Linear Regression model with Python

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1 Requirements

This en example of doing linear regression analysis using Python and statsmodels. The example requires statsmodels > 0.5 and we'll use the new formula API which makes fitting the models very familiar for R users. You'll also need Numpy, Pandas and matplolib.

The analysis can be published using the current Pweave development version.

Import libraries

```
import pandas as pd
import numpy as np
import statsmodels.formula.api as sm
import matplotlib.pyplot as plt
```

We'll use whiteside dataset from R package MASS. You can read the description of the dataset from the link, but in short it contains:

> *The weekly gas consumption and average external temperature at a house in south-east England for two heating seasons, one of 26 weeks before, and one of 30 weeks after cavity-wall insulation was installed.*

Read the data from pydatasets repo using Pandas:

```
url = 'https://raw.github.com/cpcloud/pydatasets/master/datasets/MASS/whiteside.
csv'
whiteside = pd.read_csv(url, index_col=0)
```

2 Fitting the model

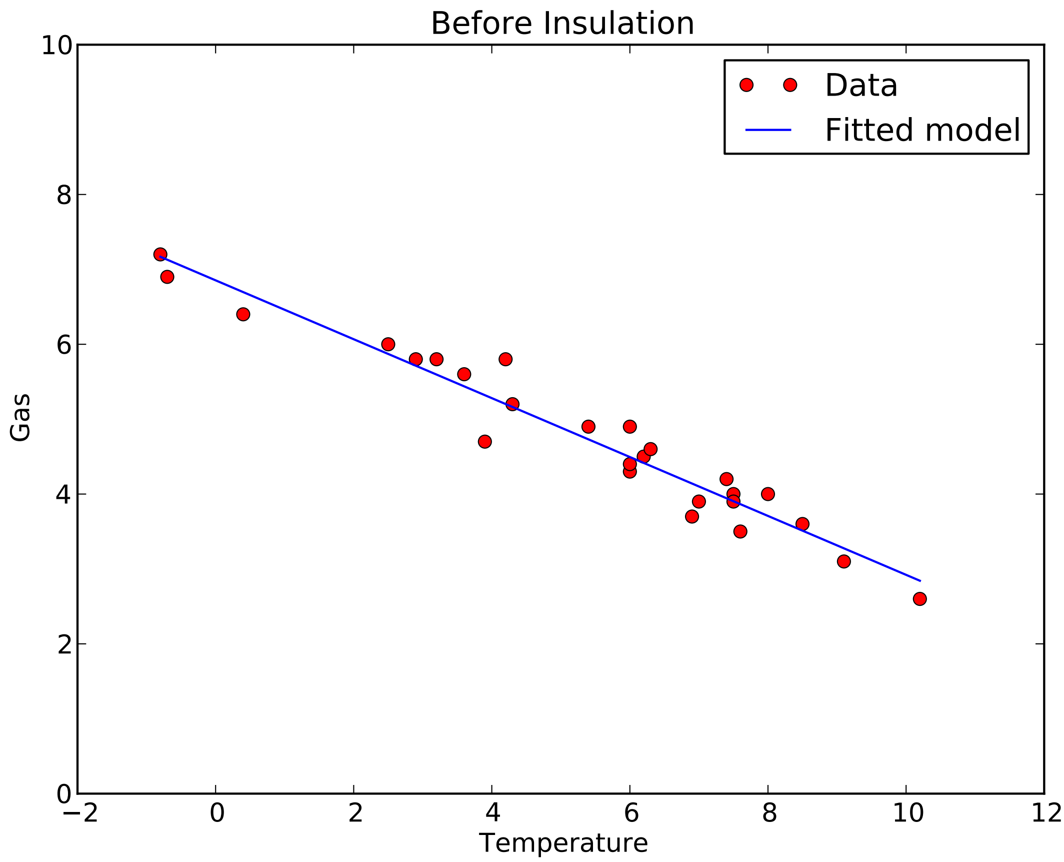
Let's see what the relationship between the gas consumption is before the insulation. See statsmodels documentation for more information about the syntax.

```
model = sm.ols(formula='Gas ~ Temp', data=whiteside, subset = whiteside['Insul']
=="Before")
fitted = model.fit()
print fitted.summary()
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    Gas   R-squared:                       0.944
Model:                            OLS   Adj. R-squared:                  0.941
Method:                 Least Squares   F-statistic:                     403.1
Date:                Mon, 22 Apr 2013   Prob (F-statistic):           1.64e-16
Time:                        13:40:33   Log-Likelihood:                -2.8783
No. Observations:                  26   AIC:                             9.757
Df Residuals:                      24   BIC:                             12.27
Df Model:                           1
==============================================================================
                 coef    std err          t      P>|t|      [95.0% Conf. Int.]
------------------------------------------------------------------------------
Intercept      6.8538      0.118     57.876      0.000         6.609     7.098
Temp          -0.3932      0.020    -20.078      0.000        -0.434    -0.353
==============================================================================
Omnibus:                        0.296   Durbin-Watson:                   2.420
Prob(Omnibus):                  0.862   Jarque-Bera (JB):                0.164
Skew:                          -0.177   Prob(JB):                        0.921
Kurtosis:                       2.839   Cond. No.                         13.3
==============================================================================
```

3 Plot the data and fit

```
Before = whiteside[whiteside["Insul"] == "Before"]
plt.plot(Before["Temp"], Before["Gas"], 'ro')
plt.plot(Before["Temp"], fitted.fittedvalues, 'b')
plt.legend(['Data', 'Fitted model'])
plt.ylim(0, 10)
plt.xlim(-2, 12)
plt.xlabel('Temperature')
plt.ylabel('Gas')
plt.title('Before Insulation')
```



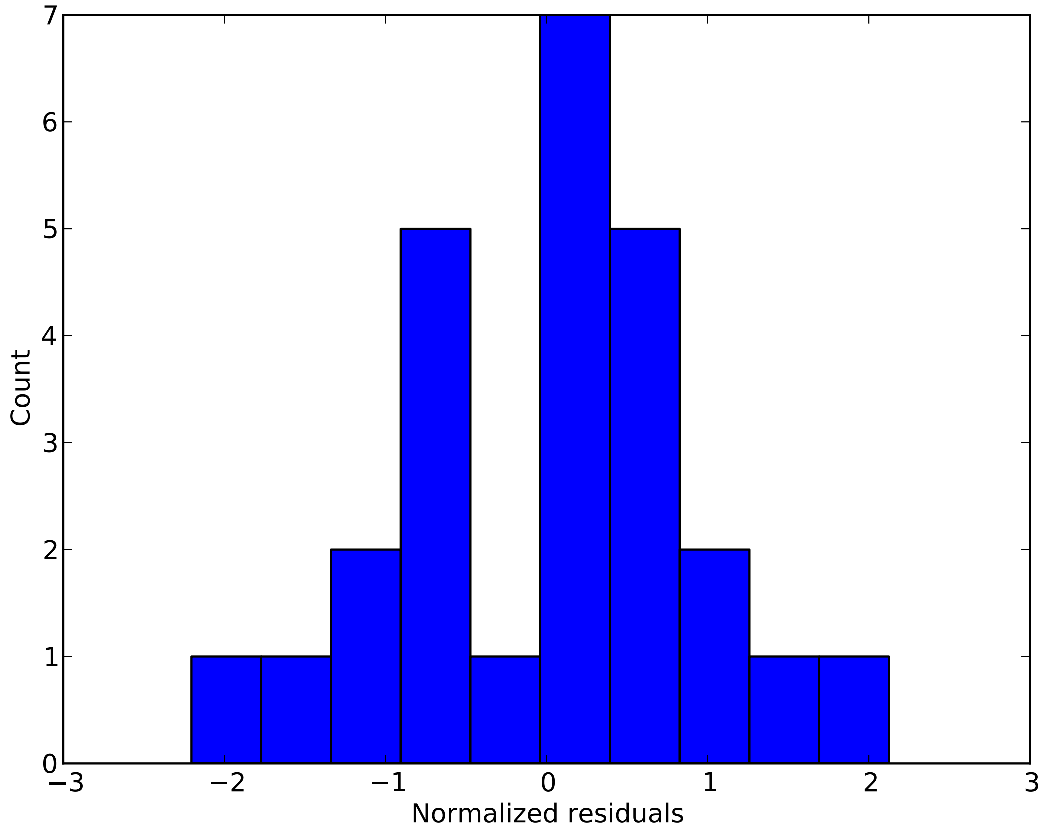
4 Fit diagnostiscs

Statsmodels OLSresults objects contain the usual diagnostic information about the model and you can use the `get_influence()` method to get more diagnostic information (such as Cook's distance).

4.1 A look at the residuals

Histogram of normalized residuals

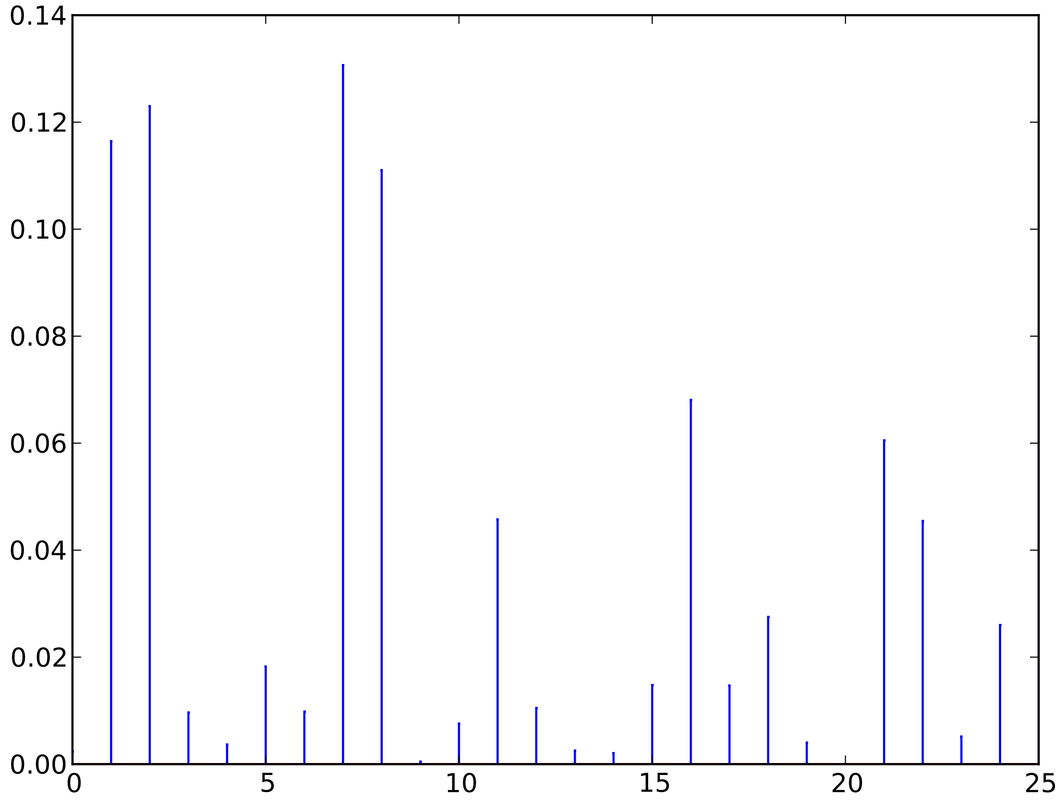
```
plt.hist(fitted.norm_resid())
plt.ylabel('Count')
plt.xlabel('Normalized residuals')
```



4.2 Cooks distance

OLSInfluence objects contain more diagnostic information

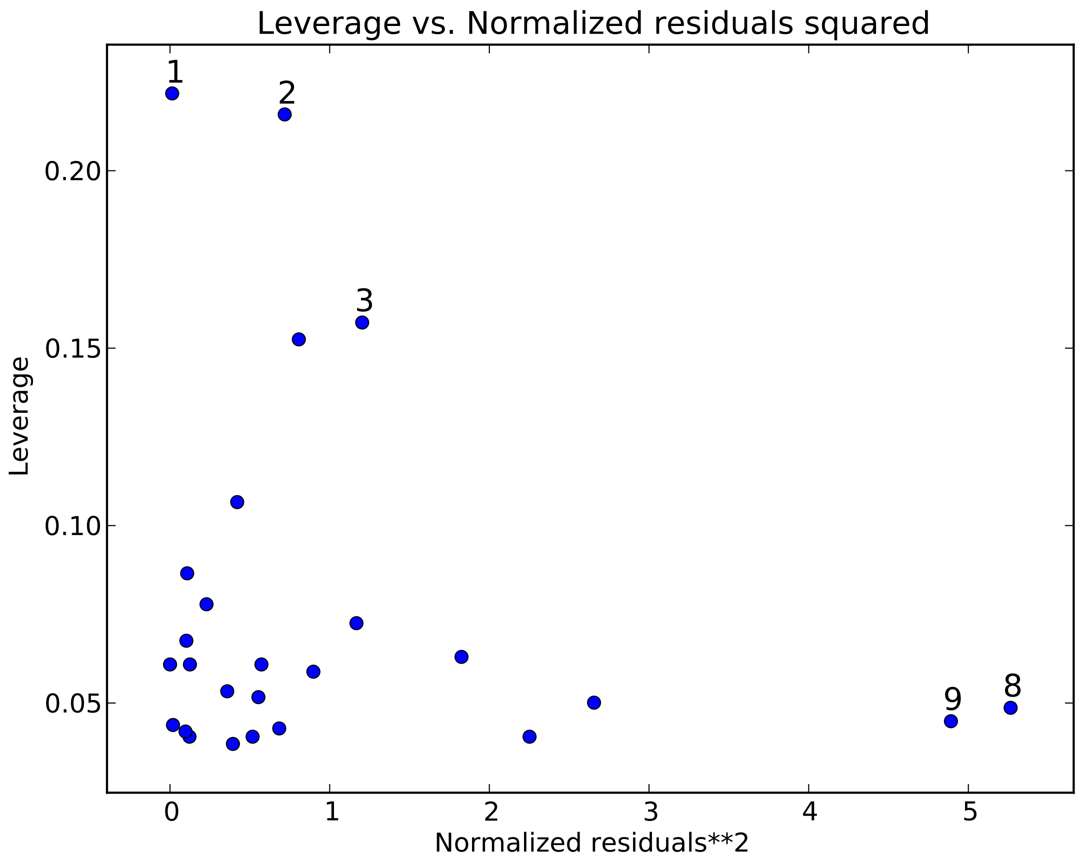
```
influence = fitted.get_influence()
#c is the distance and p is p-value
(c, p) = influence.cooks_distance
plt.stem(np.arange(len(c)), c, markerfmt=",")
```

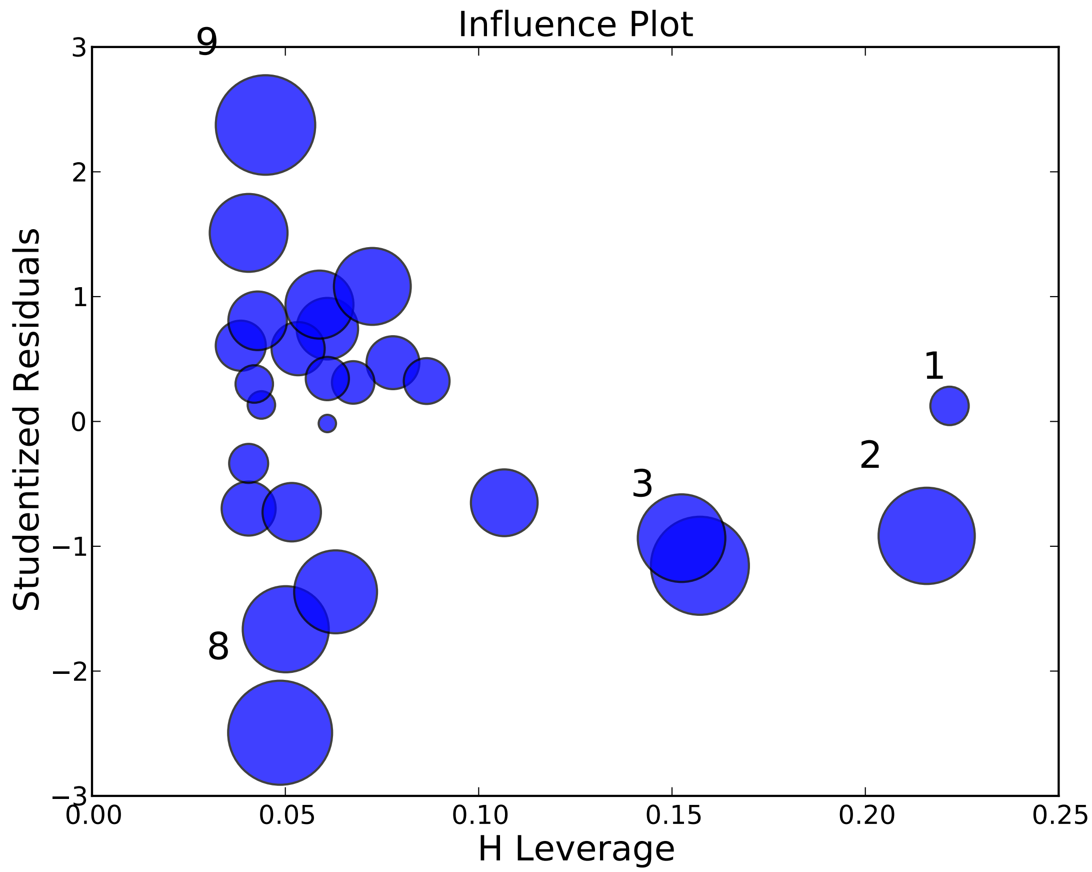


5 Statsmodels builtin plots

Statsmodels includes a some builtin function for plotting residuals against leverage:

```
from statsmodels.graphics.regressionplots import *
plot_leverage_resid2(fitted)
influence_plot(fitted)
```


Leverage vs. Normalized residuals squared
Leverage
Normalized residuals**2
0.05
0.10
0.15
0.20
0
1
2
3
4
5
1
2
3
9
8


Influence Plot
Studentized Residuals
H Leverage
−3
−2
−1
0
1
2
3
0.00
0.05
0.10
0.15
0.20
0.25
9
1
2
3
8