Assignment_2_EH

October 17, 2018

1 Assignment 2

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```
In [1]: import numpy as np
        from sklearn import linear_model
        import pandas as pd
        import matplotlib.pyplot as plt
        from sklearn.metrics import mean_squared_error, r2_score
```

1.0.3 1. Imputing age and gender

(a) My proposed strategy to impute age and gender into BestIncome.txt: First, we build two linear regression models respect to age and gender based on total income and weight in dataset SurvIncome.txt respectively. Then, we use those two models to predict the value of age and gender in Bestincone.txt. However, there is no feature called total income in BestIncome.txt, therefore, we can create the value of total income by adding labor and capital income in BestIncome.txt. Finally, we use the total income and weight in BestIncome.txt to calculate the value of age and gender for Bestlincome.txt based on those two regression models. The equations are as following:

$$Age_i = \beta_0 + \beta_1 Total\_income_i + \beta_2 Weight_i + \epsilon_i$$

$$Gender_i = \beta_0 + \beta_1 Total\_income_i + \beta_2 Weight_i + \epsilon_i$$

```
In [2]: # open and rename the column names of the imported files
        best = pd.read_csv('BestIncome.txt', sep=',', header=None)
        survey = pd.read_csv('SurvIncome.txt', sep=',', header=None)
        best = best.rename(index=int, columns={0:'lab_inc', 1:'cap_inc', 2:'hgt', 3: 'wgt'})
        survey = survey.rename(index=int, columns={0:'tot_inc',1:'wgt',2:'age',3:'gender'})
```

```
In [3]: best.describe()
```

```
Out[3]:              lab_inc       cap_inc           hgt           wgt
        count   10000.000000  10000.000000  10000.000000  10000.000000
        mean    57052.925133   9985.798563     65.014021    150.006011
        std      8036.544363   2010.123691      1.999692      9.973001
```

```
min    22917.607900   1495.191896     58.176154    114.510700
25%    51624.339880   8611.756679     63.652971    143.341979
50%    56968.709935   9969.840117     65.003557    149.947641
75%    62408.232277  11339.905773     66.356915    156.724586
max    90059.898537  19882.320069     72.802277    185.408280
```

In [4]:
```
survey.describe()
```

Out[4]:
```
            tot_inc          wgt          age      gender
count   1000.000000  1000.000000  1000.000000  1000.00000
mean   64871.210860   149.542181    44.839320     0.50000
std     9542.444214    22.028883     5.939185     0.50025
min    31816.281649    99.662468    25.741333     0.00000
25%    58349.862384   130.179235    41.025231     0.00000
50%    65281.271149   149.758434    44.955981     0.50000
75%    71749.038000   170.147337    48.817644     1.00000
max    92556.135462   196.503274    66.534646     1.00000
```

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

In [5]:
```
# create the total income value by adding labor income and capital income
tot_inc_best = best.lab_inc + best.cap_inc
x_best = np.column_stack((tot_inc_best, best.wgt))
```

In [6]:
```
# with the common features: tot_inc and wgt
# age ~ tot_inc and wgt
x = np.column_stack((survey.tot_inc, survey.wgt))
y_age = survey.age.values
y_gender = survey.gender.values

# simple linear regression: age ~ tot_inc + wgt
regr_age = linear_model.LinearRegression()
regr_age.fit(x, y_age)

# logistic regression: gender ~ tot_inc + wgt
regr_gender = linear_model.LogisticRegression()
regr_gender.fit(x, y_gender)
```

Out[6]:
```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)
```

In [7]:
```
# compute the predicted age and gender based on te information in best
pred_age = regr_age.predict(x_best)
pred_gender = regr_gender.predict(x_best)
```

In [8]:
```
# simple append the predictions onto the best dataset
imputed_best = np.column_stack((best, pred_age, pred_gender))
```

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

```
In [9]: # convert the numpy array into a pandas dataframe
        new_best = pd.DataFrame({'lab_inc':imputed_best[:,0],'cap_inc':imputed_best[:,1],
                                 'hgt':imputed_best[:,2],'wgt':imputed_best[:,3],
                                 'age':imputed_best[:,4],'gender':imputed_best[:,5]})

In [10]: new_best.describe()
```

Out[10]:

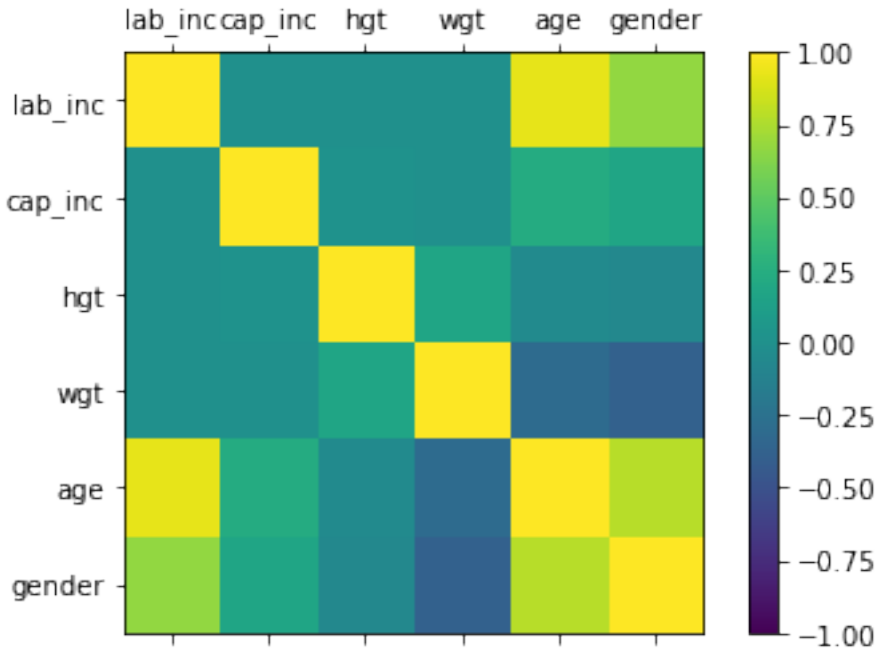
	lab_inc	cap_inc	hgt	wgt	age	gender
count	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000
mean	57052.925133	9985.798563	65.014021	150.006011	44.890828	0.471700
std	8036.544363	2010.123691	1.999692	9.973001	0.219150	0.499223
min	22917.607900	1495.191896	58.176154	114.510700	43.976495	0.000000
25%	51624.339880	8611.756679	63.652971	143.341979	44.743776	0.000000
50%	56968.709935	9969.840117	65.003557	149.947641	44.886944	0.000000
75%	62408.232277	11339.905773	66.356915	156.724586	45.038991	1.000000
max	90059.898537	19882.320069	72.802277	185.408280	45.703819	1.000000

(d) Correlation matrix for the now six variables

```
In [11]: # Correlation matrix form
         corr = new_best.corr()
         corr.style.background_gradient()

Out[11]: <pandas.io.formats.style.Styler at 0x1a162981d0>

In [12]: # Correction Matrix Plot
         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()
```

In [13]:
```
corr_plot(new_best)
```



1.0.4 2. Stationarity and data drift

(a) Estimate by OLS and report coefficients

In [14]:
```
# open and rename the column names of the imported files
inc_intel = pd.read_csv('IncomeIntel.txt', sep=',', header=None)
inc_intel = inc_intel.rename(index=int, columns={0:'grad_year', 1:'gre_qnt', 2:'salary
```

In [15]:
```
# Define Outcome and Independent Variables
outcome  = 'salary_p4'
features = ['gre_qnt']

X, y = inc_intel[features], inc_intel[outcome]
```

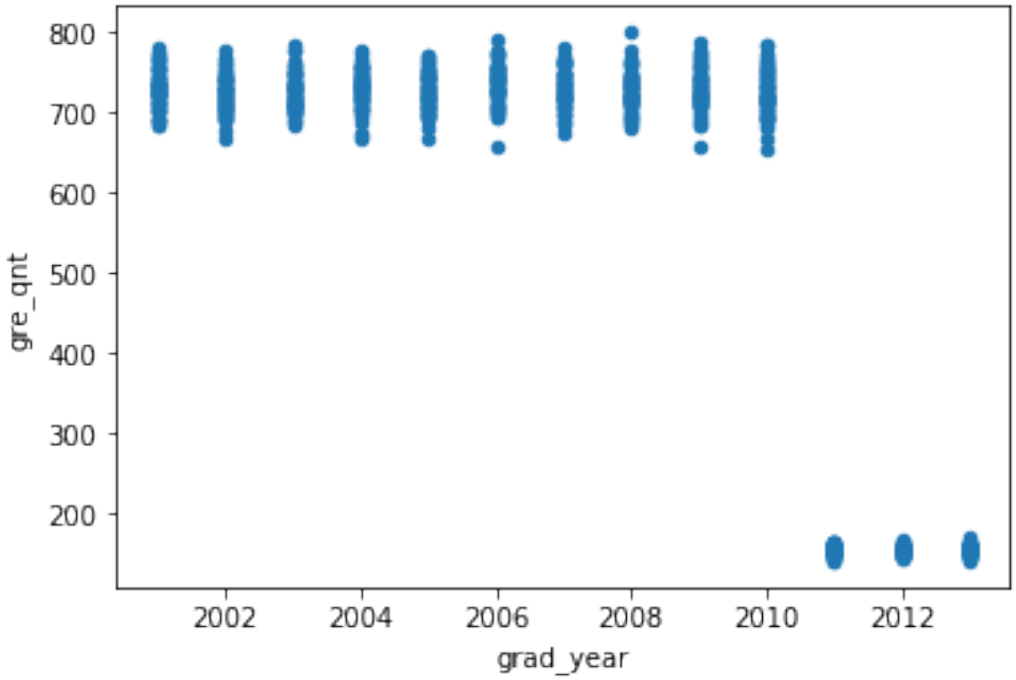
In [16]:
```
# run ols regression and report the result
import statsmodels.api as sm

X_vars = X[['gre_qnt']]
```

```
X_vars = sm.add_constant(X_vars, prepend=False)
X_vars.head()

m = sm.OLS(y, X_vars)

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:                        23:33:29   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.
```

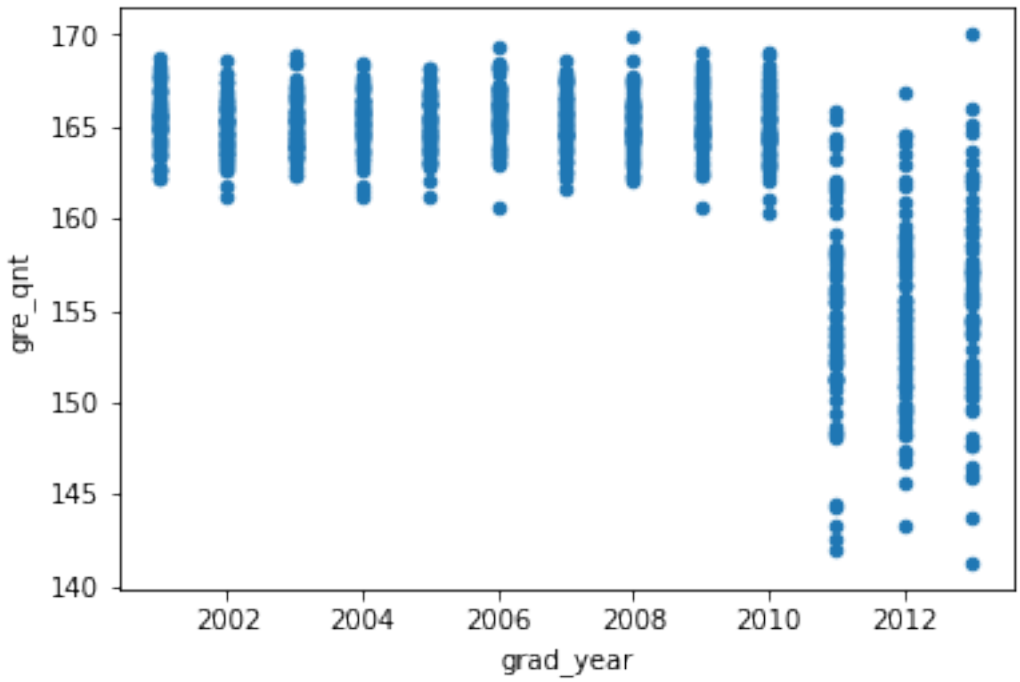
(b) Create a scatterplot of GRE score and graduation year.

```
In [17]: # make a scatterplot for gre score and graduation year
         grad_year = inc_intel['grad_year']
         gre_qnt = inc_intel['gre_qnt']
         inc_intel.plot(x='grad_year', y='gre_qnt', kind='scatter')
         plt.show()
```



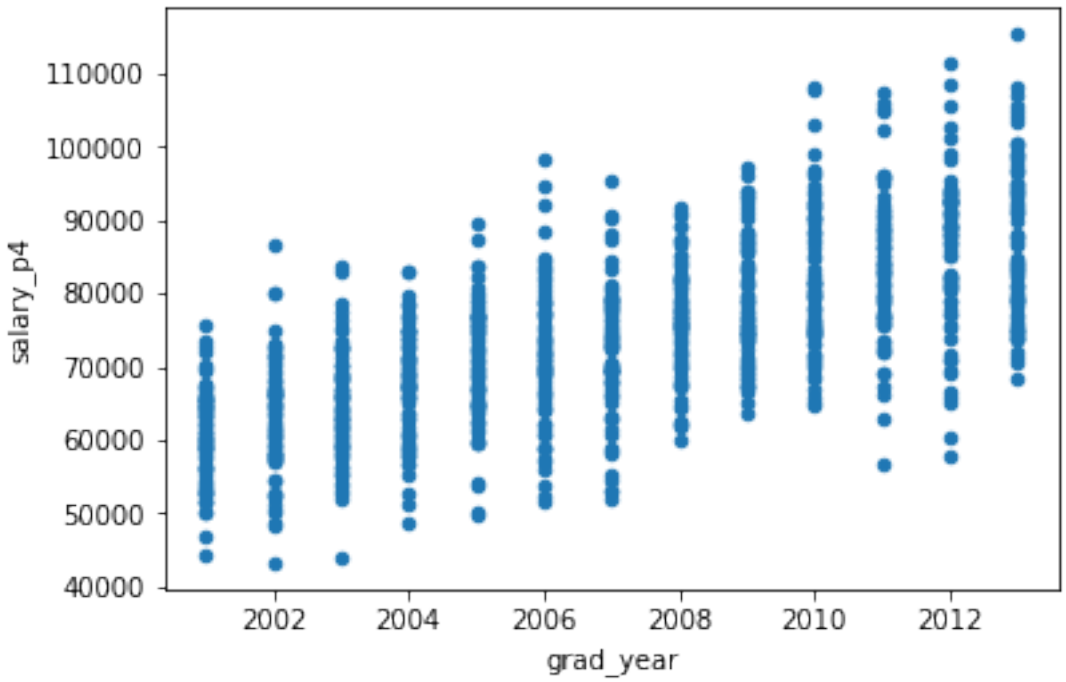
The problem here is that there is a obvious jump down on this scatterplot due to the different scales of GRE score. Before 2011, the score scale for GRE quatative was 200-800 and after that it became 130-170. Therefore, if we use this dataset to build a regression model to predict the salary, it would distort the result of linear regression. In order to solve this problem, we can convert all the GRE scores to the latter scale(130-170), so that it could become consistent. And then, we could get a more precise regression model based on the modified dataset. (Note: The conversion used is not based on percentile so the value might not be precise enough).

```
In [18]: # convert gre_qnt score
         converted_gre_qnt = inc_intel.gre_qnt[:]
         for i in range(len(inc_intel)):
             if inc_intel.grad_year[i] <= 2010.0:
                 converted_gre_qnt[i] = 130+ ((inc_intel.gre_qnt[i]-200)*40/600)
             else:
                 pass

In [19]: # a new scatterplot for converted gre score
         grad_year = inc_intel['grad_year']
         gre_qnt = converted_gre_qnt
         inc_intel.plot(x='grad_year', y='gre_qnt', kind='scatter')
         plt.show()
```



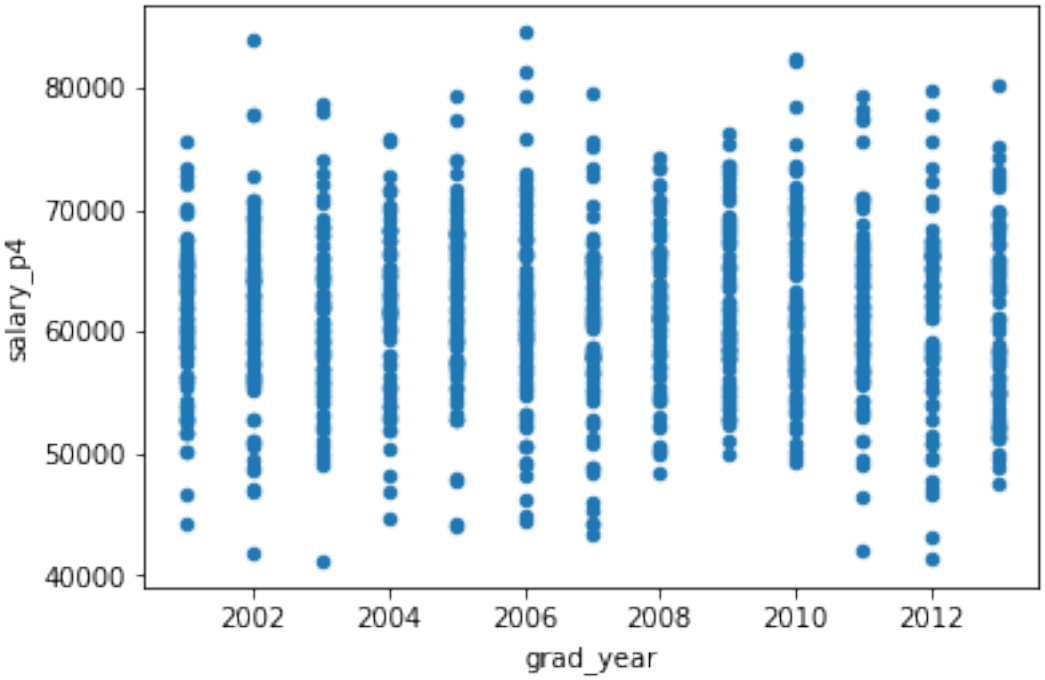
(c) Create a scatterplot of income and graduation year

```
In [20]: # create a scatterplot for income and graduation year
         grad_year = inc_intel['grad_year']
         salary_p4 = inc_intel['salary_p4']
         inc_intel.plot(x='grad_year', y='salary_p4', kind='scatter')
         plt.show()
```



The problem here is that the income is increasing over years. This is because we didn't take the inflation rate into consideration. To solve this problem, we can convert all the incomes into the present value by divided them by the inflation rate regarding to different year.

```
In [21]: # calculate the average income by year
         avg_inc_by_year = inc_intel['salary_p4'].groupby(inc_intel['grad_year']).mean().values

         # calculate the average growth rate
         avg_growth_rate = ((avg_inc_by_year[1:] - avg_inc_by_year[:-1]) / avg_inc_by_year[:-1]

In [22]: # calcualte the present value of all the incomes
         new_salary_p4 = salary_p4[:]

         for i in range(len(salary_p4)):
             if inc_intel.grad_year[i] == 2001.0:
                 new_salary_p4[i] = inc_intel.salary_p4[i]
             else:
                 new_salary_p4[i] = inc_intel.salary_p4[i] / ((1 + avg_growth_rate)**(inc_intel

In [23]: # a new scatterplot for new income value
         grad_year = inc_intel['grad_year']
         salary_p4 = new_salary_p4
         inc_intel.plot(x='grad_year', y='salary_p4', kind='scatter')
         plt.show()
```



(d) Re-estimate coefficients with updated variables.

```
In [24]: # add the modified features to inc_intel
         inc_intel['converted_gre_qnt'] = converted_gre_qnt
         inc_intel['new_salary_p4'] = new_salary_p4

         # define the outcome and features for regression model
         outcome  = 'new_salary_p4'
         features = ['converted_gre_qnt']

         X, y = inc_intel[features], inc_intel[outcome]

         # run the regression for new variables
         X_vars = X[['converted_gre_qnt']]
         X_vars = sm.add_constant(X_vars, prepend=False)
         X_vars.head()

         m = sm.OLS(y, X_vars)

         res = m.fit()
         print(res.summary())
```

```
                            OLS Regression Results
==============================================================================
```

```
Dep. Variable:          new_salary_p4   R-squared:                       0.000
Model:                            OLS   Adj. R-squared:                 -0.001
Method:                 Least Squares   F-statistic:                    0.05257
Date:                Tue, 16 Oct 2018   Prob (F-statistic):              0.819
Time:                        23:33:30   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]
------------------------------------------------------------------------------
converted_gre_qnt    -9.9681     43.474     -0.229      0.819     -95.279      75.343
const              6.304e+04   7083.395      8.900      0.000    4.91e+04    7.69e+04
==============================================================================
Omnibus:                        0.757   Durbin-Watson:                   2.026
Prob(Omnibus):                  0.685   Jarque-Bera (JB):                0.668
Skew:                           0.059   Prob(JB):                        0.716
Kurtosis:                       3.048   Cond. No.                     5.11e+03
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 5.11e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

The result of OLS regression for modified GRE score and salary shows that the new estimated coefficents became -9.9681 which is less negative than the former one. From this fact, we can know that GRE score now has less nagtive impact on salary. Before the coversion of GRE score and salary, the larger range of GRE score and abnormally distribution made GRE score have larger negative effect on salary. Therefore, after modified the dataset, the correlation between those variables become more accurate and the negative impact from GRE score on salary become less significant, which supports my hypothesis for the result of the modified regression model.

1.0.5 3. Assessment of Kossinets and Watts.

See attached PDF.