Assignment 2-Ying Sun

October 16, 2018

1 Assignment 2

1.0.1 Ying Sun

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

1.0.2 1. Imputing age and gender

(a) In order to solve this incompleteness problem, here I use the imputation strategy. I use the information (weight, age and gender) in the dataset of SurveyIncome on some people to infer attributes (age and gender) of other people in BestIncome dataset. Besides, noting that female_{i}is a categorical variable, we need to use Logistic regression to estimate. Basically, the equations should be as follows:

$$age_i = \beta_0 + \beta_1 wgt_i + \beta_2 totinc_i + \varepsilon_i$$
$$\ln(\frac{P(female_i)}{1 - P(female_i)}) = \beta_3 + \beta_4 wgt_i + \beta_5 totinc_i + \varepsilon_i$$

Then I use labor income and capital income in the BestIncome dataset to form total income:

$$totinc_i = labinc_i + capinc_i$$

Then I use weight and formed total income to impute age and gender in the BestIncome dataset.

In [2]:
```
# I may use this code cell to read in my data, name my variables, run descriptive stat
names=['lab_inc','cap_inc','hgt','wgt']
df1=pd.read_table('BestIncome.txt',names=names,sep=',')
df1['tot_inc']=df1['lab_inc']+df1['cap_inc']
df1.head()
```

Out[2]:

	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 [3]:
```
df1.tail()
```

Out[3]:

	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 [4]:
```
df1.shape
```

Out[4]: (10000, 5)

In [5]:
```
names=['tot_inc','wgt','age','female']
df2=pd.read_table('SurvIncome.txt',names=names,sep=',')
df2.head()
```

Out[5]:

	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 [6]:
```
df2.tail()
```

Out[6]:

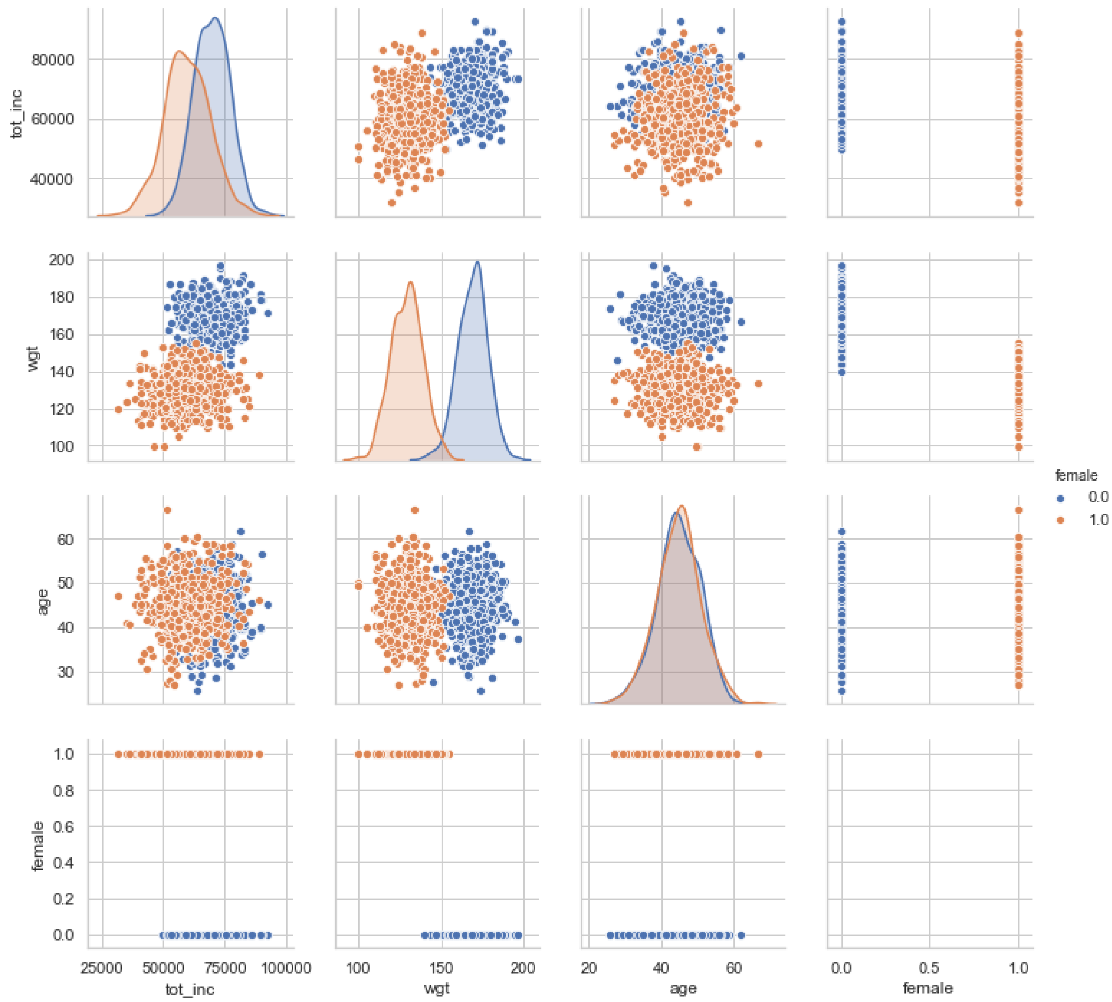
	tot_inc	wgt	age	female
995	61270.538697	184.930002	46.356881	0.0
996	59039.159876	180.482304	50.986966	0.0
997	67967.188804	156.816883	40.965268	0.0
998	79726.914251	158.935050	41.190371	0.0
999	71005.223603	169.067695	48.480007	0.0

In [7]:
```
df2.shape
```

Out[7]: (1000, 4)

In [8]:
```
import seaborn as sns
sns.set(style="white")
sns.set(style="whitegrid", color_codes=True)
sns.pairplot(df2, hue = "female")
```

Out[8]: <seaborn.axisgrid.PairGrid at 0x1facd1c6dd8>



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

In [9]:
```
# I will use this code cell to execute the code that will impute those variables.
#Define Outcome and Independent Variables
outcome   = 'age'
features = ['tot_inc','wgt']
X,y = df2[features], df2[outcome]
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]: outcome  =['age']
         features = ['tot_inc','wgt']
         X,y = df2[features], df2[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:                        19:52:37   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.
```

```
In [12]: outcome  =['female']
         features = ['tot_inc','wgt']
         X,y = df2[features], df2[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:                        19:52:38   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]
------------------------------------------------------------------------------
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.
```

In [13]:
```
df1['imputed_age_by_tot_inc_wgt'] = 2.52e-05 * df1['tot_inc']- 0.0067* df1['wgt']+ 44
df1['imputed_gender_by_tot_inc_wgt_logit'] = -0.0002 * df1['tot_inc']-0.4460* df1['wg
df1['imputed_gender_by_tot_inc_wgt_prob'] = 2.71828183**(df1['imputed_gender_by_tot_i
df1.head()
```

Out[13]:

	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_tot_inc_wgt	imputed_gender_by_tot_inc_wgt_logit	\
0	44.745897	-3.796726	
1	45.157777	-10.367048	
2	44.745701	-3.586401	
3	44.919024	-3.322583	
4	44.554687	-2.182210	

```
   imputed_gender_by_tot_inc_wgt_prob
0                            0.021951
1                            0.000031
2                            0.026951
3                            0.034805
4                            0.101359
```

We need to classify the imputed_gender_by_tot_inc_wgt_prob into two categories: 0 and 1. So here I use 0.5 as a boundary value. If imputed_gender_by_tot_inc_wgt_prob is larger than 0.5, I classify it as 1 category or I classify it as 0 category.

```
In [14]: def prob_gender(gender):
             if gender > 0.5:
                 gender =1
             else:
                 gender =0
             return gender

         df1['imputed_gender_by_tot_inc_wgt']= df1.imputed_gender_by_tot_inc_wgt_prob.apply(pro
         df1.head()
```

```
Out[14]:         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_tot_inc_wgt  imputed_gender_by_tot_inc_wgt_logit  \
         0                   44.745897                             -3.796726
         1                   45.157777                            -10.367048
         2                   44.745701                             -3.586401
         3                   44.919024                             -3.322583
         4                   44.554687                             -2.182210

            imputed_gender_by_tot_inc_wgt_prob  imputed_gender_by_tot_inc_wgt
         0                            0.021951                              0
         1                            0.000031                              0
         2                            0.026951                              0
         3                            0.034805                              0
         4                            0.101359                              0
```

```
In [15]: BestIncome=df1[['lab_inc','cap_inc','hgt','wgt','imputed_age_by_tot_inc_wgt','imputed_
         BestIncome.head()
```

```
Out[15]:         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

   imputed_age_by_tot_inc_wgt  imputed_gender_by_tot_inc_wgt
0                   44.745897                              0
1                   45.157777                              0
2                   44.745701                              0
3                   44.919024                              0
4                   44.554687                              0
```

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

In [16]:
```
# I will use this code cell to do so!
df1['imputed_age_by_tot_inc_wgt'].describe()
```

Out[16]:
```
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_tot_inc_wgt, dtype: float64
```

In [17]:
```
df1['imputed_gender_by_tot_inc_wgt'].describe()
```

Out[17]:
```
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_gender_by_tot_inc_wgt, dtype: float64
```

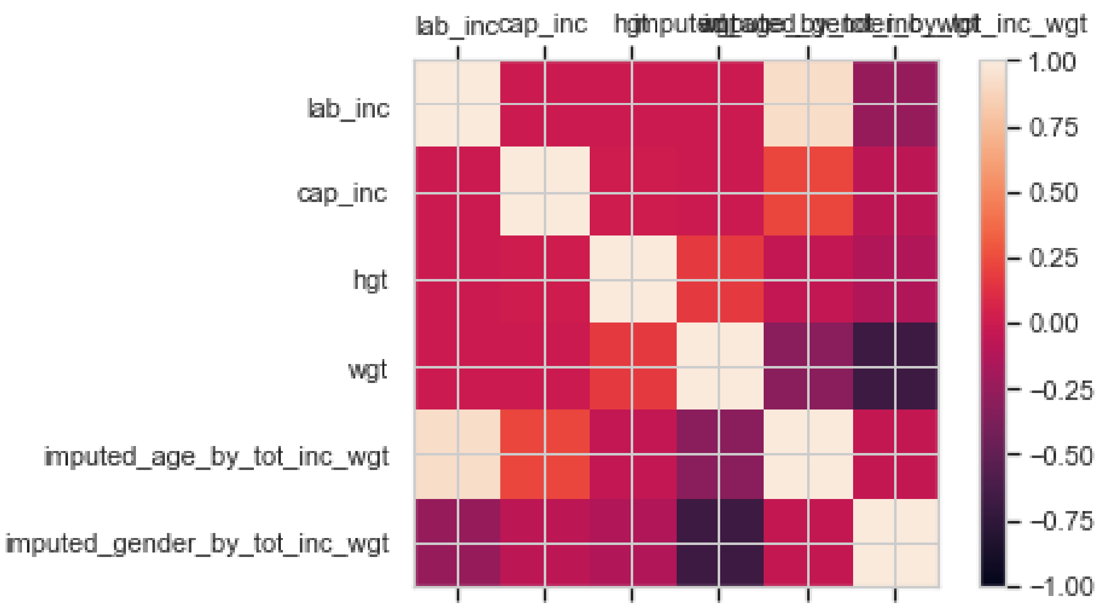
(d) Correlation matrix for the now six variables

In [18]:
```
# Correlation matrix code and output
import matplotlib.pyplot as pl
def corr_plot(df):
    import matplotlib.pyplot as plt
    import numpy as np
    import pandas as pd

    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)
```



1.0.3 2. Stationarity and data drift

(a) Estimate by OLS and report coefficients

```
In [19]: # Read in my third data set
         # Name my variables
         names=['grad_year','gre_qnt','salary_p4']
         IncomeIntel=pd.read_table('IncomeIntel.txt',names=names,sep=',')
         IncomeIntel.head()
```

```
Out[19]:    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
```

```python
In [20]: # Run regression model
         # Report coefficients and SE's
         outcome  =['salary_p4']
         features = ['gre_qnt']
         X,y = IncomeIntel[features], IncomeIntel[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:                        19:52:51   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.
```

Here we report the estimated result:

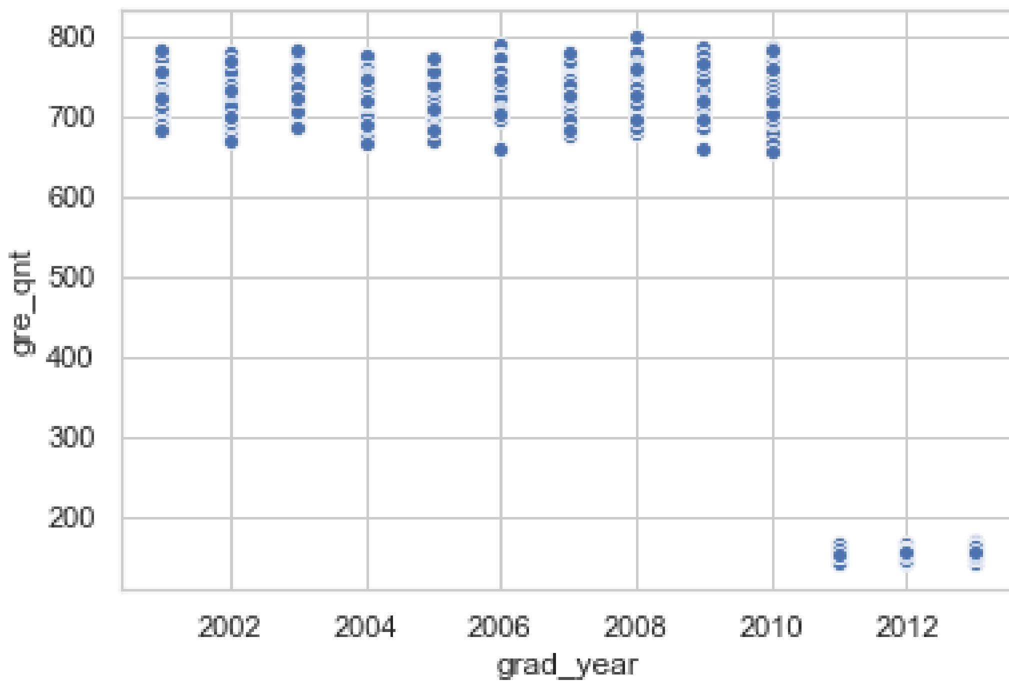
$$\beta_1 = -25.7632 \quad s.e.(\beta_1) = 1.365$$

$$constant = 89540 \quad s.e.(constant) = 878.764$$

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

In [21]:
```
# Code and output of scatterplot
x=IncomeIntel['grad_year']
y=IncomeIntel['gre_qnt']
sns.scatterplot(x,y)
```

Out[21]: <matplotlib.axes._subplots.AxesSubplot at 0x1facdeba128>



The problem is the system drift because the GRE quantitative scoring scale changed in 2011. The GRE quantitative scoring scale is 800 before 2011 and 170 after 2011 (2011 included). A possible solution of this problem is to change the old GRE quantitative scores before 2011 into new scale (170).

In [22]:
```
# Code to change the GRE quantitative scores in old scale into new scale
gre_new=IncomeIntel[['grad_year','gre_qnt']].apply(lambda x: x['gre_qnt']*(170/800) i

IncomeIntel['gre_new']=gre_new
IncomeIntel.head()
```

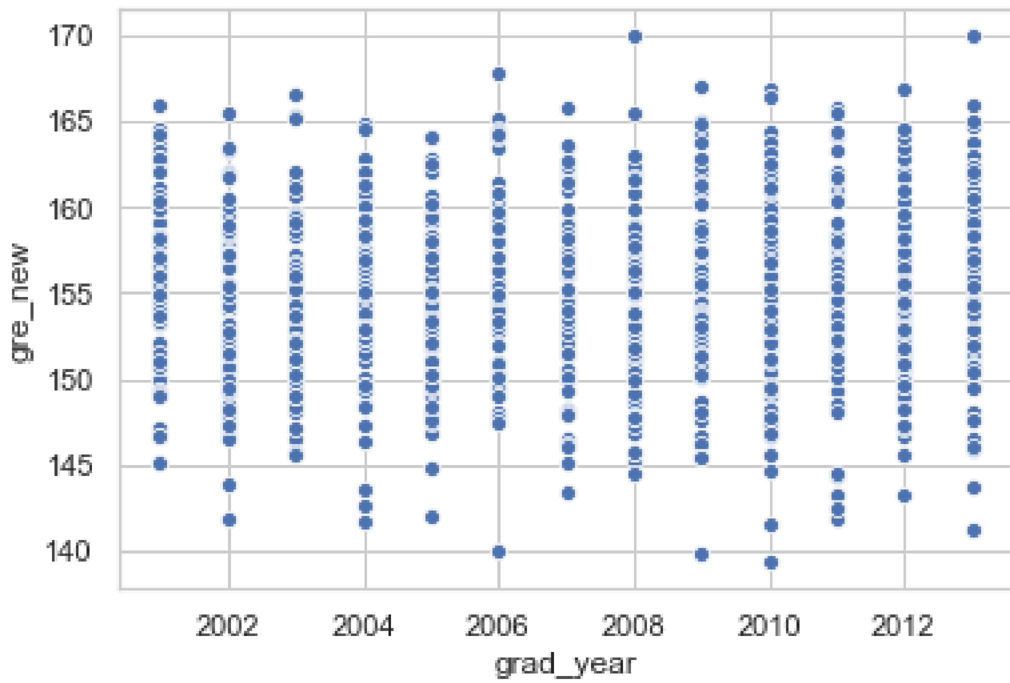
Out[22]:

	grad_year	gre_qnt	salary_p4	gre_new
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 [23]:
```python
x= IncomeIntel['grad_year']
y= IncomeIntel['gre_new']
sns.scatterplot(x,y)
```

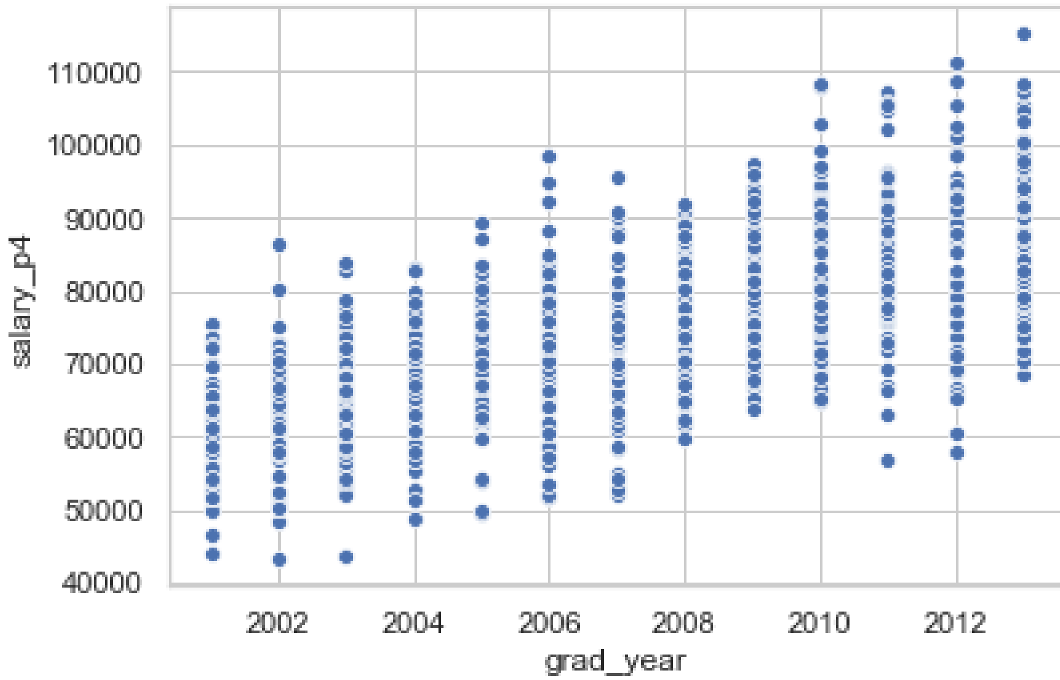
Out[23]: <matplotlib.axes._subplots.AxesSubplot at 0x1facf6597b8>



(c) Create a scatterplot of income and graduation year

In [24]:
```python
# Code and output of scatterplot
y=IncomeIntel['salary_p4']
x=IncomeIntel['grad_year']
sns.scatterplot(x,y)
```

Out[24]: <matplotlib.axes._subplots.AxesSubplot at 0x1facf6595f8>



The problem is the stationarity of salary_p4, it has a clear trend so we need to detrend salary_p4 before we do further analysis. The solution here is to: 1. Treat the first year of the data (grad_year=2001) equal to the base year. 2. Calculate the average growth rate in salary by calculate the mean salary each year and calculate the average growth rate in salaries across all 13 years.

In [25]:
```
# Code to calculate the mean salary each year
avg_inc_by_year = IncomeIntel['salary_p4'].groupby(IncomeIntel['grad_year']).mean().va
```

In [26]:
```
# Code to calculate the average growth rate in salaries across all 13 years
avg_growth_rate = ((avg_inc_by_year[1:] - avg_inc_by_year[:-1]) / avg_inc_by_year[:-1]
```

In [27]:
```
IncomeIntel['salary_new']=IncomeIntel['salary_p4']/(1 + avg_growth_rate ) ** (IncomeIn
IncomeIntel.tail()
```

Out[27]:

	grad_year	gre_qnt	salary_p4	gre_new	salary_new
995	2013.0	160.441025	100430.166532	160.441025	69757.765226
996	2013.0	160.431891	82198.200872	160.431891	57094.028581
997	2013.0	154.254526	84340.214218	154.254526	58581.849117
998	2013.0	162.036321	87600.881985	162.036321	60846.675557
999	2013.0	156.946735	82854.576903	156.946735	57549.940651

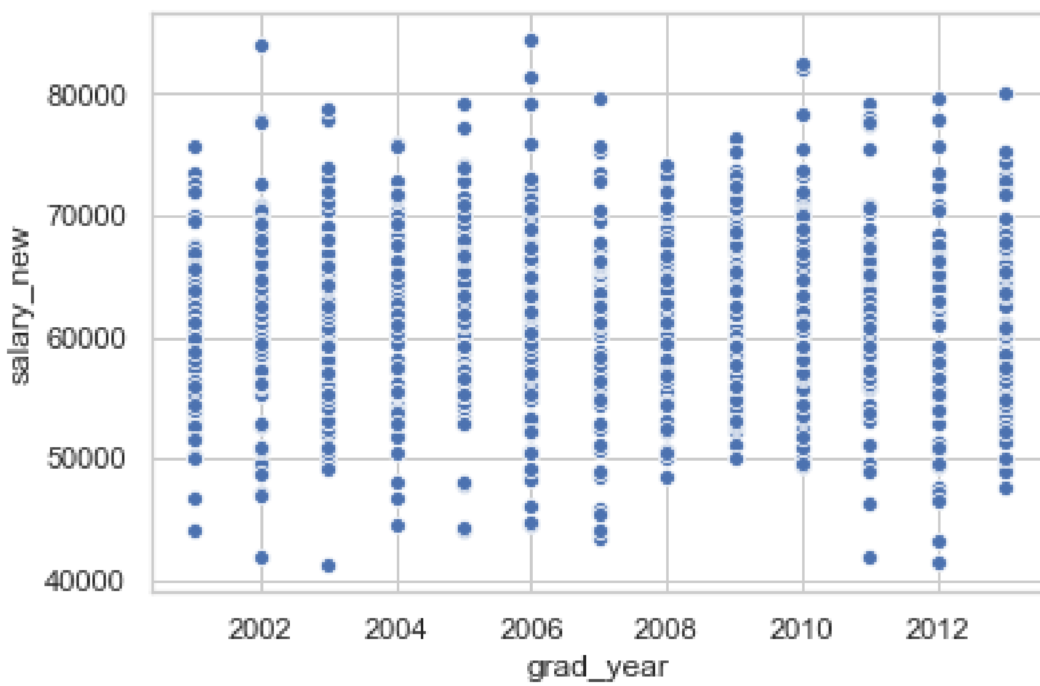
In [28]:
```
IncomeIntel['salary_new'].describe()
```

Out[28]:
```
count      1000.000000
mean      61419.808910
```

```
std        7135.610865
min       41164.726530
25%       56616.517414
50%       61467.616002
75%       66218.595876
max       84516.856633
Name: salary_new, dtype: float64
```

In [29]:
```python
y= IncomeIntel['salary_new']
x= IncomeIntel['grad_year']
sns.scatterplot(x,y)
```

Out[29]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1facf6e8518>
```



(d) Re-estimate coefficients with updated variables.

In [30]:
```python
# Code to re-estimate, output of new coefficients
outcome  =['salary_new']
features = ['gre_new']
X,y = IncomeIntel[features], IncomeIntel[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_new   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:                        19:53:05   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_new      -34.9747     44.990     -0.777      0.437    -123.260      53.311
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.                     4.78e+03
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 4.78e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Here we report our new estimated result:

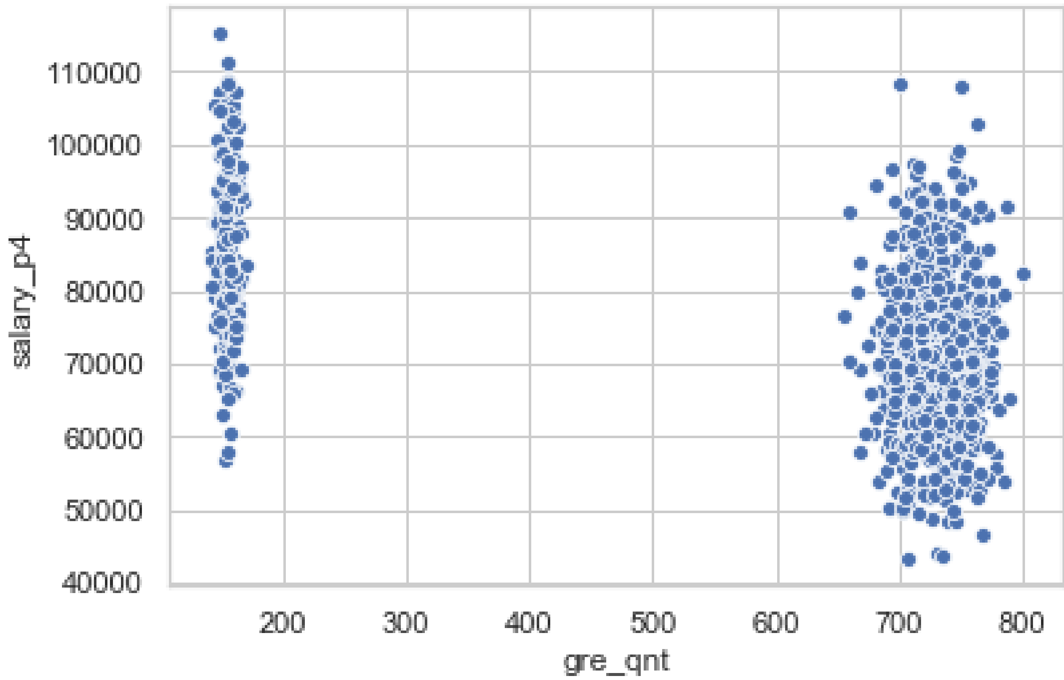
$$\beta_1 = -34.9747 \quad s.e.(\beta_1) = 44.990$$

$$constant = 66830 \quad s.e.(constant) = 6968.684$$

Now we need to compare this result with the previous result:

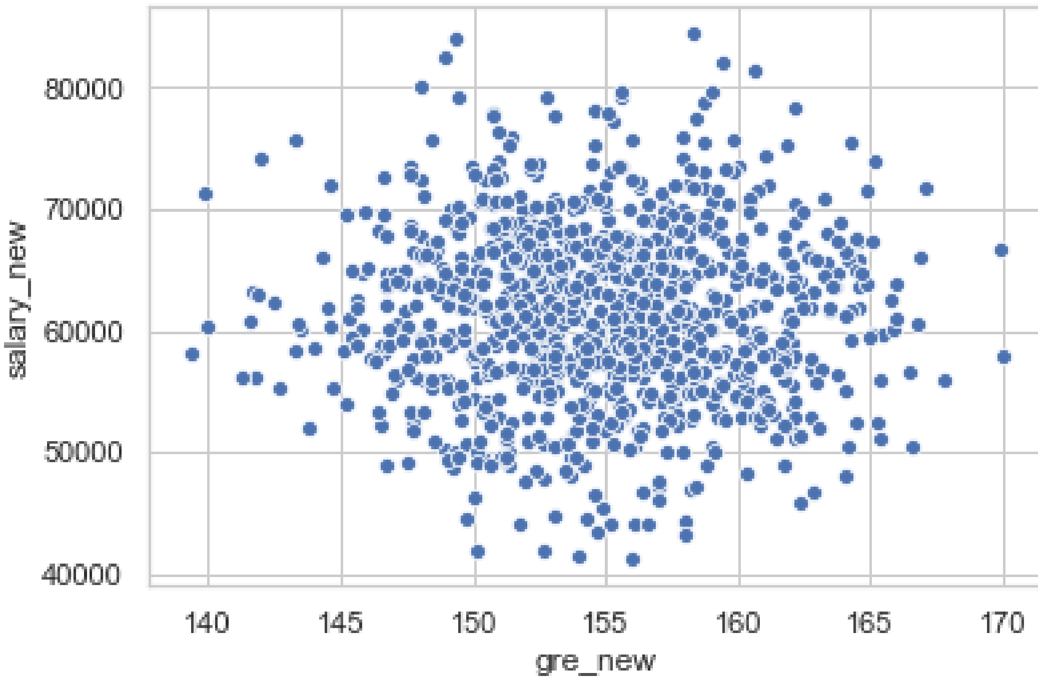
```
In [31]: x_pre = IncomeIntel['gre_qnt']
         y_pre = IncomeIntel['salary_p4']
         sns.scatterplot(x_pre, y_pre)

Out[31]: <matplotlib.axes._subplots.AxesSubplot at 0x1facdbc6f60>
```




```
In [32]: x_now = IncomeIntel['gre_new']
         y_now = IncomeIntel['salary_new']
         sns.scatterplot(x_now, y_now)

Out[32]: <matplotlib.axes._subplots.AxesSubplot at 0x1facf7d0208>
```



After we compare these two plots above,we can come to the following conclusions: Before we modify the drift problem of GRE quantitative scores and eliminate time trends, GRE quantitative scores before 2011 are mainly on the left side of the first plot and new GRE quantitative scores after 2011 (2011 included) are mainly on the right side of the second plot. And we can find the p-value (estimated coefficient of gre_qnt) is small which indicates that we may reject the null hypothesis that intelligence is not related to higher income. After we modify the drift problem of GRE quantitative scores and eliminate time trends, the distribution is much better than before. By comparing the coefficients of two regression results, we find new beta1 is more negative than before but the p-value is large so it is not significant. As a result, according to the new regression result, we cannot reject the null hypothesis that intelligence is not related to higher income.

1.0.4 3. Assessment of Kossinets and Watts.

See attached PDF.

Assessment of Kossinets and Watts

This paper mainly answers the research question that how homophily emerges over time as a function of the decisions of individuals to make and break ties in an evolving social network?

In order to answer this research question, the authors use a network dataset of a large U.S. university comprising 30396 undergraduate and graduate students, faculty and staff in which interactions are recorded in real time along with individual attributes and features of the relevant organizational structure during one academic year. This dataset, which comprises interaction, affiliation and attribute-type longitudinal data, 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 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 email-related variables (days active, message sent, messages received, in-degree, our-degree, reciprocated degree). In terms of the number of observations, after the cleaning data process, the resulting data set comprised 7,156,162 messages exchanged by 30396 stable e-mail users during 270 days of observation. We could find precise definitions and descriptions of variables in app. A. And a note about missing data appears in app. B.

A potential problem that the data cleaning process might introduce is the incompleteness of data, the data in this article lack some attributes, lack race and socioeconomic status that might be more salient with respect to the choice of interaction partners than the available variables. Besides, this article adopts the method of modal value substitution for age, gender and state, which means if there were several modes, then the most recent modal value was used, assuming that the more recent value was more likely to be correct. This assumption can be problematic because in some cases, the most recent modal value is not necessarily correct. What's more, in order to ensure that the data represents interpersonal communication, the authors includes only messages that were sent to a single recipient. However, this method may exclude some social relationships in shared groups and activities and further influence the conclusion. Also, this paper ignores the situation that a number of individuals also used accounts provided by their departments, although they can be told that such addresses are part of the university community, they cannot be matched with employee records and therefore have been excluded from this analysis. Another minor problem that may diminishes the authors' ability to answer the research question is that the authors select the population who have exchanged emails as its target sample, in other words, they think that individuals who have exchanged emails are more likely to form social relationships. But in practical, it is not rare to find automatic replies in university's email system. But this type of exchange emails doesn't mean it could form relationship between the sender and receiver. So, a more proper way is to analysis the contents of emails to exclude this situation.

From my perspective, one weakness of this match of data sources and theoretical construct is they need to estimate a suitable value for the parameter τ which could define ties properly in the method of sliding window filter to analyze and visualize networks over time. Because the particular value of τ is chosen will in general depend on the substantive question of interest. In considering of the question of interests this research concerns the tie-formation process itself so they must choose a proper τ to distinguish between ties that are forming as we observe the network and ties that have existed before and simply resumed communicating. Therefore, the value of τ that is chosen should not be too short or some ongoing relationships will be misclassified as ties that have been terminated and then reenacted. While τ should not be set too long either, or the calculation of relationship strength will be dominated by the past interactions that are no longer relevant to the present state of the relationship. Besides, the longer value of τ also has the effect of discarding more data. Considering the balance of these conflicting priorities, the authors have chosen $\tau = 60$ as a reasonable compromised value that correctly classifies 90% of terminating ties while retaining as much data as possible.