Intro to Programming for Public Policy Week 8
Statistics, Regression, and Visualizations

Eric Potash

May 17, 2018

Writing files

Reading

Recall that we could read a file as follows:

```
file = open('filename.txt')
contents = file.readlines()
```

Writing

Similarly, we can write:

```
file = open('filename.txt', 'w')
file.write('First line\n')
file.write('Second line')
file.write('Still second line\n')
file.close()
```

- Note the format argument `'w'`, indicating that we want to write to the specified file.
  - `'w'` will overwrite any existing file
  - To append, use `'a'`
- If you don't close the file when you're done, bad things can happen.

`with` block

To avoid remembering to close the file, you can wrap your witing in a `with` block. Python will automatically close the file when the block is finished.

```
with open('filename.txt', 'w') as file:
    file.write('First line\n')
    file.write('Second line')
    file.write('Still second line\n')
```

Reshaping/Pivoting

Hierarchical index

When we groupby with two keys the result has what's called a multiindex or a hierarchical index:

```
In [1]: import pandas as pd
        %matplotlib inline

In [2]: crimes = pd.read_csv('Crimes_-_2001_to_present.csv')
        crimes['Date'] = pd.to_datetime(crimes.Date)

In [10]: crimes['Day'] = crimes.Date.dt.date
         crimes['Month'] = crimes.Date.dt.month

In [16]: crime_months = crimes.groupby(['Community Area', 'Month']).size()
         crime_months

Out[16]: Community Area  Month
         0               5          1
         1               1        289
                         2        295
                         3        289
                         4        336
                         5        369
                         6        347
                         7        410
                         8        384
                         9        355
                         10       406
                         11       360
                         12       291
         2               1        307
```

Simpler example

```
>>> df = pd.DataFrame([[0, 1, 2], [3, 4, 5]],
                      index=['Ohio', 'Colorado'],
                      columns=['one', 'two', 'three'])
>>> df
          one  two  three
Ohio        0    1      2
Colorado    3    4      5
```

To *reshape* into a hierarchical index use `stack()`:

```
>>> s = df.stack()
>>> s
Ohio      one      0
          two      1
          three    2
Colorado  one      3
          two      4
          three    5
dtype: int64
```

`unstack()`

The inverse to this operation is `unstack()`:

```
>>> s.unstack()
          one  two  three
Ohio        0    1      2
Colorado    3    4      5
```

Unstack crimes

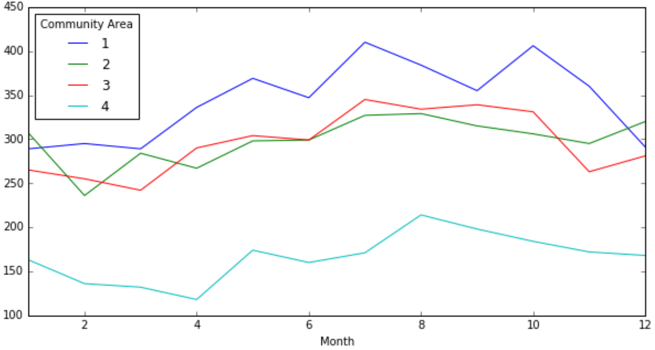
In [18]:
```
crime_months.unstack('Community Area')
```

Out[18]:

Community Area	0	1	2	3	4	5	6	7	8	9	...	68	69	70	71	72	73
Month																	
1	NaN	289.0	307.0	265.0	163.0	95.0	447.0	367.0	887.0	18.0	...	490.0	557.0	269.0	620.0	70.0	278.
2	NaN	295.0	236.0	255.0	136.0	100.0	385.0	305.0	795.0	32.0	...	392.0	451.0	226.0	572.0	68.0	199.
3	NaN	289.0	284.0	242.0	132.0	100.0	386.0	349.0	812.0	20.0	...	443.0	486.0	240.0	559.0	59.0	229.
4	NaN	336.0	267.0	290.0	118.0	93.0	470.0	308.0	908.0	17.0	...	487.0	502.0	209.0	677.0	66.0	239.
5	1.0	369.0	298.0	304.0	174.0	147.0	485.0	371.0	937.0	15.0	...	608.0	568.0	184.0	697.0	81.0	280.
6	NaN	347.0	299.0	299.0	160.0	138.0	551.0	387.0	1085.0	21.0	...	558.0	550.0	194.0	621.0	110.0	291.
7	NaN	410.0	327.0	345.0	171.0	138.0	555.0	401.0	1150.0	35.0	...	553.0	607.0	186.0	721.0	82.0	269.
8	NaN	384.0	329.0	334.0	214.0	158.0	544.0	382.0	1237.0	35.0	...	520.0	604.0	191.0	683.0	80.0	257.
9	NaN	355.0	315.0	339.0	198.0	115.0	512.0	397.0	1123.0	27.0	...	509.0	554.0	196.0	609.0	67.0	282.
10	NaN	406.0	306.0	331.0	184.0	119.0	570.0	389.0	1165.0	16.0	...	476.0	512.0	199.0	628.0	76.0	272.
11	NaN	360.0	295.0	263.0	172.0	99.0	375.0	405.0	1062.0	16.0	...	458.0	550.0	211.0	534.0	70.0	257.
12	NaN	291.0	320.0	281.0	168.0	115.0	432.0	397.0	1104.0	21.0	...	418.0	516.0	185.0	579.0	59.0	217.

Time series

```
In [19]: crime_months.unstack(level='Community Area')[[1,2,3, 4]].plot(figsize=(10,5))
Out[19]: <matplotlib.axes._subplots.AxesSubplot at 0x7ff97ba02410>
```



Visualizations

Matplotlib

- Matplotlib is the core of all plotting in python
- When you use pandas (or seaborn) to plot, it is using matplotlib.
- As a result, matplotlib settings will affect pandas plots

Matplotlib rcParams

In [75]:
```
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline

plt.rcParams['figure.figsize'] = 9,5
plt.rcParams['font.family'] = 'sans-serif'
```

Axes

Plot functions like `DataFrame.plot()` or `Series.hist()` return matplotlib `Axes` objects:

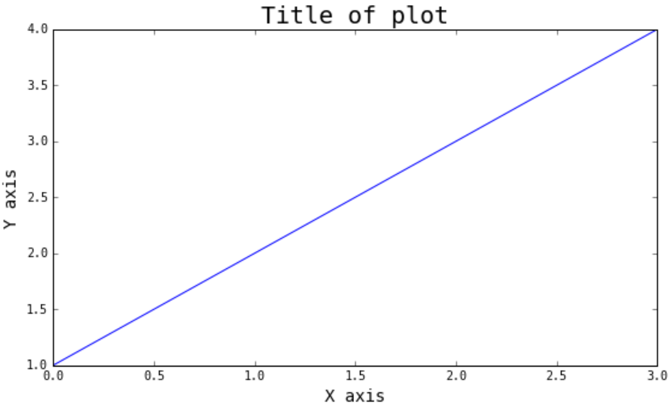
```
>>> s = pd.Series([1,2,3,4])
>>> ax = s.plot()
>>> ax
<matplotlib.axes._subplots.AxesSubplot at 0x7fa917dac410>
```

You can use these Axes objects to customize the plot.

Axes customization

In [10]:
```
ax = s.plot()
ax.set_xlabel('X axis', fontsize=14)
ax.set_ylabel('Y axis', fontsize=14)

ax.set_title('Title of plot', fontsize=20)
```

Out[10]: <matplotlib.text.Text at 0x7f9d0b7363d0>



Wages data

```
In [5]: import pandas as pd
        %matplotlib inline
```

```
In [23]: df = pd.read_csv('wages.csv')
         df
```

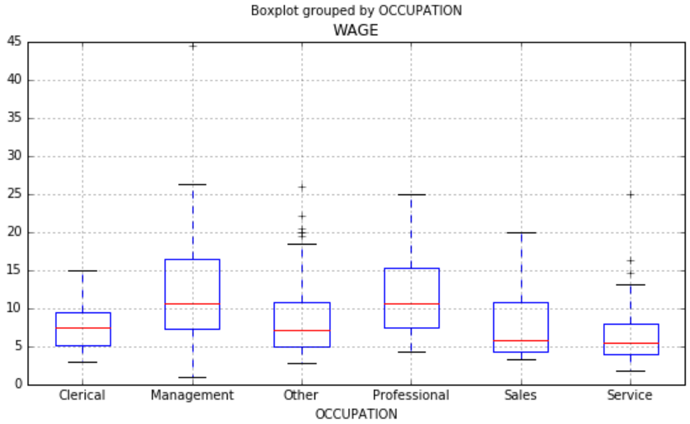
Out[23]:

	EDUCATION	SOUTH	SEX	EXPERIENCE	UNION	WAGE	AGE	RACE	OCCUPATION	SECTOR	MARR
0	8	NORTH	FEMALE	21	False	5.10	35	Hispanic	Other	Manufacturing	True
1	9	NORTH	FEMALE	42	False	4.95	57	White	Other	Manufacturing	True
2	12	NORTH	MALE	1	False	6.67	19	White	Other	Manufacturing	False
3	12	NORTH	MALE	4	False	4.00	22	White	Other	Other	False
4	12	NORTH	MALE	17	False	7.50	35	White	Other	Other	True
5	13	NORTH	MALE	9	True	13.07	28	White	Other	Other	False
6	10	SOUTH	MALE	27	False	4.45	43	White	Other	Other	False
7	12	NORTH	MALE	9	False	19.47	27	White	Other	Other	False
8	16	NORTH	MALE	11	False	13.28	33	White	Other	Manufacturing	True
9	12	NORTH	MALE	9	False	8.75	27	White	Other	Other	False
10	12	NORTH	MALE	17	True	11.35	35	White	Other	Other	True

From 1985 CPS, CSV here.

Boxplot

```
In [3]: df.boxplot('WAGE', by='OCCUPATION')
Out[3]: <matplotlib.axes._subplots.AxesSubplot at 0x7faf9368ca90>
```



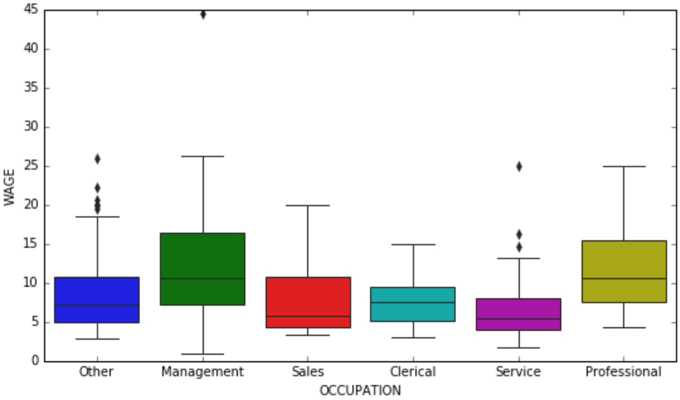
Seaborn

- Seaborn is a visualization module that builds on matplotlib
  - So what we know about matplotlib Axes and rcParams still applies
- Provides a lot of very useful plots and options

Seaborn boxplot

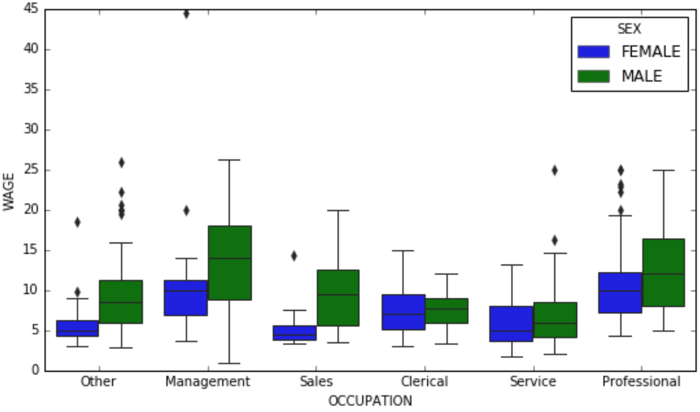
In [5]:
```
import seaborn as sns
sns.boxplot(x='OCCUPATION', y='WAGE', data=df)
```

Out[5]: `<matplotlib.axes._subplots.AxesSubplot at 0x7faf934e1a10>`



Seaborn boxplot hue

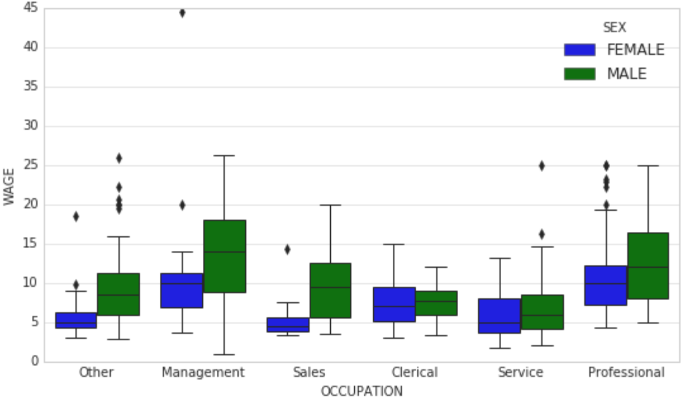
```
In [6]: sns.boxplot(x='OCCUPATION', y='WAGE', hue='SEX', data=df)

Out[6]: <matplotlib.axes._subplots.AxesSubplot at 0x7faf8b018410>
```



Seaborn aesthetics

```
In [11]: sns.set_style('whitegrid')
         sns.boxplot(x='OCCUPATION', y='WAGE', hue='SEX', data=df)
```

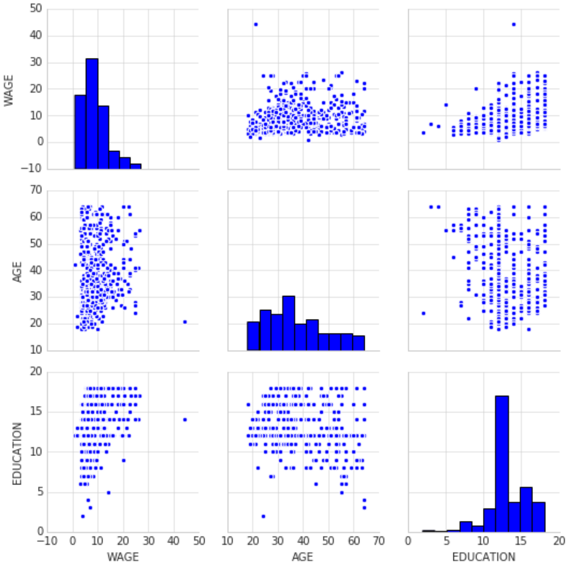
```
Out[11]: <matplotlib.axes._subplots.AxesSubplot at 0x7faf8a1fdd10>
```



Seaborn pairplot()

In [12]:
```
sns.pairplot(df, vars=['WAGE', 'AGE', 'EDUCATION'])
```

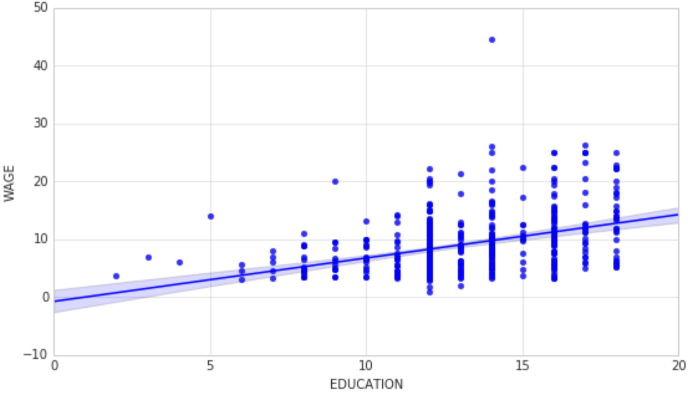
Out[12]: <seaborn.axisgrid.PairGrid at 0x7faf8a97cf50>



Seaborn `regplot()`

```
In [21]: sns.regplot('EDUCATION', 'WAGE', df)
```

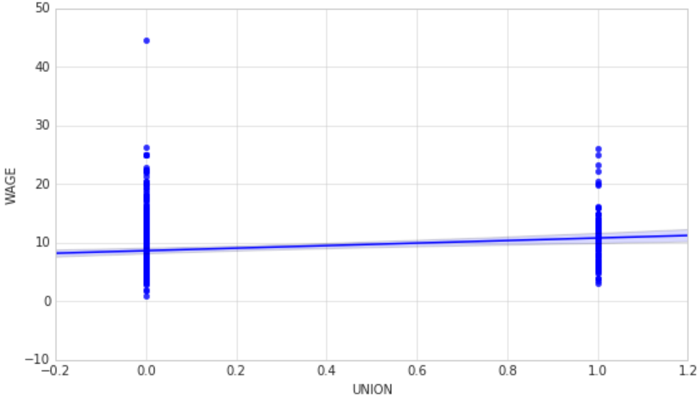
```
Out[21]: <matplotlib.axes._subplots.AxesSubplot at 0x7faf82ad7f90>
```



Another `regplot()`

```
In [23]: sns.regplot('UNION', 'WAGE', df)
```

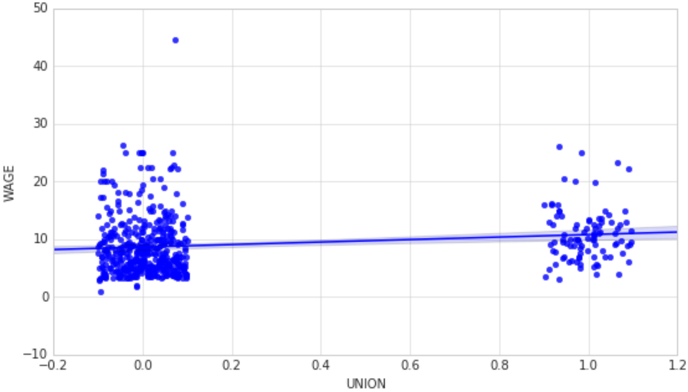
```
Out[23]: <matplotlib.axes._subplots.AxesSubplot at 0x7f9d02d00250>
```



Jittering

In [26]:
```
sns.regplot('UNION', 'WAGE', df, x_jitter=.1)
```

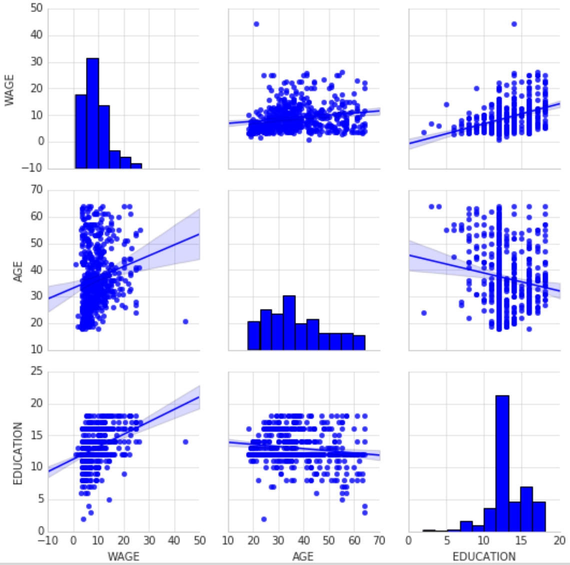
Out[26]: <matplotlib.axes._subplots.AxesSubplot at 0x7f9d02a13250>



pairplot kind='reg'

In [13]:
```
sns.pairplot(df, vars=['WAGE', 'AGE', 'EDUCATION'], kind='reg')
```

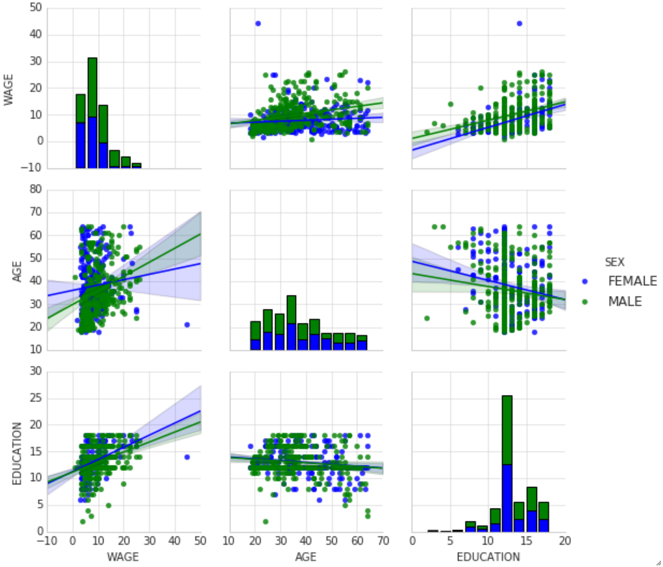
Out[13]: <seaborn.axisgrid.PairGrid at 0x7faf8a97cc10>



pairplot hue

In [25]:
```
sns.pairplot(df, vars=['WAGE', 'AGE', 'EDUCATION'], kind='reg', hue='SEX')
```

Out[25]: <seaborn.axisgrid.PairGrid at 0x7faf8367b910>



Regression in Python

Statsmodels

- Statsmodels is an econometrics/statistics library for python.
- It provides OLS, logistic and other regression functions.
- There are other modules that can perform regression (e.g. `scipy` and `sklearn`)
  - But statsmodels has the best output

X,y

One way to run a regression with statsmodels is to provide a exogenous design matrix and an endogenous outcome vector:

In [26]:
```
from statsmodels.regression.linear_model import OLS
```

In [28]:
```
X = df[['AGE', 'EDUCATION']]
y = df['WAGE']
```

statsmodels regression

```
In [32]: res = OLS(y, X)
         type(res)

Out[32]: statsmodels.regression.linear_model.OLS
```

```
In [34]: fit = res.fit()
         type(fit)

Out[34]: statsmodels.regression.linear_model.RegressionResultsWrapper
```

Regression summary()

In [36]:
```
fit.summary()
```

Out[36]:

OLS Regression Results

Dep. Variable:	WAGE	**R-squared:**	0.798
Model:	OLS	**Adj. R-squared:**	0.797
Method:	Least Squares	**F-statistic:**	1051.
Date:	Thu, 17 May 2018	**Prob (F-statistic):**	1.73e-185
Time:	00:05:00	**Log-Likelihood:**	-1580.3
No. Observations:	534	**AIC:**	3165.
Df Residuals:	532	**BIC:**	3173.
Df Model:	2		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[95.0% Conf. Int.]**
AGE	0.0595	0.014	4.309	0.000	0.032 0.087
EDUCATION	0.5351	0.040	13.311	0.000	0.456 0.614

Omnibus:	230.878	**Durbin-Watson:**	1.789
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1396.245
Skew:	1.805	**Prob(JB):**	6.45e-304
Kurtosis:	10.052	**Cond. No.**	8.47

Add a constant

You could add a constant like this and then rerun the regression:

In [52]:
```
X['Intercept'] = 1
fit = OLS(y,X).fit()
fit.summary()
```

Out[52]:

OLS Regression Results

Dep. Variable:	WAGE	**R-squared:**	0.202
Model:	OLS	**Adj. R-squared:**	0.199
Method:	Least Squares	**F-statistic:**	67.21
Date:	Thu, 17 May 2018	**Prob (F-statistic):**	9.57e-27
Time:	00:08:41	**Log-Likelihood:**	-1571.1
No. Observations:	534	**AIC:**	3148.
Df Residuals:	531	**BIC:**	3161.
Df Model:	2		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[95.0% Conf. Int.]**
AGE	0.1050	0.017	6.112	0.000	0.071 0.139
EDUCATION	0.8211	0.077	10.657	0.000	0.670 0.972
Intercept	-5.5342	1.279	-4.326	0.000	-8.047 -3.021

Fitted values

In [53]:
```
fit.fittedvalues
```

Out[53]:
```
0      4.710601
1      7.842321
2      6.314583
3      6.629667
4      7.995029
5      8.080941
6      7.193038
7      7.154806
8     11.069402
9      7.154806
10     7.995029
11     8.205085
12     5.340768
13     6.581986
14     6.476958
15    10.095586
16     6.200107
17     8.940280
18     6.963866
19     9.675475
```

Residuals

In [54]:
```
fit.resid
```

Out[54]:
```
0      0.389399
1     -2.892321
2      0.355417
3     -2.629667
4     -0.495029
5      4.989059
6     -2.743038
7     12.315194
8      2.210598
9      1.595194
10     3.354971
11     3.294915
12     1.159232
13    -0.331986
14    13.503042
15    -2.795586
16     1.799893
17    [illegible]
```

Coefficients

```
In [55]: fit.params

Out[55]: AGE           0.105028
         EDUCATION     0.821107
         Intercept    -5.534232
         dtype: float64
```

Formulas

It's more convenient to run a regression using formulas:

In [56]:
```
import statsmodels.formula.api as smf
```

In [57]:
```
fit = smf.ols('WAGE ~ AGE + EDUCATION', df).fit()
fit.summary()
```

Out[57]:

OLS Regression Results

Dep. Variable:	WAGE	**R-squared:**	0.202
Model:	OLS	**Adj. R-squared:**	0.199
Method:	Least Squares	**F-statistic:**	67.21
Date:	Thu, 17 May 2018	**Prob (F-statistic):**	9.57e-27
Time:	00:09:02	**Log-Likelihood:**	-1571.1
No. Observations:	534	**AIC:**	3148.
Df Residuals:	531	**BIC:**	3161.
Df Model:	2		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[95.0% Conf. Int.]**
Intercept	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Formula anatomy

```
WAGE ~ AGE + EDUCATION
```

- The variable on the left of the ~ is the outcome
- The variables on the right are separated by plus signs

Formula intercepts

- Formulas include an intercept term on the right-hand side by default. To remove it use

```
WAGE ~ EDUCATION + AGE - 1
```

- You can also specify the intercept explicitly (same as not specifying it):

```
WAGE ~ EDUCATION + AGE + 1
```

Formulas with numpy functions

With formulas you can apply functions to the covariates or dependent variable:

```
np.log(WAGE) ~ EDUCATION + AGE + 1
```

Formula interactions

Formulas allow you to play around with different specifications easily.

- To add the interaction of two variables use `SEX:EDUCATION`
- To add the variables and their interaction use `SEX*EDUCATION`
  - So `a*b` is equivalent to `SEX + EDUCATION + SEX:EDUCATION`

Formulas with categorical variables

By default, variables with string values become dummy variables (fixed effects) in the regression:

In [59]:
```
fit = smf.ols('WAGE ~ AGE + EDUCATION + OCCUPATION', df).fit()
fit.summary()
```

Out[59]:

OLS Regression Results

Dep. Variable:	WAGE	**R-squared:**	0.272
Model:	OLS	**Adj. R-squared:**	0.262
Method:	Least Squares	**F-statistic:**	28.09
Date:	Thu, 17 May 2018	**Prob (F-statistic):**	7.28e-33
Time:	00:14:41	**Log-Likelihood:**	-1546.5
No. Observations:	534	**AIC:**	3109.
Df Residuals:	526	**BIC:**	3143.
Df Model:	7		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[95.0% Conf. Int.]
Intercept	-4.6162	1.566	-2.949	0.003	-7.692 -1.541
OCCUPATION[T.Management]	3.9994	0.764	5.235	0.000	2.499 5.500
OCCUPATION[T.Other]	2.0634	0.589	3.503	0.000	0.906 3.221

Formula C()

For numeric columns to be interpreted as categories use C():

In [68]:
```
fit = smf.ols('WAGE ~ AGE + C(EDUCATION) + OCCUPATION + SECTOR + UNION', df).fit()
fit.summary()
```

Out[68]:

OLS Regression Results

Dep. Variable:	WAGE	**R-squared:**	0.320
Model:	OLS	**Adj. R-squared:**	0.286
Method:	Least Squares	**F-statistic:**	9.560
Date:	Thu, 17 May 2018	**Prob (F-statistic):**	2.88e-29
Time:	00:18:46	**Log-Likelihood:**	-1528.4
No. Observations:	534	**AIC:**	3109.
Df Residuals:	508	**BIC:**	3220.
Df Model:	25		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[95.0% Conf. Int.]
Intercept	2.6712	4.533	0.589	0.556	-6.235 11.578
C(EDUCATION)[T.3]	-2.9981	6.223	-0.482	0.630	-15.225 9.229
C(EDUCATION)[T.4]	-1.2337	6.180	-0.200	0.842	-13.375 10.908
C(EDUCATION)[T.5]	5.2968	6.252	0.847	0.397	-6.985 17.579
C(EDUCATION)[T.6]	-5.1672	5.088	-1.015	0.310	-15.164 4.830
C(EDUCATION)[T.7]	-2.1600	4.800	-0.450	0.653	-11.589 7.269

Other models

- Logit
- Weighted least squares

Statistical testing

SciPy

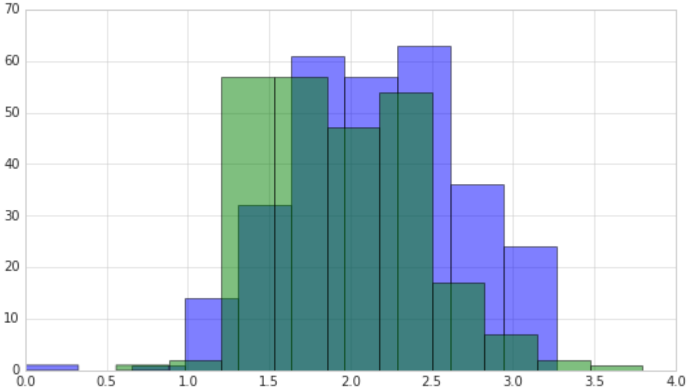
`SciPy` (Scientific Python) is a library of scientific tools for python. It includes, among many other things, a submodule `scipy.stats` with a many statistical test functions.

Log wages by sex

In [40]:
```
male_wages = df['WAGE'][df.SEX == 'MALE']
female_wages = df['WAGE'][df.SEX=='FEMALE']
```

In [46]:
```
np.log(male_wages).hist(alpha=.5)
np.log(female_wages).hist(alpha=.5)
```

Out[46]: <matplotlib.axes._subplots.AxesSubplot at 0x7f9d02327f90>



t-test

In [47]:
```
from scipy.stats import ttest_ind
ttest_ind(np.log(male_wages), np.log(female_wages))
```

Out[47]:
```
Ttest_indResult(statistic=5.1658066558780682, pvalue=3.3904092752343325e-07)
```

Other stats

- 1 sample t-test
- 1- and 2-sample z-test
- Spearman's rank correlation