# Linear Regression - Example

SSSA - Applied Statistics - Chiara Seghieri and Costanza Tortù

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### **Preliminaries**

### Recall packages

#### Import Data

The data consists of a number of demographic variables (age, race, academic background, and previous real earnings), as well as a treatment indicator, and the real earnings in the year 1978 (the response).

Robert Lalonde, "Evaluating the Econometric Evaluations of Training Programs", American Economic Review, Vol. 76, pp. 604-620

```
rm(list=ls())
data("lalonde")
```

### Have a first look at data

```
dim(lalonde) # units x variables
## [1] 614
head(lalonde)
##
       treat age educ
                        race married nodegree re74 re75
                                                               re78
                   11 black
## NSW1
           1 37
                                   1
                                            1
                                                         9930.0460
## NSW2
           1 22
                     9 hispan
                                   0
                                             1
                                                  0
                                                       0 3595.8940
              30
                                   0
                                            0
                                                  0
## NSW3
           1
                    12 black
                                                       0 24909.4500
           1 27
                                   0
                                            1
                                                  0
                                                         7506.1460
## NSW4
                    11
                       black
                                            1
## NSW5
            1 33
                    8 black
                                   0
                                                           289.7899
## NSW6
              22
                     9 black
                                                       0 4056.4940
```

#### Inspect variables

```
colnames(lalonde)

## [1] "treat" "age" "educ" "race" "married" "nodegree" "re74"

## [8] "re75" "re78"

quantitative_variables <- c("age", "educ", "re74", "re75", "re78")
qualitative_variables <- c("treat", "race", "married", "nodegree")

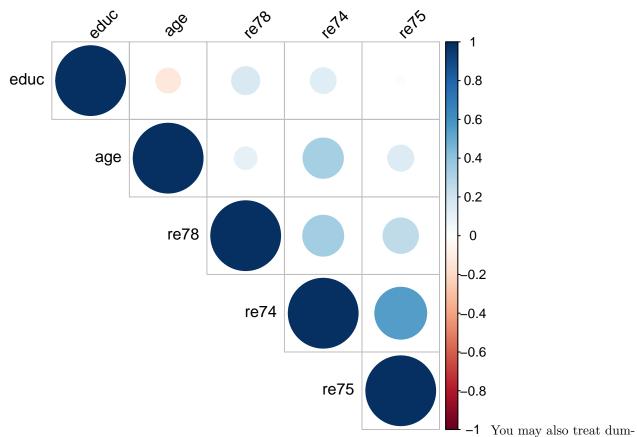
dummies <- c("treat", "married", "nodegree")</pre>
```

```
lalonde$treat_factor <- as.factor(lalonde$treat)</pre>
lalonde$race_factor <- as.factor(lalonde$race)</pre>
lalonde$married_factor <- as.factor(lalonde$married)</pre>
lalonde$nodegree_factor <- as.factor(lalonde$nodegree)</pre>
qualitative_variables_factors <- c("treat_factor", "race_factor",</pre>
                                    "married_factor", "nodegree_factor")
all_variables <- c(quantitative_variables, qualitative_variables_factors)</pre>
Let's focus on quantitative variables
pairs.panels(lalonde[, quantitative_variables],
             method = "pearson", # correlation method
             hist.col = "#00AFBB",
             density = TRUE, # show density plots
             ellipses = TRUE # show correlation ellipses
                                                    10000
                      5 10 15
                                                            25000
       age
                                                                    0.11
                                     0.33
                                                    0.14
                      -0.13
                      educ
                                                                    0.16
                                     0.14
                                                    0.02
                                     re74
                                                                    0.34
                                                    0.55
                                                     re75
                                                                    0.26
                                                                    re78
```

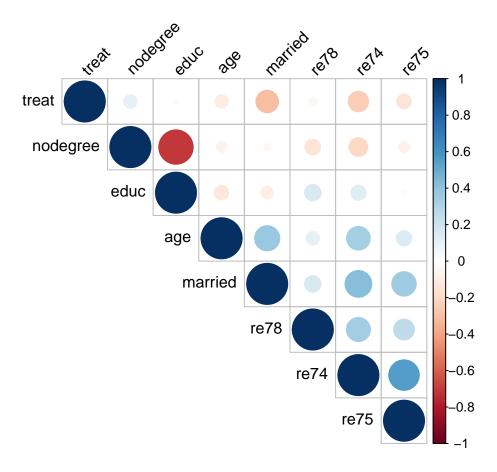
35000

0 20000 50000

15000



mies as quantitative variables and compute correlation, but pay attention to the interpretation!!!!!!



# Run a regression model

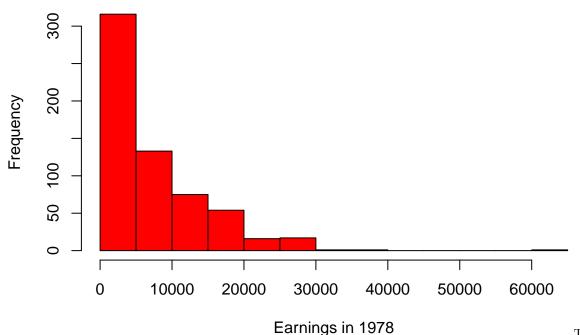
The response variable measures earnings in 1978 while the marital status the age, the education, the race and the training program are independent variables.

# Make sure your data meet the normality assumption

Let's have a look at the distribution of earnings in 1978

```
hist(lalonde$re78,
    main ="Histogram of real earnings in 1978",
    col = "red",
    xlab = "Earnings in 1978")
```

# Histogram of real earnings in 1978



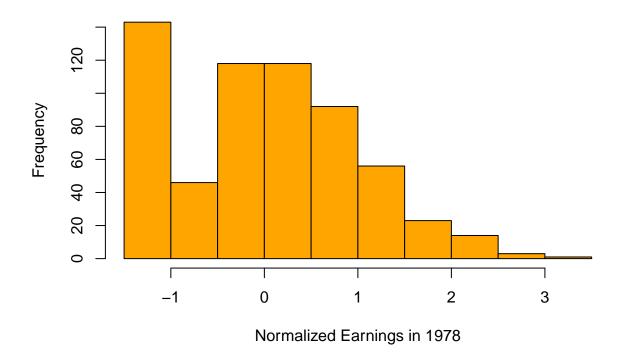
, c

This is far

from normality, let's apply a normalization trasformation  $\,$ 

```
re78_BN <- bestNormalize(lalonde$re78)</pre>
re78_BN
## Best Normalizing transformation with 614 Observations
## Estimated Normality Statistics (Pearson P / df, lower => more normal):
  - arcsinh(x): 12.5241
##
##
  - Center+scale: 7.1465
##
   - Double Reversed Log_b(x+a): 8.3531
##
   - Log_b(x+a): 17.6774
  - orderNorm (ORQ): 3.7705
  - sqrt(x + a): 3.7965
## - Yeo-Johnson: 5.2671
## Estimation method: Out-of-sample via CV with 10 folds and 5 repeats
##
## Based off these, bestNormalize chose:
## orderNorm Transformation with 614 nonmissing obs and ties
   - 457 unique values
   - Original quantiles:
##
##
          0%
                   25%
                             50%
                                        75%
                                                 100%
       0.000
               238.283 4759.018 10893.592 60307.930
lalonde$re78_normalized <- re78_BN$x.t</pre>
hist(lalonde$re78_normalized,
     main ="Histogram of normalized real earnings in 1978",
     col = "orange",
     xlab = "Normalized Earnings in 1978")
```

# Histogram of normalized real earnings in 1978

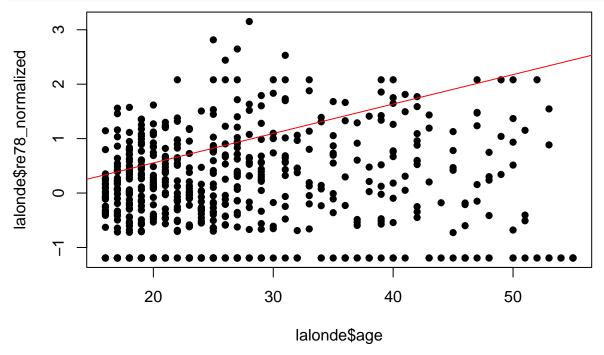


### Simple Linear Regression

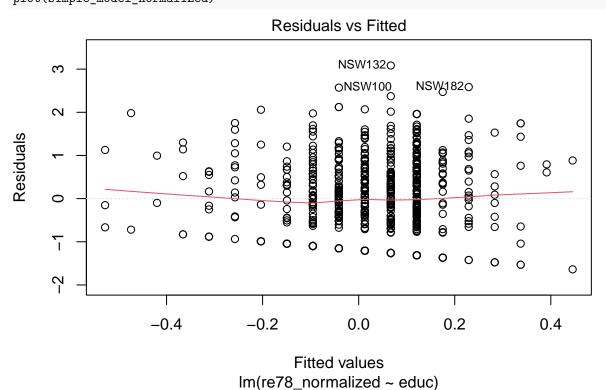
We investigate the relationship between the education and the real earnings in the year 1978 educ: years of education re78: earnings in 1978

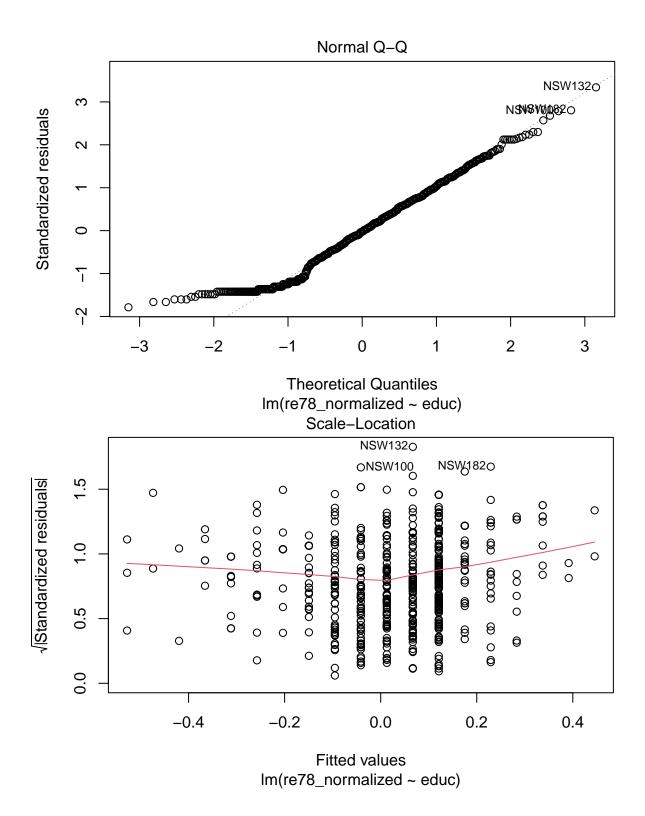
```
##
## Call:
## lm(formula = re78_normalized ~ educ, data = lalonde)
##
## Residuals:
##
                 1Q
                      Median
## -1.63840 -0.69846 -0.02051 0.64832 3.08381
##
## Coefficients:
              Estimate Std. Error t value Pr(>|t|)
##
                          0.15053 -3.507 0.000486 ***
## (Intercept) -0.52797
## educ
               0.05408
                           0.01420
                                    3.808 0.000154 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## Residual standard error: 0.9242 on 612 degrees of freedom
## Multiple R-squared: 0.02315,
                                   Adjusted R-squared: 0.02155
## F-statistic: 14.5 on 1 and 612 DF, p-value: 0.0001542
```

plot(lalonde\$age, lalonde\$re78\_normalized, pch=16)
abline(simple\_model\_normalized, col="red" )

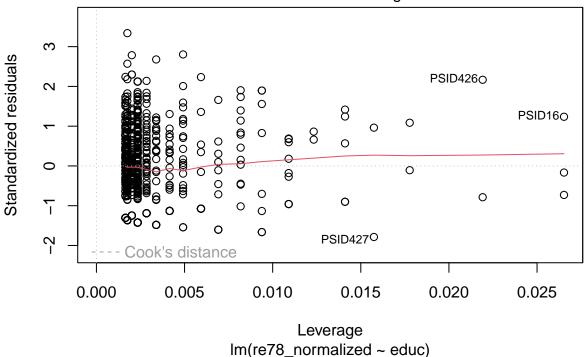


Further inspect your model plot(simple\_model\_normalized)





## Residuals vs Leverage



# Multiple Regression

We investigate the determinants of real earnings in the year 1978

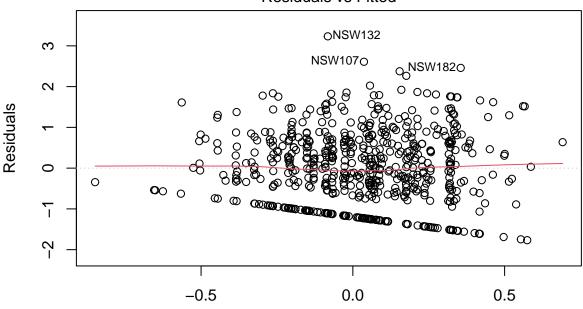
age: gae (years), numeric treat: attendence of a training program educ: years of education married: marital status re78: earnings in 1978

```
##
## Call:
  lm(formula = re78_normalized ~ age + educ + as.factor(race) +
       married + treat + nodegree, data = lalonde)
##
##
## Residuals:
##
                1Q Median
                                 3Q
                                        Max
  -1.7674 -0.6991 -0.0141 0.6426
                                    3.2332
## Coefficients:
##
                           Estimate Std. Error t value Pr(>|t|)
## (Intercept)
                                     0.3191322
                                                 -2.955 0.00325 **
                         -0.9429339
## age
                           0.0009189
                                     0.0041241
                                                  0.223
                                                         0.82377
## educ
                           0.0602261
                                      0.0206487
                                                  2.917
                                                         0.00367 **
## as.factor(race)hispan
                          0.3542669
                                      0.1331197
                                                  2.661
                                                         0.00799 **
## as.factor(race)white
                           0.2565782
                                     0.1003492
                                                  2.557
                                                         0.01080 *
## married
                           0.2604112 0.0853849
                                                  3.050
                                                         0.00239 **
```

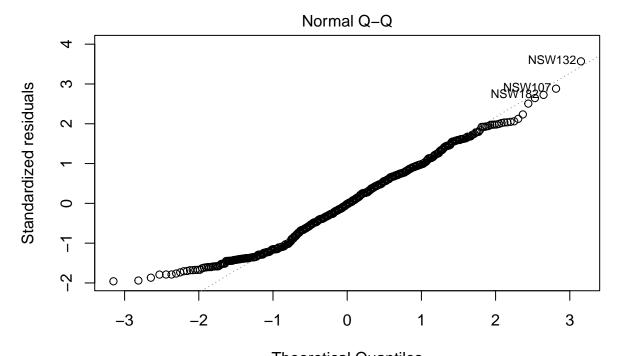
Furtehr inspect your model

plot(multiple\_model\_normalized)

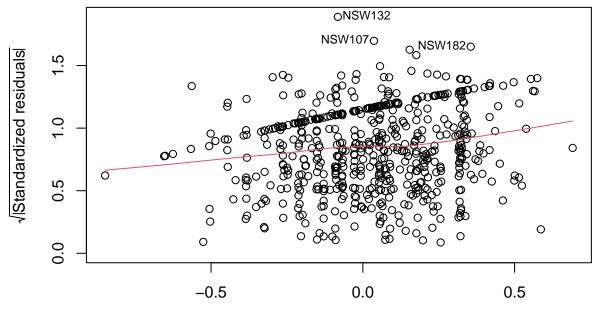
### Residuals vs Fitted



Fitted values
Im(re78\_normalized ~ age + educ + as.factor(race) + married + treat + nodeg ...

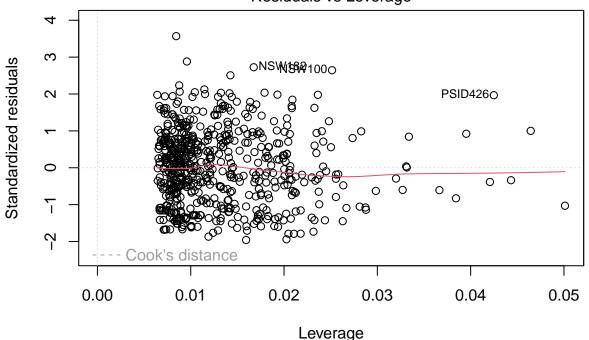


Theoretical Quantiles
Im(re78\_normalized ~ age + educ + as.factor(race) + married + treat + nodeg ...
Scale-Location



Fitted values
Im(re78\_normalized ~ age + educ + as.factor(race) + married + treat + nodeg ...

## Residuals vs Leverage



lm(re78\_normalized ~ age + educ + as.factor(race) + married + treat + nodeg ...

Add valuable interactions

```
##
## Call:
## lm(formula = re78_normalized ~ age + educ + as.factor(race) +
##
       married + treat + nodegree + as.factor(race) * educ + treat *
       nodegree, data = lalonde)
##
##
## Residuals:
##
       Min
                1Q Median
                                 3Q
                                        Max
  -1.8607 -0.6772 0.0010 0.6355
                                     3.2442
##
## Coefficients:
##
                                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)
                               -1.0857162
                                           0.3831280
                                                      -2.834
                                                               0.00475 **
## age
                                0.0009009
                                           0.0041194
                                                        0.219
                                                               0.82695
                                           0.0295796
                                                               0.02000 *
##
  educ
                                0.0689941
                                                        2.332
## as.factor(race)hispan
                                0.9586613
                                           0.4438597
                                                               0.03118 *
                                                        2.160
## as.factor(race)white
                                0.0731624
                                           0.3724158
                                                        0.196
                                                               0.84432
## married
                                0.2573807
                                           0.0857845
                                                        3.000
                                                               0.00281 **
## treat
                                0.2720856
                                           0.1625284
                                                        1.674
                                                               0.09463
## nodegree
                                0.0862717
                                                               0.50415
                                           0.1290781
                                                        0.668
## educ:as.factor(race)hispan -0.0666634 0.0445307
                                                      -1.497
                                                               0.13491
```