Assignment_2_HaowenShang

October 16, 2018

1 Assignment 2

1.0.1 MACS 30000, Dr. Evans

1.0.2 Haowen Shang

Due Wednesday, Oct. 17 at 11:30 AM

```
In [1]: # Import packages
        import numpy as np
        import pandas as pd
        import statsmodels.api as sm
        import matplotlib.pyplot as plt
        import math
        plt.style.use('seaborn')

        import warnings
        warnings.filterwarnings('ignore')
```

1.0.3 1. Imputing age and gender

(a) Here is where I will describe my proposed strategy ... and so on and so forth. First, we can use data in "SurveyIncome.txt" and do inear regression to find linear relationship between age, gender, total income and weight. Then, we can use these linear models and data of income and weight from "BestIncome.txt" to impute age and gender variables (total income can be calculated by labor income plus capital income). The linear models are as following:

$$\widehat{age}_i = \widehat{\alpha}_0 + \widehat{\alpha}_1 \cdot totl\_inc_i + \widehat{\alpha}_2 \cdot wgt_i$$

$$P(\widehat{female}_i = 1 \mid totl\_inc_i, wgt_i) = \frac{e^{\widehat{\beta_0} + \widehat{\beta_1} \cdot totl\_inc_i + \widehat{\beta_2} \cdot wgt_i}}{1 + e^{\widehat{\beta_0} + \widehat{\beta_1} \cdot totl\_inc_i + \widehat{\beta_2} \cdot wgt_i}}$$

```
In [2]: # I use the following code cells to read in my data of SurvIncome.txt, name my variabl
        survey_income_raw = "SurvIncome.txt"
        survey = pd.read_table(survey_income_raw, sep=",", header=None)

        survey_cols = [ 'total_inc', 'wgt', 'age', 'female']
        survey.columns = survey_cols
```

In [3]:
```
survey.head()
```

Out[3]:

	total_inc	wgt	age	female
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

In [4]:
```
survey.tail()
```

Out[4]:

	total_inc	wgt	age	female
995	61270.538697	184.930002	46.356881	0.0
996	59039.159876	180.482304	50.986966	0.0
997	67967.188804	156.816883	40.965268	0.0
998	79726.914251	158.935050	41.190371	0.0
999	71005.223603	169.067695	48.480007	0.0

In [5]:
```
survey.describe()
```

Out[5]:

	total_inc	wgt	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

In [6]:
```
# I use the following code cells to read in my data of BestIncome.txt, name my variabl
best_income_raw = "BestIncome.txt"
best = pd.read_table(best_income_raw, sep=",", header=None)

best_cols = [ 'lab_inc', 'cap_inc', 'hgt', 'wgt']
best.columns = best_cols

best['tot_inc'] = best.lab_inc +best.cap_inc
```

In [7]:
```
best.head()
```

Out[7]:

	lab_inc	cap_inc	hgt	wgt	tot_inc
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 [8]:
```
best.tail()
```

```
Out[8]:            lab_inc       cap_inc        hgt         wgt       tot_inc
        9995  51502.225233  14786.050723  66.781187  154.645212  66288.275956
        9996  52624.117104  11048.811747  64.499036  165.868002  63672.928851
        9997  50725.310645  13195.218100  64.508873  154.657639  63920.528745
        9998  56392.824076   8470.592718  62.161556  145.498194  64863.416794
        9999  44274.098164  12765.748454  64.974145  135.936862  57039.846618
```

```
In [9]: best.describe()
```

```
Out[9]:             lab_inc       cap_inc           hgt           wgt       tot_inc
        count  10000.000000  10000.000000  10000.000000  10000.000000  10000.000000
        mean   57052.925133   9985.798563     65.014021    150.006011  67038.723697
        std     8036.544363   2010.123691      1.999692      9.973001   8294.497996
        min    22917.607900   1495.191896     58.176154    114.510700  33651.691815
        25%    51624.339880   8611.756679     63.652971    143.341979  61452.517672
        50%    56968.709935   9969.840117     65.003557    149.947641  67042.751487
        75%    62408.232277  11339.905773     66.356915    156.724586  72636.874684
        max    90059.898537  19882.320069     72.802277    185.408280  98996.053756
```

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

```
In [10]: # I will use the following code cells to execute the code that will impute those vari
         outcome = 'age'
         features =  ['total_inc', 'wgt']
         X, y = survey[features], survey[outcome]
         X = sm.add_constant(X, prepend=False)

         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:                        18:46:15   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_inc    2.52e-05   2.26e-05      1.114      0.266   -1.92e-05    6.96e-05
wgt           -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 [11]: ols_survey = pd.concat([y, X], axis=1)
         ols_survey.head()
```

Out[11]:

	age	total_inc	wgt	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 [12]: ols_survey['agehat'] = res.predict(X)
         ols_survey.head()
```

Out[12]:

	age	total_inc	wgt	const	agehat
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 [13]: outcome = 'female'
         features =  ['total_inc', 'wgt']
         X, y = survey[features], survey[outcome]
         X = sm.add_constant(X, prepend=False)

         m = sm.Logit(y, X)
         res = m.fit()
         print(res.summary())
```

```
Optimization terminated successfully.
         Current function value: 0.036050
         Iterations 11
                           Logit Regression Results
==============================================================================
Dep. Variable:                 female   No. Observations:                 1000
Model:                          Logit   Df Residuals:                      997
```

```
Method:                           MLE   Df Model:                            2
Date:                Tue, 16 Oct 2018   Pseudo R-squ.:                  0.9480
Time:                        18:46:17   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_inc     -0.0002   4.25e-05     -3.660      0.000      -0.000   -7.22e-05
wgt           -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.
```

In [14]:
```python
logit_survey = pd.concat([y, X], axis=1)
logit_survey.head()
```

Out[14]:

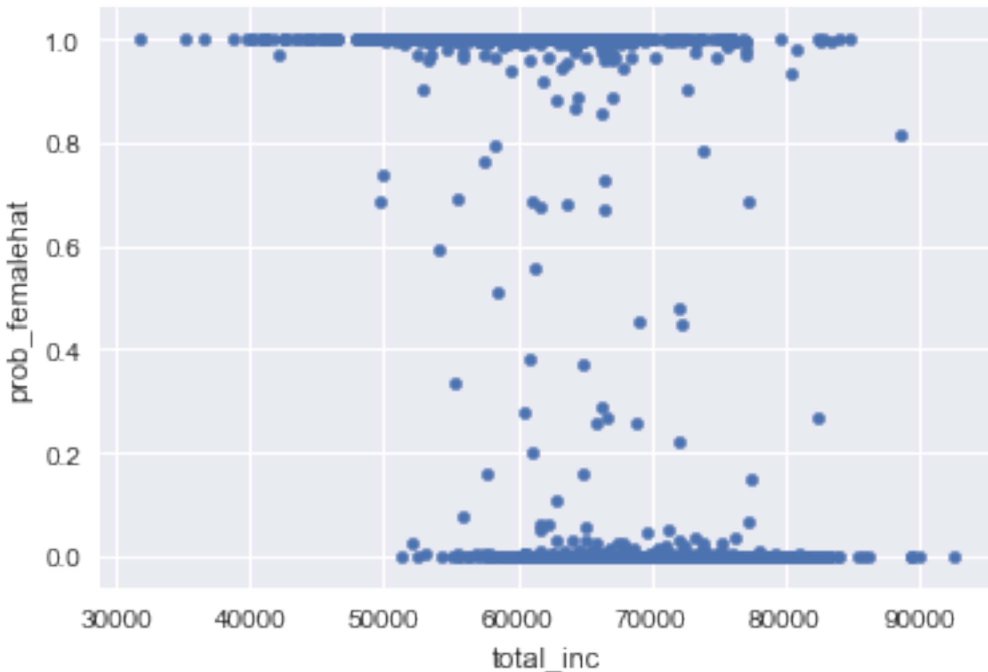
	female	total_inc	wgt	const
0	1.0	63642.513655	134.998269	1.0
1	1.0	49177.380692	134.392957	1.0
2	1.0	67833.339128	126.482992	1.0
3	1.0	62962.266217	128.038121	1.0
4	1.0	58716.952597	126.211980	1.0

In [15]:
```python
logit_survey['prob_femalehat'] = res.predict(X)
logit_survey.head()
```

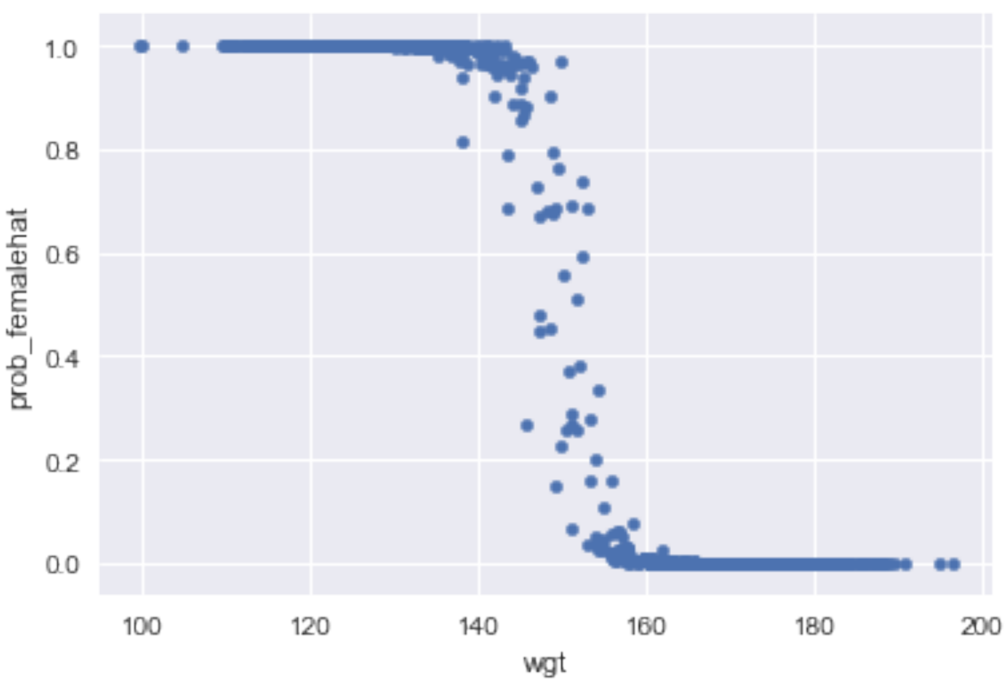
Out[15]:

	female	total_inc	wgt	const	prob_femalehat
0	1.0	63642.513655	134.998269	1.0	0.998746
1	1.0	49177.380692	134.392957	1.0	0.999899
2	1.0	67833.339128	126.482992	1.0	0.999946
3	1.0	62962.266217	128.038121	1.0	0.999949
4	1.0	58716.952597	126.211980	1.0	0.999988

In [16]:
```python
probability_of_being_female = logit_survey['prob_femalehat']
total_income = logit_survey['total_inc']
logit_survey.plot(x='total_inc', y='prob_femalehat', kind='scatter')
plt.show()
```



In [17]:
```
probability_of_being_female = logit_survey['prob_femalehat']
weight = logit_survey['wgt']
logit_survey.plot(x='wgt', y='prob_femalehat', kind='scatter')
plt.show()
```



```
In [18]: def prob_female(gender):
             '''
             fuction to convert probability to dummy variable
             '''
             if gender > 0.5:
                 gender = 1
             else:
                 gender = 0
             return gender

         logit_survey['femalehat'] = logit_survey.prob_femalehat.apply(prob_female)
         logit_survey.head()
```

Out[18]:

	female	total_inc	wgt	const	prob_femalehat	femalehat
0	1.0	63642.513655	134.998269	1.0	0.998746	1
1	1.0	49177.380692	134.392957	1.0	0.999899	1
2	1.0	67833.339128	126.482992	1.0	0.999946	1
3	1.0	62962.266217	128.038121	1.0	0.999949	1
4	1.0	58716.952597	126.211980	1.0	0.999988	1

```
In [19]: # I will use the following code cells to execute the code that will impute those vari

         best['imputed_age_by_inc_wgt'] = 44.2097 + 2.52e-05*best.tot_inc \
                                             + (-0.0067)*best.wgt
         e = math.exp(1)
         best['imputed_probfemale_by_inc_wgt'] = e**(76.7929+(-0.0002)*best.tot_inc+\
          (-0.4460)*best.wgt)/(1+e**(76.7929+(-0.0002)*best.tot_inc+(-0.4460)*best.wgt))
         best['imputed_female_by_inc_wgt'] = best.imputed_probfemale_by_inc_wgt.\
                                                             apply(prob_female)

         best.head()
```

Out[19]:

	lab_inc	cap_inc	hgt	wgt	tot_inc	\
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_by_inc_wgt	imputed_probfemale_by_inc_wgt	\
0	44.745897	0.021951	
1	45.157777	0.000031	
2	44.745701	0.026951	
3	44.919024	0.034805	
4	44.554687	0.101359	

```
   imputed_female_by_inc_wgt
0                          0
1                          0
2                          0
3                          0
4                          0
```

In [20]:
```
best.tail()
```

Out[20]:
```
            lab_inc       cap_inc        hgt         wgt       tot_inc  \
9995  51502.225233  14786.050723  66.781187  154.645212  66288.275956
9996  52624.117104  11048.811747  64.499036  165.868002  63672.928851
9997  50725.310645  13195.218100  64.508873  154.657639  63920.528745
9998  56392.824076   8470.592718  62.161556  145.498194  64863.416794
9999  44274.098164  12765.748454  64.974145  135.936862  57039.846618

      imputed_age_by_inc_wgt  imputed_probfemale_by_inc_wgt  \
9995               44.844042                       0.004336
9996               44.702942                       0.000049
9997               44.784291                       0.006905
9998               44.869420                       0.255027
9999               44.736327                       0.991483

      imputed_female_by_inc_wgt
9995                          0
9996                          0
9997                          0
9998                          0
9999                          1
```

In [21]:
```
BestIncome = best[['lab_inc', 'cap_inc', 'hgt','wgt', 'imputed_age_by_inc_wgt', \
                   'imputed_female_by_inc_wgt']]
BestIncome.head()
```

Out[21]:
```
         lab_inc       cap_inc        hgt         wgt  imputed_age_by_inc_wgt  \
0   52655.605507   9279.509829  64.568138  152.920634               44.745897
1   70586.979225   9451.016902  65.727648  159.534414               45.157777
2   53738.008339   8078.132315  66.268796  152.502405               44.745701
3   55128.180903  12692.670403  62.910559  149.218189               44.919024
4   44482.794867   9812.975746  68.678295  152.726358               44.554687

   imputed_female_by_inc_wgt
0                          0
1                          0
2                          0
3                          0
4                          0
```

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

In [22]:
```
# I will use the following code cells to do so!
BestIncome['imputed_age_by_inc_wgt'].describe()
```

Out[22]:
```
count    10000.000000
mean        44.894036
std          0.219066
min         43.980016
25%         44.747065
50%         44.890281
75%         45.042239
max         45.706849
Name: imputed_age_by_inc_wgt, dtype: float64
```

For imputed age (age_i) variable: The mean is 44.894036, the standard deviation is 0.219066, the minimum is 43.980016, the maximum is 45.706849 and number of observations is 10000.

In [23]:
```
BestIncome['imputed_female_by_inc_wgt'].describe()
```

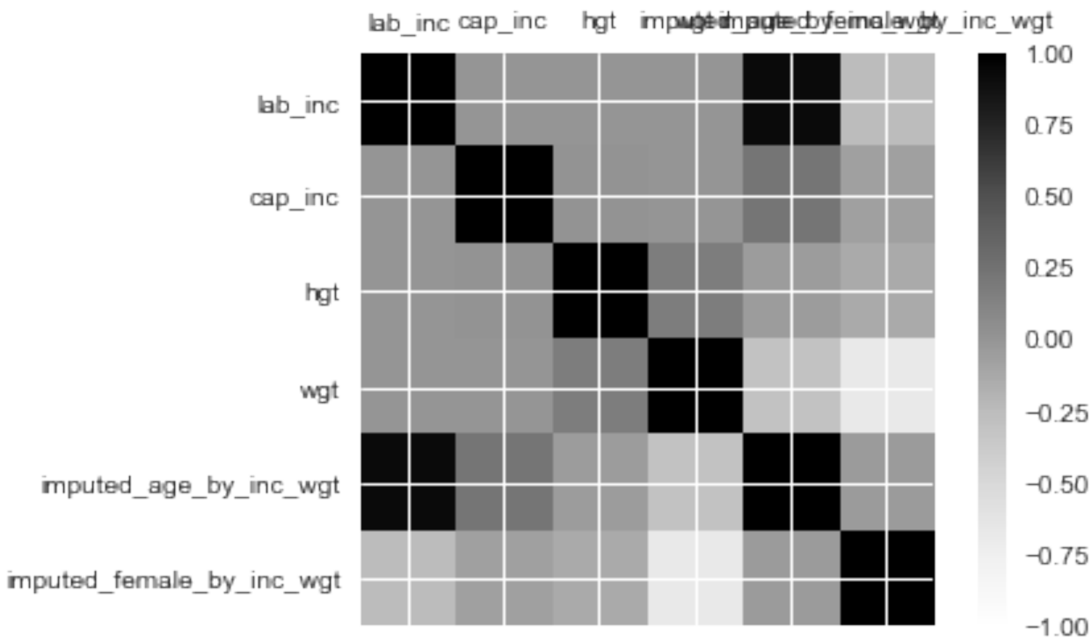
Out[23]:
```
count    10000.000000
mean         0.229400
std          0.420468
min          0.000000
25%          0.000000
50%          0.000000
75%          0.000000
max          1.000000
Name: imputed_female_by_inc_wgt, dtype: float64
```

For imputed gender ($female_i$) variable: The mean is 0.229400, the standard deviation is 0.420468, the minimum is 0, the maximum is 1 and number of observations is 10000.

(d) Correlation matrix for the now six variables

In [24]:
```
# Correlation matrix code and output
def corr_plot(BestIncome):
    names = BestIncome.columns
    N = len(names)

    correlations = BestIncome.corr()
    fig = plt.figure()
    ax = fig.add_subplot(111)
    cax = ax.matshow(correlations, vmin=-1, vmax=1)
    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.show()

corr_plot(BestIncome)
```



In [25]:
```
#In Matrix Form
corr = BestIncome.corr()
corr.style.background_gradient()
```

Out[25]:
```
<pandas.io.formats.style.Styler at 0x1c1efd50f0>
```

1.0.4 2. Stationarity and data drift

(a) Estimate by OLS and report coefficients

In [26]:
```
# Read in my third data set
income_intel_raw =  "IncomeIntel.txt"
income = pd.read_table(income_intel_raw, sep=",", header=None)

# Name my variables
income_cols = [ 'grad_year', 'gre_qnt', 'salary_p4']
income.columns = income_cols
income.head()
```

Out[26]:
```
   grad_year     gre_qnt     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
```

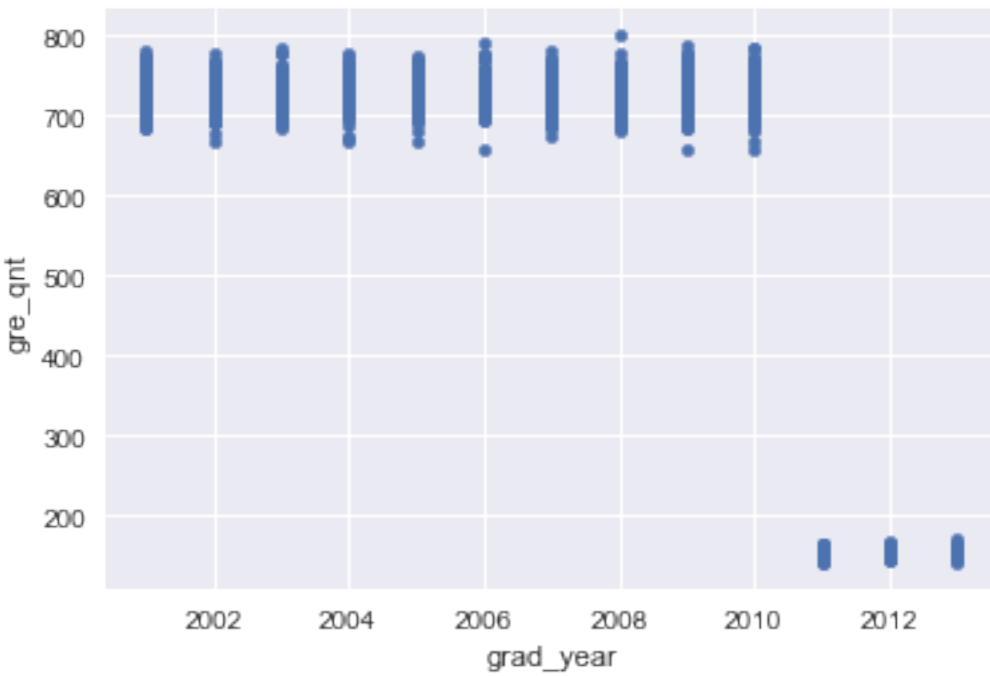
In [27]:
```python
# Run regression model
outcome = ['salary_p4']
features =  ['gre_qnt']
X, y = income[features], income[outcome]

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

m = sm.OLS(y, X)
res = m.fit()
print(res.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              salary_p4   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:                        18:46:30   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.
```

#Report coefficients and SE's Estimated coefficient β_0 is 8.954e+04, standard errors of β_0 is 878.764, estimated coefficient β_1 is (-25.7632) , standard errors of β_1 is 1.365.

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

```
In [28]: # Code and output of scatterplot
         grad_year = income['grad_year']
         gre_qnt = income['gre_qnt']
         income.plot(x='grad_year', y='gre_qnt', kind='scatter')
         plt.show()
```



Here is where I'll discuss any problems that jump out. I'll propose a solution here as well.

Problems: Compared data before 2011 and data after 2011, we can see that the GRE quatitative score changed a lot. In other words, the data of GRE quantitative score are drifting because scoring scale changed in 2011. Because the data of GRE quatitative score are not stationary, it can cause problems when using the ordinary least squares regression model and thus the estimated coefficients are not reliable.

Solution: We know that the GRE quantitative scoring scale is 800 before 2011 and is 170 after 2011, so we can change the data scale after 2011, which means changing the raw score in scale 170 to relative score in scale of 800 using equation (relative_score=raw_score*800/170). In this way, the the GRE quantitative scoring scale is same before 2011 and after 2011.

```
In [29]: # Code to implement solution
         income_aft2011 = income[income.grad_year >= 2011]
         income_aft2011.head()
```

Out[29]:

	grad_year	gre_qnt	salary_p4
770	2011.0	148.413532	90834.606478
771	2011.0	154.123690	87255.408421

```
772     2011.0  155.493697  76069.366122
773     2011.0  152.551097  92160.481069
774     2011.0  156.142446  78490.139535
```

In [30]:
```
income_aft2011['gre_qnt'].describe()
```

Out[30]:
```
count    230.000000
mean     154.894160
std        5.197198
min      141.261398
25%      151.293028
50%      154.626456
75%      158.185442
max      170.000000
Name: gre_qnt, dtype: float64
```

In [31]:
```
def gre_qnt_modified(gre_qnt):
    """
    function to convert GRE quantitative raw score to relative score.
    """
    gre_qnt_modified = (gre_qnt*800)/170
    return gre_qnt_modified

income_aft2011['gre_qnt_modified'] = income_aft2011.gre_qnt.apply(gre_qnt_modified)
income_aft2011.head()
```

Out[31]:

	grad_year	gre_qnt	salary_p4	gre_qnt_modified
770	2011.0	148.413532	90834.606478	698.416619
771	2011.0	154.123690	87255.408421	725.287951
772	2011.0	155.493697	76069.366122	731.735044
773	2011.0	152.551097	92160.481069	717.887515
774	2011.0	156.142446	78490.139535	734.787980

In [32]:
```
income_aft2011['gre_qnt_modified'].describe()
```

Out[32]:
```
count    230.000000
mean     728.913694
std       24.457401
min      664.759519
25%      711.967192
50%      727.653911
75%      744.402079
max      800.000000
Name: gre_qnt_modified, dtype: float64
```

In [33]:
```
income_bf2011 = income[income.grad_year < 2011]
income_bf2011.head()
```

Out[33]:

	grad_year	gre_qnt	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 [34]:
```
income_bf2011['gre_qnt'].describe()
```

Out[34]:
```
count    770.000000
mean     728.421378
std       23.377864
min      655.702537
25%      712.768894
50%      727.992935
75%      744.340352
max      799.715533
Name: gre_qnt, dtype: float64
```

In [35]:
```
income_bf2011['gre_qnt_modified'] = income_bf2011.gre_qnt
income_bf2011.head()
```

Out[35]:
```
   grad_year     gre_qnt     salary_p4  gre_qnt_modified
0     2001.0  739.737072  67400.475185        739.737072
1     2001.0  721.811673  67600.584142        721.811673
2     2001.0  736.277908  58704.880589        736.277908
3     2001.0  770.498485  64707.290345        770.498485
4     2001.0  735.002861  51737.324165        735.002861
```

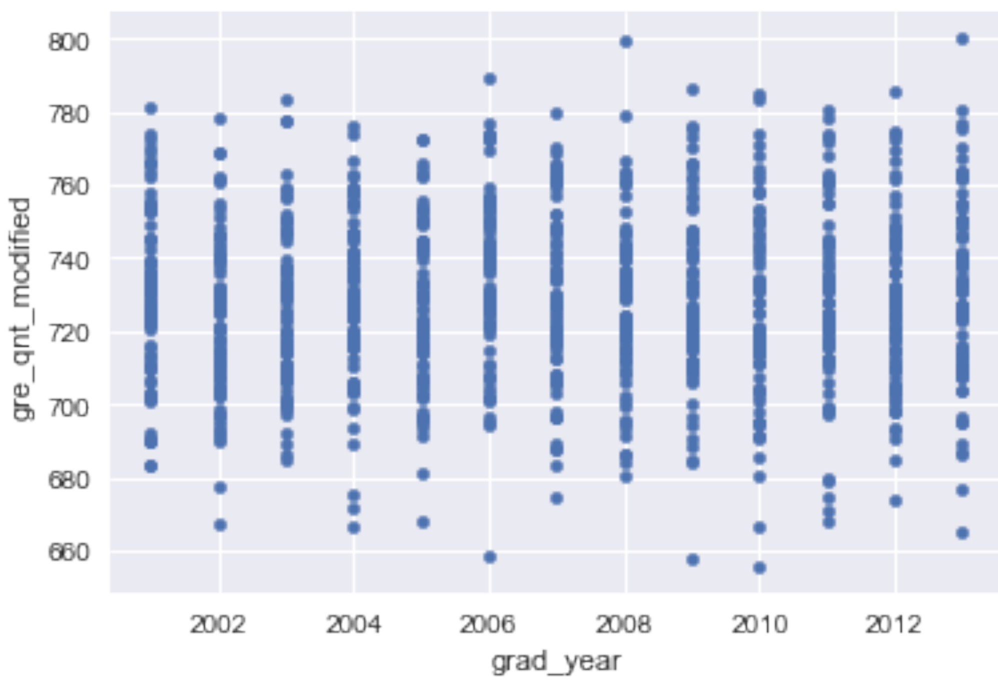
In [36]:
```
frames = [income_bf2011, income_aft2011]
income_mod =  pd.concat(frames)

income_mod.head()
```

Out[36]:
```
   grad_year     gre_qnt     salary_p4  gre_qnt_modified
0     2001.0  739.737072  67400.475185        739.737072
1     2001.0  721.811673  67600.584142        721.811673
2     2001.0  736.277908  58704.880589        736.277908
3     2001.0  770.498485  64707.290345        770.498485
4     2001.0  735.002861  51737.324165        735.002861
```

In [37]:
```
income_mod.tail()
```

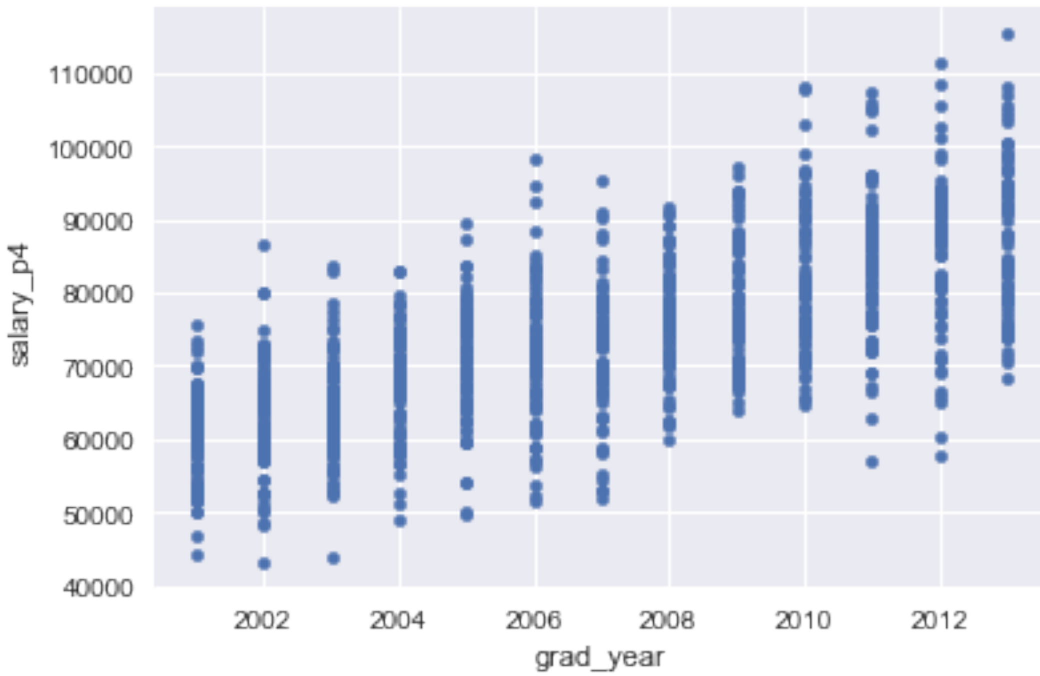
Out[37]:
```
     grad_year     gre_qnt      salary_p4  gre_qnt_modified
995     2013.0  160.441025  100430.166532        755.016586
996     2013.0  160.431891   82198.200872        754.973607
997     2013.0  154.254526   84340.214218        725.903653
998     2013.0  162.036321   87600.881985        762.523863
999     2013.0  156.946735   82854.576903        738.572869
```

In [38]:
```
grad_year = income_mod['grad_year']
gre_qnt = income_mod['gre_qnt_modified']
income_mod.plot(x='grad_year', y='gre_qnt_modified', kind='scatter')
plt.show()
```



(c) Create a scatterplot of income and graduation year

```
In [39]: # Code and output of scatterplot
         grad_year = income['grad_year']
         salary = income['salary_p4']
         income.plot(x='grad_year', y='salary_p4', kind='scatter')
         plt.show()
```



Here is where I'll discuss any problems again ... and propose another solution.

Problems: The scatter plot above shows that the data of income 4 years after graduation are not stationary. There is a increasing trend that the mean of salary_p4 in each year increases along with the grad_year variable.

Solution:To address this problem, we need to do some linear modification of salary_p4 data. In particular, I will calculate the average salary for each graduation year, and use the following equation to standardize the salary for each year(use 2001 as the base year):

$$salary\_modified = \frac{salary\_p4}{(1 + avg\_growth\_rate)^{grad\_year - 2001}}$$

In [40]:
```
#  Code to implement a solution
#Calculate the mean salary each year
avg_inc_by_year = income['salary_p4'].groupby(income['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()
```

In [41]:
```
#Divide each salary by (1 + avg_growth_rate) ** (grad_year - 2001)
income_mod['salary_modified'] =  income['salary_p4']/\
((1 + avg_growth_rate) ** (income['grad_year'] - 2001))
income_mod.head()
```

Out[41]:

	grad_year	gre_qnt	salary_p4	gre_qnt_modified	salary_modified
0	2001.0	739.737072	67400.475185	739.737072	67400.475185

```
1     2001.0  721.811673  67600.584142        721.811673     67600.584142
2     2001.0  736.277908  58704.880589        736.277908     58704.880589
3     2001.0  770.498485  64707.290345        770.498485     64707.290345
4     2001.0  735.002861  51737.324165        735.002861     51737.324165
```

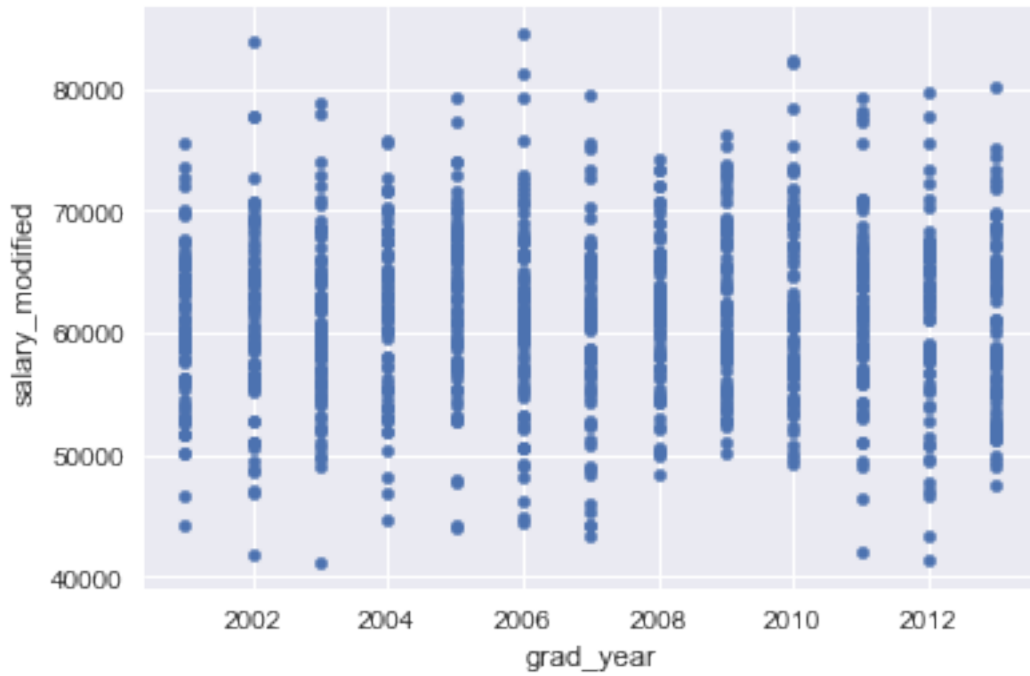
In [42]: income_mod.tail()

```
Out[42]:      grad_year     gre_qnt      salary_p4  gre_qnt_modified  salary_modified
         995     2013.0  160.441025  100430.166532        755.016586     69757.765226
         996     2013.0  160.431891   82198.200872        754.973607     57094.028581
         997     2013.0  154.254526   84340.214218        725.903653     58581.849117
         998     2013.0  162.036321   87600.881985        762.523863     60846.675557
         999     2013.0  156.946735   82854.576903        738.572869     57549.940651
```

In [43]: income_mod.describe()

```
Out[43]:          grad_year      gre_qnt      salary_p4  gre_qnt_modified  \
         count  1000.000000  1000.000000    1000.000000       1000.000000
         mean   2006.994000   596.510118   74173.293777        728.534611
         std       3.740582   242.361960   12173.767372         23.619014
         min    2001.000000   141.261398   43179.183141        655.702537
         25%    2004.000000   684.983551   65778.240317        712.274822
         50%    2007.000000   719.106878   73674.204810        727.910127
         75%    2010.000000   739.332537   81838.874129        744.392487
         max    2013.000000   799.715533  115367.665815        800.000000

                salary_modified
         count      1000.000000
         mean      61419.808910
         std        7135.610865
         min       41164.726530
         25%       56616.517414
         50%       61467.616002
         75%       66218.595876
         max       84516.856633
```

```
In [44]: grad_year = income_mod['grad_year']
         logsalary = income_mod['salary_modified']
         income_mod.plot(x='grad_year', y='salary_modified', kind='scatter')
         plt.show()
```



(d) Re-estimate coefficients with updated variables.

```
In [45]: # Code to re-estimate, output of new coefficients
         outcome = ['salary_modified']
         features =  ['gre_qnt_modified']
         X, y = income_mod[features], income_mod[outcome]
         X = sm.add_constant(X, prepend=False)

         m = sm.OLS(y, X)
         res = m.fit()
         print(res.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:        salary_modified   R-squared:                       0.001
Model:                            OLS   Adj. R-squared:                 -0.000
Method:                 Least Squares   F-statistic:                    0.6043
Date:                Tue, 16 Oct 2018   Prob (F-statistic):              0.437
Time:                        18:46:45   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]
```

```
------------------------------------------------------------------------------------
gre_qnt_modified    -7.4321      9.560     -0.777      0.437     -26.193      11.329
const             6.683e+04   6968.684      9.591      0.000    5.32e+04    8.05e+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.                     2.25e+04
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.25e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Here is where I'll discuss how the coefficients differ, where I'll interpret why the changes result in new coefficient changes, and where I'll discuss what this suggests about the answer to the question.

Estimated coefficient β_0 is 6.683e+04, standard errors of β_0 is 6968.684, estimated coefficient β_1 is (-7.4321) , standard errors of β_1 is 9.560.

The estimated coefficient β_0 is still near zero, and the standard error of β_0 increases by 8 times. The absolute value of coefficient β_1 is just 30% of the previous one because we changed the scale of part of gre_qnt data(increase the scale of data after 2011) and we eliminated potential time trend in the salary_p4 data. The standard errors of β_1 increased by 7 times. Compared to previous OLS results, we find that β_1 is less negative and isn't statistically significant, which is much more reliable than previous significant result.

The p-value is large and the coefficient β_1 is not statistically significant, so the OLS regression result gives no evidence that higher intelligence is associated with higher income.

1.0.5 3. Assessment of Kossinets and Watts.

Please see attached PDF.

Assessment of Kossinets and Watts (2009)

The fundamental question the paper is trying to answer is "What are the mechanisms of homophily emergent over time based on the decisions of individuals to make and break ties?"

In order to answer this question, the author did the analysis based on the population of 30,396 undergraduate and graduate students, faculty, and staff in a large U.S. university, who used their university e-mail accounts to both send and receive messages during one academic year. The data set comprised 7,156,162 messages exchanged by 30,396 stable e-mail users during 270 days of observation. The sources of the data set are **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. In the analysis, the number of observations are **30396** for personal characteristics, organizational affiliations, and course-related variables; the number of observations are **7,156,162** for email messages; and the time period of the data is **270 days**. The author listed the description and definition of all the variables in '**APPENDIX A**'.

However, I find a potential problem in the data cleaning process, which is that only e-mail accounts on the central university server were included in the data set. But in fact, a number of individuals also used accounts provided by their departments, such as xyz@department.university.edu (mostly the faculty and graduate students in departments such as computer science, mathematics, and physics). The departments of computer science, mathematics, and physics provide basic courses which most students would be involved in, so people who use e-mail accounts provided by departments have extensive interaction with other people. Excluding these data will lose some information and sources of homophily.

Besides the data cleaning process, there is also one weakness of matching theory variable to data variable. In particular, in this paper, theory variable is "social relationships" and data variable is e-mail logs linked to other characteristics of the senders and receivers. In order to understand how homophily emerges over time as a function of the decisions of individuals to make and break ties, the author focus highly on the formation of new ties. One kind of tie formation mechanisms is 'focal closure', which is defined as the various groups, contexts, and activities around which social life is organized and which in turn facilitate interpersonal interactions. When matching the 'focal closure' to the data set, the author is supposed to have a record of all possible focal activities, including classes, social groups, sporting and cultural organizations, shared housing, and so forth—so that he could study separately their effects on social interactions over time. However, the data set can just provide classes administered by the university registrar as explicit foci, which are certainly not the only foci of interaction. The author overcome this practical obstacle in part by mining the available data in more creative ways. Specifically, he makes use of the "bulk" messages which are defined as having more than one recipient and are used to infer the presence of shared groups and activities that were not otherwise recorded in the data set. The author treats bulk messages as indicators of social foci, defined broadly as any kind of shared affiliation, group, or activity that generates a demand for group-oriented communication. In this way, there is a much better match between focal closure and the dataset.