Assignment 2

MACS 30000

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Due Wednesday, Oct. 17 at 11:30 AM

1. Imputing age and gender

(a) Propose a strategy for imputing age (age) and gender (female) variables into the BestIncome.txt data by using information from the SurveyIncome.txt data. Describe your proposed method, including equations.

We want to replace the missing values for *age* and *gender* in *BestIncome* with substituted values. As *BestIncome* and *SurveyIncome* have common variables of *totinc* (sum of `lab_inc` and `cap_inc` in `BestIncome`) and *weight*, we could predict the missing values using the regression models trained by *SurveyIncome* data.

Linear regression for *age*:

$$Age_i = \alpha_0 + \alpha_1 totinc_i + \alpha_2 wgt_i + \epsilon_i$$

where:

α_0 is the intercept of the linear line on the y-axis

α_1 and α_2 represent the marginal effect on age when variables change 1 unit

ϵ_i is an error term (deviations of observations from the linear)

Logistic regression for dichotomous variable *gender*:

$$log(\frac{p(X)}{1-P(X)}) = \beta_0 + \beta_1 totinc_i + \beta_2 wgt_i + \epsilon_i$$

where X=(*totinc*, *wgt*) are two predictors. The left-hand side is called the log-odds.

(b)Using your proposed method from part (a), impute the variables age (age) and gender (female) into the BestIncome.txt data.

In [12]:
```
# Import packages
import numpy as np
import pandas as pd
import statsmodels.api as sm
import matplotlib.pyplot as plt
plt.style.use('seaborn')
import warnings
warnings.filterwarnings("ignore")
```

In [3]:
```
# Read in data, name four variables, descrptive statistics
Best = pd.read_csv('BestIncome.txt', header=None,names = ['lab_inc','cap_inc',
'hgt','wgt'])
Best.head()
```

Out[3]:

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

In [4]:
```
Surv = pd.read_csv('SurvIncome.txt', header = None,names = ['tot_inc','wgt','a
ge','female'])
Surv.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

Impute `age` in `BestIncome` using the models constructed from `SurveyIncome`

In [6]:
```
#OLS Regression for predictting 'age' using 'tot_inc' and 'wgt' uisng SurveyIn
come
X, y = sm.add_constant(Surv[['wgt','tot_inc']], prepend=False), Surv['age']
m= sm.OLS(y, X).fit()
print(m.summary())
```

```
                            OLS Regression Results
==============================================================================
=
Dep. Variable:                    age   R-squared:                       0.00
1
Model:                            OLS   Adj. R-squared:                 -0.00
1
Method:                 Least Squares   F-statistic:                    0.632
6
Date:                Mon, 15 Oct 2018   Prob (F-statistic):              0.53
1
Time:                        22:26:11   Log-Likelihood:                -3199.
4
No. Observations:                1000   AIC:                             640
5.
Df Residuals:                     997   BIC:                             641
9.
Df Model:                           2

Covariance Type:            nonrobust

==============================================================================
=
                 coef    std err          t      P>|t|      [0.025      0.97
5]
------------------------------------------------------------------------------
-
wgt           -0.0067      0.010     -0.686      0.493      -0.026       0.01
3
tot_inc      2.52e-05   2.26e-05      1.114      0.266   -1.92e-05    6.96e-0
5
const         44.2097      1.490     29.666      0.000      41.285      47.13
4
==============================================================================
=
Omnibus:                        2.460   Durbin-Watson:                   1.92
1
Prob(Omnibus):                  0.292   Jarque-Bera (JB):                2.32
2
Skew:                          -0.109   Prob(JB):                        0.31
3
Kurtosis:                       3.092   Cond. No.                     5.20e+0
5
==============================================================================
=

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correc
tly specified.
[2] The condition number is large, 5.2e+05. This might indicate that there ar
e
strong multicollinearity or other numerical problems.
```

In [7]:
```
# Apply the model to impute 'age' in BestIncome
#tot_inc = F(K,L) = YK + YL = capital income + labor income='lab_inc'+'cap_in
c'
Best['tot_inc']=Best['lab_inc']+Best['cap_inc']
Best['const'] = 1
Best['age'] = m.predict(Best[['wgt', 'tot_inc', 'const']])
```

Impute *gender* in *BestIncome* using the models constructed from *SurveyIncome*

In [8]:
```
#Logistic Regression for predictting 'female' using 'tot_inc' and 'wgt' uisng
 SurveyIncome
X, y = sm.add_constant(Surv[['wgt','tot_inc']], prepend=False), Surv['female']
m2= sm.Logit(y, X).fit()
print(m2.summary())
```

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

=============================================================================
=
Dep. Variable:                female   No. Observations:                 100
0
Model:                         Logit   Df Residuals:                      99
7
Method:                          MLE   Df Model:
2
Date:               Mon, 15 Oct 2018   Pseudo R-squ.:                  0.948
0
Time:                       22:27:35   Log-Likelihood:                -36.05
0
converged:                      True   LL-Null:                       -693.1
5
                                       LLR p-value:                4.232e-28
6
=============================================================================
=
                 coef    std err          z      P>|z|      [0.025      0.97
5]
-----------------------------------------------------------------------------
-
wgt           -0.4460      0.062     -7.219      0.000      -0.567      -0.32
5
tot_inc       -0.0002   4.25e-05     -3.660      0.000      -0.000   -7.22e-0
5
const         76.7929     10.569      7.266      0.000      56.078      97.50
8
=============================================================================
=

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]:
```
# Apply the model to impute 'female' in BestIncome
#Define threshold of female=1 when p>=0.5, female=0 when p<0.5
Best['female'] = m2.predict(Best[['wgt','tot_inc', 'const']])
Best['female'][Best['female']>0.5]=1
Best['female'][Best['female']<0.5]=0
```

In [14]:
```
Best.head()
```

Out[14]:

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

(c) Report the descriptive statistics for my new imputed variables

In [15]:
```
Best['age'].describe()[['mean', 'std', 'min', 'max', 'count']]
```

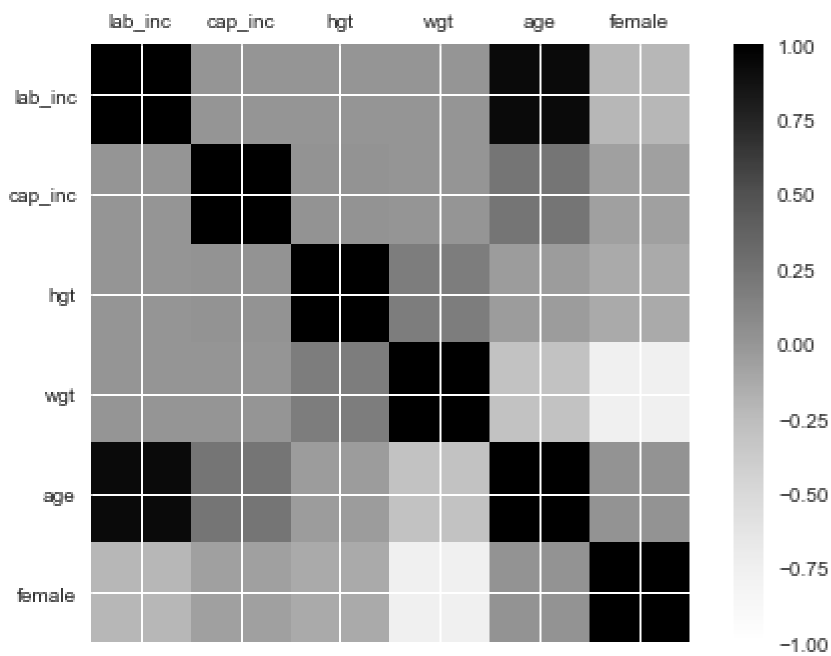
Out[15]:
```
mean        44.890828
std          0.219150
min         43.976495
max         45.703819
count    10000.000000
Name: age, dtype: float64
```

In [16]:
```
Best['female'].describe()[['mean', 'std', 'min', 'max', 'count']]
```

Out[16]:
```
mean         0.454600
std          0.497959
min          0.000000
max          1.000000
count    10000.000000
Name: female, dtype: float64
```

(d) Report the correlation matrix for the now six variables—labor income (lab inc, capital income cap inc , height (hgt), weight (wgt) age (age), and gender (female) —in the BestIncome.txt data.

In [17]:
```
# Correlation matrix

def corr_plot(df):

    names = df.columns
    N = len(names)

    correlations = df.corr()
    fig = plt.figure()
    ax = fig.add_subplot(111)
    cax = ax.matshow(correlations, vmin=-1, vmax=1)
    fig.colorbar(cax)
    ticks = np.arange(0,N,1)
    ax.set_xticks(ticks)
    ax.set_yticks(ticks)
    ax.set_xticklabels(names)
    ax.set_yticklabels(names)
    plt.show()

corr_plot((Best[['lab_inc', 'cap_inc', 'hgt', 'wgt', 'age', 'female']]))
corr=Best[['lab_inc', 'cap_inc', 'hgt', 'wgt', 'age', 'female']].corr()
print(corr)
```




```
          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
```

2. Stationarity and data drift

(a) Estimate by OLS and report coefficients

In [73]:
```
# Read in my third data set
Data= pd.read_csv('IncomeIntel.txt', header=None,names = ['grad_year','gre_qn
t','salary_p4'])
Data.head()
```

Out[73]:

	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 [74]:
```
# Run regression model
X, y = sm.add_constant(Data['gre_qnt'], prepend=False), Data['salary_p4']
reg= sm.OLS(y, X).fit()
print(reg.summary())
```

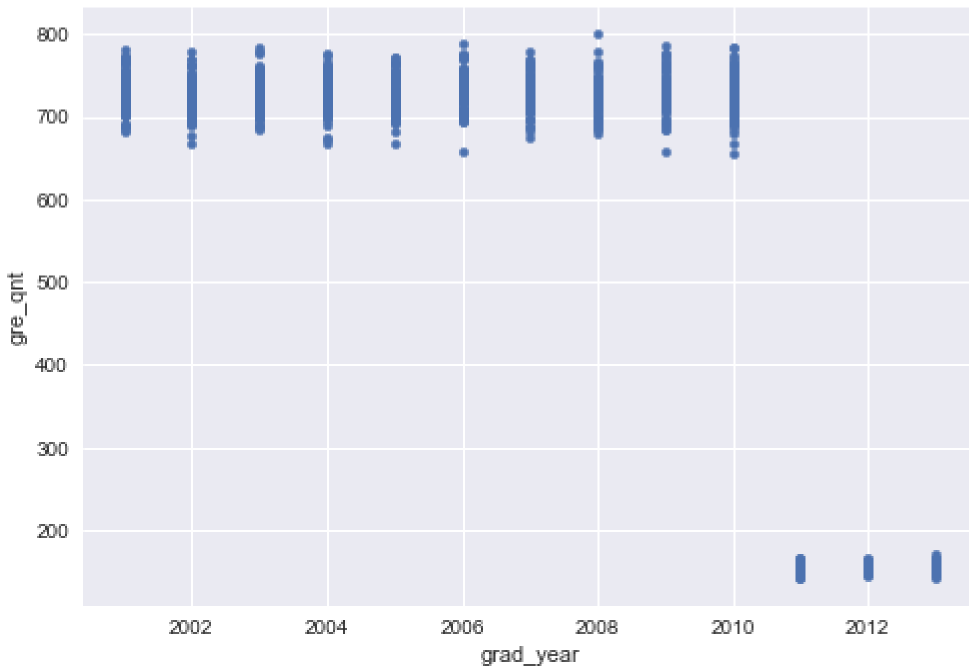
```
                            OLS Regression Results
==============================================================================
=
Dep. Variable:              salary_p4   R-squared:                       0.26
3
Model:                            OLS   Adj. R-squared:                  0.26
2
Method:                 Least Squares   F-statistic:                     356.
3
Date:                Mon, 15 Oct 2018   Prob (F-statistic):           3.43e-6
8
Time:                        23:23:56   Log-Likelihood:                -1067
3.
No. Observations:                1000   AIC:                        2.135e+0
4
Df Residuals:                     998   BIC:                        2.136e+0
4
Df Model:                           1

Covariance Type:            nonrobust

==============================================================================
=
                 coef    std err          t      P>|t|      [0.025      0.97
5]
------------------------------------------------------------------------------
-
gre_qnt      -25.7632      1.365    -18.875      0.000     -28.442     -23.08
5
const       8.954e+04    878.764    101.895      0.000    8.78e+04    9.13e+0
4
==============================================================================
=
Omnibus:                        9.118   Durbin-Watson:                   1.42
4
Prob(Omnibus):                  0.010   Jarque-Bera (JB):                9.10
0
Skew:                           0.230   Prob(JB):                       0.010
6
Kurtosis:                       3.077   Cond. No.                     1.71e+0
3
==============================================================================
=

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correc
tly specified.
[2] The condition number is large, 1.71e+03. This might indicate that there a
re
strong multicollinearity or other numerical problems.
```

The estimated regression model is : \begin{equation} \widehat{salary-p4_i} = 8.954*10^4 -25.7632* \widehat{gre_qnt_i} \end{equation} where β_0=8.954e+04 and β_1=-25.7632

The standard errors is 878.764 for β_0 and 1.365 for β_1.

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

In [24]:
```
Data.plot(x='grad_year', y='gre_qnt', kind='scatter')
plt.show()
```



The scoring scale for GRE quantitative part was changed to a 130-170 scale from the 200-800 scale in 2011. As a result, the values of scores since 2011 are much smaller than the ones before. This is a system drift (change in the system itself). If we don't recognize this issue, we'll probably underestimate the marginal effect of `gre_qnt` on predictting `salary_p4`. The hypothesis that the estimated coefficient β_1 is zero will likely be accepted using this raw data.

One solution is to normalize the `gre_qnt`using z-score with each year. The standard scores are not affected by different scales.

$$z_{i,j} = \frac{gre\_qnt_{i,j} - \mu_j}{\sigma_j}$$

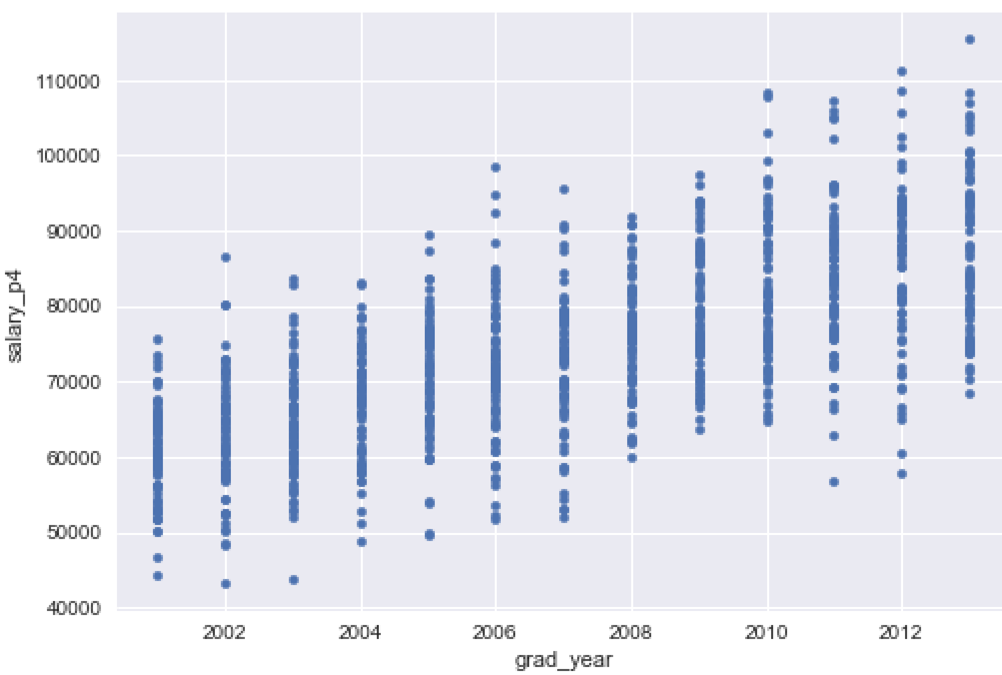
where i means different observations within j-th year.

In [82]:
```
Data['gre_qnt']=Data.groupby('grad_year').transform(lambda x: (x-x.mean())/x.s
td())['gre_qnt']
gre_z=Data['gre_qnt'].values
normx=sm.add_constant(gre_z)
```

In [83]:
```
#Scatter plot with z-score of 'gre_qnt`
Data.plot(x='grad_year', y='gre_qnt', kind='scatter')
plt.show()
```

(c) Create a scatterplot of income and graduation year

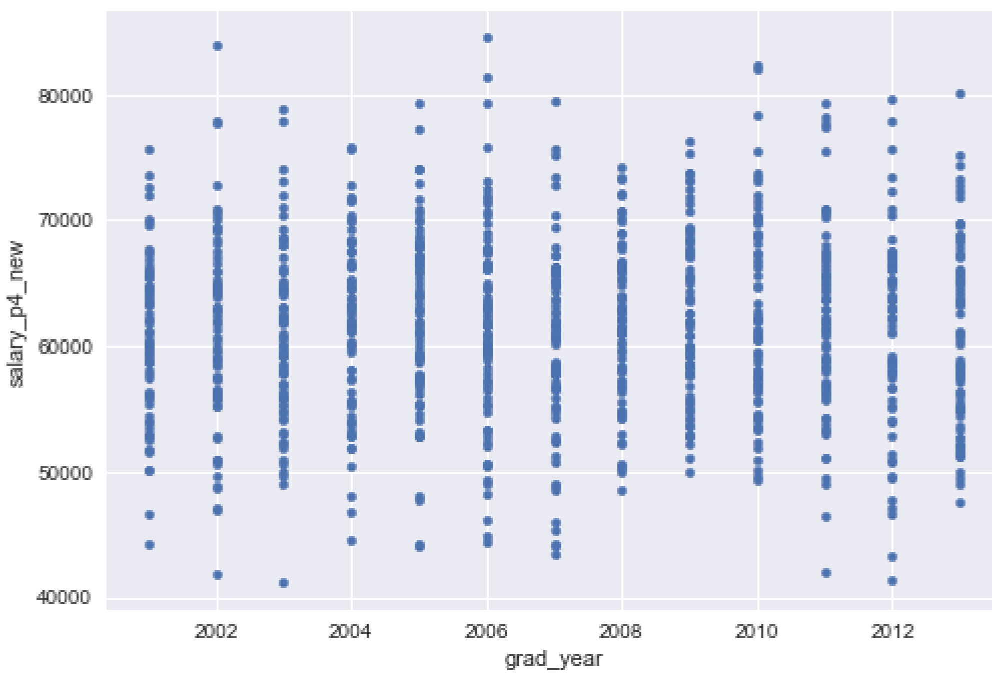
In [81]:
```
Data.plot(x='grad_year', y='salary_p4', kind='scatter')
plt.show()
```



Across different years, the means of income seem to be growing. Thus the `salary_p4` is not stationary. We need to de-trend this variable for the analysis. This could be done by calculting the average growth rate in salaries across all 13 years and dividing each salary by (1 + avg_growth_rate) ** (grad_year - 2001).

In [84]:
```
#Calculate the mean salary each year
avg_inc_by_year = Data['salary_p4'].groupby(Data['grad_year']).mean().values

#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_y
ear[:-1]).mean()
#avg_growth_rate=0.030835347092883603


#Divide each salary by (1 + avg_growth_rate) ** (grad_year - 2001)
Data['rate']=(1 + avg_growth_rate) ** (Data['grad_year']-2001)
Data['salary_p4_new']=Data['salary_p4']/Data['rate']
```

In [78]:
```
Data.plot(x='grad_year', y='salary_p4_new', kind='scatter')
plt.show()
```



(d) Re-estimate coefficients with updated variables.

In [85]:
```
# Code to re-estimate, output of new coefficients
X, y = sm.add_constant(Data['gre_qnt'], prepend=False),Data['salary_p4_new']
reg2= sm.OLS(y,X).fit()
print(reg2.summary())
```

```
                            OLS Regression Results                            
==============================================================================
=
Dep. Variable:          salary_p4_new   R-squared:                       0.00
0
Model:                            OLS   Adj. R-squared:                 -0.00
1
Method:                 Least Squares   F-statistic:                    0.439
5
Date:                Mon, 15 Oct 2018   Prob (F-statistic):              0.50
8
Time:                        23:26:23   Log-Likelihood:                 -1029
1.
No. Observations:                1000   AIC:                        2.059e+0
4
Df Residuals:                     998   BIC:                        2.060e+0
4
Df Model:                           1                                         

Covariance Type:            nonrobust                                         

==============================================================================
=
                 coef    std err          t      P>|t|      [0.025      0.97
5]
------------------------------------------------------------------------------
-
gre_qnt     -150.6097    227.193     -0.663      0.508    -596.440     295.22
1
const       6.142e+04    225.711    272.117      0.000     6.1e+04    6.19e+0
4
==============================================================================
=
Omnibus:                        0.776   Durbin-Watson:                   2.02
5
Prob(Omnibus):                  0.678   Jarque-Bera (JB):                0.68
7
Skew:                           0.059   Prob(JB):                        0.70
9
Kurtosis:                       3.049   Cond. No.                         1.0
1
==============================================================================
=

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

The estimated coefficients are β_0 is 6.142e+04 and β_1 is -150.6097. The standard error is 225.711 for β_0 and 227.193 for β_1.

The new β_0 is a bit smaller to the previous one. But the new β_1 is much smaller. Also we notice that the estimate of old β_1 is statisically significant, while the new β_1 is not. If we ignore the stationarity and data drift problems, we might falsely reject the null hypothesis that higher intelligence is not associated with higher income. Now we cannot reject the null hypothesis. We might want to conclude that higher intelligence is not associated with higher income.

In [87]:
```
Data.plot(x='gre_qnt', y='salary_p4_new', kind='scatter')
x1=np.linspace(-4,4)
y1=-150.6097*x1+6.142e+04
plt.plot(x1,y1,'-r')
plt.show()
```

3. Assessment of Kossinets and Watts.

The research question of the paper is: What could explain the mechanism of homophily generation in a dynamic social network?

The authors merged three databases to cover interaction, affiliation, and attribute-type longitudinal data of 30,396 observations. These observations are undergraduate and graduate students, faculty, and staff in a large U.S. university, who were active email users in that academic year. In particular, the three datasets are:

(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.);

(3) records of course registration, in which courses were recorded separately for each semester.

The variables for the network modeling are 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).

After the data cleaning, the authors got 7,156,162 messages exchanged by 30,396 stable e-mail users during the 270 days period. Appendix A provides a description and definition of these variables.

One potential problem about the dataset is that only e-mail accounts on the central university server were included. The authors addressed the problem that department-specified email accounts such as such as "xyz@department.university.edu" cannot be matched with employee records and therefore have been deleted. Another fact is that many people might choose to use their oown email account such as "@gmail.com" for communciations with others for better functionalities. Although these records are much harder to obtain, excluding them from the analysis might make the social network of interest incomplete and biased.

Matching the email-logs and characteristics of the senders and receivers to construct "social relationship" is a challenge task. E-mail exchanges comprise discrete and intermittent “spike trains” that are often “bursty” in nature (Cortes et al. 2003; Eckmann, Moses, and Sergi 2004). One weekness is that it couldn't track the timing of the tie formation. To address this weekness, the authors introduced the sliding window filter model to construct instantaneous network approximations from discrete dyadic interactions. This technique often is employed to analyze and visualize networks over time (Cortes et al. 2003; Moody et al. 2005; Kossinets and Watts 2006)