drift

October 16, 2018

0.1 Dealing with Drift

We will be attempting to see if intelligence and higher income have any correlation. Let us start with our imports and loading our dataset.

```
In [1]: import pandas as pd

In [2]: incomeintel = pd.read_csv('IncomeIntel.txt')

In [3]: incomeintel

Out[3]:      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
        5       2001.0  763.876037   64010.822579
        6       2001.0  738.758659   60080.107481
        7       2001.0  706.407471   56263.309815
        8       2001.0  705.886037   62109.859243
        9       2001.0  700.971986   50189.704747
        10      2001.0  709.754522   58721.753127
        11      2001.0  734.854582   65380.594586
        12      2001.0  753.384151   52857.212365
        13      2001.0  690.312090   63572.217765
        14      2001.0  774.154371   65892.177035
        15      2001.0  726.377225   67454.545201
        16      2001.0  702.735945   59346.670232
        17      2001.0  723.806542   70031.012603
        18      2001.0  758.051159   53441.672888
        19      2001.0  711.063082   61008.652046
        20      2001.0  702.975969   50065.932451
        21      2001.0  733.877837   75612.225369
        22      2001.0  735.918767   59580.620375
        23      2001.0  749.069115   57825.611782
        24      2001.0  732.581793   52809.225854
        25      2001.0  728.050446   57492.084316
        26      2001.0  690.265988   64686.224351
```

```
27      2001.0  732.448836   53067.021394
28      2001.0  724.755887   58902.707320
29      2001.0  721.739038   62094.061567
..         ...         ...            ...
970     2013.0  158.578197   79263.470892
971     2013.0  147.667305  104782.627567
972     2013.0  160.086274   94013.946074
973     2013.0  156.289493   74032.543183
974     2013.0  150.340044   84220.290724
975     2013.0  163.054596   74940.546965
976     2013.0  157.624151   83293.343135
977     2013.0  150.927266   78340.908128
978     2013.0  157.393763   91066.889575
979     2013.0  154.449630   87169.012509
980     2013.0  153.756644   90033.601423
981     2013.0  150.796371   98650.768576
982     2013.0  150.691700   70455.885421
983     2013.0  153.639896   91133.301177
984     2013.0  150.374470   91796.617819
985     2013.0  162.350725   73780.832249
986     2013.0  155.803279   96927.925237
987     2013.0  159.111662   71875.246552
988     2013.0  158.338350  103357.966587
989     2013.0  162.308518   73780.472319
990     2013.0  156.651125   79055.571295
991     2013.0  153.836045   91529.313046
992     2013.0  149.542467   75940.200168
993     2013.0  155.349020   97688.397380
994     2013.0  161.767399   75260.194609
995     2013.0  160.441025  100430.166532
996     2013.0  160.431891   82198.200872
997     2013.0  154.254526   84340.214218
998     2013.0  162.036321   87600.881985
999     2013.0  156.946735   82854.576903

[1000 rows x 3 columns]
```

Now that we have our data loaded up let us the Statsmodel for our OLS model. It allows for more information about the model unlike our previously used scikit-learn model.

```
In [4]: import statsmodels.api as sm

        y, X = incomeintel['salary_p4'], incomeintel['gre_qnt']
        X = sm.add_constant(X, prepend=False)

        ols = sm.OLS(y, X)
        ols_result = ols.fit()
        ols_result.summary()
```

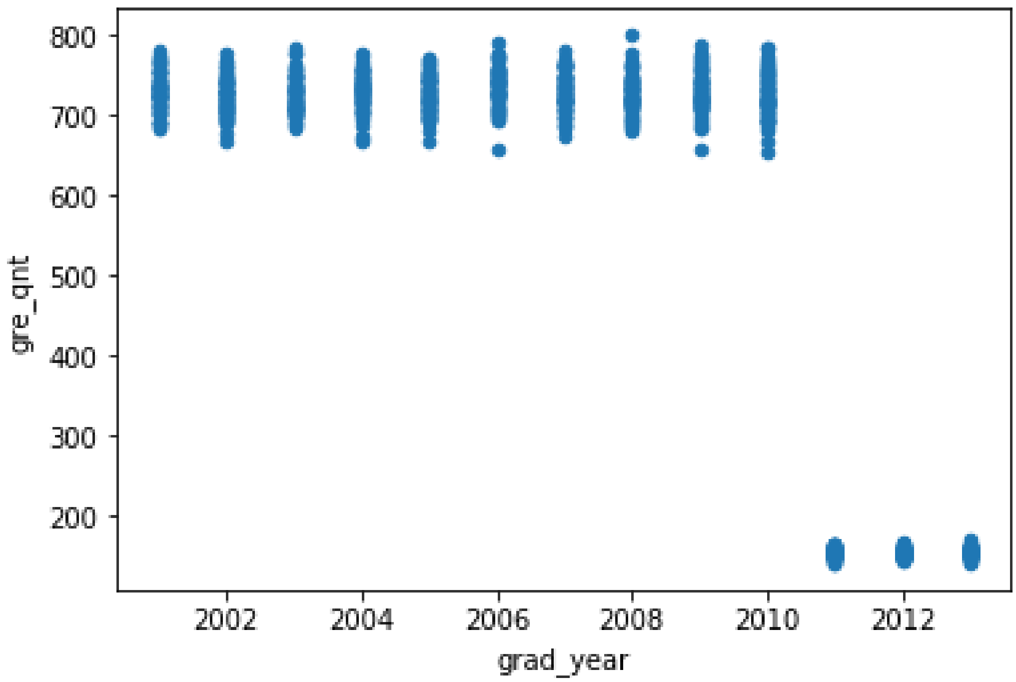
```
Out[4]: <class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:              salary_p4   R-squared:                       0.263
Model:                            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:                        20:45:05   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 specifi
[2] The condition number is large, 1.71e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

The coefficient is 103.0949 and the standard error is 1.733. We can see the rest of the results of the OLS when we run the `ols.summary()` function. The result is significant. The coefficient is -25.7632 and the standard error is 1.365. We will now plot the data on a a scatterplot. We'll be using the standard scatter method which pandas provides us.

```
In [5]: incomeintel.plot.scatter(x='grad_year', y='gre_qnt')

Out[5]: <matplotlib.axes._subplots.AxesSubplot at 0x1144a1cf8>
```



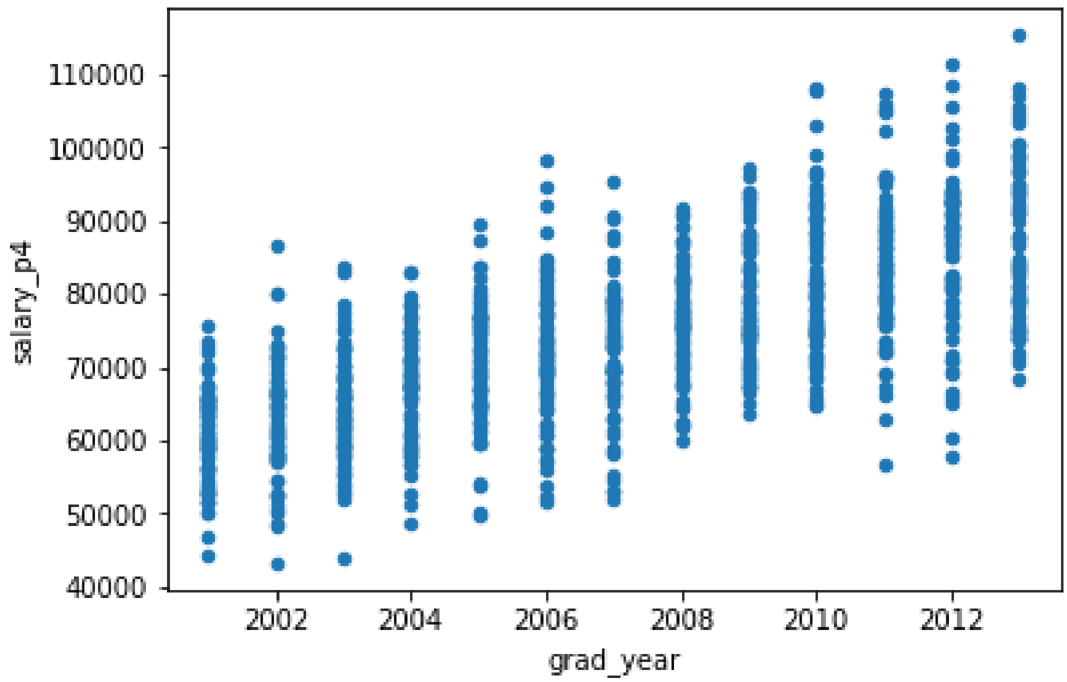
We can see a clear problem come up - in 2011 the scoring system for the GRE changed. A score of 750 doesn't even exist post 2011! For us to have any kind of meaningful analysis we must scale these values.

The ideal way to scale these values would be to have the percentile values for each of the observations, and report all the scores as percentiles. The GRE website also gives us a convertion rate which we can use, which should also give us acceptable results. What we will resort to is simply scale the values, by multiplying all the values post 2011 with 800/170. We would like to stress that this is not an ideal approach, but will suffice to go through this experiment.

```
In [6]: incomeintel.loc[incomeintel.grad_year > 2011, 'gre_qnt'] = incomeintel.loc[incomeintel.g
```

```
In [7]: incomeintel.plot.scatter(x='grad_year', y='salary_p4')
```

```
Out[7]: <matplotlib.axes._subplots.AxesSubplot at 0x1172dfe48>
```



We can see a trend here - with increasing year, there is an increase in the salary. This might effect our results, and we would need to detrend our data. Because it is not panel data, we cannot use differencing or log differencing methods. We can attempt to fix this instead by finding the average increase per year to find the average growth rate. We then adjust by dividing all the salaries by `(1 + avg_growth_rate) ** (grad_year - 2001)`. This will not affect the first year, but adjust the rest of the years. We add a new column called `adjusted_salary` to store these new values.

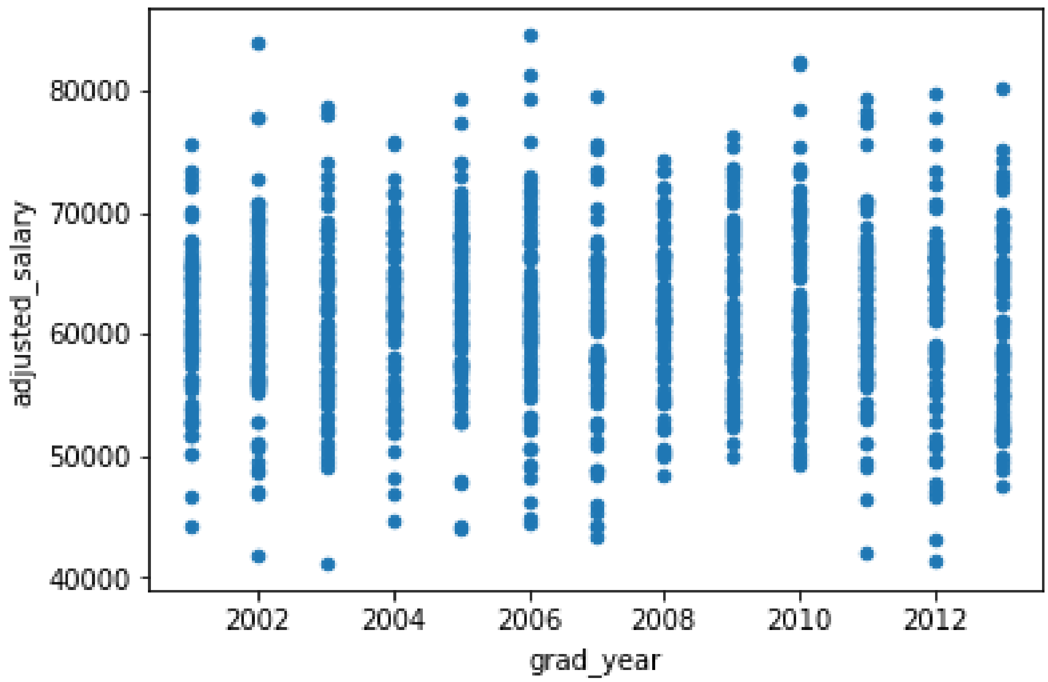
```
In [8]: avg_inc_by_year = incomeintel['salary_p4'].groupby(incomeintel['grad_year']).mean().valu

In [9]: avg_growth_rate = ((avg_inc_by_year[1:] - avg_inc_by_year[:-1]) / avg_inc_by_year[:-1]).

In [10]: incomeintel['adjusted_salary'] = incomeintel['salary_p4'] / ((1 + avg_growth_rate) ** (

In [11]: incomeintel.plot.scatter(x='grad_year', y='adjusted_salary')

Out[11]: <matplotlib.axes._subplots.AxesSubplot at 0x11733dcc0>
```



We've now adjusted our salary, and also adjusted for the GRE scores which have changed. Let us now try and train another model which can better represent our question!

In [12]:
```
y, X = incomeintel['adjusted_salary'], incomeintel['gre_qnt']

X = sm.add_constant(X, prepend=False)

newols = sm.OLS(y, X)
newols_result = newols.fit()
newols_result.summary()
```

Out[12]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:        adjusted_salary   R-squared:                       0.000
Model:                            OLS   Adj. R-squared:                 -0.001
Method:                 Least Squares   F-statistic:                    0.1814
Date:                Tue, 16 Oct 2018   Prob (F-statistic):              0.670
Time:                        20:45:06   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]
```

```
------------------------------------------------------------------------------
gre_qnt       -0.6217      1.460     -0.426      0.670      -3.486       2.242
const       6.185e+04   1024.106     60.390      0.000    5.98e+04    6.39e+04
==============================================================================
Omnibus:                        0.758   Durbin-Watson:                   2.026
Prob(Omnibus):                  0.685   Jarque-Bera (JB):                0.672
Skew:                           0.059   Prob(JB):                        0.715
Kurtosis:                       3.046   Cond. No.                     3.18e+03
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specif
[2] The condition number is large, 3.18e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

After we adjust for time drift and fix the GRE scores, we get a coefficient of -0.6217, and standard error of 1.460, and we can see that the result is not significant. This means that GRE quant scores doesn't really account for your salary. This is a very important example of how we need to carefully examine our data and the nature of our data before we proceed with any analysis!