Assign2 SiyuanPeng

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1 Assignment 2

1.0.1 MACS 30000, Dr. Evans

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

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

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

1.0.3 1. Imputing age and gender

(a) Considering that these two data bases share two variables, which are income and weight, we could use these two variables as explanatory variables to build model with age and gender using survey income database. To be specifc, that is:

$age = \alpha_0 + \alpha_1 * weight + \alpha_2 * tot\_inc + \epsilon$

$female = \beta_0 + \beta_1 weight + \beta_2 * tot\_inc + \epsilon$

Then, we could use the result of α and β to calculate the age and gender in best income database.

(b) First, I must import the data.

```
In [2]: # I may use this code cell to read in my data and name the variables which have been d
        best_income = pd.read_csv('BestIncome.txt', header = None)
        best_income.columns = ['lab_inc', 'cap_inc', 'hgt', 'wgt']

        survey_income = pd.read_csv('SurvIncome.txt', header = None)
        survey_income.columns = ['tot_inc', 'wgt', 'age', 'female']
```

```
In [3]: # I shall start with the age model, which should be a simple OLS regression model.
        Y1 = survey_income['age']
        survey_income['cons'] = 1
        X1 = survey_income[['wgt', 'tot_inc', 'cons']]
        ols = sm.OLS(Y1, X1,).fit()

        #Use the ols result to calculate the age of the BestIncome database.
        best_income['tot_inc'] = best_income['lab_inc'] + best_income['cap_inc']
        best_income['cons'] = 1
        best_income['age'] = ols.predict(best_income[['wgt', 'tot_inc', 'cons']])
```

```
In [4]: # Secondly, I shall compute the gender model. Considering that gender is a 0\1 variabl
        Y2 = survey_income['female']
        X2 = survey_income[['wgt', 'tot_inc', 'cons']]
        logit = sm.Logit(Y2,X2).fit()

        #Use the logit result to calculate the gender of the BestIncome database.
        best_income['female'] = logit.predict(best_income[['wgt', 'tot_inc', 'cons']])

        #Check the value of the gender variable.
        check = best_income['female'][:]
        check[check >= 0.5] = 1
        check[check < 0.5] = 0
        best_income['female'] = check
```

```
Optimization terminated successfully.
         Current function value: 0.036050
         Iterations 11
```

(c) The report of the variables are listed below.

```
In [5]: # Firstly, report the age.
        print(best_income['age'].describe()[['mean', 'std', 'min', 'max', 'count']])

        #Secondly, report the gender.
        print(best_income['female'].describe()[['mean', 'std', 'min', 'max', 'count']])
```

```
mean        44.890828
std          0.219150
min         43.976495
max         45.703819
count    10000.000000
Name: age, dtype: float64
mean         0.454600
std          0.497959
min          0.000000
max          1.000000
```

```
count    10000.000000
Name: female, dtype: float64
```

(d) The correlation matrix is shown below.

```
In [6]: show_list = best_income[['lab_inc','cap_inc','hgt','wgt','age','female']]
        cor = show_list.corr()
        cor.style.background_gradient()
        print(cor)
```

```
          lab_inc   cap_inc       hgt       wgt       age    female
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
female  -0.215469 -0.062569 -0.127416 -0.763821  0.020059  1.000000
```

1.0.4 2. Imputing age and gender

(a) Just compute the raw data.

```
In [7]: # I may use this code cell to read in my data and name the variables which have been d
        income_intel = pd.read_csv('IncomeIntel.txt', header = None)
        income_intel.columns = ['grad_year', 'gre_qnt', 'salary_p4']
```

```
In [8]: # Then, I shall simply compute the raw data use the OLS model as stated in the assignm
        Y1 = income_intel['salary_p4']
        income_intel['cons'] = 1
        X1 = income_intel[['gre_qnt', 'cons']]
        ols = sm.OLS(Y1,X1).fit()
        print(ols.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:                        17:52:49   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]
------------------------------------------------------------------------------
```

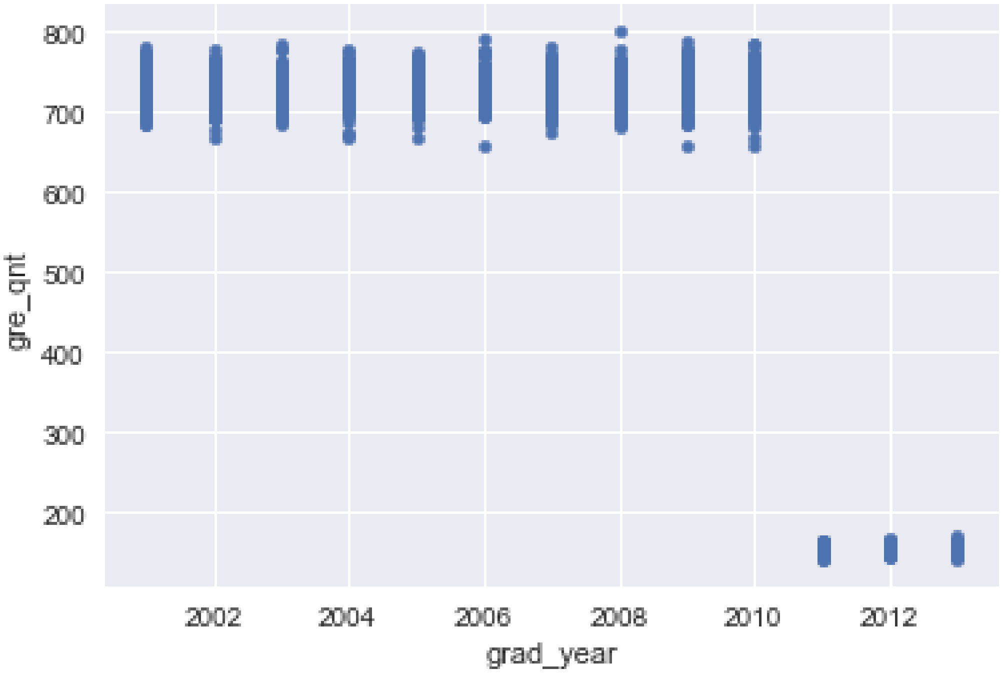
```
gre_qnt       -25.7632      1.365    -18.875      0.000     -28.442     -23.085
cons         8.954e+04    878.764    101.895      0.000    8.78e+04    9.13e+04
==============================================================================
Omnibus:                        9.118   Durbin-Watson:                   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.
```

As shown above, the coefficient of GRE quantitative score is -25.7632 and its standard error is 1.365. As for the coefficient of cons, it is 8.954 * 10ˆ4 and its standard error is 878.764.

(b) Draw the scatterplot and find the problem.

```
In [9]: # draw the scatterplot.
        income_intel.plot(x = 'grad_year', y = 'gre_qnt', kind = 'scatter')
        plt.show()
```



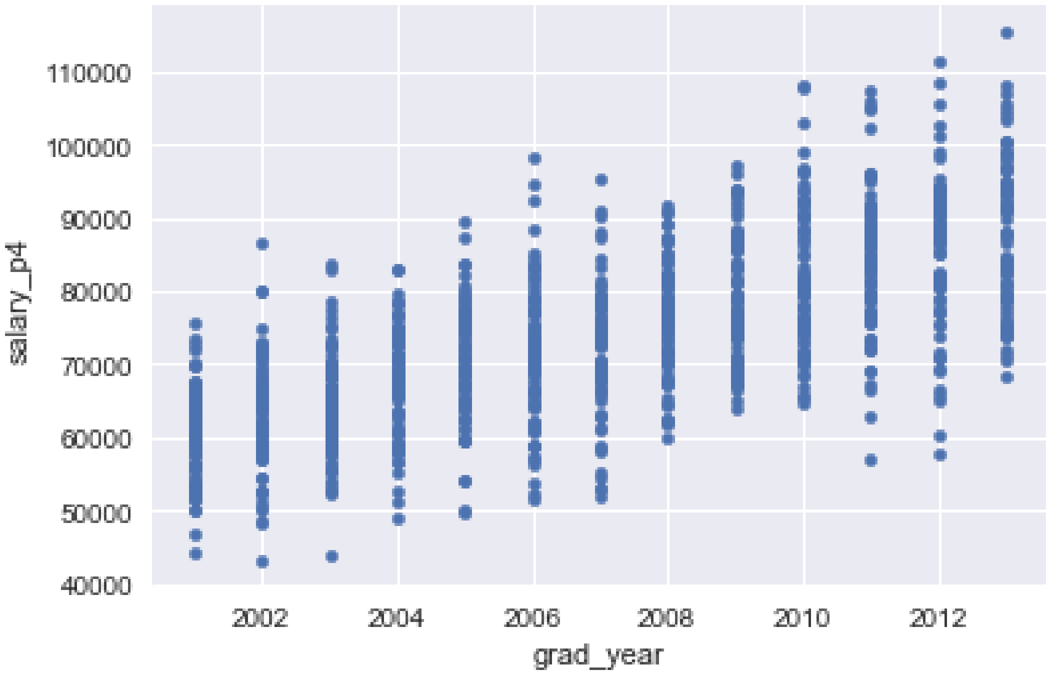
Here is where I'll discuss any problems that jump out. I'll propose a solution here as well.

The above scatterplot shows clearly that the GRE quatitative score changed dramatically after 2011. Considering that the scale of this score has changed in 2011, we could use the concordance table provided by the official ETS to transform the old score to the latest version to make sure our regression is consistent.

The link of the concordance table is : https://www.ets.org/s/gre/pdf/concordance_information.pdf

(c) Draw the scatterplot and find the problem.

```
In [10]: # draw the scatterplot.
         income_intel.plot(x = 'grad_year', y = 'salary_p4', kind = 'scatter')
         plt.show()
```



The scatterplot shows clearly that there is a increasing trend of salary acrossing years. Therefore, we need to detrend the salary firstly. The solution will be shown as follows: (1) Treat the first year of the data, which is 2001, equal to the base year. (2) Calculate the average growth rate in salary. (3) Divide each salary by the (1 + avg_growth_rate) ** (grad_year - 2001). All of the equations related to this method are provided by Professor Evans.

(d) Re-estimate.

```
In [11]: # Use the concordance table to transform the old score to the latest version.
         def concordance(qnt_score):
             old_version = [800, 790, 780, 770, 760, 750, 740, 730, 720, 710, 690, 680, 670, 65
             lat_version = [166, 164, 163, 161, 160, 159, 158, 157, 156, 155, 154, 153, 152, 15
             if qnt_score < 171:
```

```python
                return qnt_score
            else:
                for i,val in enumerate(lat_version):
                    if qnt_score <= old_version[i] and qnt_score > old_version[i+1]:
                        return val

income_intel['lat_score'] = [[]] * len(income_intel['gre_qnt'])
for i in range(len(income_intel['lat_score'])):
    income_intel['lat_score'][i] = concordance(income_intel['gre_qnt'][i])

# Calculate the detrend salary.
avg_inc_by_year = income_intel['salary_p4'].groupby(income_intel['grad_year']).mean()
avg_growth_rate = ((avg_inc_by_year[1:] - avg_inc_by_year[:-1]) / avg_inc_by_year[:-1
income_intel['det_salary'] = [[]] * len(income_intel['salary_p4'])
for i in range(2001, 2014):
    income_intel['det_salary'][income_intel['grad_year'] == i] = income_intel['salary_

# Calculate the new OLS model.
Y2 = income_intel['det_salary']
X2 = income_intel[['lat_score', 'cons']]
ols = sm.OLS(Y2.astype(float),X2.astype(float)).fit()
print(ols.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:             det_salary   R-squared:                       0.000
Model:                            OLS   Adj. R-squared:                 -0.001
Method:                 Least Squares   F-statistic:                    0.4730
Date:                Tue, 16 Oct 2018   Prob (F-statistic):              0.492
Time:                        17:53:27   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]
------------------------------------------------------------------------------
lat_score    -46.0587     66.967     -0.688      0.492    -177.471      85.354
cons        6.865e+04    1.05e+04      6.532      0.000     4.8e+04    8.93e+04
==============================================================================
Omnibus:                        0.757   Durbin-Watson:                   2.025
Prob(Omnibus):                  0.685   Jarque-Bera (JB):                0.667
Skew:                           0.058   Prob(JB):                        0.717
Kurtosis:                       3.050   Cond. No.                     7.31e+03
==============================================================================

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

```
[2] The condition number is large, 7.31e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

The above result shows that while the coefficient of the GRE quantitative score is still negative, it becomes insiginificant.

In our common sense, person who has higher mathmatics score should has higher salary. However, the result of our original model conflicts this common sense. Therefore, when we modify our model by use the same scale of the GRE score and detrend salary, even though the coefficient is still negative, it becomes insiginificant, which means that there is no relationship between GRE score and salary. I think we could see this change as a improvement. At least the model doesn't conflict our common sense now.

As for the reason for this relatively small Rˆ2 and insignificant coefficient, I think it is mainly due to the fact that mathmatic score doesn't have a linear relationship with salary at all.

1.0.5 3. Assessment of Kossinets and Watts.

See attached PDF.

3. Assessment of Kossinets and Watts (2009)

The research question of this paper, just like its title, is ‘what’s the origin of the homophily in an evolving social network?’, or, to be specific, ‘what’s the sequence and priority of different mechanisms behind the formation of homophily principle?’ The author cited *McPherson and Smith-Lovin 1987*’s paper to illustrate two mechanisms, which are called choice homophily and induced homophily. The author just used the same definition of these two mechanisms by *McPherson and Smith-Lovin* and used them to illustrate the aforementioned question.

The author’s analysis is based on the data set of a large U.S. university, who used their university e-mail accounts to both send and receive messages during one academic year. This data set 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 resulting data set comprised 7,156,162 messages exchanged by 30,396 stable e-mail users during 270 days of observation. The description and definition of all the variables could be found in Appendix A.

In the data cleaning process, the author said that only e-mail accounts on the central university server were included in the data set and they have excluded the email accounts which provided by university’s departments. Considering that, usually one person could have multiple email addresses, like using both university’s email address and department’s email address, this kind of data cleaning would lead to data deficiency to represent the whole picture of a person’s social relationship. Therefore, it could lead to severe problem which may made me suspect about the accuracy of the result.

As for the weakness of the match of data source and social relationship, as the author mentioned in the network construction part, the building of social relationship is dynamic and continuous while E-mail exchanges is discrete and intermittent. To conquer this problem, the author employ a simple but effective method known as a *sliding window filter*—a technique often employed to analyze and visualize networks over time (Cortes et al. 2003; Moody et al. 2005; Kossinets and Watts 2006). This method uses geometric average of the number of messages exchanged by users per unit of time, summed over the past X time units. While moving along time, keep X as fixed, just like moving a window with constant length on a track. Therefore, by summing the Email exchanges in a fixed period, we could view it as continuous in time.

References

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

All the above answers are cited from this paper.