Assignment 2

Fulin Guo

In [22]:

```
import numpy as np
import pandas as pd
import statsmodels.api as sm
import math
import sklearn as sk
```

1. Imputing age and gender

(a) First, conduct OLS regression based on observations from SurveyIncome.txt. The explanatory variables are tot_inc and wgt, and the dependent variable would be age, female respectively. Second, we can use the estimated parameters to impute age and gender variable in BestIncome.txt based on labor income, capital income and weight variable in that dataset. Lastly, we should ensure that the female variable be either 0 or 1 by making the following transformation: If estimated female value is smaller than 0.5, female equals to 0. Otherwise, female equals to 1.

(Equations and more details are in the pdf file: answer_fulinguo.pdf)

In [23]:

```
f=pd.read_table('/Users/fulinguo/Desktop/persp-analysis_A18/Assignments/A2/SurvIncor
                header=None,names=['tot_inc','wgt','age','female'])
f1=pd.read_table('/Users/fulinguo/Desktop/persp-analysis_A18/Assignments/A2/BestInco
                 header=None,names=['lab_inc','cap_inc','hgt','wgt'])
```

(b) Use my proposed method from part (a) to impute variables into the BestIncome.txt data. Here are the codes and results.

In [24]:

```
outcome='age'
features=['tot_inc','wgt']
import statsmodels.api as sm
```

```
# OLS(age)
X=f[features]
y=f[outcome]
X=sm.add_constant(X)
m_age=sm.OLS(y,X)
res=m_age.fit()
print(res.summary())

# OLS(female)
outcome2='female'
y2=f[outcome2]
m_fel=sm.OLS(y2,X)
res=m_fel.fit()
print(res.summary())

# impute age
def imp_age(x):
    tot_inc=x[0]+x[1]
    wgt=x[2]
    age=44.2097+2.52*10**(-5)*tot_inc-0.0067*wgt
    return age

# impute female
def imp_female(x):
    tot_inc=x[0]+x[1]
    wgt=x[2]
    gender=3.7611-5.25*10**(-6)*tot_inc-0.0195*wgt
    if gender>=0.5:
        gender=1
    else:
        gender=0
    return gender

f1['imputed_age']=f1[['lab_inc','cap_inc','wgt']].apply(imp_age,axis=1)
f1['imputed_female']=f1[['lab_inc','cap_inc','wgt']].apply(imp_female,axis=1)
print(f1[['imputed_age','imputed_female']].head()) # print first five rows of impute
```

```
                            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:                        21:38:28   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]
----------------------------------------------------------------------
--------
const         44.2097      1.490     29.666      0.000      41.285
47.134
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
======================================================================
========
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 t
here are
strong multicollinearity or other numerical problems.
                            OLS Regression Results
======================================================================
========
Dep. Variable:                 female   R-squared:
0.834
Model:                            OLS   Adj. R-squared:
0.834
Method:                 Least Squares   F-statistic:
2513.
Date:                Tue, 16 Oct 2018   Prob (F-statistic):
0.00
Time:                        21:38:28   Log-Likelihood:
173.49
No. Observations:                1000   AIC:
-341.0
Df Residuals:                     997   BIC:
-326.3
Df Model:                           2
Covariance Type:            nonrobust
```

```
==============================================================================
========
                 coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
--------
const          3.7611      0.051     73.600      0.000       3.661
3.861
tot_inc     -5.25e-06   7.76e-07     -6.765      0.000   -6.77e-06   -
3.73e-06
wgt           -0.0195      0.000    -58.098      0.000      -0.020
-0.019
==============================================================================
========
Omnibus:                        0.170   Durbin-Watson:
1.634
Prob(Omnibus):                  0.918   Jarque-Bera (JB):
0.114
Skew:                          -0.022   Prob(JB):
0.945
Kurtosis:                       3.029   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 t
here are
strong multicollinearity or other numerical problems.
   imputed_age  imputed_female
0    44.745897               0
1    45.157777               0
2    44.745701               0
3    44.919024               0
4    44.554687               0
```

(c) The codes and outcomes of the descriptive statistics for imputed variables.

In [25]:

```
print(f1['imputed_age'].describe())
print(f1['imputed_female'].describe())
```

```
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, dtype: float64
count    10000.000000
mean         0.470500
std          0.499154
min          0.000000
25%          0.000000
50%          0.000000
75%          1.000000
max          1.000000
Name: imputed_female, dtype: float64
```

(d) Correlation matrix for the now six variables

In [26]:

```
f1.corr()
```

Out[26]:

	lab_inc	cap_inc	hgt	wgt	imputed_age	imputed_female
lab_inc	1.000000	0.005325	0.002790	0.004507	0.924329	-0.164857
cap_inc	0.005325	1.000000	0.021572	0.006299	0.234234	-0.046594
hgt	0.002790	0.021572	1.000000	0.172103	-0.044927	-0.134172
wgt	0.004507	0.006299	0.172103	1.000000	-0.299395	-0.778537
imputed_age	0.924329	0.234234	-0.044927	-0.299395	1.000000	0.074288
imputed_female	-0.164857	-0.046594	-0.134172	-0.778537	0.074288	1.000000

2. Stationarity and data drift

(a) Estimate by OLS: The dependent variable is salary_p4, and the explanatory variable is gre_gnt. Here are the codes and results

In [27]:

```
import pandas as pd
import numpy as np
f=pd.read_csv('/Users/fulinguo/Desktop/persp-analysis_A18/Assignments/A2/IncomeInte
              delimiter=',',names=['grad_year','gre_qnt','salary_p4'])
X=f['gre_qnt']
y=f['salary_p4']
import statsmodels.api as sm
X=sm.add_constant(X)
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:                        21:41:41   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]
----------------------------------------------------------------------
--------
const       8.954e+04    878.764    101.895      0.000    8.78e+04
9.13e+04
gre_qnt      -25.7632      1.365    -18.875      0.000     -28.442
-23.085
```

```
==============================================================================
========
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.
```

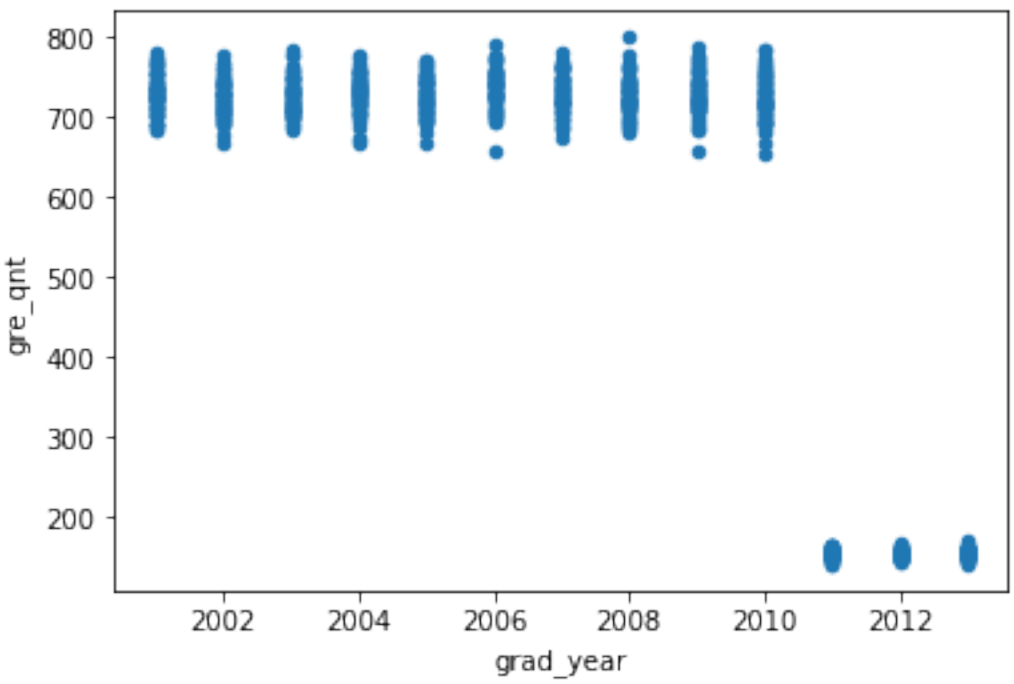
(b) Create a scatterplot of GRE score and graduation year.

In [28]:

```
from ggplot import *
grad_year=f['grad_year']
gre=f['gre_qnt']
f.plot(x='grad_year',y='gre_qnt',kind='scatter')
```

Out[28]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1c1aa12f60>
```



The problem is that the gre_gnt variable has an obvious relationship with grad_year. That is, the gre_gnt variable is between 600 and 800 when grad_year is smaller than 2011 and less than 200 when grad_year is larger than or equal to 2011. This is a potential problem when testing the hypothesis since the correlation between gre_qnt and salary_p4 showed in part(a) might just because the two variables both have a correlation with the third variable grad_year and there is no causal correlation between gre_qnt and salary_p4. This is a biased estimation. To solve this problem, I remove the influence of grad_year on gre_qnt by conducting the OLS regression where the dependent variable is gre_qnt and the explanatory variable is a dummy variable which equals to 1 if the grad_year is larger than or equal to 2011 and 0 if grad_year is smaller than 2011. The last step is to calculate updated_gre = gre_qnt – 573.5272 for all observations before 2011 where 573.5272 is the averge difference between gre_qnt after 2011 and before 2011.

(Equations and more details are in the pdf file: answer_fulinguo.pdf)

In [31]:

```
def y_2011(x):
    grad=x[0]
    if grad>=2011:
        aft=1
```

```python
        aft=1
    else:
        aft=0
    return aft

f['aft_2011']=f[['grad_year']].apply(y_2011,axis=1)
X=f['aft_2011']
y=f['gre_qnt']
X=sm.add_constant(X,prepend=False)
m=sm.OLS(y,X)
res=m.fit()
print(res.summary())
def updated_gre(x):
    aft=x[0]
    gre=x[1]
    if aft==1:
        upd_gre=gre
    else:
        upd_gre=gre-573.5252
    return upd_gre

f['updated_gre']=f[['aft_2011','gre_qnt']].apply(updated_gre,axis=1)
print(f[['updated_gre']].head())
```

```
                            OLS Regression Results                            
======================================================================
========
Dep. Variable:                gre_qnt   R-squared:                       
0.993
Model:                            OLS   Adj. R-squared:                  
0.993
Method:                 Least Squares   F-statistic:                     1
.363e+05
Date:                Tue, 16 Oct 2018   Prob (F-statistic):              
0.00
Time:                        22:00:00   Log-Likelihood:                 
-4446.7
No. Observations:                1000   AIC:                            
8897.
Df Residuals:                     998   BIC:                            
8907.
Df Model:                           1                                         
Covariance Type:            nonrobust                                         
======================================================================
========
                 coef    std err          t      P>|t|      [0.025      
0.975]
----------------------------------------------------------------------
--------
aft_2011    -573.5272      1.553   -369.222      0.000    -576.575    
-570.479
const        728.4214      0.745    977.806      0.000     726.960    
729.883
======================================================================
```

```
========
Omnibus:                       10.161   Durbin-Watson:
1.952
Prob(Omnibus):                  0.006   Jarque-Bera (JB):
15.242
Skew:                          -0.003   Prob(JB):
0.000490
Kurtosis:                       3.605   Cond. No.
2.53
==============================================================================
========

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
   updated_gre
0   166.211872
1   148.286473
2   162.752708
3   196.973285
4   161.477661
```

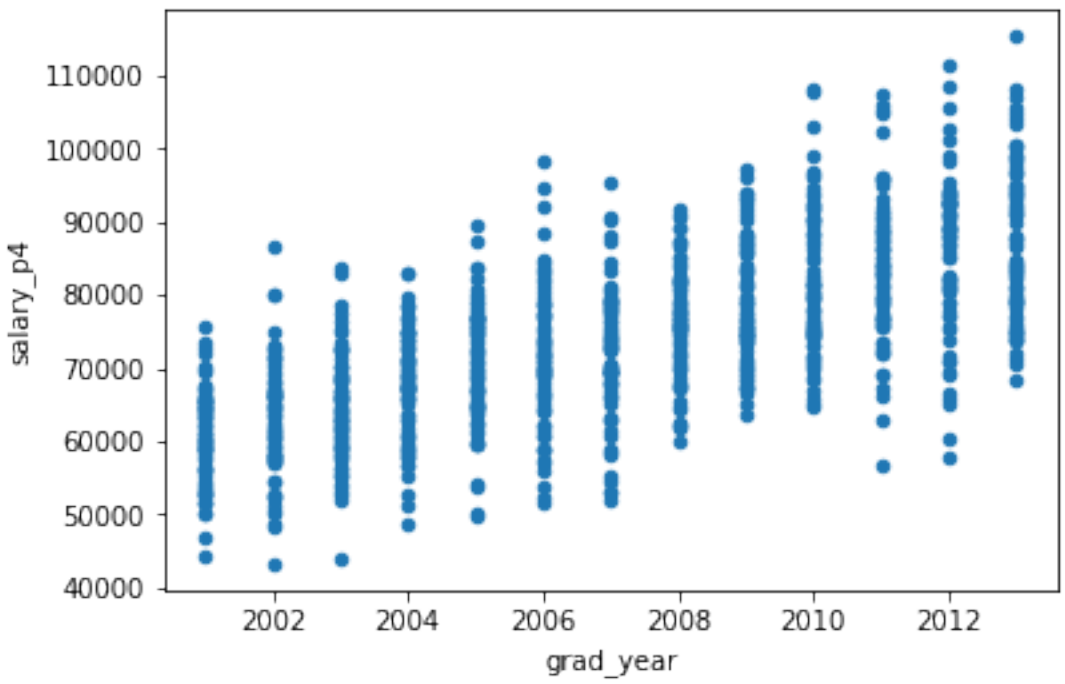
(c) Create a scatterplot of income and graduation year

In [32]:

```
f.plot(x='grad_year',y='salary_p4',kind='scatter')
```

Out[32]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1c1b688ac8>
```



The problem is that the salary_p4 variable has an obvious relationship with grad_year variable. That is, the salary_p4 variable has an increasing trend. This is a potential problem when testing the hypothesis since the correlation between gre_qnt and salary_p4 showed in part(a) might just because the two variables both have a correlation with the third variable grad_year and there is no causal correlation between gre_qnt and salary_p4, which results in a biased estimation.

To solve this problem, I remove the influence of grad_year on salary_p4 by estimating the following OLS regression where the dependent variable is log(salary_p4) and the explanatory variable is the grad_year. Then I use salary_p4 minus exp(the fitted value of this regression) as the updated_sal.

Equations and more details are in the pdf file: answer_fulinguo.pdf

In [33]:

```
import math

X=f['grad_year']
y=[math.log(c) for c in f['salary_p4']]
X=sm.add_constant(X,prepend=False)
m=sm.OLS(y,X)
res=m.fit()
print(res.summary())

def updated_sal(x):
    grad=x[0]
    upd=x[1]-math.e**(-50.7169+0.0309*grad)
    return upd
f['updated_sal']=f[['grad_year','salary_p4']].apply(updated_sal,axis=1)
print(f.head())
```

```
                            OLS Regression Results
======================================================================
========
Dep. Variable:                      y   R-squared:
0.490
Model:                            OLS   Adj. R-squared:
0.489
Method:                 Least Squares   F-statistic:
957.7
Date:                Tue, 16 Oct 2018   Prob (F-statistic):          5
.73e-148
Time:                        22:00:23   Log-Likelihood:
720.33
No. Observations:                1000   AIC:
-1437.
Df Residuals:                     998   BIC:
-1427.
Df Model:                           1
Covariance Type:            nonrobust
```

```
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
grad_year      0.0309      0.001     30.947      0.000       0.029       0.033
const        -50.7169      2.001    -25.349      0.000     -54.643     -46.791
==============================================================================
Omnibus:                       16.351   Durbin-Watson:                   2.019
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               16.700
Skew:                          -0.304   Prob(JB):                     0.000236
Kurtosis:                       3.177   Cond. No.                     1.08e+06
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.08e+06. This might indicate that there are
strong multicollinearity or other numerical problems.
   grad_year     gre_qnt     salary_p4  aft_2011  updated_gre   updated_sal
0     2001.0  739.737072  67400.475185         0   166.211872    296.403632
1     2001.0  721.811673  67600.584142         0   148.286473    496.512589
2     2001.0  736.277908  58704.880589         0   162.752708  -8399.190964
3     2001.0  770.498485  64707.290345         0   196.973285  -2396.781208
4     2001.0  735.002861  51737.324165         0   161.477661 -15366.747388
```

(d) Because I have eliminated the influence of grad_year on both salary_p4 and gre_qnt, using updated_sal and updated_gre variable to test the hypothesis will reflect the net correlation between salary and GRE score (without the influence of grad_year). Here are the codes and results:

In [35]:

```
y=f['updated_sal']
X=f['updated_gre']
```

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

```
                            OLS Regression Results
==============================================================================
========
Dep. Variable:            updated_sal   R-squared:
0.000
Model:                            OLS   Adj. R-squared:
-0.001
Method:                 Least Squares   F-statistic:
0.3956
Date:                Tue, 16 Oct 2018   Prob (F-statistic):
0.529
Time:                        22:01:37   Log-Likelihood:
-10495.
No. Observations:                1000   AIC:                             2
.099e+04
Df Residuals:                     998   BIC:                             2
.100e+04
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
=========
                 coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
---------
const      -5819.1738   2094.231     -2.779      0.006   -9928.776
-1709.572
updated_gre   -8.4296     13.402     -0.629      0.529     -34.728
17.869
==============================================================================
========
Omnibus:                        1.261   Durbin-Watson:
2.030
Prob(Omnibus):                  0.532   Jarque-Bera (JB):
1.164
Skew:                          -0.006   Prob(JB):
0.559
Kurtosis:                       3.167   Cond. No.
1.18e+03
==============================================================================
========

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 1.18e+03. This might indicate that
there are
strong multicollinearity or other numerical problems.
```

```
        The estimated beta0 is -5819.7318, the standard errors of beta0 is 2
094.231.
        The estimated beta1 is -8.4296, the standard errors of beta1 is 13.4
02.
```

Compare the result of (d) and (a), firstly, I find that the estimated constant beta0 is smaller in (d) than (a). This is just because the updated_sal is smaller than the origin variable salary_p4 because in part(c), we remove the influence of grad_year on salary_p4 by "updated_sal equals to salary_p4 minus exp(the fitted value of this regression) as the updated_sal".

The more important change is beta1, which is larger in (d) than it is in part (a). The p-value in part (a) is 0.000, but in part (d), the p=value is 0.529. This means we cannot reject the hypothesis that beta1=0 in part (d) while I need to reject this hypothesis in part(a). This big difference is because in part (a), we do not remove the influence of grad_year on gre_qnt and salary_p4. The salary_p4 variable increases as the grad_year increases and gre_qnt is smaller when the grad_year is larger than 2011 than when the grad_year is smaller than 2011. Because the positive correlation between salary_p4 and grad_year as well as the negative correlation (although not linear) between gre_qnt and grad_year, the salary_p4 and gre_qnt will have a negative correlation due to the third variable grad_year, which means in part(a), I underestimate the coefficient beta1. In part(d), the result shows there is no significant negative correlation between salary and GRE after removing the influence of graduation year. In conclusion, there is no evidence that "higher intelligence is associated with higher income".

The complete answer is in the attached pdf file: answer_fulinguo.pdf

3. Assessment of Kossinets and Watts.¶ See attached PDF.

The research question in the paper is “To what extent can observed homophily be attributed to individual preference (choice homophily) and structural constraints (induced homophily) respectively?”

To answer this question, the authors utilize a network data which records interactions between students, faculty, and staff as well as individual features and structural organizations. There are three different data sources: The first is the logs of e-mail interactions between individuals in a U.S. university. The second is the data of individual attributes, including status, gender, age, etc. The third data source is the record of course registration. There are 30396 individuals in the data, including undergraduate students (21%), graduate and professional students (27%), faculty (13%), and staff (13.4%) in the university (There were 43,553 individuals who used university e-mail to both send and receive messages during the academic year. However, the authors only include 30,396 individuals among them who exchanged messages with others that are active in both fall and spring semester). The authors only include email that were sent to singer recipient other than the sender, which has 7,156,162 messages, accounting for 82% of all email. The time period is one fall semester and one spring semester, 270 days in total (Though the full data set spans two calendar years, the authors only analyze one calendar years). The description and definition of all variable are in appendix A of the paper.

In the footnote 23 on the page 423 of the paper, the authors indicate the method of treating missing variables when calculating the aggregate measure of pairwise similarity, which is using the population mean for this similarity-scale component. The authors said that the missing values are nonrandom, like nonstudents having more missing data than students. The problem is that the group that has more missing data might also has higher/lower similarity (i.e. There is a correlation between the proportion of missing data and similarity). For example, if faculty have more missing values of age than others, suppose that either faculty i or j has a missing value age, and according to the authors’ suggestions, we would assign age match (i, j) = 0.175 for faculty i and j because 17.5% of all pairs are of the same age in the university. The problem is that the differences in age between faculty might be larger than that between students, indicating that 0.175 overestimates the similarity between faculty i and j. Similarity is a very important variable in the paper. If at the same time, faculty are more or less likely to form new ties with others, there would be a biased estimation of the correlation between similarity and relationship forming.

There are some weakness of the match of data source and theoretical construct. For instance, some email contact might not represent interpersonal relationship, like the email sent from an administrative staff to all students in a department. The authors address this weakness by including only messages that were sent to a single recipient other than the sender (eliminating multi-recipient e-mail). The authors also eliminate the simultaneous messages from the same sender that differed in size by less than 100 bytes. Therefore, after eliminating the email logs which do not represent interpersonal communication, the match between theoretical construct and data improves.

In [ ]: