Assignment2

October 15, 2018

1 Assignment 2

1.0.1 MACS 30000, Dr. Evans

1.0.2 Shanglun Li

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
        from sklearn import preprocessing
        import matplotlib.pyplot as plt
        plt.rc("font", size=14)
        from sklearn.linear_model import LogisticRegression
        # from sklearn.cross_validation import train_test_split
        import seaborn as sns
        sns.set(style="white")
        sns.set(style="whitegrid", color_codes=True)

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

1.0.3 1. Imputing age and gender

(a) In order to impute age (age_i) and gender ($female_i$) variables into the BestIncome.txt data by using information from the SurveyIncome.txt data, I will fit a linear regression model and a logistic model using SurveyIncome.txt:

For the linear regression model, I will set age as the response variable, total income (tot_inc) and weight (wgt) as the explanatory variables.

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

For the logistic regression model, I will set gender as the response variable, total income and weight as the explanatory variables.

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

Then, I will use the linear regression models to predict the age variable in BestIncome.txt using the total income and weight variables (Note that total income can be calculated by adding labor income, lab_inc, and capital income, cap_inc, together) and use logistic regression model to predict the gender variable in BestIncome.txt using total income and weight variables.

$$age_{pred} = b_0 + b_1 \times totinc + b_2 \times wgt$$

$$P(female) = \frac{\exp(b_0 + b_1 \times totinc + b_2 \times wgt)}{1 + \exp(b_0 + b_1 \times totinc + b_2 \times wgt)}$$

Then, to categorize the predicted observation to female when the predicted value is greater than or equal to 0.5 and to male when the predicted value is less than 0.5.

```
In [2]: # Read Data
        BestIncome = pd.read_csv('BestIncome.txt', header = None, names = ["lab_inc", "cap_inc",
        BestIncome.head()
```

Out[2]:

	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 [3]: BestIncome.shape

Out[3]: (10000, 4)

In [4]: SurveyIncome = pd.read_csv('SurvIncome.txt', header = None, names = ["tot_inc", "wgt", "
        SurveyIncome.head()
```

Out[4]:

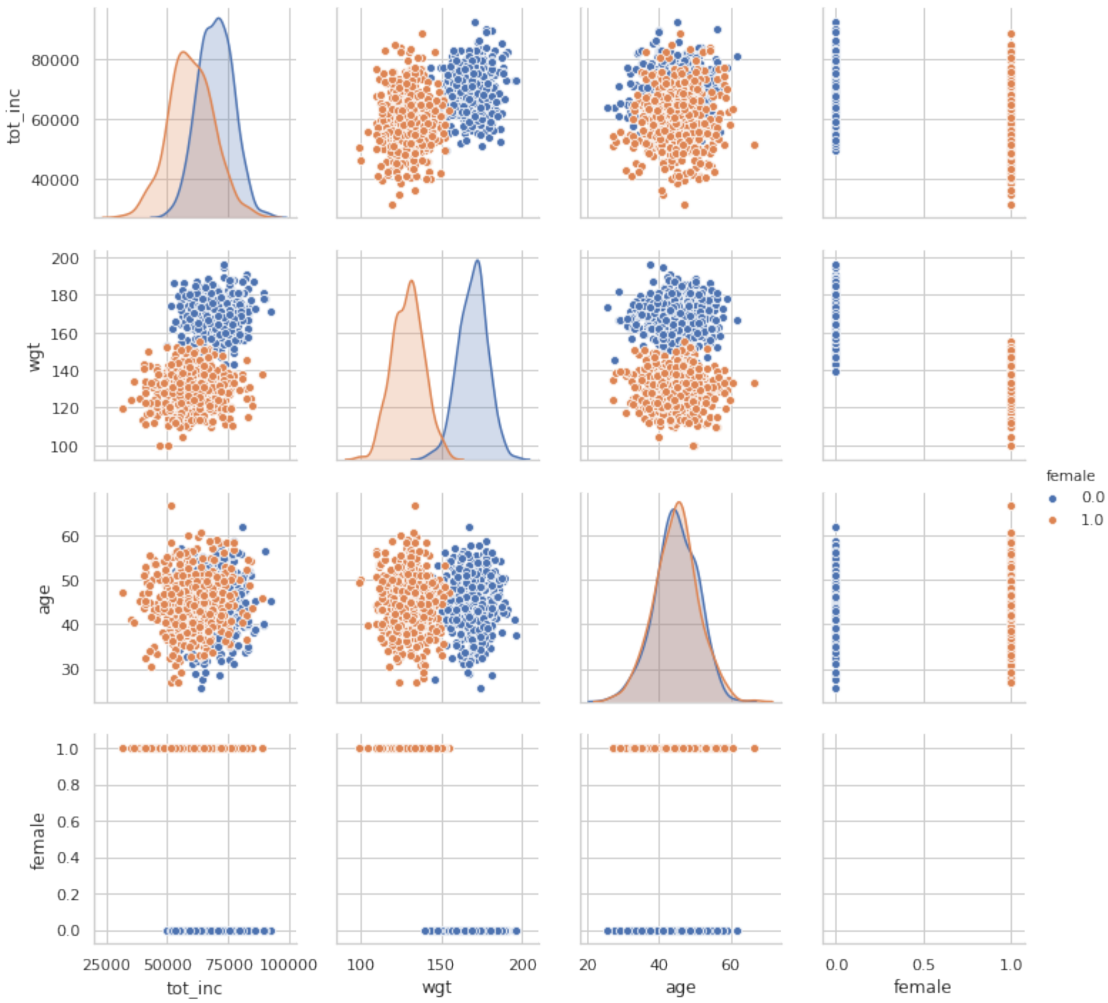
	tot_inc	wgt	age	female
0	63642.513655	134.998269	46.610021	1.0
1	49177.380692	134.392957	48.791349	1.0
2	67833.339128	126.482992	48.429894	1.0
3	62962.266217	128.038121	41.543926	1.0
4	58716.952597	126.211980	41.201245	1.0

```
In [5]: SurveyIncome.shape

Out[5]: (1000, 4)

In [6]: sns.pairplot(SurveyIncome, hue = "female")

Out[6]: <seaborn.axisgrid.PairGrid at 0x120d60400>
```




```
In [7]: count_male = len(SurveyIncome[SurveyIncome['female'] == 0])
        count_female = len(SurveyIncome[SurveyIncome['female'] == 1])
        print(count_male, count_female)
        pct_of_female = count_female / (count_male + count_female)
        print("percentage of female is", pct_of_female * 100)
        pct_of_male = count_male / (count_male + count_female)
        print("percentage of male", pct_of_male * 100)
```

```
500 500
percentage of female is 50.0
percentage of male 50.0
```

As we can see from the percentage calculation result shown below, we can see that the count of male and female are same.

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

```
In [8]: # Define response and explanatory variables
        res  = 'age'
        expl = ['tot_inc', 'wgt']

        X, y = SurveyIncome[expl], SurveyIncome[res]

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

Out[11]:         tot_inc         wgt  const
         0  63642.513655  134.998269    1.0
         1  49177.380692  134.392957    1.0
         2  67833.339128  126.482992    1.0
         3  62962.266217  128.038121    1.0
         4  58716.952597  126.211980    1.0

In [12]: 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:                Mon, 15 Oct 2018   Prob (F-statistic):              0.531
Time:                        14:22:17   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.
```

As we can see from the output, we will have the following linear regression equation:

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

Then, we can do prediction as follows:

In [13]:
```python
# Calculate the total income by adding labor income and capital income together
BestIncome['tot_inc'] = BestIncome['lab_inc'] + BestIncome['cap_inc']
BestIncome.head()
X = BestIncome[expl]
X = sm.add_constant(X, prepend = False)
X.head()
```

Out[13]:

	tot_inc	wgt	const
0	61935.115336	152.920634	1.0
1	80037.996127	159.534414	1.0
2	61816.140654	152.502405	1.0
3	67820.851305	149.218189	1.0
4	54295.770612	152.726358	1.0

In [14]:
```python
BestIncome['age'] = res.predict(X)
BestIncome.head()
```

Out[14]:

	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

Next, we will impute the gender variable using logistic regression model:

```
In [15]: # Define response and explanatory variables
         res  = 'female'
         expl = ['tot_inc', 'wgt']

         X, y = SurveyIncome[expl], SurveyIncome[res]
```

```
In [16]: X = sm.add_constant(X, prepend = False)
         X.head()
```

```
Out[16]:        tot_inc         wgt  const
         0  63642.513655  134.998269    1.0
         1  49177.380692  134.392957    1.0
         2  67833.339128  126.482992    1.0
         3  62962.266217  128.038121    1.0
         4  58716.952597  126.211980    1.0
```

```
In [17]: 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:                Mon, 15 Oct 2018   Pseudo R-squ.:                  0.9480
Time:                        14:22:18   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.
```

As we can see from the output, the logistic regression model is

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

```
In [18]: X = BestIncome[expl]
         BestIncome = BestIncome.drop(columns = "tot_inc")
         X = sm.add_constant(X, prepend = False)
         X.head()
```

```
Out[18]:        tot_inc         wgt  const
         0  61935.115336  152.920634    1.0
         1  80037.996127  159.534414    1.0
         2  61816.140654  152.502405    1.0
         3  67820.851305  149.218189    1.0
         4  54295.770612  152.726358    1.0
```

```
In [19]: BestIncome['female'] = res.predict(X)
         BestIncome['female'][BestIncome['female'] >= 0.5] = 1
         BestIncome['female'][BestIncome['female'] < 0.5] = 0
         BestIncome.head()
```

```
Out[19]:        lab_inc       cap_inc        hgt         wgt        age  female
         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]: # Calculate the mean, standard deviation, minimum, maximum and number of observations c
         predvar = BestIncome[['age', 'female']]
         predvar.describe()
```

```
Out[20]:                age        female
         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
```

As we can see from the output, for the predicted age variable in BestIncome.txt, the mean is 44.890828, the standard deviation is 0.219150, the minimum is 43.976495, the maximum is 45.703819, the number of observations is 10000. For the predicted female variable in BestIncome.txt, the mean is 0.4546, the standard deviation is 0.497959, the minimum is 0, the maximum is 1, the number of observations is 10000.

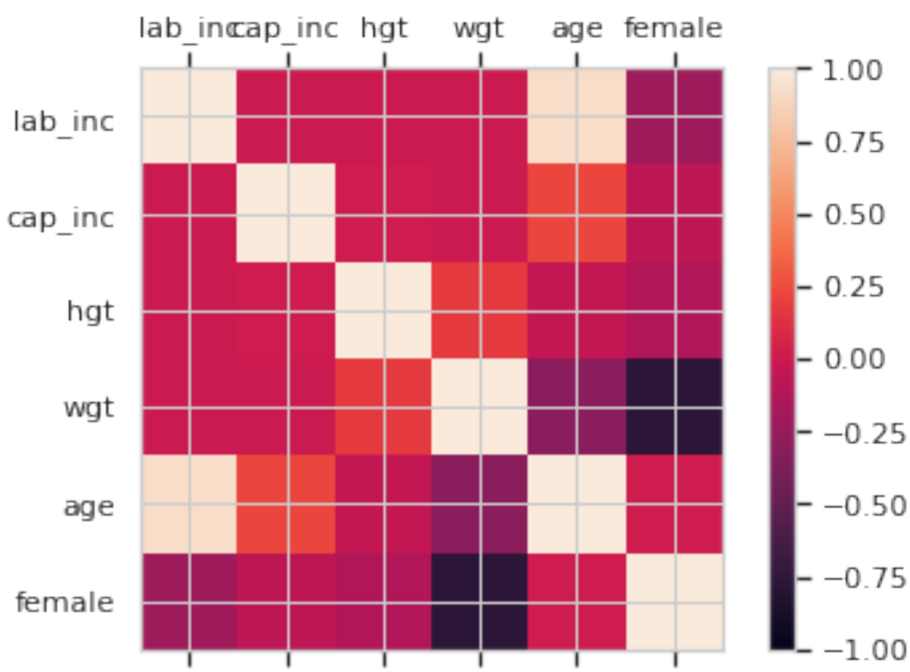
(d) Correlation matrix for the now six variables

```
In [21]: # Correlation matrix code and output
         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)
```




```
In [22]: corr = BestIncome.corr()
         corr.style.background_gradient()
```

Out[22]: <pandas.io.formats.style.Styler at 0x123b8c828>

1.0.4 2. Stationarity and data drift

(a) Estimate by OLS and report coefficients

In [23]:
```
# Read in my third data set
IncomeIntel = pd.read_csv('IncomeIntel.txt', header = None, names = ["grad_year", "gre_
IncomeIntel.head()
```

Out[23]:

	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 [24]:
```
# Run regression model
X = IncomeIntel["gre_qnt"]
X = sm.add_constant(X, prepend = False)
y = IncomeIntel["salary_p4"]
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:                Mon, 15 Oct 2018   Prob (F-statistic):           3.43e-68
Time:                        14:22:18   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

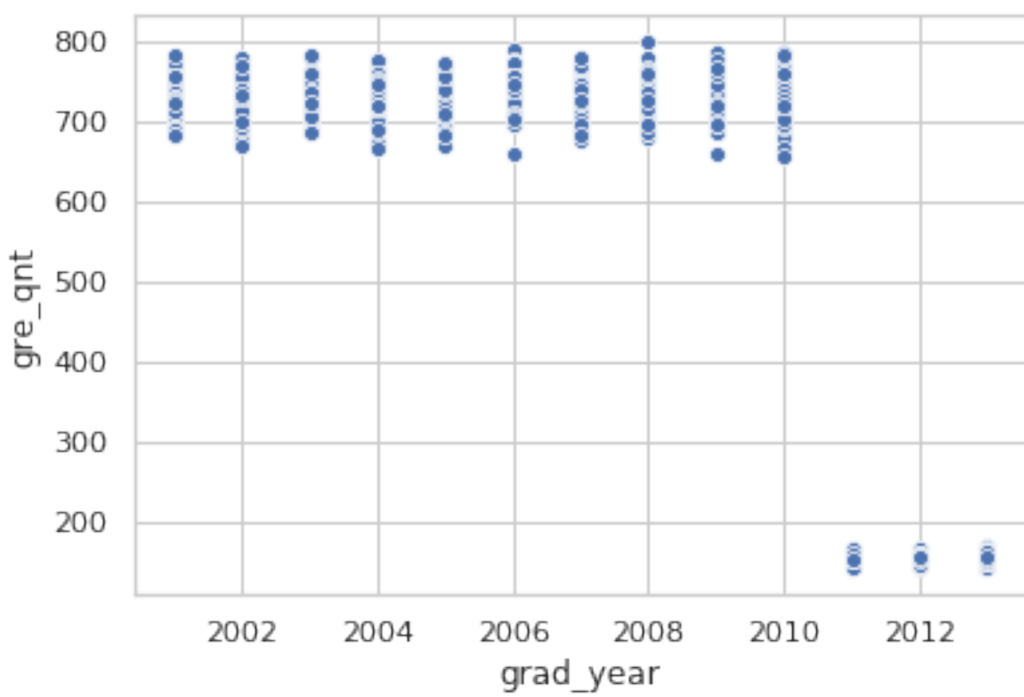
$$\beta_0 = 89540 \qquad s.e.(\beta_0) = 878.764$$

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

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

```
In [25]: # Code and output of scatterplot
         x = IncomeIntel['grad_year']
         y = IncomeIntel['gre_qnt']
         sns.scatterplot(x,y)
```

```
Out[25]: <matplotlib.axes._subplots.AxesSubplot at 0x1241db828>
```



As we can see from the output, the scatterplot has a huge change starting year 2011, which is the year that 800 score scale has changed to 170. Thus, our linear regression model used previously is not reasonable, since the GRE quant scores are not on a same scale. In addition, the difficulty of GRE quant is different among different years. In order to modify this, we have to figure out a way to make GRE quant score on the same scale.

The solution is that I will calculate the Z-score for each year scores, and then concate them. Then, the GRE score will uniquely represent the position of the students' performance.

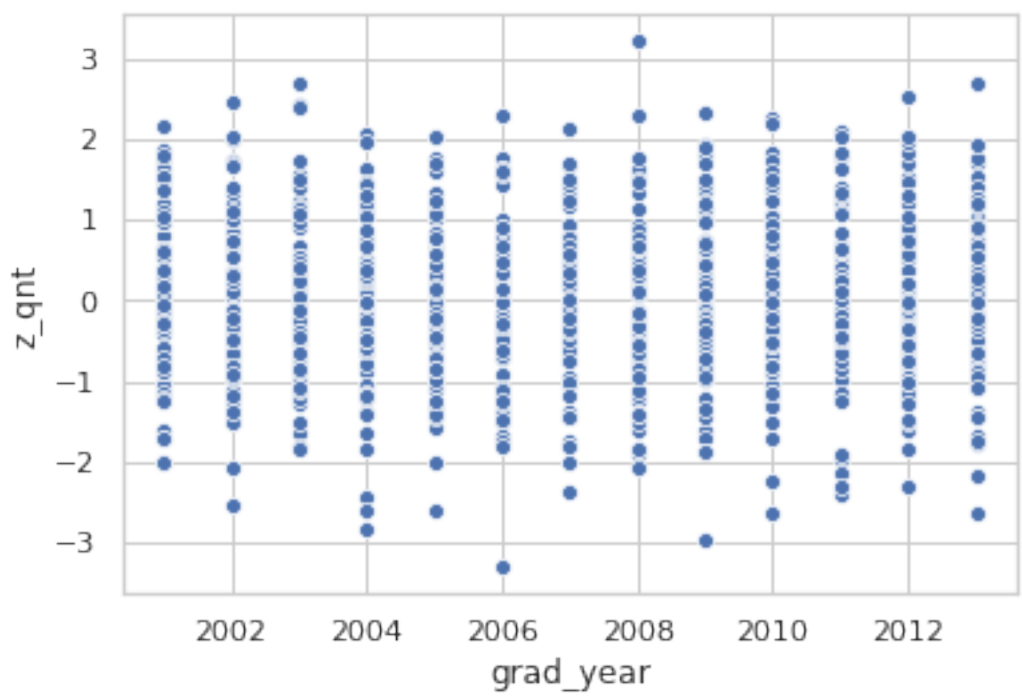
In [26]:
```
# Code to implement solution
mean_gre = {}
sd_gre = {}
for i in range(2001, 2014):
    gre = IncomeIntel['gre_qnt'][IncomeIntel['grad_year'] == i]
    mean_gre[i] = gre.mean()
    sd_gre[i] = gre.std()
IncomeIntel['z_qnt'] = 0
for i in range(2001, 2014):
    IncomeIntel['z_qnt'][IncomeIntel['grad_year'] == i] = (IncomeIntel['gre_qnt'][Incom
IncomeIntel.head()
```

Out[26]:

	grad_year	gre_qnt	salary_p4	z_qnt
0	2001.0	739.737072	67400.475185	0.406740
1	2001.0	721.811673	67600.584142	-0.356635
2	2001.0	736.277908	58704.880589	0.259427
3	2001.0	770.498485	64707.290345	1.716750
4	2001.0	735.002861	51737.324165	0.205128

In [27]:
```
# Code and output of new scatterplot
x = IncomeIntel['grad_year']
y = IncomeIntel['z_qnt']
sns.scatterplot(x,y)
```

Out[27]: <matplotlib.axes._subplots.AxesSubplot at 0x12402ca90>

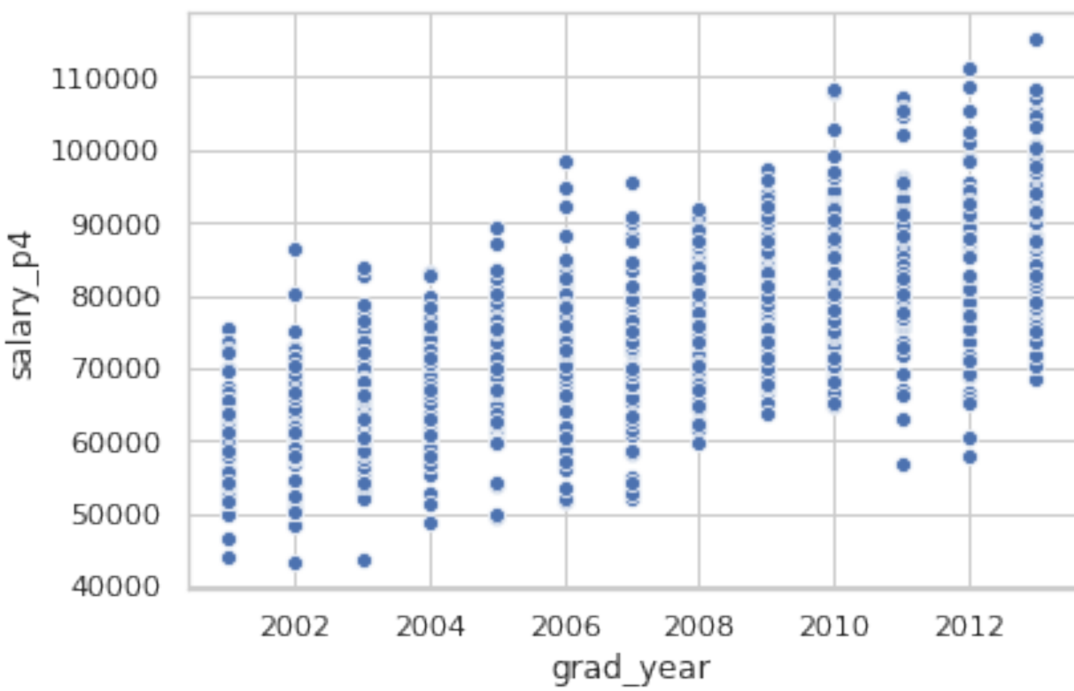


As we can see from the new scatterplot of the z-score of GRE quantitative score, the plot looks much better than the old one. The change of score scale has been solved.

(c) Create a scatterplot of income and graduation year

```
In [28]: # Code and output of scatterplot
         x = IncomeIntel['grad_year']
         y = IncomeIntel['salary_p4']
         sns.scatterplot(x,y)
```

```
Out[28]: <matplotlib.axes._subplots.AxesSubplot at 0x123b507f0>
```



As we can see from the scatterplot above, we can see that there is an increasing pattern in the plot, which implies that the data is not stationary. In order to deal with this, we can estimate the growth rate and eliminate the effect of it.
Specifically, we can first take the average salary of each year and estimate the growth rate by taking the average of each year's growth rate. For each year's growth rate, we can use the following equation:

$$growth\ rate_{year_i} = \frac{average\ salary\ of\ year_i - average\ salary\ of\ year_{i-1}}{average\ salary\ of\ year_{i-1}}$$

```
In [29]: #  Code to implement a solution
         avg_inc_by_year = IncomeIntel['salary_p4'].groupby(IncomeIntel['grad_year']).mean().val
         later_year = avg_inc_by_year[1:]
         former_year = avg_inc_by_year[0:-1]
```

```
growth_rate_by_year = ((later_year - former_year) / former_year).mean()
growth_rate = growth_rate_by_year.mean()
growth_rate
```

Out[29]: 0.030835347092883603

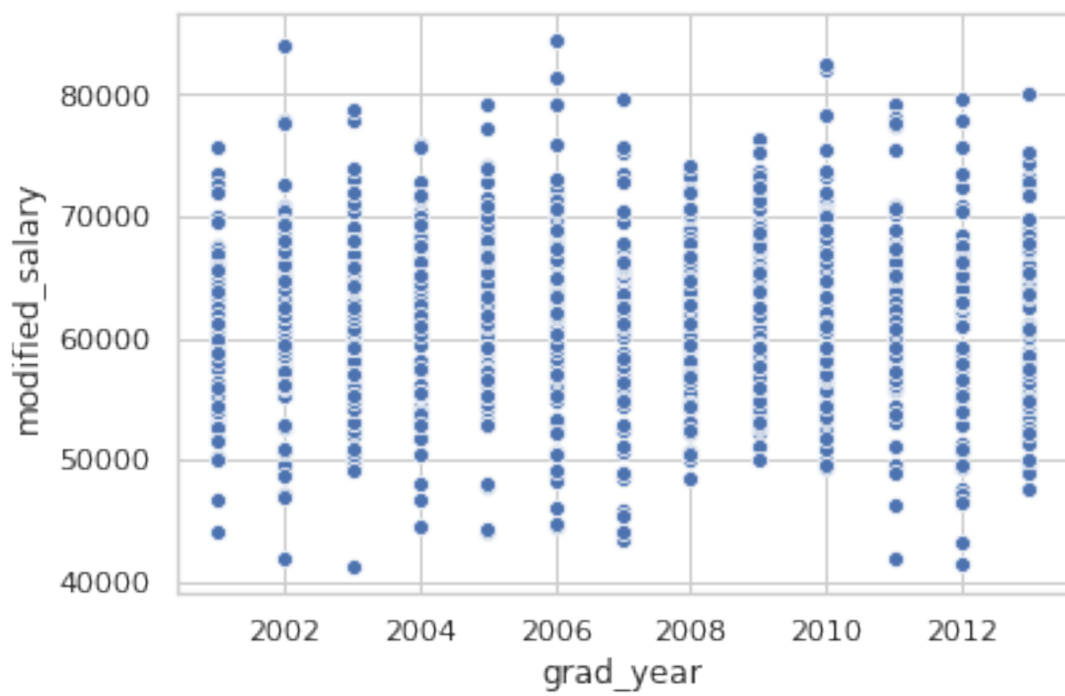
In [30]:
```
IncomeIntel['modified_salary'] = 0
for i in range(2001, 2014):
    IncomeIntel['modified_salary'][IncomeIntel['grad_year'] == i] = IncomeIntel['salary
IncomeIntel.head()
```

Out[30]:

	grad_year	gre_qnt	salary_p4	z_qnt	modified_salary
0	2001.0	739.737072	67400.475185	0.406740	67400.475185
1	2001.0	721.811673	67600.584142	-0.356635	67600.584142
2	2001.0	736.277908	58704.880589	0.259427	58704.880589
3	2001.0	770.498485	64707.290345	1.716750	64707.290345
4	2001.0	735.002861	51737.324165	0.205128	51737.324165

In [31]:
```
# Code and output of scatterplot
x = IncomeIntel['grad_year']
y = IncomeIntel['modified_salary']
sns.scatterplot(x,y)
```

Out[31]: <matplotlib.axes._subplots.AxesSubplot at 0x12497f278>



As we can see from the scatterplot, the increasing pattern has been removed.

(d) Re-estimate coefficients with updated variables.

```
In [32]: # Code to re-estimate, output of new coefficients
         # Run regression model
         X = IncomeIntel["z_qnt"]
         X = sm.add_constant(X, prepend = False)
         y = IncomeIntel["modified_salary"]
         m = sm.OLS(y, X)
         res = m.fit()
         print(res.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:        modified_salary   R-squared:                       0.000
Model:                            OLS   Adj. R-squared:                 -0.001
Method:                 Least Squares   F-statistic:                    0.4395
Date:                Mon, 15 Oct 2018   Prob (F-statistic):              0.508
Time:                        14:22:19   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]
------------------------------------------------------------------------------
z_qnt       -150.6097    227.193     -0.663      0.508    -596.440     295.221
const        6.142e+04   225.711    272.117      0.000     6.1e+04    6.19e+04
==============================================================================
Omnibus:                        0.776   Durbin-Watson:                   2.025
Prob(Omnibus):                  0.678   Jarque-Bera (JB):                0.687
Skew:                           0.059   Prob(JB):                        0.709
Kurtosis:                       3.049   Cond. No.                         1.01
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

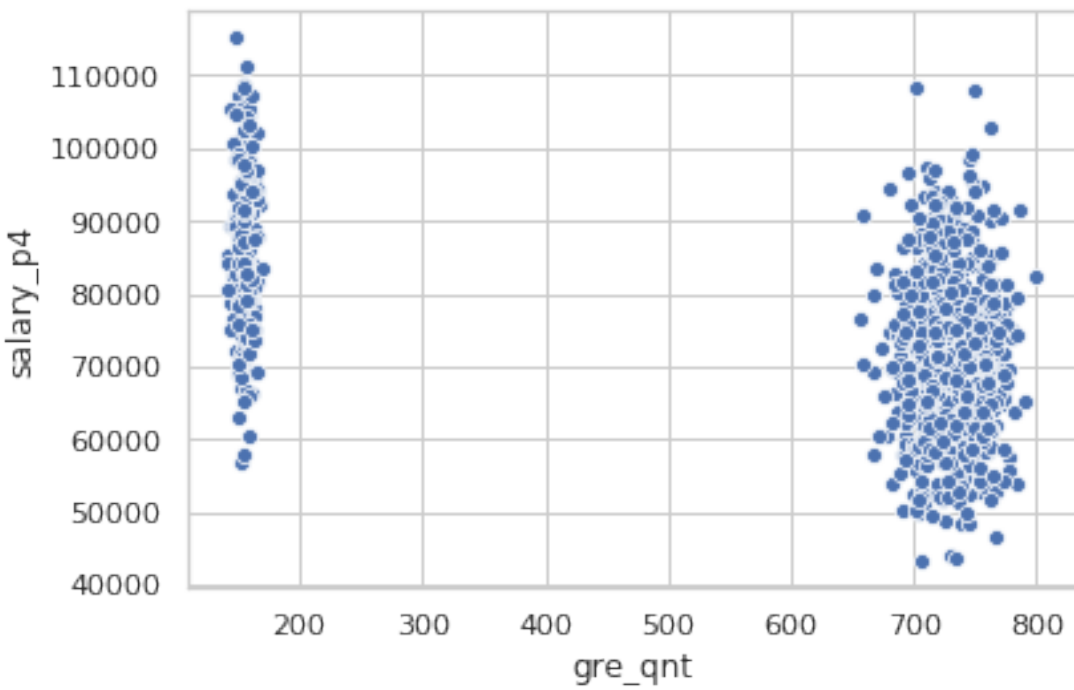
Report new coefficients and SE's

$$\beta_0 = 61420 \qquad s.e.(\beta_0) = 225.711$$

$$\beta_1 = -150.6097 \qquad s.e.(\beta_1) = 227.193$$

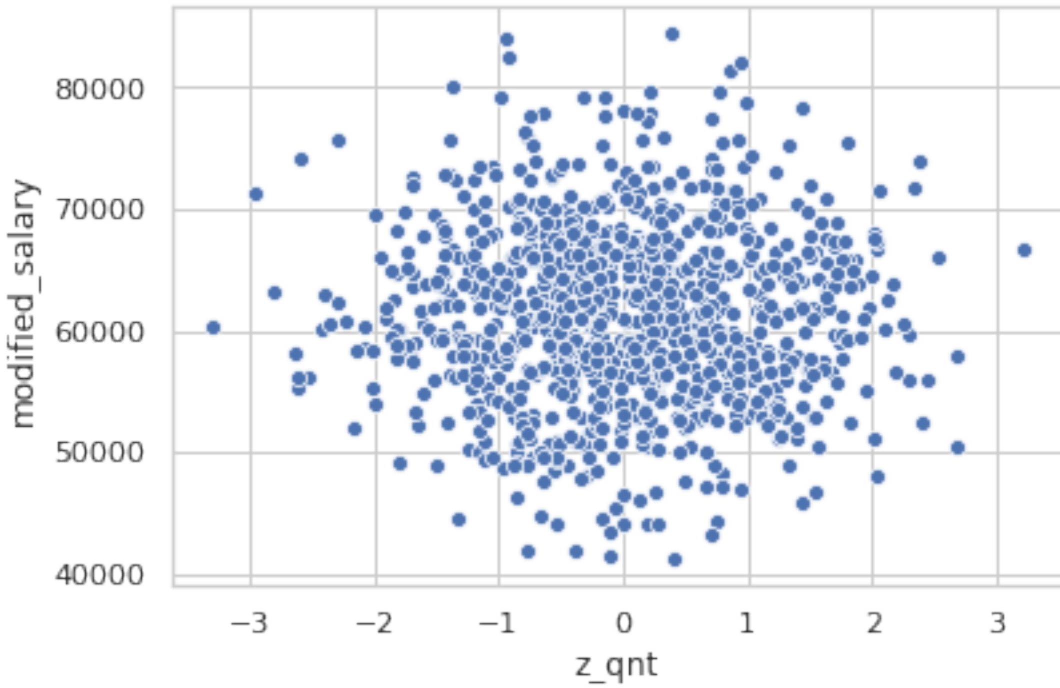
```
In [33]: x_old = IncomeIntel['gre_qnt']
         y_old = IncomeIntel['salary_p4']
         sns.scatterplot(x_old, y_old)
```

```
Out[33]: <matplotlib.axes._subplots.AxesSubplot at 0x123eaf780>
```




```
In [34]: x_new = IncomeIntel['z_qnt']
         y_new = IncomeIntel['modified_salary']
         sns.scatterplot(x_new, y_new)
```

```
Out[34]: <matplotlib.axes._subplots.AxesSubplot at 0x12490f5c0>
```



Before we changed the variables, we can see from the scatterplot of the old variables version that the scatteplot actually plots the latest years' salaries on the left and old years' salaries on the right. Thus, since the salary is increasing by year, we have a negitive relationship between gre_qnt and salary_p4.
On the other hand, after we modified the gre_qnt to z_qnt and salary_p4 to modified_salary, we can see that the scatterplot looks much better. Thus, the final result of the linear regression will be more informative than the old one. Therefore, we can conclude that the GRE quantitative score is negatively associated with the salary after 4 years of graduation, since the coefficient of β_1 is negative.

1.0.5 3. Assessment of Kossinets and Watts.

See attached PDF.

3. Assessment of Kossinets and Watts (2009)

In this sociology-related paper, the author targeted on the following research question: "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 this research question, the author conducted his analysis based on the population of 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 author selected 30,396 observations, who sent and received e-mail using their university e-mail accounts in both the first and the last months of the academic year. The data set was constructed by merging three different databases, including the logs of e-mail interactions, individual attributes, and records of course registration. The available variables were 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). For e-mail interactions data, the author included only messages that were sent to a single recipient other than the sender, which accounted for 82% of all e-mail, in order to ensure that the data present interpersonal communication. As a result of this, the author got 7,156,162 messages exchanged by 30,396 stable e-mail users during 270 days of observation.

As we mentioned previously, the author collected the data and did the data cleaning process. However, there is a potential problem that the process intro- duce in a way that diminishes the authors' ability to answer the research question. In the paper, the author selected the students who sent and received e-mail in both the first and the last months of the academic year to ensure that the analysis was unaffected by population turnover. Since the author eliminated around 13,000 individuals, which is more than 25% of the 43,553 individuals, the selection process is very influential to the result. This selection process may include many students who did not send and receive e-mail for the rest of months, and exclude many students who just did not send and receive e-mail for the first month but did for the rest months. This population selection can make the result of the analysis be biased. In addition, many students may use forward function in school e-mail system, which will forward all the e-mails to his own e-mail address instead of the university e-mail. Thus, I think the author did not take care of these issues when he cleaned the data.

In this paper, the underlying theoretical construct is "social relationships" and the data are e-mail logs linked to other characteristics of the senders and receivers. One weakness of this match of data source and theoretical construct is that the measure of individual similarity acts, in effect, as an indicator variable for sharing a class, since for students, a number of its components are highly correlated with choice of class. To address this potential systematic bias in the data, the author found that the similarity values and variance tend to be higher when individuals share same class, share same explicit foci, or same implicit foci. Furthermore, the increasing of variance for sharing implicit foci is higher than the other two. Since the author found that implicit foci, when properly calibrated, were qualitatively similar to explicit foci, and also because implicit foci apply to the entire population rather than just to students, the author used implicit foci as his primary measure of shared affiliation, whenever appropriate.