Assignment_2_Solution

October 17, 2018

1 Assignment 2

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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 matplotlib.pyplot as plt
        # plt.style.use('seaborn')
        import seaborn as sns

        #Turn of Notebook Package Warnings
        import warnings
        warnings.filterwarnings('ignore')
```

1.0.3 1. Imputing age and gender

(a) Proposed solution For the age, I will use variables total income and weight in SurveyIncome.txt to fit a linear regression model. Then, I will use weight and the sum of labor income and capital income in BestIncome.txt to predict age into the BestIncome.txt.

$$age = \beta_0 + \beta_1 \times totinc + \beta_2 \times wgt + \epsilon$$

For the gender, I will use variables total income and weight in SurveyIncome.txt to fit a logit model. Then, I will use weight and the sum of labor income and capital income in BestIncome.txt to predict age into the BestIncome.txt.

$$logit(female) = \beta_0 + \beta_1 \times totinc + \beta_2 \times wgt + \epsilon$$

To calculate the sum of labor income and capital income, I will use the following equation:

```
In [2]: # read in my data of BestIncome.txt
        BestIncome = pd.read_csv("BestIncome.txt", header=None)
        BestIncome.head()
```

Out[2]:

	0	1	2	3
0	52655.605507	9279.509829	64.568138	152.920634
1	70586.979225	9451.016902	65.727648	159.534414
2	53738.008339	8078.132315	66.268796	152.502405
3	55128.180903	12692.670403	62.910559	149.218189
4	44482.794867	9812.975746	68.678295	152.726358

In [3]:
```
# name my variables of BestIncome.txt
BestIncome_cols = ['lab_inc','cap_inc','hgt','wgt']
BestIncome.columns = BestIncome_cols
BestIncome.head()
```

Out[3]:

	lab_inc	cap_inc	hgt	wgt
0	52655.605507	9279.509829	64.568138	152.920634
1	70586.979225	9451.016902	65.727648	159.534414
2	53738.008339	8078.132315	66.268796	152.502405
3	55128.180903	12692.670403	62.910559	149.218189
4	44482.794867	9812.975746	68.678295	152.726358

In [4]:
```
# run descriptive statistics of BestIncome.txt
BestIncome.describe()
```

Out[4]:

	lab_inc	cap_inc	hgt	wgt
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 [5]:
```
# read in my data of SurveyIncome.txt
SurveyIncome = pd.read_csv("SurveyIncome.txt", header=None)
SurveyIncome.head()
```

Out[5]:

	0	1	2	3
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 [6]:
```
# name my variables of SurveyIncome.txt
SurveyIncome_cols = ['tot_inc','wgt','age','female']
SurveyIncome.columns = SurveyIncome_cols
SurveyIncome.head()
```

Out[6]:

	tot_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 [7]: # run descriptive statistics of SurveyIncome.txt
        SurveyIncome.describe()
```

```
Out[7]:            tot_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
```

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

```
In [8]: # Define Outcome and Independent Variables
        outcome = 'age'
        features = ['tot_inc','wgt']

        X,y = SurveyIncome[features], SurveyIncome[outcome]
```

```
In [9]: X.head()
```

```
Out[9]:         tot_inc         wgt
        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 [10]: y.head()
```

```
Out[10]: 0    46.610021
         1    48.791349
         2    48.429894
         3    41.543926
         4    41.201245
         Name: age, dtype: float64
```

```
In [11]: # run regression

         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:                Wed, 17 Oct 2018   Prob (F-statistic):              0.531
Time:                        10:55:26   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]
------------------------------------------------------------------------------
tot_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.
```

I obtained the following linear regression equation:

$$age = 44.2097 + 0.0000252 totinc - 0.0067 wgt$$

Then, I will predict age in BestIncome.txt:

```
In [12]: # get total income by adding labor income and capital income toghether
         BestIncome['tot_inc'] = BestIncome['lab_inc'] + BestIncome['cap_inc']
```

```
In [13]: # predit age
         X = BestIncome[features]
         X = sm.add_constant(X, prepend = False)
         BestIncome['age'] = res.predict(X)
         BestIncome.head()
```

Out[13]:

	lab_inc	cap_inc	hgt	wgt	tot_inc	age
0	52655.605507	9279.509829	64.568138	152.920634	61935.115336	44.742614
1	70586.979225	9451.016902	65.727648	159.534414	80037.996127	45.154387
2	53738.008339	8078.132315	66.268796	152.502405	61816.140654	44.742427
3	55128.180903	12692.670403	62.910559	149.218189	67820.851305	44.915836
4	44482.794867	9812.975746	68.678295	152.726358	54295.770612	44.551391

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

In [14]:
```
# Define Outcome and Independent Variables
outcome = 'female'
features = ['tot_inc','wgt']

X,y = SurveyIncome[features], SurveyIncome[outcome]
```

In [15]:
```
X.head()
```

Out[15]:

	tot_inc	wgt
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 [16]:
```
y.head()
```

Out[16]:
```
0    1.0
1    1.0
2    1.0
3    1.0
4    1.0
Name: female, dtype: float64
```

In [17]:
```
# run regression

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:                Wed, 17 Oct 2018   Pseudo R-squ.:                  0.9480
Time:                        10:55:26   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]
------------------------------------------------------------------------------
tot_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.
```

I obtained the following logit regression equation:

$$logit(female) = 76.7929 - 0.0002 \times totinc - 0.4460 \times wgt$$

Then, I will predict gender in BestIncome.txt:

```
In [18]: # predict gender
         X = BestIncome[features]
         X = sm.add_constant(X, prepend = False)
         BestIncome['gender'] = res.predict(X)
         BestIncome['gender'][BestIncome['gender'] >= 0.5] = 1
         BestIncome['gender'][BestIncome['gender'] < 0.5] = 0
         BestIncome.head()
```

```
Out[18]:         lab_inc       cap_inc        hgt         wgt        tot_inc        age  \
         0  52655.605507   9279.509829  64.568138  152.920634  61935.115336  44.742614
         1  70586.979225   9451.016902  65.727648  159.534414  80037.996127  45.154387
         2  53738.008339   8078.132315  66.268796  152.502405  61816.140654  44.742427
         3  55128.180903  12692.670403  62.910559  149.218189  67820.851305  44.915836
         4  44482.794867   9812.975746  68.678295  152.726358  54295.770612  44.551391

            gender
         0     0.0
         1     0.0
         2     0.0
         3     0.0
         4     1.0
```

```
In [19]: # drop total income in BestIncome.txt and obtain the final result
         BestIncome = BestIncome.drop(columns = "tot_inc")
         BestIncome.head()
```

```
Out[19]:         lab_inc       cap_inc        hgt         wgt        age  gender
         0  52655.605507   9279.509829  64.568138  152.920634  44.742614     0.0
         1  70586.979225   9451.016902  65.727648  159.534414  45.154387     0.0
         2  53738.008339   8078.132315  66.268796  152.502405  44.742427     0.0
         3  55128.180903  12692.670403  62.910559  149.218189  44.915836     0.0
         4  44482.794867   9812.975746  68.678295  152.726358  44.551391     1.0
```

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

```
In [20]: # select age and gender from BestIncome.txt
         Imputed = BestIncome[['age', 'gender']]
         Imputed.head()
```

```
Out[20]:          age  gender
         0  44.742614     0.0
         1  45.154387     0.0
         2  44.742427     0.0
         3  44.915836     0.0
         4  44.551391     1.0
```

```
In [21]: # descriptive statistics of imputed variables
         Imputed.describe()
```

```
Out[21]:                 age        gender
         count  10000.000000  10000.000000
         mean      44.890828      0.454600
         std        0.219150      0.497959
         min       43.976495      0.000000
         25%       44.743776      0.000000
         50%       44.886944      0.000000
         75%       45.038991      1.000000
         max       45.703819      1.000000
```

(d) Correlation matrix for the now six variables

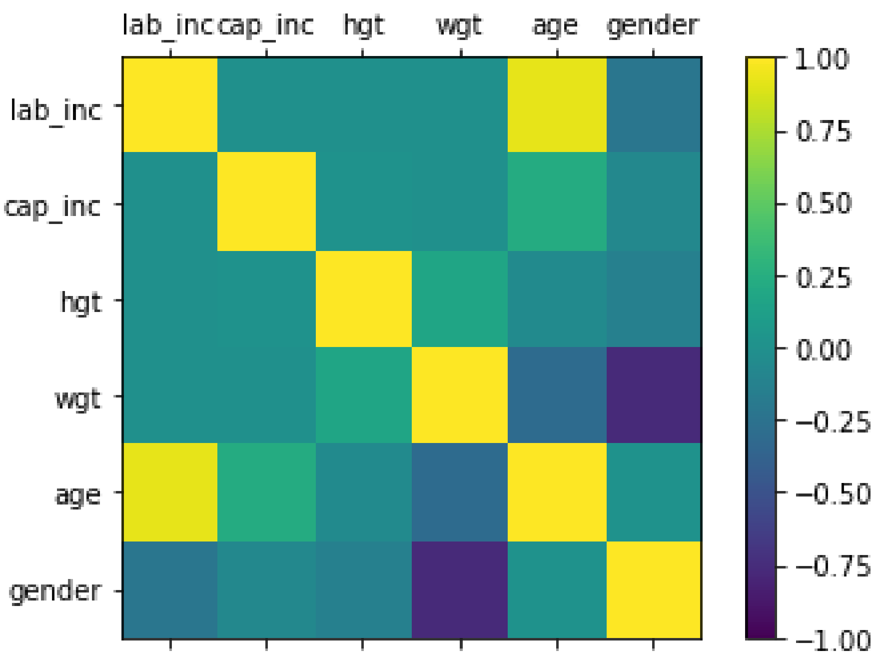
```
In [22]: # Correlation Matrix Plot

         def corr_plot(df):
             names = df.columns
             N = len(names)

             correlations = df.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 [23]:
```
# In Matrix Form
corr = BestIncome.corr()
corr.style.background_gradient()
corr
```

Out[23]:

	lab_inc	cap_inc	hgt	wgt	age	gender
lab_inc	1.000000	0.005325	0.002790	0.004507	0.924053	-0.215469
cap_inc	0.005325	1.000000	0.021572	0.006299	0.234159	-0.062569
hgt	0.002790	0.021572	1.000000	0.172103	-0.045083	-0.127416
wgt	0.004507	0.006299	0.172103	1.000000	-0.300288	-0.763821
age	0.924053	0.234159	-0.045083	-0.300288	1.000000	0.020059
gender	-0.215469	-0.062569	-0.127416	-0.763821	0.020059	1.000000

1.0.4 2. Stationarity and data drift

(a) Estimate by OLS and report coefficients

In [24]:
```
# Read in my third data set
IncomeIntel = pd.read_csv('IncomeIntel.txt', header=None)
```

In [25]:
```python
# Name my variables
IncomeIntel_col = ['grad_year','gre_qnt','salary_p4']
IncomeIntel.columns = IncomeIntel_col
IncomeIntel.head()
```

Out[25]:

	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 [26]:
```python
# Run regression model
outcome = 'salary_p4'
features = ['gre_qnt']

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

In [27]:
```python
X.head()
```

Out[27]:

	gre_qnt
0	739.737072
1	721.811673
2	736.277908
3	770.498485
4	735.002861

In [28]:
```python
y.head()
```

Out[28]:
```
0    67400.475185
1    67600.584142
2    58704.880589
3    64707.290345
4    51737.324165
Name: salary_p4, dtype: float64
```

In [29]:
```python
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:                Wed, 17 Oct 2018   Prob (F-statistic):           3.43e-68
Time:                        10:55:28   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
I obtained the following OLS regression equation:

$$salaryp4 = 89540 - 25.7632 greqnt$$

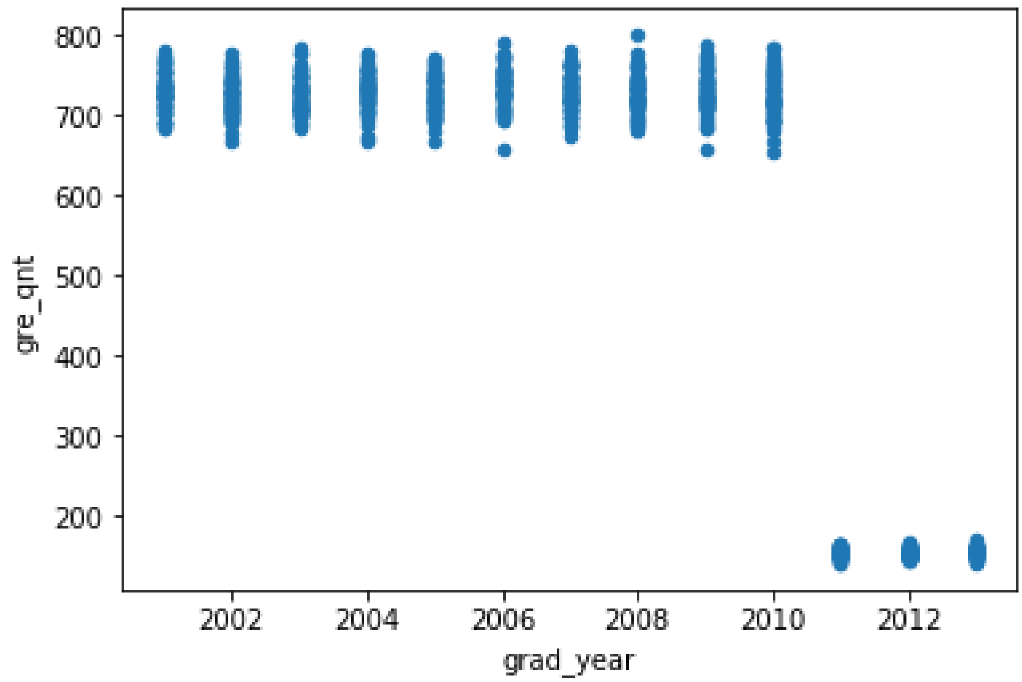
and the estimated coefficients and standard errors are:

$$\beta_0 = 89540 \quad SE(\beta_0) = 878.764$$

$$\beta_1 = -25.7632 \quad SE(\beta_1) = 1.365$$

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

```
In [30]: # Code and output of scatterplot
         grad_year = IncomeIntel['grad_year']
         gre_qnt = IncomeIntel['gre_qnt']
         IncomeIntel.plot(x='grad_year', y='gre_qnt', kind='scatter')
         plt.show()
```



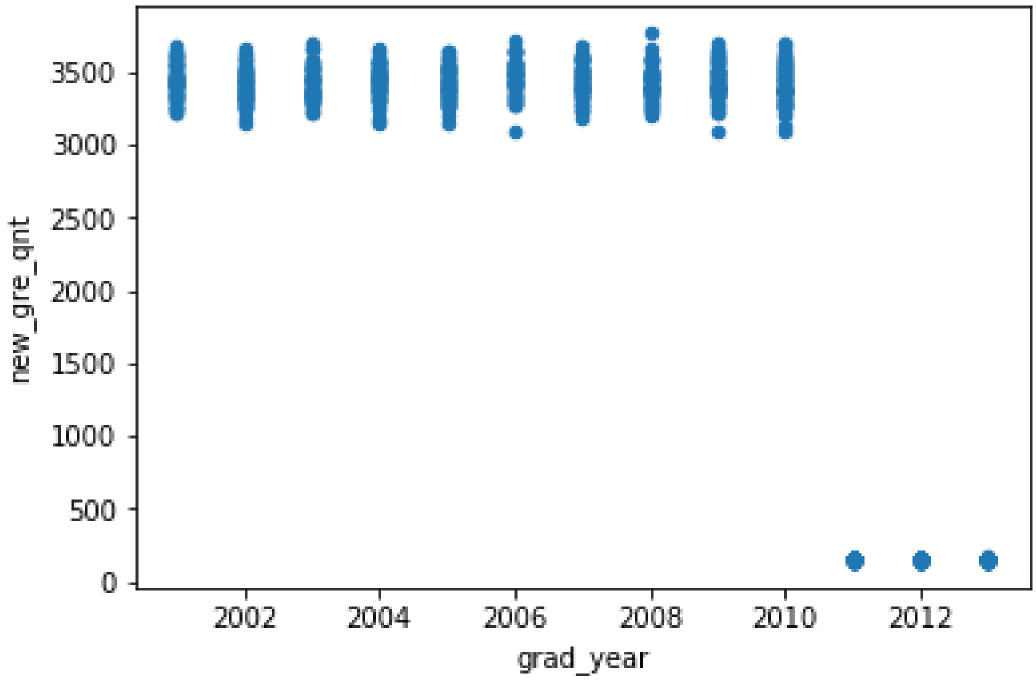
As we can see from the scatterplot above and the exercise, GRE quantitative scoring scale changed in 2011. My proposed solution is to convert two ways of scaling into one.

```
In [31]: # Implement the solution
         # Convert two scaling methods into one by zscore each gre_qnt
         IncomeIntel['new_gre_qnt'] = IncomeIntel.apply(lambda x: x.gre_qnt/170*800
                                                         if x.grad_year<2011
                                                         else x.gre_qnt, axis=1)
         IncomeIntel.describe()
```

Out[31]:

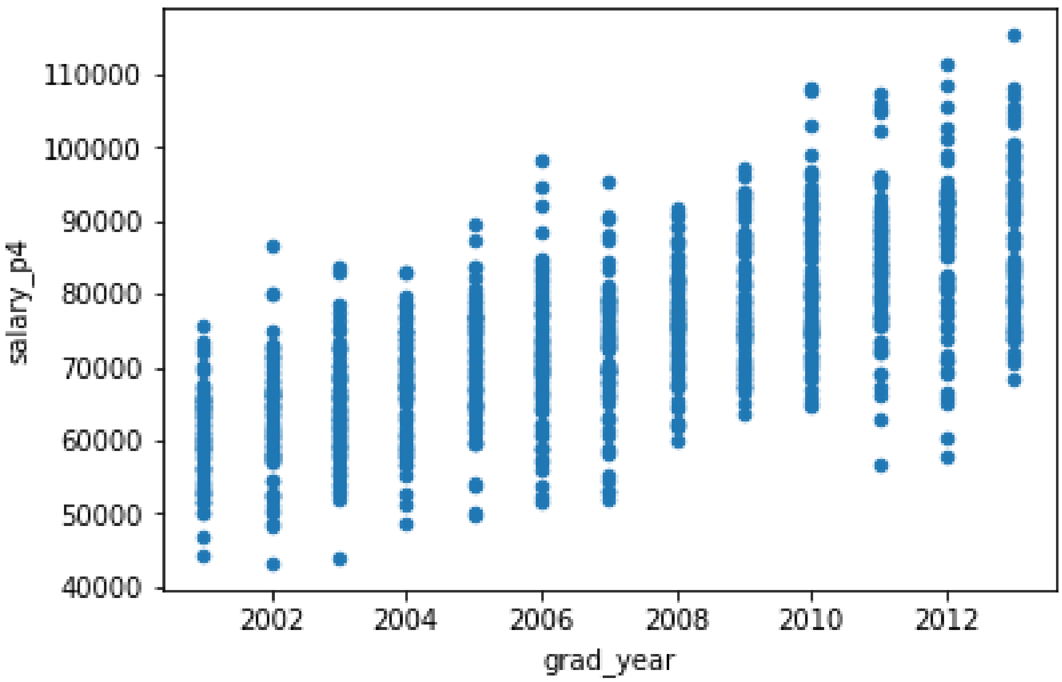
	grad_year	gre_qnt	salary_p4	new_gre_qnt
count	1000.000000	1000.000000	1000.000000	1000.000000
mean	2006.994000	596.510118	74173.293777	2675.081944
std	3.740582	242.361960	12173.767372	1381.440256
min	2001.000000	141.261398	43179.183141	141.261398
25%	2004.000000	684.983551	65778.240317	3223.452004
50%	2007.000000	719.106878	73674.204810	3384.032365
75%	2010.000000	739.332537	81838.874129	3479.211940
max	2013.000000	799.715533	115367.665815	3763.367215

```
In [32]: # Code and output of scatterplot
         grad_year = IncomeIntel['grad_year']
         gre_qnt = IncomeIntel['new_gre_qnt']
         IncomeIntel.plot(x='grad_year', y='new_gre_qnt', kind='scatter')
         plt.show()
```



(c) Create a scatterplot of income and graduation year

```
In [33]: # Code and output of scatterplot
         grad_year = IncomeIntel['grad_year']
         salary_p4 = IncomeIntel['salary_p4']
         IncomeIntel.plot(x='grad_year', y='salary_p4', kind='scatter')
         plt.show()
```



Because these data are not panel data, we cannot use differencing or log differencing methods to detrend them. So I will use the following method to modify the data.

In [34]:
```
IncomeIntel.describe()
```

Out[34]:

	grad_year	gre_qnt	salary_p4	new_gre_qnt
count	1000.000000	1000.000000	1000.000000	1000.000000
mean	2006.994000	596.510118	74173.293777	2675.081944
std	3.740582	242.361960	12173.767372	1381.440256
min	2001.000000	141.261398	43179.183141	141.261398
25%	2004.000000	684.983551	65778.240317	3223.452004
50%	2007.000000	719.106878	73674.204810	3384.032365
75%	2010.000000	739.332537	81838.874129	3479.211940
max	2013.000000	799.715533	115367.665815	3763.367215

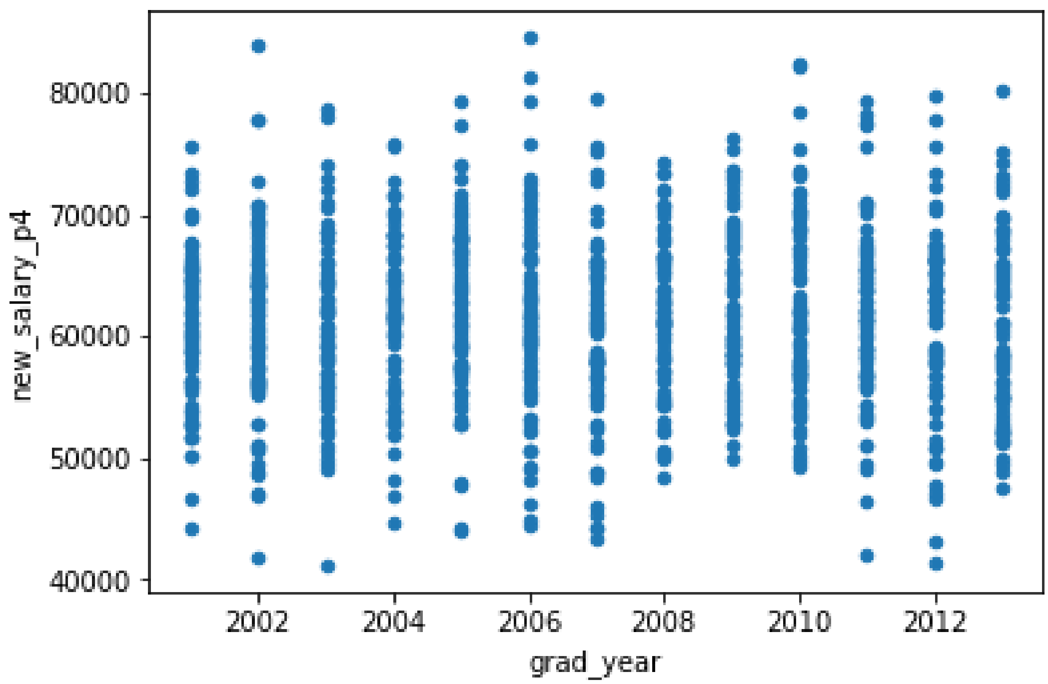
In [35]:
```
#  Code to implement a solution
avg_inc_by_year = IncomeIntel['salary_p4'].groupby(IncomeIntel['grad_year']
                                                    ).mean().values
avg_growth_rate = ((avg_inc_by_year[1:] - avg_inc_by_year[:-1]
                   ) / avg_inc_by_year[:-1]).mean()
IncomeIntel['new_salary_p4'] = IncomeIntel['salary_p4'] / ((1 + avg_growth_rate
                                                            ) ** (grad_year - 2001))
IncomeIntel.describe()
```

Out[35]:

	grad_year	gre_qnt	salary_p4	new_gre_qnt	new_salary_p4
count	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000

```
mean    2006.994000   596.510118   74173.293777  2675.081944   61419.808910
std        3.740582   242.361960   12173.767372  1381.440256    7135.610865
min     2001.000000   141.261398   43179.183141   141.261398   41164.726530
25%     2004.000000   684.983551   65778.240317  3223.452004   56616.517414
50%     2007.000000   719.106878   73674.204810  3384.032365   61467.616002
75%     2010.000000   739.332537   81838.874129  3479.211940   66218.595876
max     2013.000000   799.715533  115367.665815  3763.367215   84516.856633
```

In [36]:
```python
# Code and output of scatterplot
grad_year = IncomeIntel['grad_year']
new_salary_p4 = IncomeIntel['new_salary_p4']
IncomeIntel.plot(x='grad_year', y='new_salary_p4', kind='scatter')
plt.show()
```



(d) Re-estimate coefficients with updated variables.

In [37]:
```python
# Code to re-estimate, output of new coefficients
outcome = ['new_salary_p4']
features = ['new_gre_qnt']

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

In [38]:
```python
X = sm.add_constant(X, prepend=False)
m = sm.OLS(y, X)
res = m.fit()
print(res.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:           new_salary_p4   R-squared:                       0.000
Model:                             OLS   Adj. R-squared:                 -0.001
Method:                  Least Squares   F-statistic:                   0.06051
Date:                 Wed, 17 Oct 2018   Prob (F-statistic):              0.806
Time:                         10:55:29   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]
-------------------------------------------------------------------------------
new_gre_qnt     0.0402      0.164      0.246      0.806      -0.281       0.361
const        6.131e+04    492.204    124.567      0.000    6.03e+04    6.23e+04
==============================================================================
Omnibus:                         0.776   Durbin-Watson:                   2.026
Prob(Omnibus):                   0.678   Jarque-Bera (JB):                0.690
Skew:                            0.060   Prob(JB):                        0.708
Kurtosis:                        3.046   Cond. No.                     6.56e+03
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 6.56e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

I obtained the following OLS regression equation:

$$newsalaryp4 = 6131 - 0.0402 newgreqnt$$

and estimated coefficients and standard errors are:

$$\beta_0 = 6131 \quad SE(\beta_0) = 492.204$$

$$\beta_1 = 0.0402 \quad SE(\beta_1) = 0.164$$

Compared to the former result, this result is more reasonable after solving problems in both GRE quantitative and salary after 4 years. In the former interpretation of intercept estimator, a people with 0 GRE quantitative score can earn 89540 dollars per year. In the new model, If GRE quantitative score is 0, salary after 4 years is 6131 dollars, which is more realistic. However, the GRE quantitative have a minimum score of 130, so it is over extrapolation of intercept estimator. For the slope estimator, with each addition of GRE quantitative score, the salary after 4 years decrease 10.0695 dollars in the new model and increase 0.0402 dollars in the previous model. The hypothesis is that people with higher GRE quantitative score normally earns more salary. So the new model proved my hypothesis. But in both model, the result is not significant.

1.0.5 3. Assessment of Kossinets and Watts.

In this paper, the authors shortly present a literature review on homophily and then, bring out the research question which focuses on the origin of homophily: on what grounds do individuals selectively make or break some ties over others, and how do these choices shed light on the observation that similar people are more likely to become acquainted than dissimilar people?

To investigate more on this question, they using network data of a large university community which interactions, attributes, and affiliations are recorded. To construct the dataset, the authors merged 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. Dataset comprised 7,156,162 messages exchanged by 30,396 stable e-mail users during 270 days of observation. The available variables could be categorized into four groups: personal characteristics (age, gender, home state, formal status, years in school); organizational affiliations (primary department, school, campus, dormitory, academic field); course-related variables (courses taken, courses taught); and e-mail-related variables (days active, messages sent, messages received, in-degree, out-degree, reciprocated degree). A precise definitions of all variables are provided in APPENDIX. A.

In the data cleaning process, from 43,553 individuals, the authors identified 34,574 users who were active throughout both semesters by the principle of sending and receiving e-mail in both the first and the last months of the academic year. However, 43,553 individuals sent and received messages during the academic year. It is highly possible that they just didn't send or receive e-mail in both the first and the last months of the academic year. Simply dropped 8,979 individuals may result in a biased model and diminish the authors' ability to answer the research question.

When match the data source to theoretical construct, the authors arbitrarily suppose that the university e-mail logs fully represents the social relationships of an individual. Nevertheless, it is not necessarily the case. Let's say a student seldom use e-mail to reach his friends. Instead, apps like Whatsup and Lines replaced e-mail with their convenience. This student is likely to be removed from the dataset in the context. Here is another example about the implicit closure. If there is a fraternity which never emails its member but has a fixed time and location for gathering, e-mail logs can't reflect the existence of this implicit foci. After two people from one class made friends in the gathering before they become friends through class, they may communicate with each other through e-mail. Then, the e-mail logs may indicates that they are friends with the explicit foci, which is that they are in the same class. Therefore, the dataset may fail to capture the real case.

In the chapter of origins of homophily, the authors proposed some problem on observed homophily.One might concerned that our measure of individual similarity acts, in effect, as an indicator variable for sharing a class, and that controlling for shared classes would effectively eliminate the potential for similarity to have any additional impact on tie formation, thereby artificially increasing the apparent importance of induced homophily vis-a-vis choice homophily. In order to address this potential systematic bias, the author consider in figure 7 (top row) the distribution of similarity for student pairs who shared classes with that for student pairs who did not. As expected from figure 6, students who shared classes (fig. 7, pt. B) are, on average, much more similar than students who did not (pt. A). However, its higher average notwithstanding, the distribution in part B of figure 7 also exhibits higher variance (1.8) than that in part A (1.3); thus, the potential for differences in similarity to impact tie formation is not in fact diminished for pairs who share classes versus those who do not. As a further check the authors compare distributions of similarity for pairs who share implicit foci (fig. 7, pt. D) with those who do not (pt. C). In this way, the concern can be properly addressed.

Reference:

Kossinets, Gueorgi and Duncan J. Watts, "Origins of Homophily in an Evolving Social Network," American Journal of Sociology 115:2, (2009), pp. 405-450.