

# Linear regression II

2024-09-02

```
stopifnot(  
  require(tidyverse),  
  require(patchwork),  
  require(httr),  
  require(glue),  
  require(broom)  
)  
old_theme <- theme_set(theme_minimal())
```

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## ! Objectives

## Linear fit using ordinary least squares (OLS)

- Perform linear regression of SAL\_ACTUEL with respect to SAL\_EMBAUCHE. Store the result in an object denoted by `lm_1`
- Inspect the numerical summary of `lm_1`
- Use **Environment** panel (Rstudio), to explore the structure of `lm_1`. Try to understand the signification of each element.

```
datapath <- '../DATA'  
fname <- 'Banque.csv'  
fpath <- paste(datapath, fname, sep="/")  
  
if (!file.exists(fpath)) {  
  baseurl <- 'https://stephane-v-boucheron.fr/data'  
  download.file(url=paste(baseurl, fname, sep="/"),  
                destfile=fpath)  
  print(glue::glue('File {fname} downloaded at {fpath}!'))  
}
```

```

} else {
  print(glue::glue('File {fname} already exists at {fpath}!'))
}

```

File Banque.csv already exists at ../DATA/Banque.csv!

```

bank <- readr::read_table(fpath,
  col_types = cols(
    SEXE = col_factor(levels = c("0", "1")),
    CATEGORIE = col_integer(),
    NB_ETUDES = col_integer(),
    SATIS_EMPLOI = col_factor(levels = c("non", "oui")),
    SATIS_CHEF = col_factor(levels = c("non", "oui")),
    SATIS_SALAIRE = col_factor(levels = c("non", "oui")),
    SATIS_COLLEGUES = col_factor(levels = c("non", "oui")),
    SATIS_CE = col_factor(levels = c("non", "oui"))
  )
)

```

- Make the model summary a dataframe/tibble using `broom::tidy()`
- Make model diagnostic information a dataframe/tibble using `broom::glance()`
- Preparing for diagnostic plots using `broom::augment()`

The output of `augment` may be described as adding 6 columns to dataframe `bank`. The six columns are built using items from `lm_1`. Can you explain their meaning and why they are relevant to diagnosing?

Let base R produce diagnostic plots

```
plot(lm_1, which = 1:6)
```

We will reproduce (and discuss) four of the six diagnostic plots provided by the `plot` method from base R (1,2,3,5).

- Reproduce first diagnostic plot with `ggplot` using the augmented version of `lm_1` (`augment(lm_1)`).
- Comment Diagnostic Plot 1.
- Compute the correlation coefficient between residuals and fitted values.
- Make your graphic pipeline a reusable function.
- What are *standardized residuals* ?
- Build the third diagnostic plot (square root of absolute values of standardized residuals versus fitted values) using `ggplot`.
- Why should we look at the square root of standardized residuals?

Make your graphic pipeline a reusable function.

- What is leverage ?

- Build the fifth diagnostic plot (standardized residuals versus leverage) using `ggplot`.

In the second diagnostic plot (the residuals qqplot), we build a quantile-quantile plot by plotting function  $F_n^{\leftarrow} \circ \Phi$  where  $\Phi$  is the ECDF of the standard Gaussian distribution while  $F_n^{\leftarrow}$ .

Build the second diagnostic plot using `ggplot`

Use package `patchwork::...` to collect your four diagnostic plots

Plot actual values against fitted values for `SAL_ACTUEL`

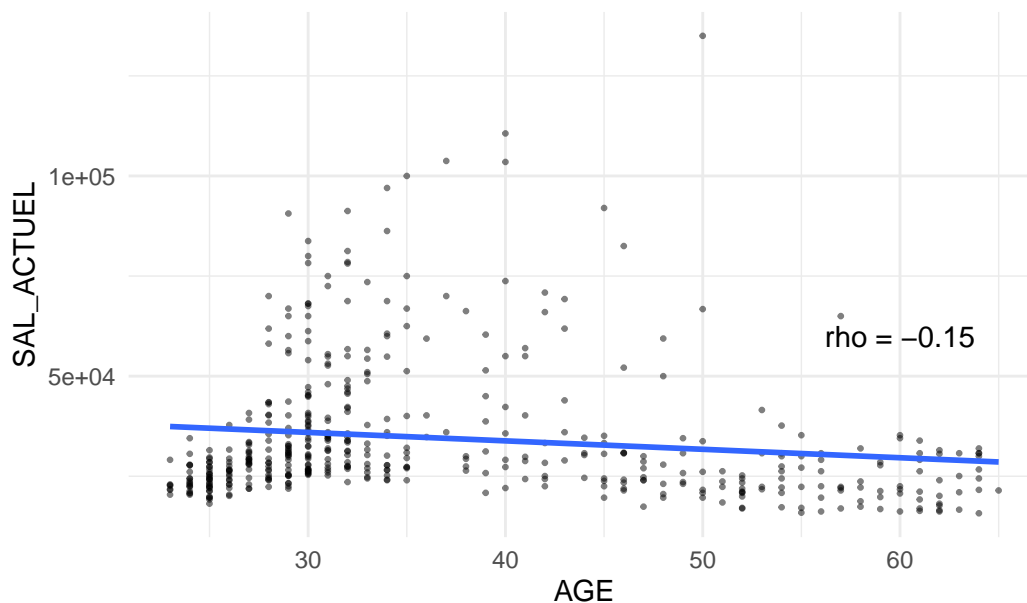
Play it again with `AGE` and `SAL_ACTUEL`

Redo the above described steps and call the model `lm_2`.

- `ggplot` programming : write a function with arguments `df`, `varx` and `vary` where `varx` and `vary` are two strings denoting numerical columns in `df`, that outputs a `ggplot` object made of a scatterplot of columns `vary` and `varx`, a linear regression of `vary` against `varx`. The `ggplot` plot object should be annotated with the linear correlation coefficient of `vary` and `varx` and equipped with a title.

```
bank %>%
  ggplot() +
  aes(x=AGE, y=SAL_ACTUEL) +
  geom_point(alpha=.5, size=.5, ) +
  geom_smooth(method="lm", formula= y ~ x, se=F) +
  annotate(geom="text", x=60, y=60000,
          label=str_c("rho = ",
                      round(cor(bank$SAL_ACTUEL, bank$AGE), 2))) +
  ggtitle("Bank dataset")
```

Bank dataset



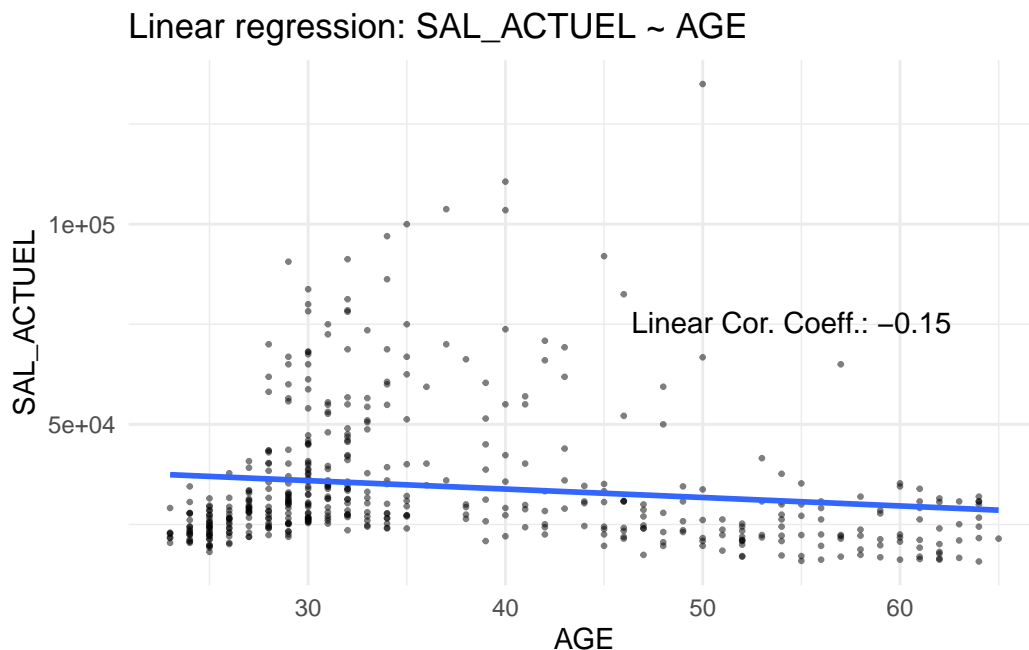
```

ggplot_lin_reg <- function(df, varx, vary){
  rho <- round(cor(df[[varx]], df[[vary]]), 2)
  posx <- sum(range(df[[varx]])*c(.25 , .75))
  posy <- sum(range(df[[vary]])*c(.5 , .5))

  df %>%
    ggplot() +
    aes(x=.data[[varx]], y=.data[[vary]]) +
    geom_point(alpha=.5, size=.5, ) +
    geom_smooth(method="lm", formula= y ~ x, se=F) +
    annotate(geom="text", x=posx, y=posy,
             label=glue("Linear Cor. Coeff.: {rho}")) +
    ggtitle(glue("Linear regression: {vary} ~ {varx}"))
}

ggplot_lin_reg(bank, "AGE", "SAL_ACTUEL")

```



Inspect rows with high Cook's distance

Discuss the relevance of Simple Linear Regression for analyzing the connection between SAL\_ACTUEL and AGE

Compute the Pearson correlation coefficient for every pair of quantitative variable? Draw corresponding scatterplots.

**Predictive linear regression of SAL\_ACTUEL as a function of age AGE**

To perform linear fitting, we choose 450 points amongst the 474 sample points: the 24 remaining points are used to assess the merits of the linear fit.

**Randomly select 450 rows in the banque dataframe.**

Function `sample` from base R is convenient. You may also enjoy `slice_sample()` from `dplyr`. Denote by `trainset` the vector of selected indices. Bind the vector of left behind indices to variable `testset`. Functions `match`, `setdiff` or operator `%in%` may be useful.

- ☐ Linear fit of `SAL_ACTUEL` with respect to `AGE`, on the training set. Call the result `lm_3`.
- ☐ How do you feel about such a linear fit? (Use diagnostic plots)

Inspecting points with high Cook's distance

- ☐ Use `lm_3` to predict the values of `SAL_ACTUEL` as an affine function of `AGE` on the testing set `testset` (`broom::augment()` with optional argument `newdata` may be useful). Compare the data frame with the one obtained from `augment(lm_3)`.
- ☐ Compare training error and testing error
- ☐ Analyse residuals (prediction errors) on the testing set. Compare with training set

## Expectations under Gaussian Linear Modelling Assumptions

$$(Y) = (\mathbb{Z}) \times \beta + \sigma(\epsilon)$$