Statistical modelling with Python

Simple linear Regression with Python-native SkiKit-Learn Package

Imports necessary for Regression models with SciKitLearn

In [2]:

```
# imports necessary for statistical modelling
# convention is to define imports at the top of scripts

import numpy as np
import pandas as pd
import seaborn as sns
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
```

Using the ALLBUS data set for standard linear regressions

In [3]:

```
# import data set, set directory
home_dir = "/home/tobias_giesemann/Dropbox/Uni_Master/02SS19/01Advanced_Statistical_Modelling/Essay/"

# using pandas dataframe as a similar data structure to R dataframes
allbus_df = pd.read_csv(home_dir+"data/allbus_small.csv", index_col=0)

#show head
allbus_df.head()
```

Out[3]:

	income	sex	age	eduyears	eastwest	socialclass_self	leftright
1	1800.0	FRAU	47.0	13.0	NEUE BUNDESLAENDER	MITTELSCHICHT	2.0
2	2000.0	MANN	52.0	13.0	NEUE BUNDESLAENDER	MITTELSCHICHT	4.0
3	2500.0	MANN	61.0	9.0	ALTE BUNDESLAENDER	MITTELSCHICHT	8.0
4	860.0	FRAU	54.0	12.0	ALTE BUNDESLAENDER	NaN	3.0
5	NaN	MANN	71.0	NaN	ALTE BUNDESLAENDER	OBERSCHICHT	7.0

In [4]:

```
#description of numeric variables
allbus_df.describe()
```

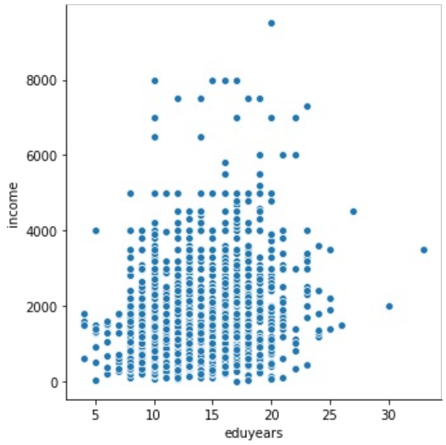
Out[4]:

	income	age	eduyears	leftright
count	2654.000000	3486.000000	3303.000000	3335.000000
mean	1609.666164	51.143144	12.632758	5.078561
std	1100.712568	17.567575	3.694805	1.700014
min	1.000000	18.000000	4.000000	1.000000
25%	850.000000	37.000000	10.000000	4.000000
50%	1400.000000	52.000000	12.000000	5.000000
75%	2000.000000	65.000000	15.000000	6.000000
max	9500.000000	97.000000	33.000000	10.000000

Plotting in Python with package "Seaborn"

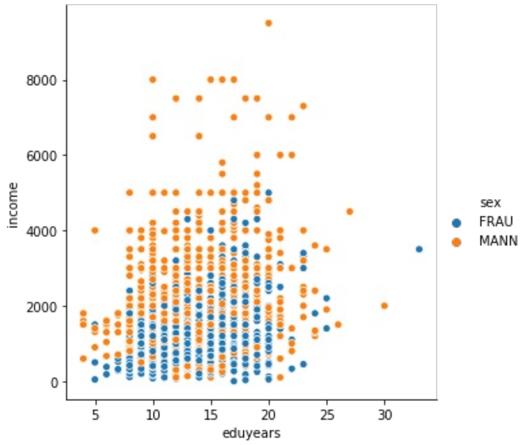
In [13]:

```
# basic plotting with seaborn plotting package
basic_plot = sns.relplot(x="eduyears",y="income", data=allbus_df)
```



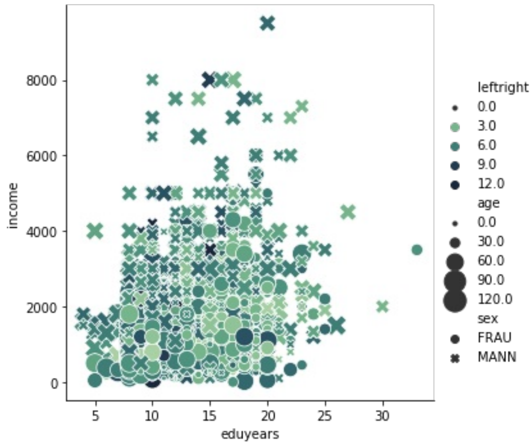
In [12]:

```
# little more advanced plotting
fair_plot = sns.relplot(x="eduyears",y="income", hue="sex", data=allbus_df)
```



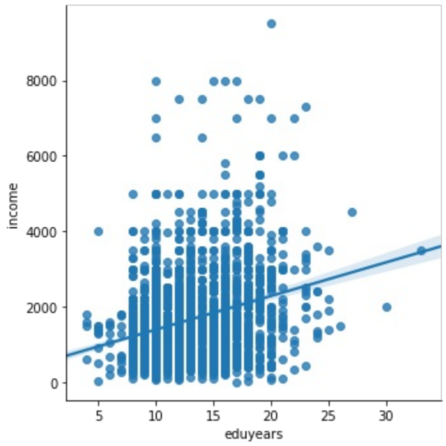
In [11]:

```
# too much for one plot, but great features
overly_advanced_plot = sns.relplot(x="eduyears",
            y="income",
            hue="leftright",
            style="sex",
            size="age",
            palette="ch:r=-.5,l=.75",
            sizes=(10,300),
            data=allbus_df)
overly_advanced_plot.savefig(home_dir+'figures/python/overly_advanced_plot.pdf')
```



In [10]:

```
# simple and fast plot for linear models -> very powerful
lm_plot = sns.lmplot('eduyears', 'income', data=allbus_df, fit_reg=True)
```



Linear Models with SciKit Learn

In [4]:

```
# reshape input variables
regression_df1 = allbus_df[['income','age']]
regression_df1.dropna(inplace=True)
X = np.array([regression_df1.age]).reshape(-1, 1)
y = np.array([regression_df1.income]).reshape(-1, 1)

# define model
regression_model = LinearRegression()
regression_model.fit(X, y)

y_predicted = regression_model.predict(X)

# model evaluation
mse = mean_squared_error(y, y_predicted)
r2 = r2_score(y, y_predicted)

# printing values
print('Estimate Std.:' ,regression_model.coef_)
print('Intercept:', regression_model.intercept_)
print('Mean squared error: ', mse)
print('R2 score: ', r2)
```

```
Estimate Std.: [[2.79715344]]
Intercept: [1465.57232066]
Mean squared error:  1208951.0226202777
R2 score:  0.002015611062190281

/home/tobias_giesemann/.local/lib/python3.6/site-packages/ipykernel_launcher.py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-
versus-a-copy
  This is separate from the ipykernel package so we can avoid doing imports until
```

Linear Regression with Package StatsModels

In [23]:

```
import statsmodels.api as sm

# import data set, set directory
home_dir = "/home/tobias_giesemann/Dropbox/Uni_Master/02SS19/01Advanced_Statistical_Modelling/Essay/"

# using pandas dataframe as a similar data structure to R dataframes
allbus_df = pd.read_csv(home_dir+"data/allbus_small.csv", index_col=0)

#show head
allbus_df.head()

# drop nan values
allbus_df. dropna(inplace = True)
```

Linear Regression

As we can see, this emulation of the R syntax is much easier to implement

In [25]:

```python
import statsmodels.formula.api as smf

lm1 = smf.ols('income ~ 1+age+sex+eduyears+eastwest+leftright', data=allbus_df).fit()
print(lm1.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                 income   R-squared:                       0.218
Model:                            OLS   Adj. R-squared:                  0.216
Method:                 Least Squares   F-statistic:                     134.5
Date:                Thu, 25 Jul 2019   Prob (F-statistic):          4.95e-126
Time:                        16:40:57   Log-Likelihood:                -20109.
No. Observations:                2418   AIC:                         4.023e+04
Df Residuals:                    2412   BIC:                         4.026e+04
Df Model:                           5
Covariance Type:            nonrobust
==================================================================================================
                                     coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------------------------
Intercept                       -412.2895    128.587     -3.206      0.001    -664.442    -160.137
sex[T.MANN]                      647.4251     40.427     16.015      0.000     568.149     726.701
eastwest[T.NEUE BUNDESLAENDER]  -371.3275     42.863     -8.663      0.000    -455.380    -287.275
age                                8.8806      1.188      7.477      0.000       6.552      11.210
eduyears                          99.1138      5.674     17.468      0.000      87.987     110.240
leftright                         27.9986     11.870      2.359      0.018       4.722      51.275
==============================================================================
Omnibus:                      730.914   Durbin-Watson:                   1.999
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             3151.537
Skew:                           1.402   Prob(JB):                         0.00
Kurtosis:                       7.839   Cond. No.                         356.
==============================================================================

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

Residual Plot with Python

As this plot is often needed to check for homoscedascity, I will check if there is an easy implementation in python as well. As we will see, this is not the case, and we rather need to build our own plot.

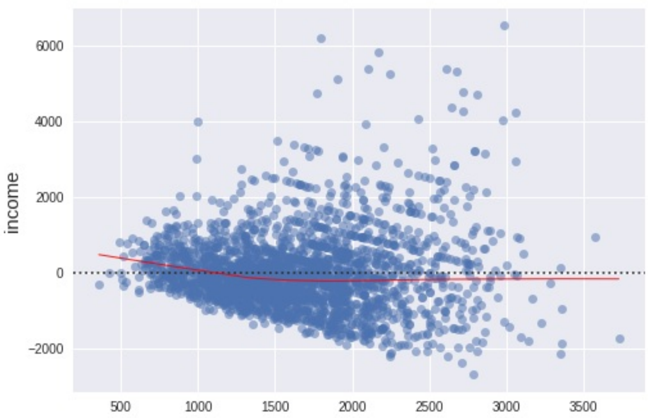
In [41]:

```python
# fitted values (need a constant term for intercept)
model_fitted_y = lm1.fittedvalues

# residual plot
sns.residplot(x=model_fitted_y,
              y="income",
              data=allbus_df,
              lowess = True,
              scatter_kws={'alpha':0.5},
              line_kws={"color": "red", "lw": 1, "alpha": 0.9})
```

Out[41]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f0e6a0f6438>
```



Here, we would rather have to check for heteroscedascity and maybe consider a quantile-regression model