interaction, their structural dynamics, and link these factors to attribute similarities. Also, the variance in variables allows for setting up different models, testing for different contexts, rooting for adequate investigation of intended research subject.

However, the university dataset is inherently exclusive to other social communities, and email logs are insufficiently revealing of one's social ties. I will come back to discuss the data selection later. We may also wonder, is the conclusion reached in the end internally valid, given the data used? **Minor problems in data cleaning process have mitigated the credibility of the article. For example: the sample was finanlly limited to population who have exchanged emails, in other words, individuals who are likely to have or form solid social ties with the community. But it is very important to perform text analysis at this step, since most university email systems encourage the use of automatic or other quick replies, which can deceive the following analysis based on these email-related variables.**

Finally, I would like to urge a deliberate reconsideration of the data selection, that is, is email-log data and their corresponding individual characterisctics compatible with the underlying theoretical construct 'social relationships'? My short answer would be: probably no. **There are two facts that demeans integrity between theoretical construct and empirical analysis: (1) Social engagement read from email exchanges underrepresents one's networks. It is a good expectation members in this university community use university emails quite formally. Informal but solid social interactions are absent for the research. Saying that, information of afiinity extracted from the dataset might be incomplete or even biased. (2) Secondly, social interactions in a university context systematically distinguishes from others. With only university emails studied, extrapolation to other forms of community become questionable.