Tutorial : Dynamic data visualization with R

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Presentation

This tutorial provides some **R** tools for **data visualization**. You can find

- materials (slides) associated with this tutotial as well as datasets at https://lrouviere.github.io/DATAVIZ/ ;
- tutorial without correction at https://lrouviere.github.io/TUTO_DATAVIZ/ ;
- tutorial with corrections at https://lrouviere.github.io/TUTO_DATAVIZ/correction/.

I strongly encourage to use **mozilla firefox** to read this tutorial.

Basics on **R** and computer programming are necessary. The tutorial is divided into tree parts :

- `Visualization with ggplot2` : presentation of the **ggplot2** grammar ;
- `Mapping with R` : how to build map with `ggmap`, `sf` and `leaflet` ;
- `Dynamic visualization` : some tools to make interactive visusalization (rAmCharts, plotly), dasboard and web applications (shiny).

1 Data visualization with ggplot2

Graphs are often the starting point for statistical analysis. One of the main advantages of **R** is how easy it is for the user to create many different kinds of graphs. We begin this chapter by studying conventional

graphs, followed by an examination of some more complex representations. This final (and main) part uses the **ggplot2** package.

1.1 Conventional Graphical Functions

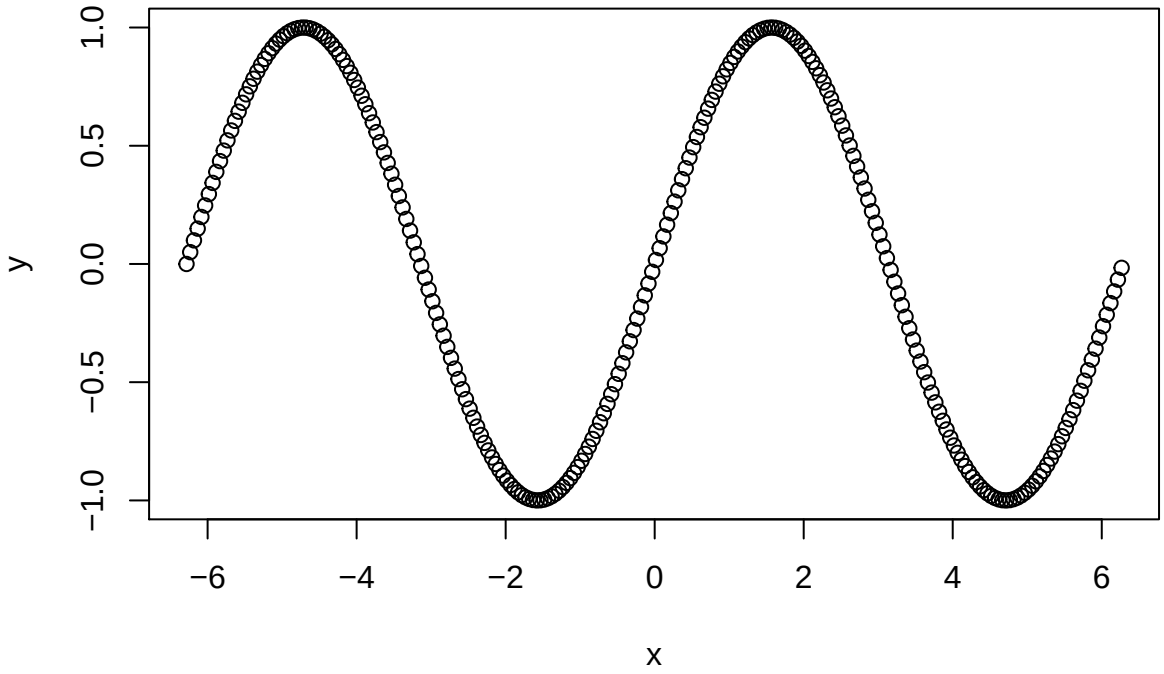
To begin with, it may be interesting to examine few examples of graphical representations which can be constructed with **R**. We use the **demo** function :

```
demo(graphics)
```

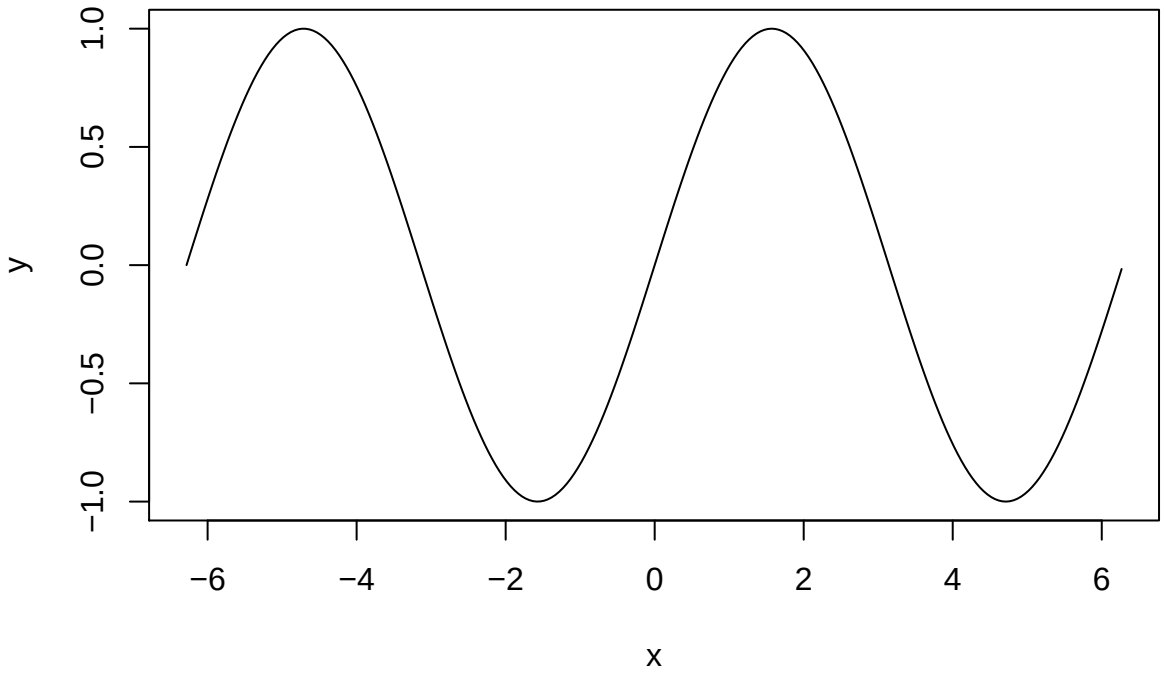
1.1.1 The plot function

The **plot** function is a **generic function** used to represent all kinds of data. Classical use of the **plot** function consists of representing a scatterplot for a variable y according to another variable x. For example, to represent the graph of the function $x \mapsto \sin(2\pi x)$ on $[0, 1]$, at regular steps we use the following commands :

```
x <- seq(-2*pi,2*pi,by=0.05)
y <- sin(x)
plot(x,y) #points (par défaut)
```




```
plot(x,y,type="l") #représentation sous forme de ligne
```



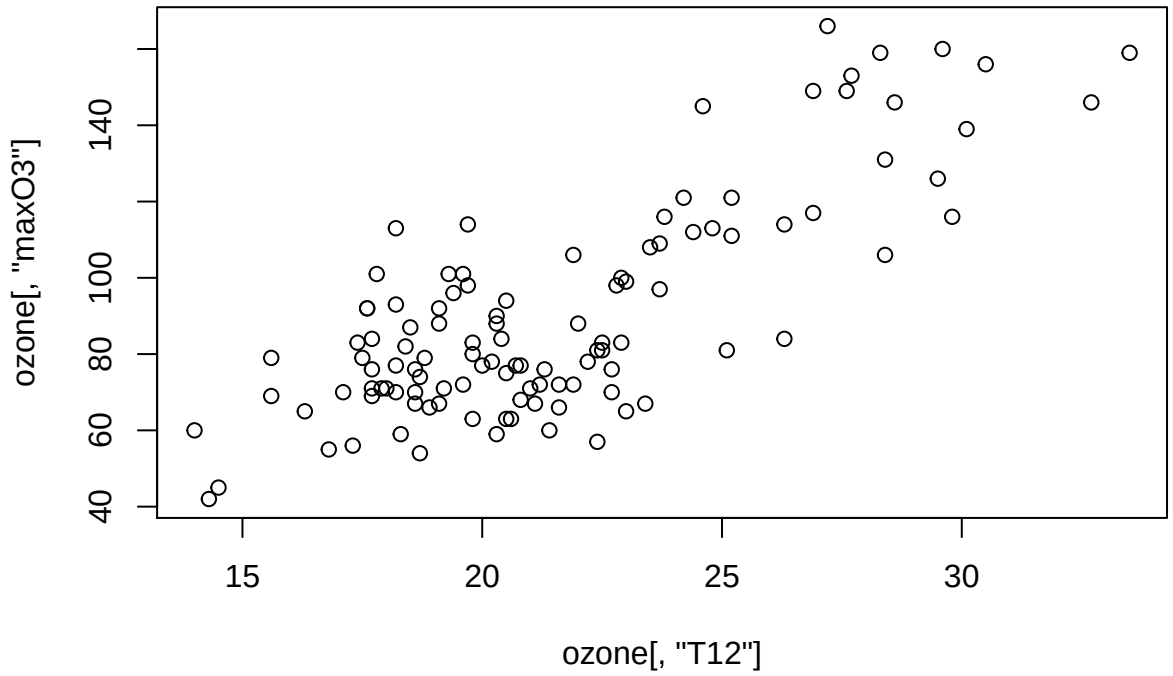
We provide examples of representations for quantitative and qualitative variables. We use the data file **ozone.txt** :

```
ozone <- read.table("data/ozone.txt")
summary(ozone)
     maxO3              T9             T12
 Min.   : 42.00   Min.   :11.30   Min.   :14.00
 1st Qu.: 70.75   1st Qu.:16.20   1st Qu.:18.60
 Median : 81.50   Median :17.80   Median :20.55
 Mean   : 90.30   Mean   :18.36   Mean   :21.53
 3rd Qu.:106.00   3rd Qu.:19.93   3rd Qu.:23.55
 Max.   :166.00   Max.   :27.00   Max.   :33.50
      T15              Ne9             Ne12
 Min.   :14.90   Min.   :0.000   Min.   :0.000
 1st Qu.:19.27   1st Qu.:3.000   1st Qu.:4.000
 Median :22.05   Median :6.000   Median :5.000
 Mean   :22.63   Mean   :4.929   Mean   :5.018
 3rd Qu.:25.40   3rd Qu.:7.000   3rd Qu.:7.000
 Max.   :35.50   Max.   :8.000   Max.   :8.000
      Ne15            Vx9             Vx12
 Min.   :0.00   Min.   :-7.8785   Min.   :-7.878
 1st Qu.:3.00   1st Qu.:-3.2765   1st Qu.:-3.565
 Median :5.00   Median :-0.8660   Median :-1.879
 Mean   :4.83   Mean   :-1.2143   Mean   :-1.611
 3rd Qu.:7.00   3rd Qu.: 0.6946   3rd Qu.: 0.000
 Max.   :8.00   Max.   : 5.1962   Max.   : 6.578
      Vx15            maxO3v           vent
 Min.   :-9.000   Min.   : 42.00   Length:112
 1st Qu.:-3.939   1st Qu.: 71.00   Class :character
 Median :-1.550   Median : 82.50   Mode  :character
 Mean   :-1.691   Mean   : 90.57
 3rd Qu.: 0.000   3rd Qu.:106.00
 Max.   : 5.000   Max.   :166.00
```

```
   pluie
Length:112
Class :character
Mode  :character
```

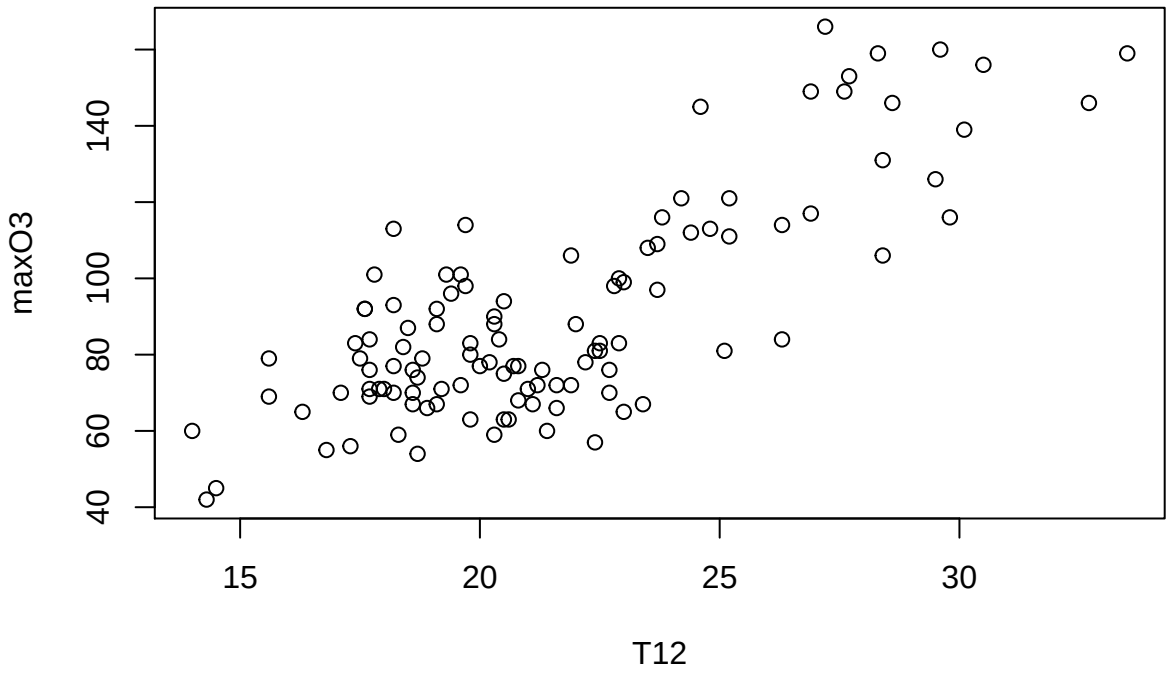
Let us start by representing two quantitative variables : maximum ozone concentrations **maxO3** in term of temperatures **T12** :

```
plot(ozone[,"T12"],ozone[,"maxO3"])
```



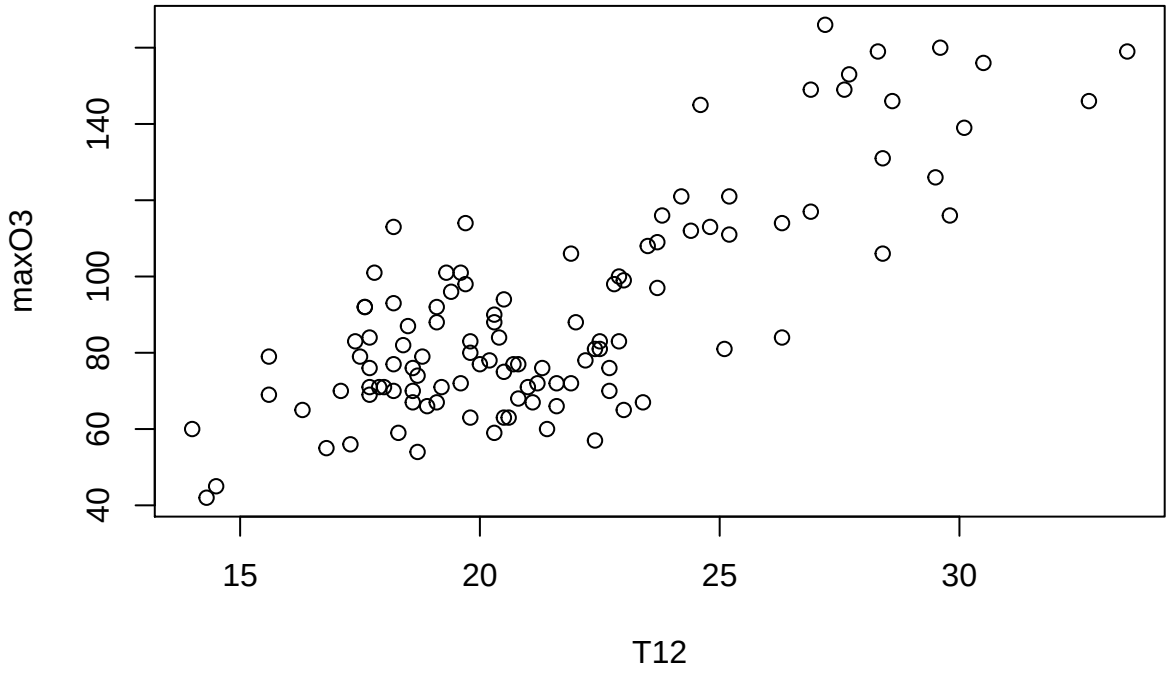
As the two variables are contained and named within the same table, a simpler syntax can be used, which automatically inserts the variables as labels for the axes :

```
plot(maxO3~T12,data=ozone)
```



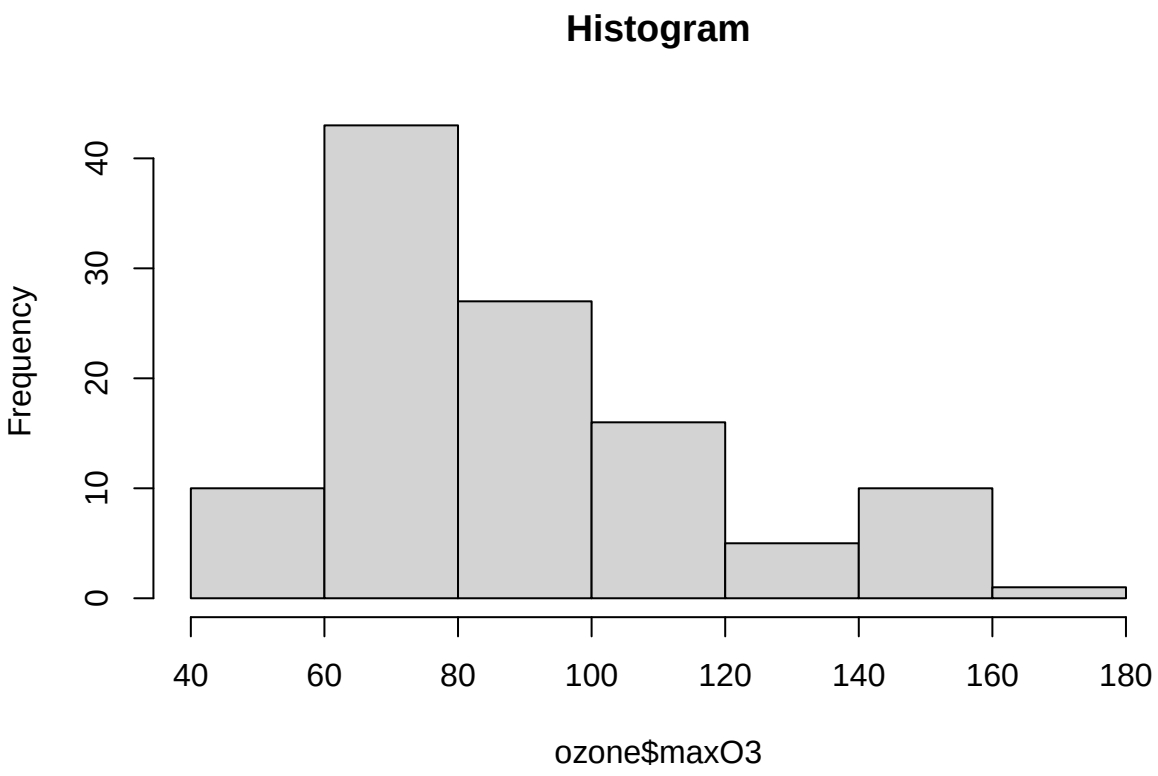
We can also use (more complicated and less interesting)

```
plot(ozone[,"T12"],ozone[,"maxO3"],xlab="T12",ylab="maxO3")
```

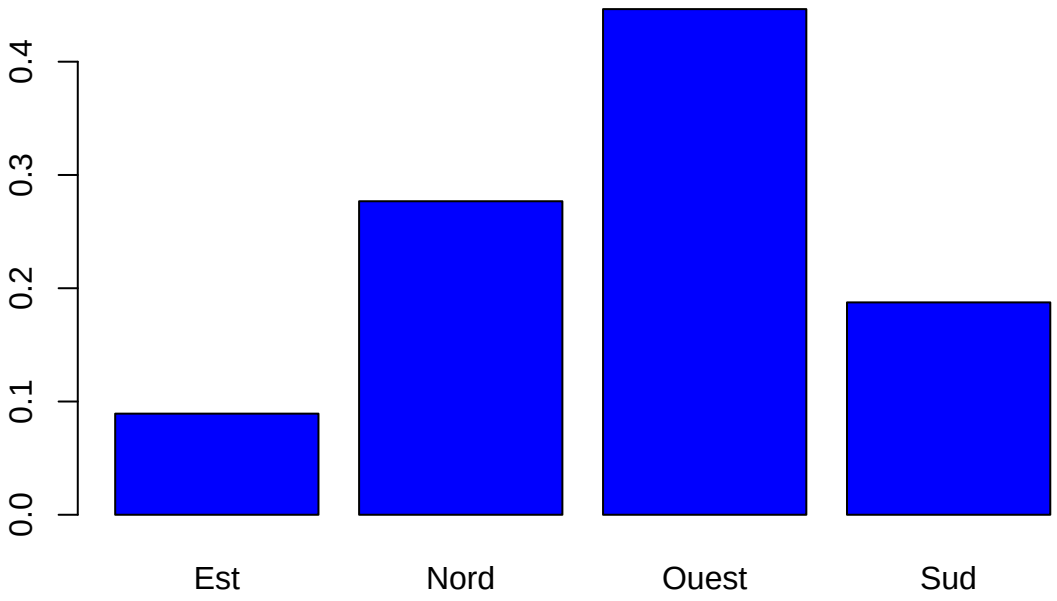


We have specific functions for each kind of charts, for instance

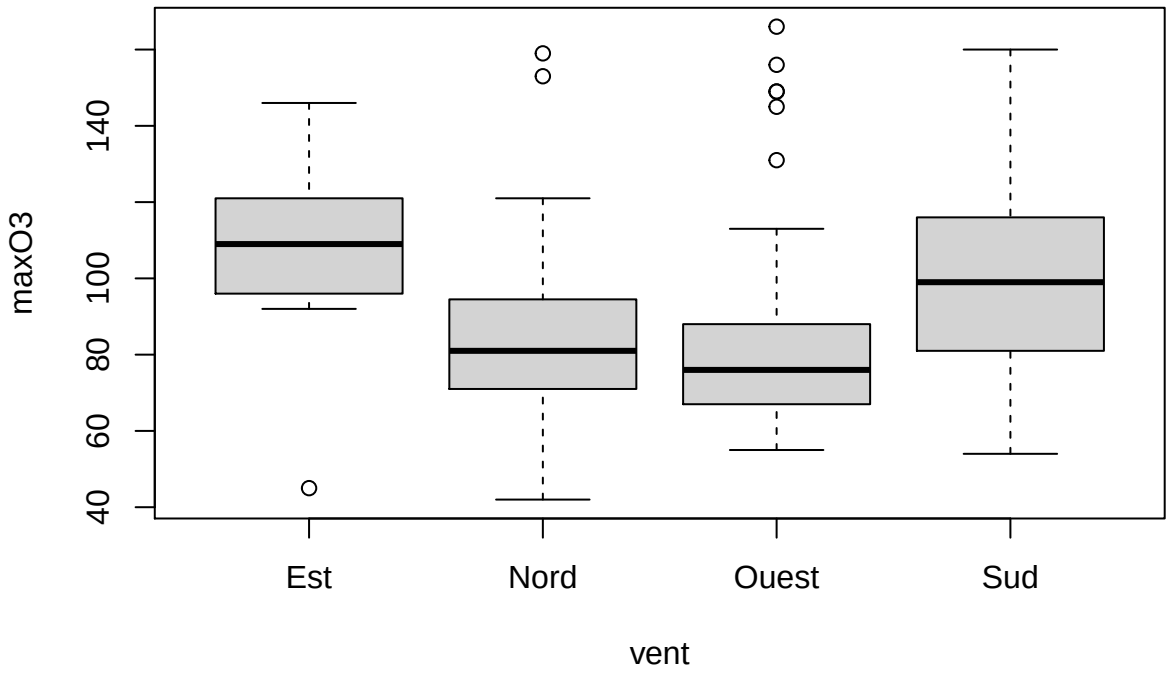
```
hist(ozone$maxO3,main="Histogram")
```




```
barplot(table(ozone$vent)/nrow(ozone),col="blue")
```



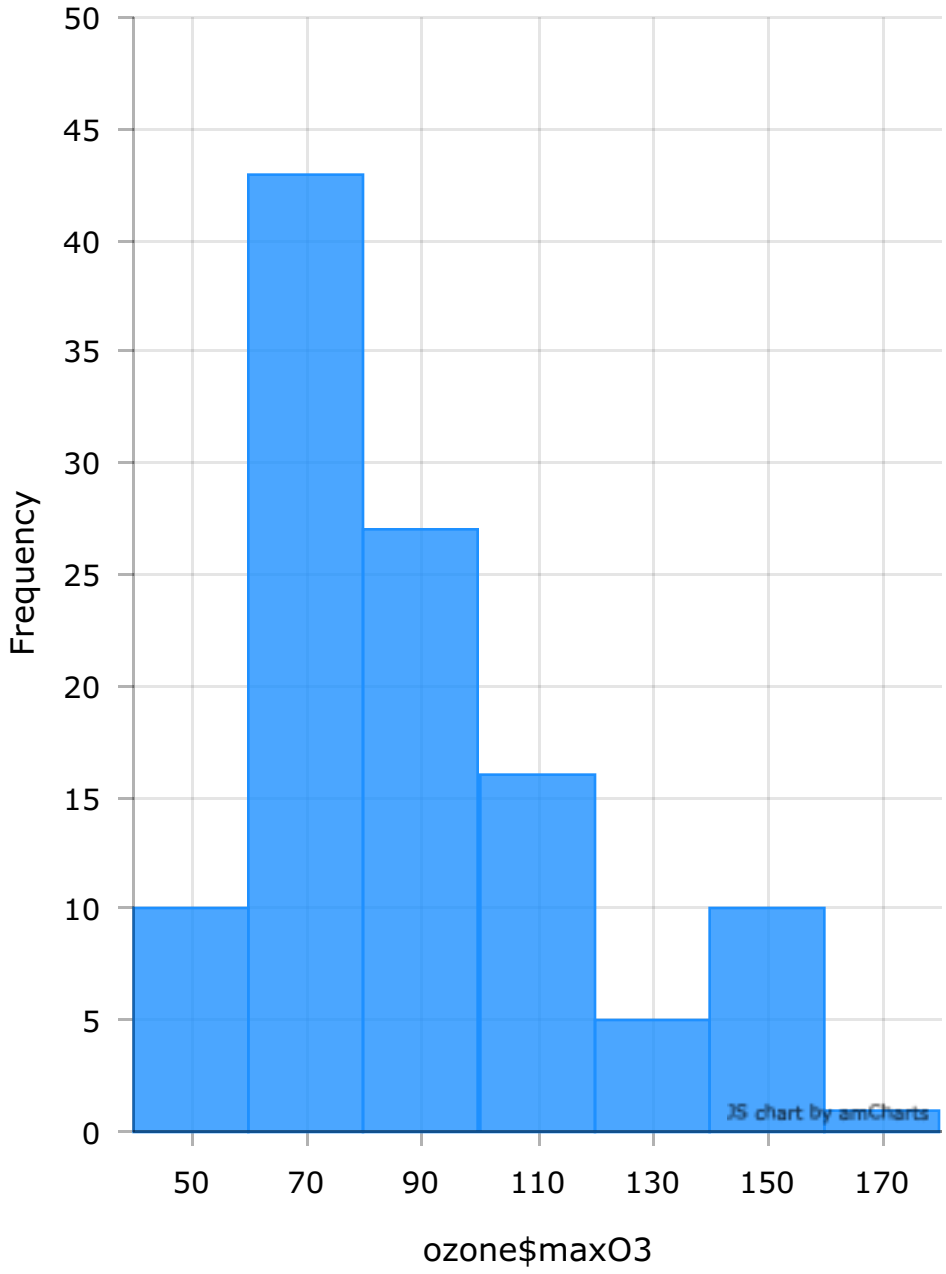

```
boxplot(maxO3~vent,data=ozone)
```



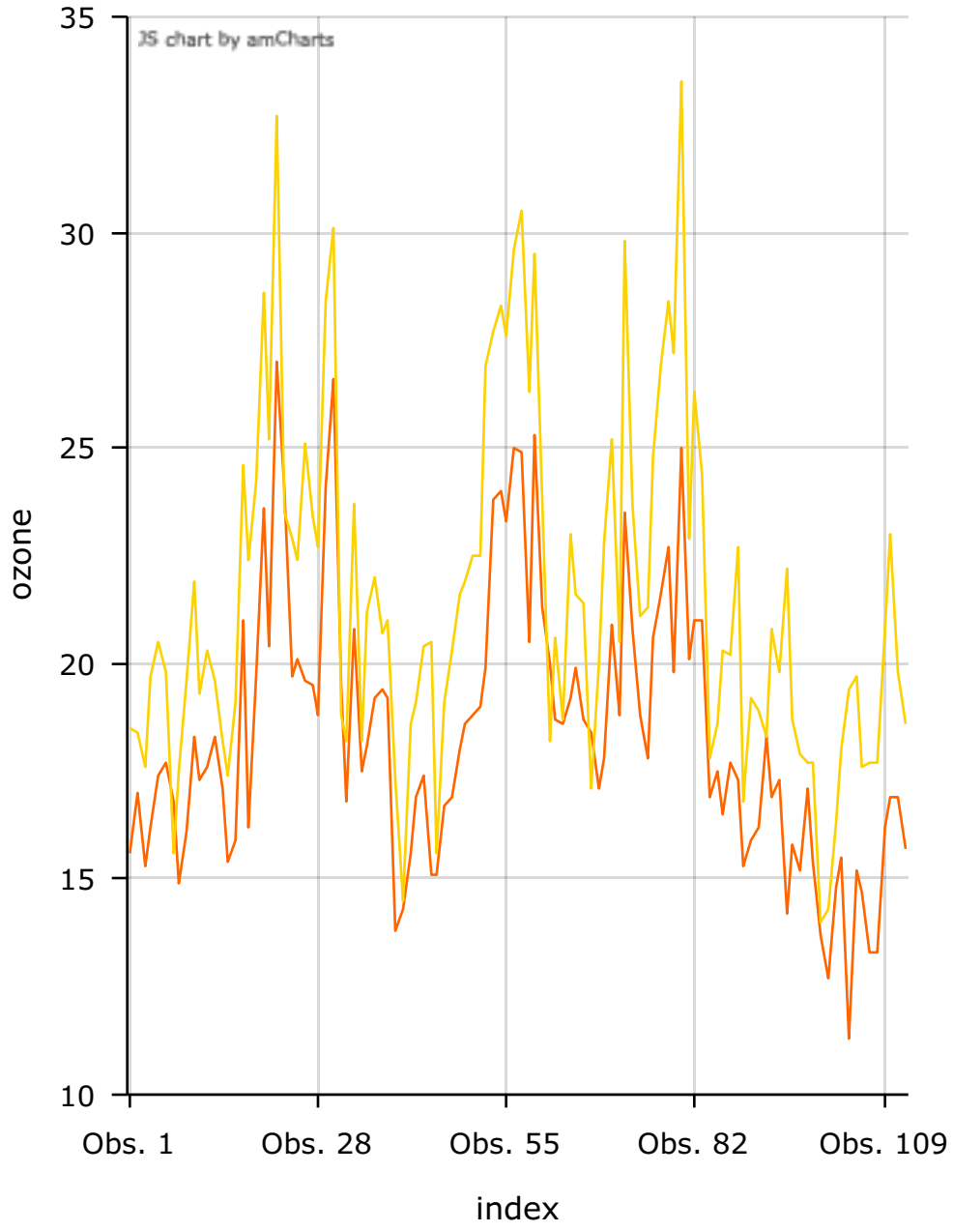
1.1.2 Interactive graphs with rAmCharts

We can use this package to obtain dynamic graphs. It is easy, we just have to use the prefix **am** before the name of the function :

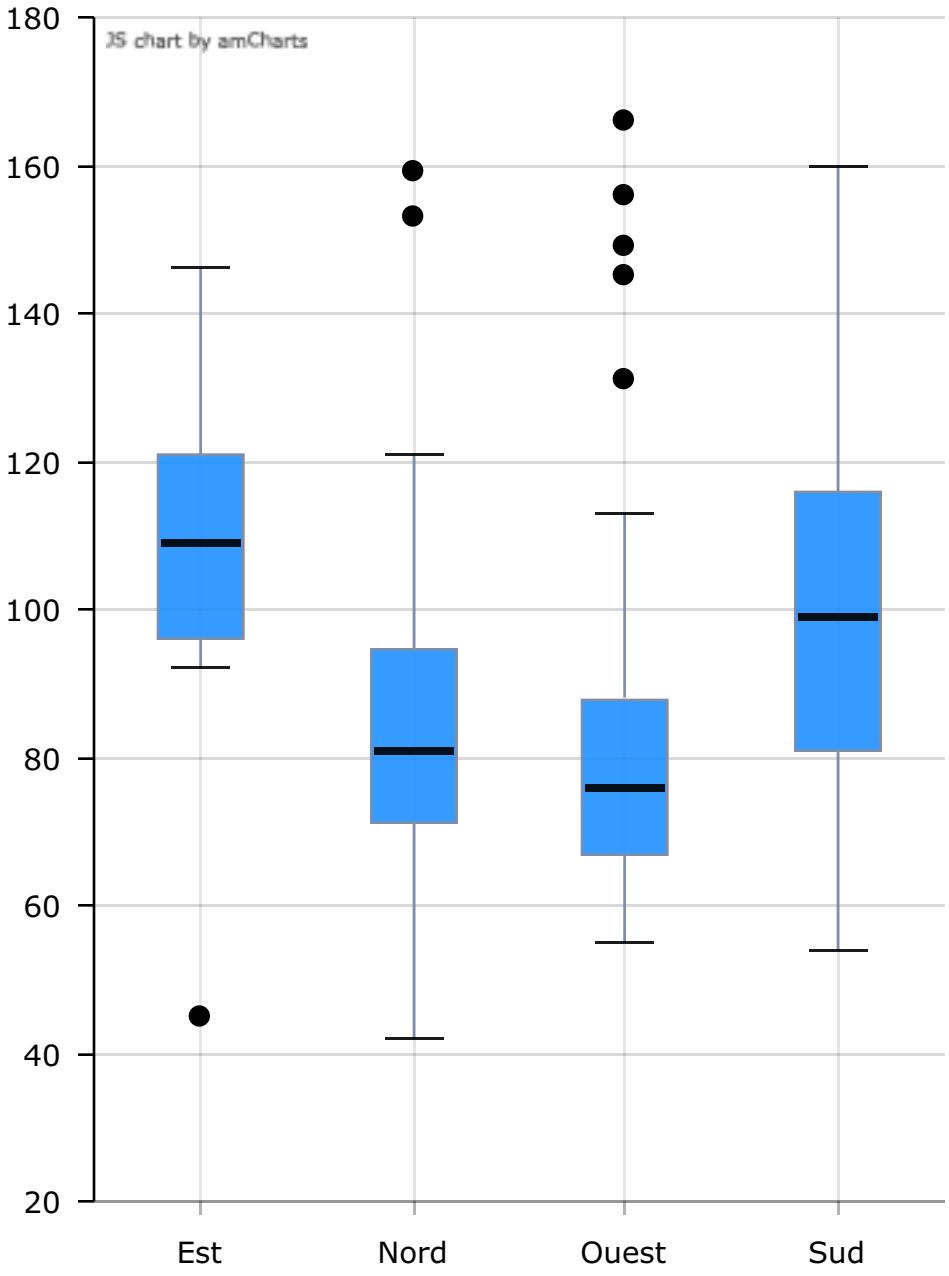
```
library(rAmCharts)
amHist(ozone$maxO3)
```




```
amPlot(ozone,col=c("T9","T12"))
```




```
amBoxplot(max03~vent,data=ozone)
```



1.1.3 Some exercises

Exercise 1.1 (First chart)**.**

1. Draw the **sine** function between 0 and 2π.
2. Add the following title : **Plot of the sine function**, you can use the function **title**.

Exercise 1.2 (Gaussian density distribution)**.**

1. Draw the pdf (probability distribution function) of the standard Gaussian distribution between -4 and 4 (use **dnorm**).
2. Add a vertical dashed line of equation $x = 0$ (use **abline**).

3. On the same graph, draw Student's t-distribution to 5 and 30 degrees of freedom (use **dt**). Use the **lines** function and a different colour for each density.
4. Add a legend at the top left to differentiate between each distribution (use **legend**).

Exercise 1.3 (Draw sunspots)**.**

1. Read the file **taches_solaires.csv** series which details, data by data, the relative number of sunspots.
2. Using the **cut_interval** function from the *tidyverse* package, create a qualitative variable which separates the dates into 8 intervals. We call **period** this variable.
3. Use the following levels for **period**

```
mycolors <- c("yellow", "magenta", "orange", "cyan",
              "grey", "red", "green", "blue")
```

4. Expliquer la sortie de la fonction
5. Visualize the sunspot series with a diffrect color for the 8 periods.

Exercise 1.4 (Layout)**.**

We consider the **ozone** dataset. With the **layout** function, split the window into two lines with

1. the scatter plot **maxO3 vs T12** on the first line ;
2. 2 graphs on the second lines : histogram of **T12** et boxplot of **maxO3**.

1.2 Ggplot2 grammar

ggplot2 is a plotting system for R based on the grammar of graphics (as **dplyr** to manipulate data). We can find documentation at http://ggplot2.org and https://ggplot2-book.org. We consider a subsample of the diamond dataset from the package **ggplot2** (or **tidyverse**) :

1.2.1 First charts with `ggplot2`

We consider a subsample of the `diamond dataset` from the package **ggplot2** (or **tidyverse**) :

```
library(tidyverse)
set.seed(1234)
diamonds2 <- diamonds[sample(nrow(diamonds),5000),]
summary(diamonds2)
```

```
     carat               cut        color       clarity
 Min.   :0.2000   Fair      : 158   D: 640   SI1     :1189
 1st Qu.:0.4000   Good      : 455   E: 916   VS2     :1157
 Median :0.7000   Very Good:1094   F: 900   SI2     : 876
 Mean   :0.7969   Premium   :1280   G:1018   VS1     : 738
 3rd Qu.:1.0400   Ideal     :2013   H: 775   VVS2    : 470
 Max.   :4.1300                    I: 481   VVS1    : 326
                                   J: 270   (Other): 244
     depth           table           price
 Min.   :43.00   Min.   :49.00   Min.   :  365
 1st Qu.:61.10   1st Qu.:56.00   1st Qu.:  945
 Median :61.80   Median :57.00   Median : 2376
 Mean   :61.76   Mean   :57.43   Mean   : 3917
 3rd Qu.:62.50   3rd Qu.:59.00   3rd Qu.: 5294
 Max.   :71.60   Max.   :95.00   Max.   :18757

       x                y               z
 Min.   : 0.000   Min.   :3.720   Min.   :0.000
 1st Qu.: 4.720   1st Qu.:4.720   1st Qu.:2.920
```

```
 Median : 5.690   Median :5.700   Median :3.520
 Mean   : 5.728   Mean   :5.731   Mean   :3.538
 3rd Qu.: 6.530   3rd Qu.:6.520   3rd Qu.:4.030
 Max.   :10.000   Max.   :9.850   Max.   :6.430

help(diamonds)
```

A graph is always defined from many **layers**. We usually have to specify :

— the data
— the variables we want to plot
— the type of representation (scatterplot, boxplot…).

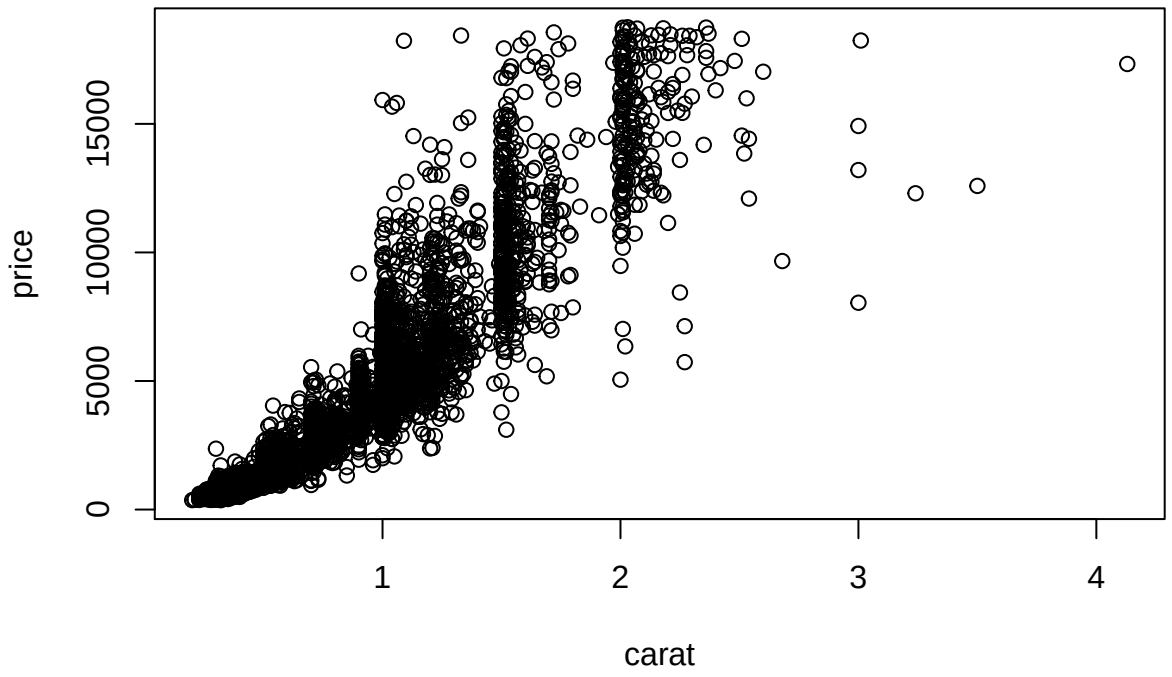
Ggplot graphs are defined from these layers. We have to specify each layer with a ggplot function :

— the data with **ggplot**
— the variables with **aes** (aesthetics)
— the type of representation with **geom_**

These layers are gathered with the + operator.

The scatterplot **carat vs price** is obtained with the **plot** function with

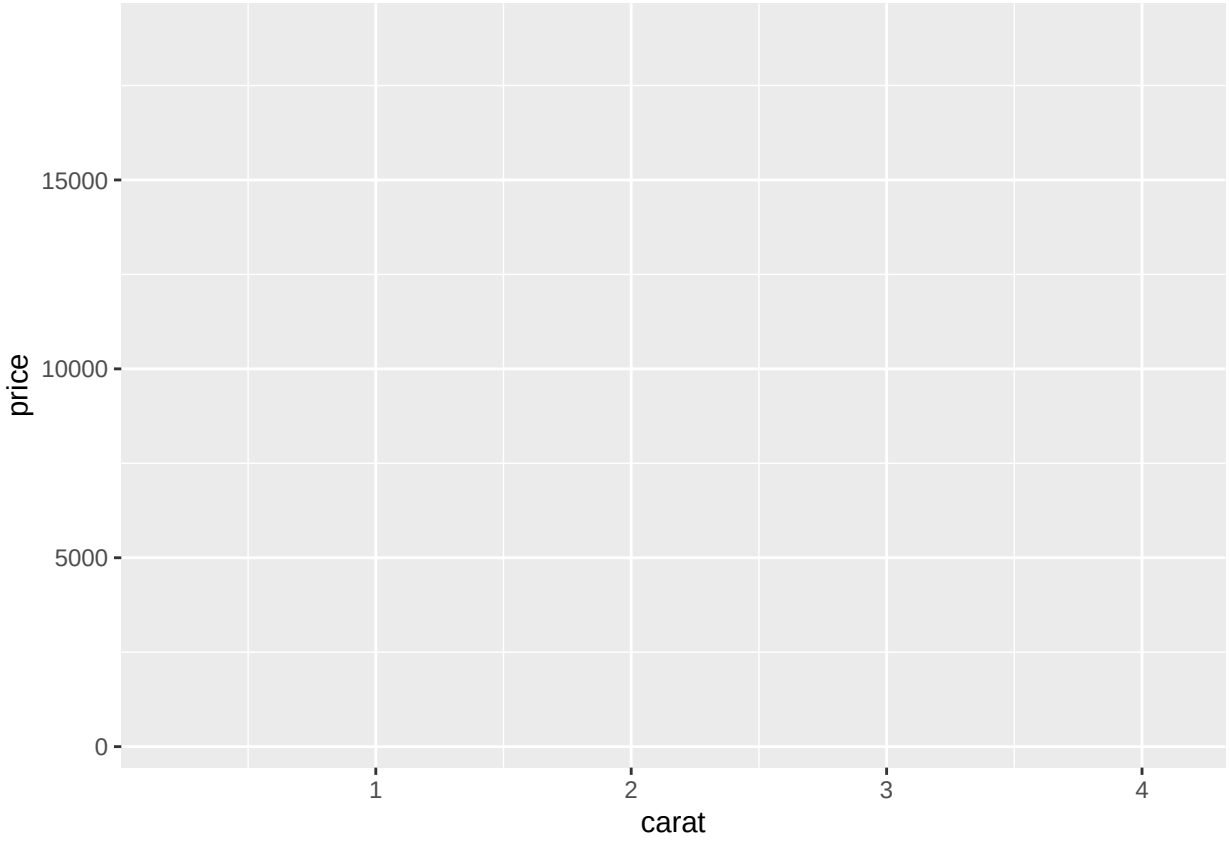
```
plot(price~carat,data=diamonds2)
```



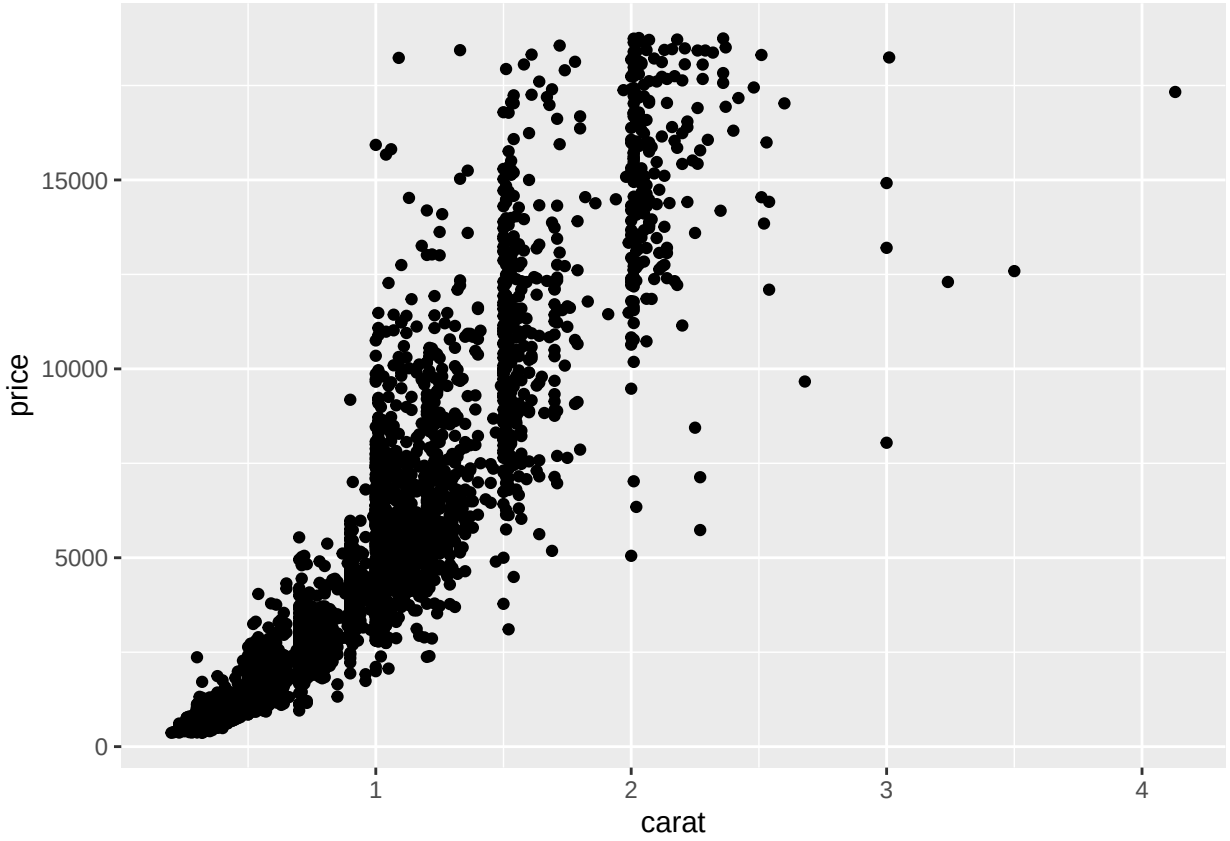
With **ggplot**, we use

```
ggplot(diamonds2) #nothing
```

```
ggplot(diamonds2)+aes(x=carat,y=price) #nothing
```




```
ggplot(diamonds2)+aes(x=carat,y=price)+geom_point() #OK
```



Exercise 1.5 (Histograms and barplot with ggplot2)**.**

1. Draw the histogram of **carat** (use **geom_histogram**)
2. Draw the histogram of **carat** with 10 bins (**help(geom_histogram)**)
3. Draw the barplot for the variable **cut** (use **geom_bar**)

To summarize, ggplot syntax is defined from independent elements. These elements define the **grammar** of **ggplot**. Main elements of the grammar include :

— **Data** (`ggplot`) : the dataset, it should be a dataframe or a **tibble**.
— **Aesthetics** (`aes`) : to describe the way that variables in the data are mapped. We have to specify **all** variables used to build the graph in **aes**.
— **Geometrics** (`geom_...`) : to control the type of plot (scaterplot, histogram…)
— **Statistics** (`stat_...`) : to describe transformations of the data needed for the chart.
— **Scales** (`scale_...`) : to control the mapping from data to aesthetic attributes (change of colors, options for the axis…)

All these elements are combined with a +.

1.2.2 Data et aesthetics

We have two use these elements for all graphs. **ggplot** verb is used to indicate the dataset. If the syntax is efficient, you will never have to use the name of the dataset to obtain the required graph. **aes** verb is used to specify the variables we want to visualize. For instance, for a scaterplot **price vs carat**, the syntax should start with

```
ggplot(diamonds2)+aes(x=carat,y=price)
```

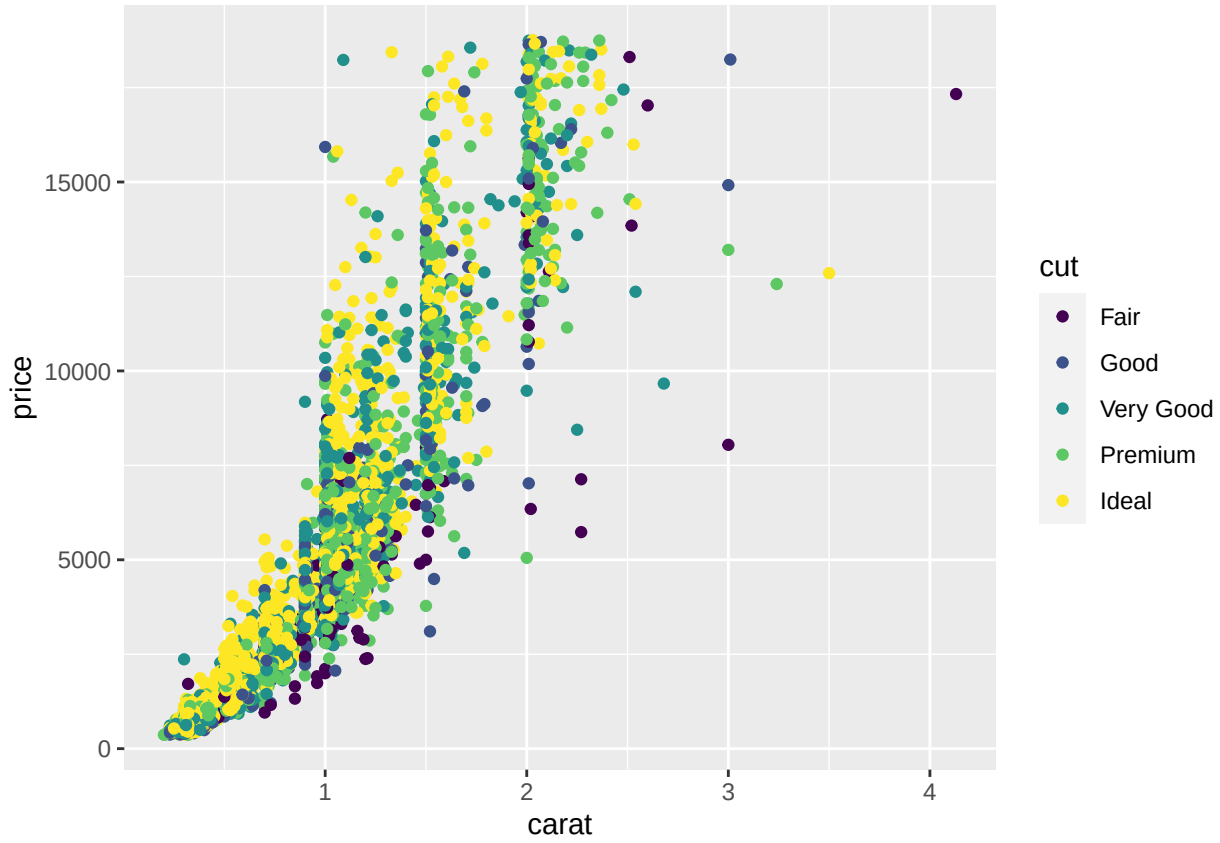
aes also possesses arguments such as **color**, **size**, **fill**. We use these options as soon as a color or a size is defined from a **variable of the dataset**. For instance

```
ggplot(diamonds2)+aes(x=carat,y=price,color=cut)
```

1.2.3 Geometrics

To draw a graph, we need to specify the type of representation. We have to use **geometrics** to do that. For a scatter plot, we use **geom_point** :

```
ggplot(diamonds2)+aes(x=carat,y=price,color=cut)+geom_point()
```



Observe that **ggplot** adds the lengend automatically. Examples of **geometrics** are described here :

TABLE 1 : Main geometrics

Geom	Description	Aesthetics
geom_point()	Scatter plot	x, y, shape, fill
geom_line()	Line (ordered according to x)	x, y, linetype
geom_abline()	Line	slope, intercept
geom_path()	Line (ordered according to the index)	x, y, linetype
geom_text()	Text	x, y, label, hjust, vjust
geom_rect()	Rectangle	xmin, xmax, ymin, ymax, fill, linetype
geom_polygon()	Polygone	x, y, fill, linetype
geom_segment()	Segment	x, y, xend, yend, fill, linetype
geom_bar()	Barplot	x, fill, linetype, weight
geom_histogram()	Histogram	x, fill, linetype, weight
geom_boxplot()	Boxplots	x, y, fill, weight
geom_density()	Density	x, y, fill, linetype
geom_contour()	Contour lines	x, y, fill, linetype

Geom	Description	Aesthetics
geom_smooth() All	Smoothers (linear or non linear)	x, y, fill, linetype color, size, group

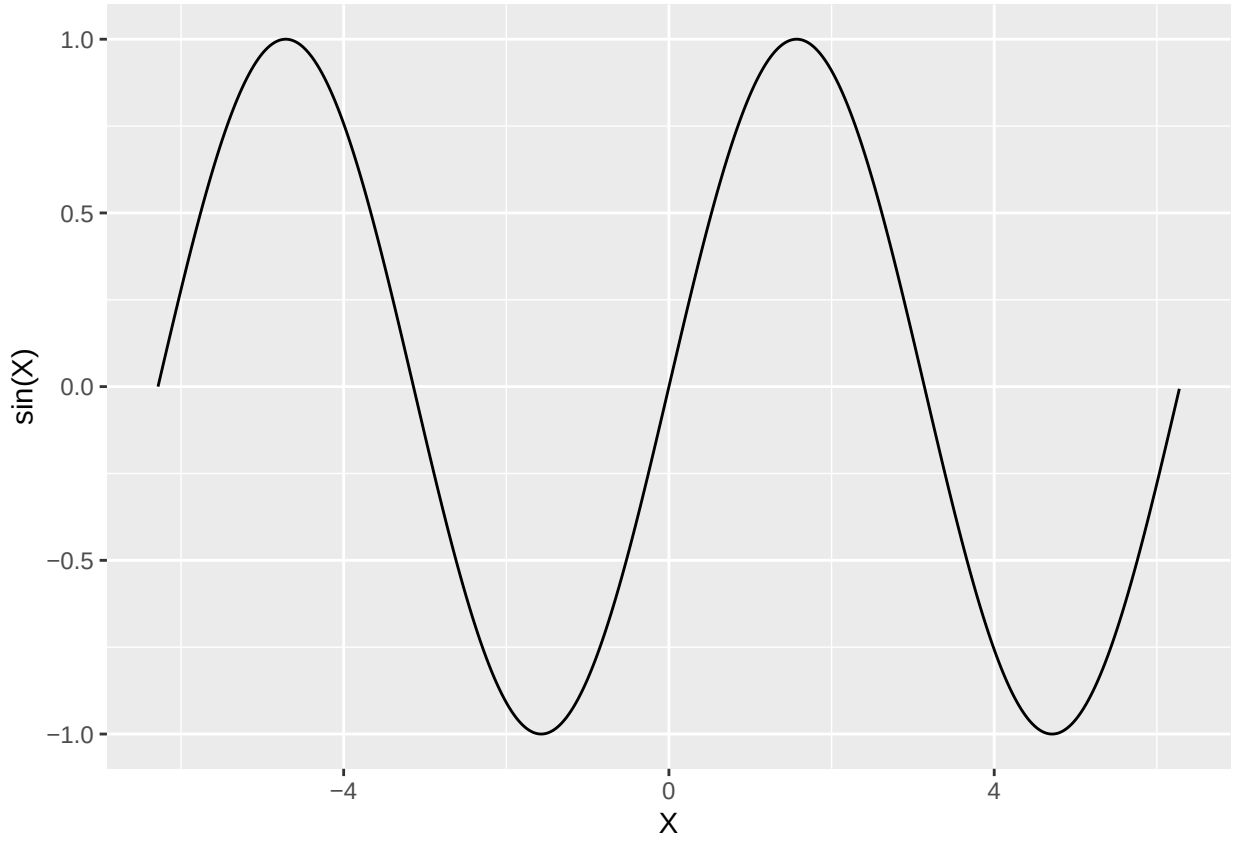
Exercise 1.6 (Barplots)**.**

1. Draw the barplot of **cut** (with blue bars).
2. Draw the barplot of **cut** with one color for each modality of cut. Add a legend.
3. Draw the barplot of **cut** with one color **of your choice** for each modality of cut (and without lengend since it is not useful here).

1.2.4 Statistics

Many graphs need transformations the data to make the representation. Ut is for example the case for histogram or barplot : we have to calculate the heights for rectangles or bars. These heigths are not explicitely specified in the dataset. Simple transformations can be obtained quickly with **ggplot2**. For instance we can draw the sine function with

```
D <- data.frame(X=seq(-2*pi,2*pi,by=0.01))
ggplot(D)+aes(x=X,y=sin(X))+geom_line()
```



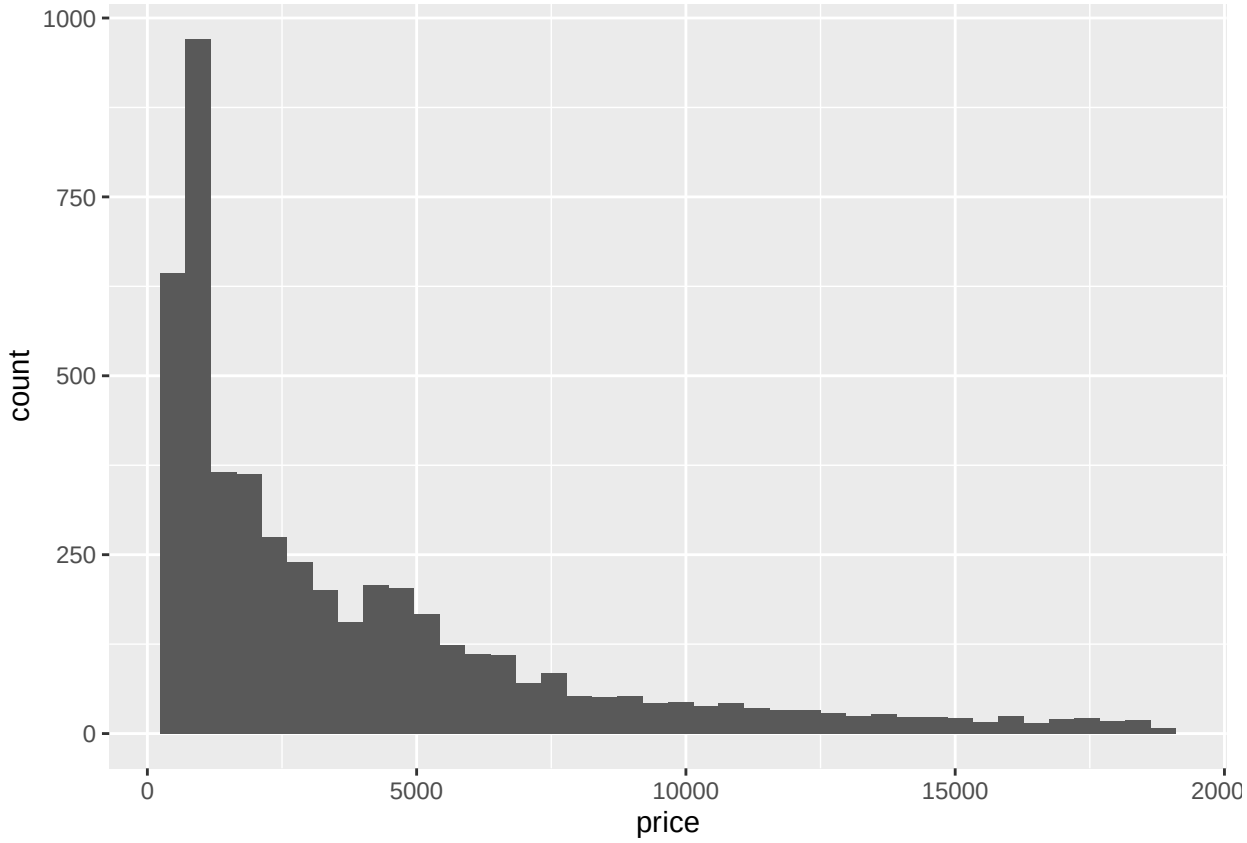
The sine transformation is indicated in **aes**. For more complex transformations, we have to used **statistics**. A **stat** function takes a dataset as input and returns a dataset as output, and so a stat can add new variables to the original dataset. It is then possible to map aesthetics to these new variables. For example, **stat_bin** function, the statistic used to make histograms, produces the following variables :

— `count`, the number of observations in each bin ;

— `density`, the density of observations in each bin (percentage of total / bar width) ;
— `x`, the center of the bin.

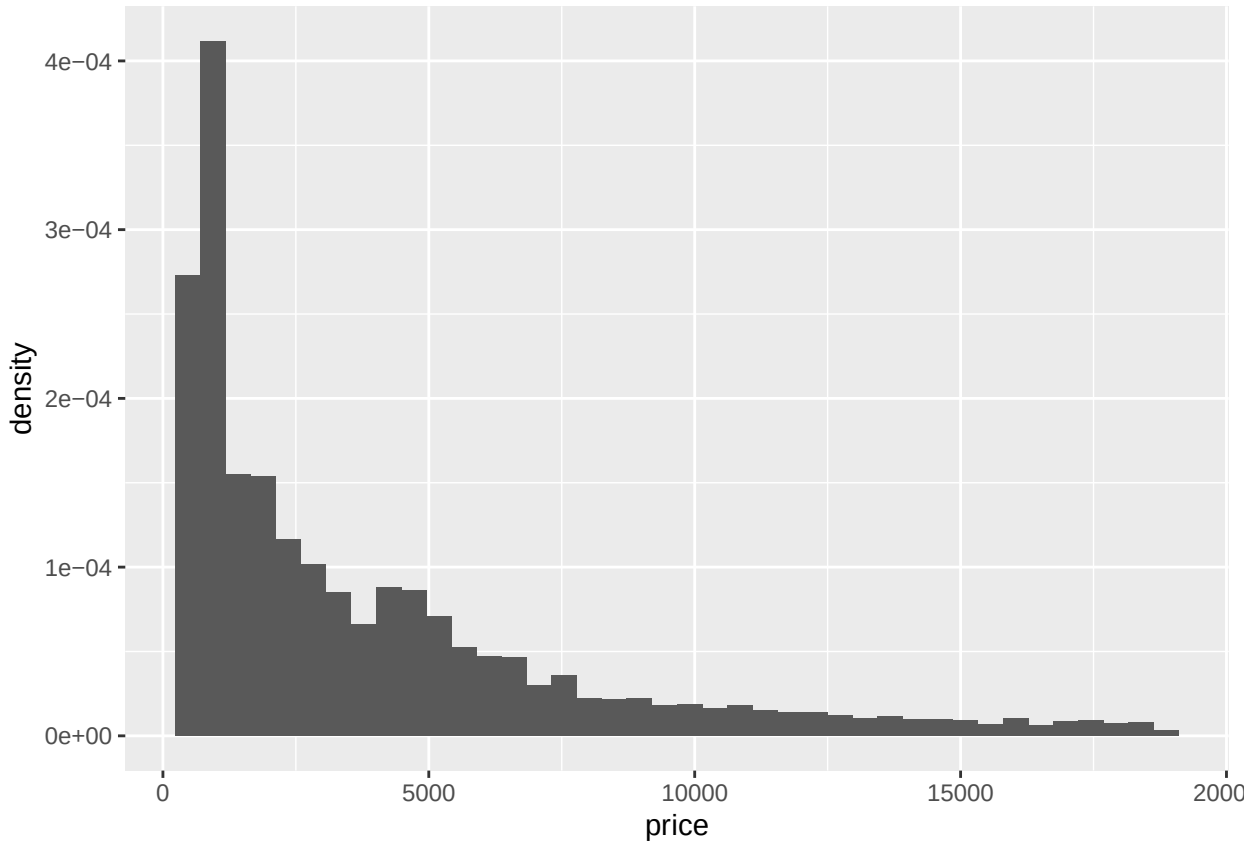
By default *geom_histogram* represents on the y-axis the number of observations in each bin (the output **count**).

```
ggplot(diamonds2)+aes(x=price)+geom_histogram(bins=40)
```



If we are interested by another output of `stat_bin`, the density for instance, we have to use

```
ggplot(diamonds2)+aes(x=price,y=..density..)+geom_histogram(bins=40)
```



ggplot proposes another way to make the representations : we can use *stat_* instead of *geom_*. Formally, each **stat_...** function has a **geom_...** and each **geom_...** has a **stat_...**. We can draw the same graph as above with

```
ggplot(diamonds2)+aes(x=price,y=..density..)+stat_bin()
```

Here are some examples of **stat functions** :

TABLE 2 : Examples of statistics.

Stat	Description	Parameters
stat_identity()	No transformation	
stat_bin()	Count	binwidth, origin
stat_density()	Density	adjust, kernel
stat_smooth()	Smoother	method, se
stat_boxplot()	Boxplot	coef

stat and *geom* are not always easy to combine. For beginners, we recommend to use *geom* for beginners.
Exercise 1.7 (A "very simple" barplot...)**.**

We consider a color variable X with probability distribution

$$P(X = red) = 0.3,\ P(X = blue) = 0.2,\ P(X = green) = 0.4,\ P(X = black) = 0.1$$

Draw the barplot of this distribution.
Exercise 1.8 (Lissage)**.**

1. Visualize the non lineaar smoother for the variable `price` in terms of `carat`. You can use `geom_smooth`, then `stat_smooth`.

2. Same question but use a dotted line instead of a solid line.

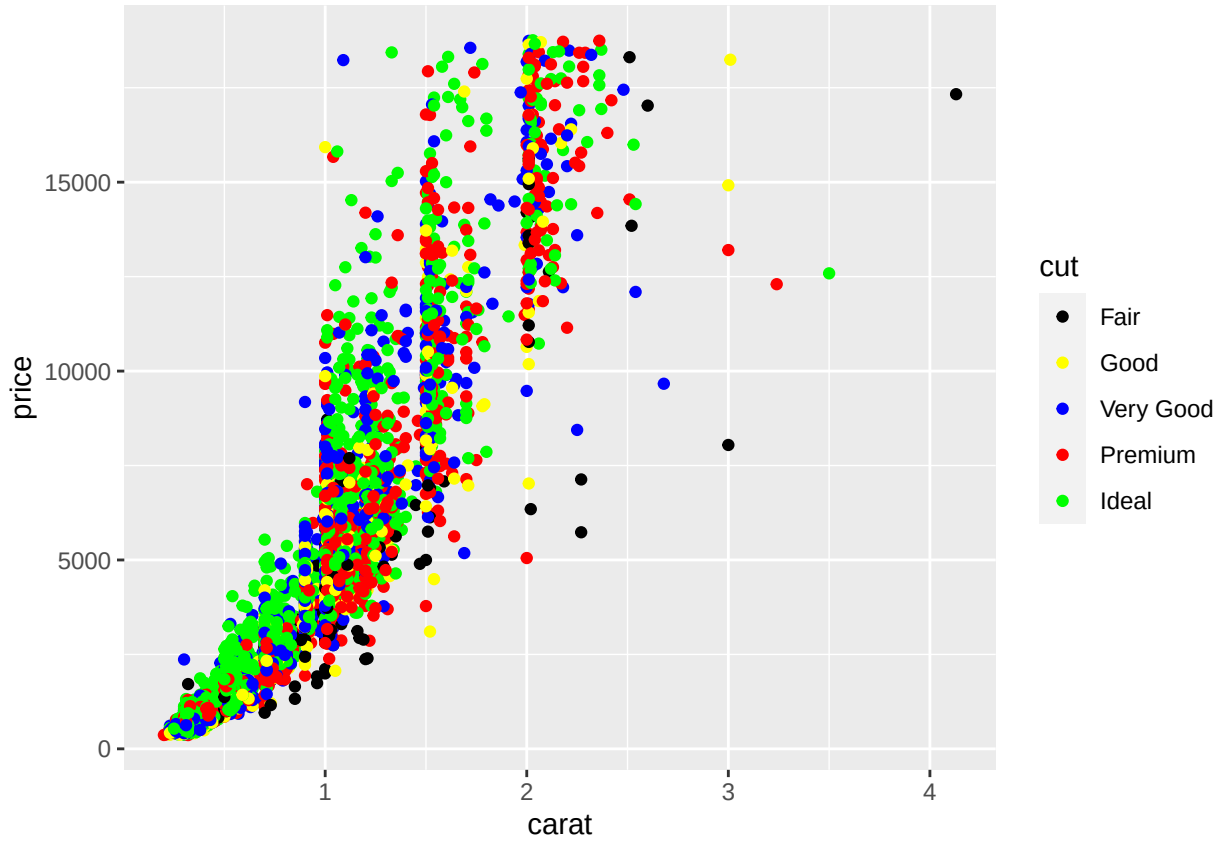
1.2.5 Scales

Scales control the mapping from data to aesthetic attributes (change of colors, sizes…). We generally use this element at the end of the process to refine the graph. Scales are defined as follows :

— begin with `scale_`
— add the aesthetics we want to change (`color`, `fill`, `x_`)
— end with the name of the scale (`manual`, `identity`…)

For instance,

```
ggplot(diamonds2)+aes(x=carat,y=price,color=cut)+geom_point()+
  scale_color_manual(values=c("Fair"="black","Good"="yellow",
                              "Very Good"="blue","Premium"="red","Ideal"="green"))
```



Here are the main scales :

Table 3 : Main scales

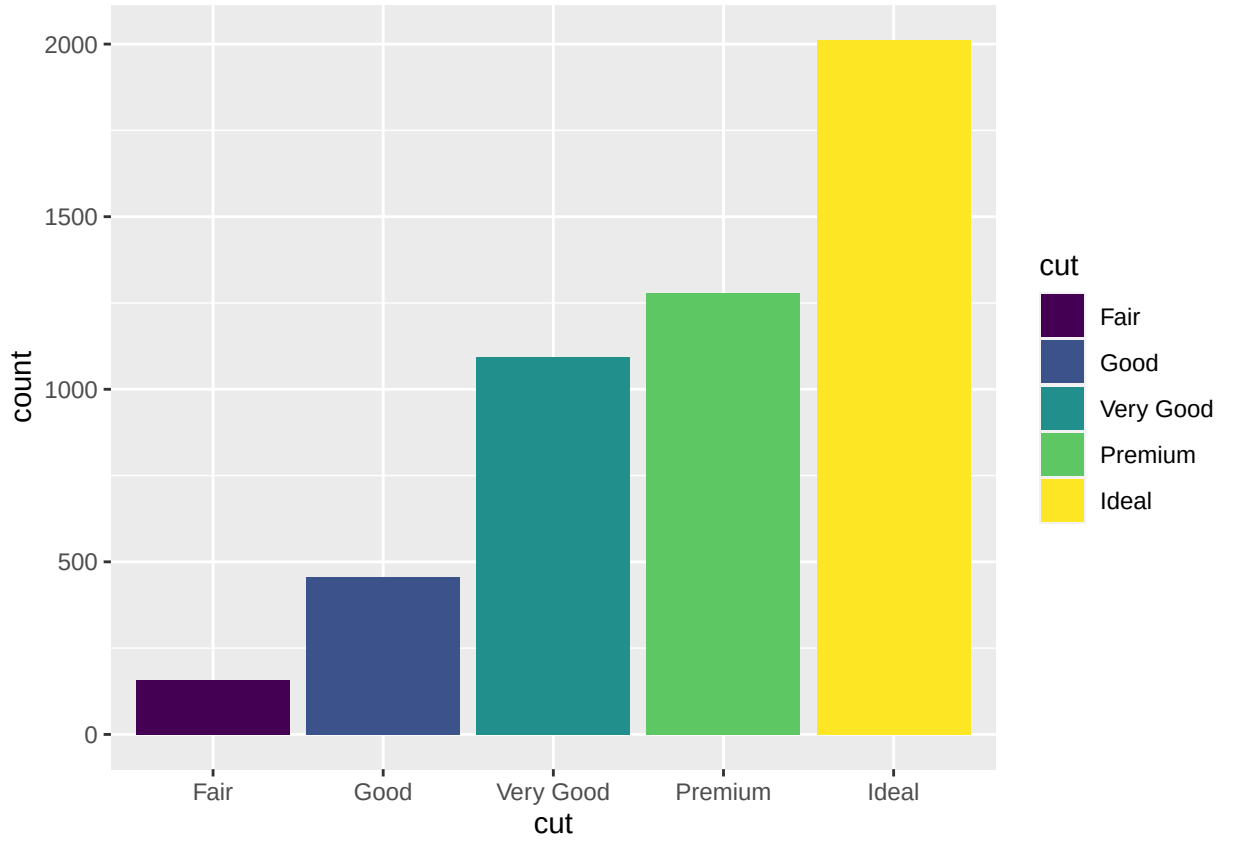
aes	Discrete	Continuous
Color (color et fill)	brewer	gradient
-	grey	gradient2
-	hue	gradientn
-	identity	
-	manual	
Position (x and y)	discrete	continous
-		date

aes	Discrete	Continuous
Shape	shape	
-	identity	
-	manual	
Size	identity	size
-	manual	

We now present some examples on **scales** :

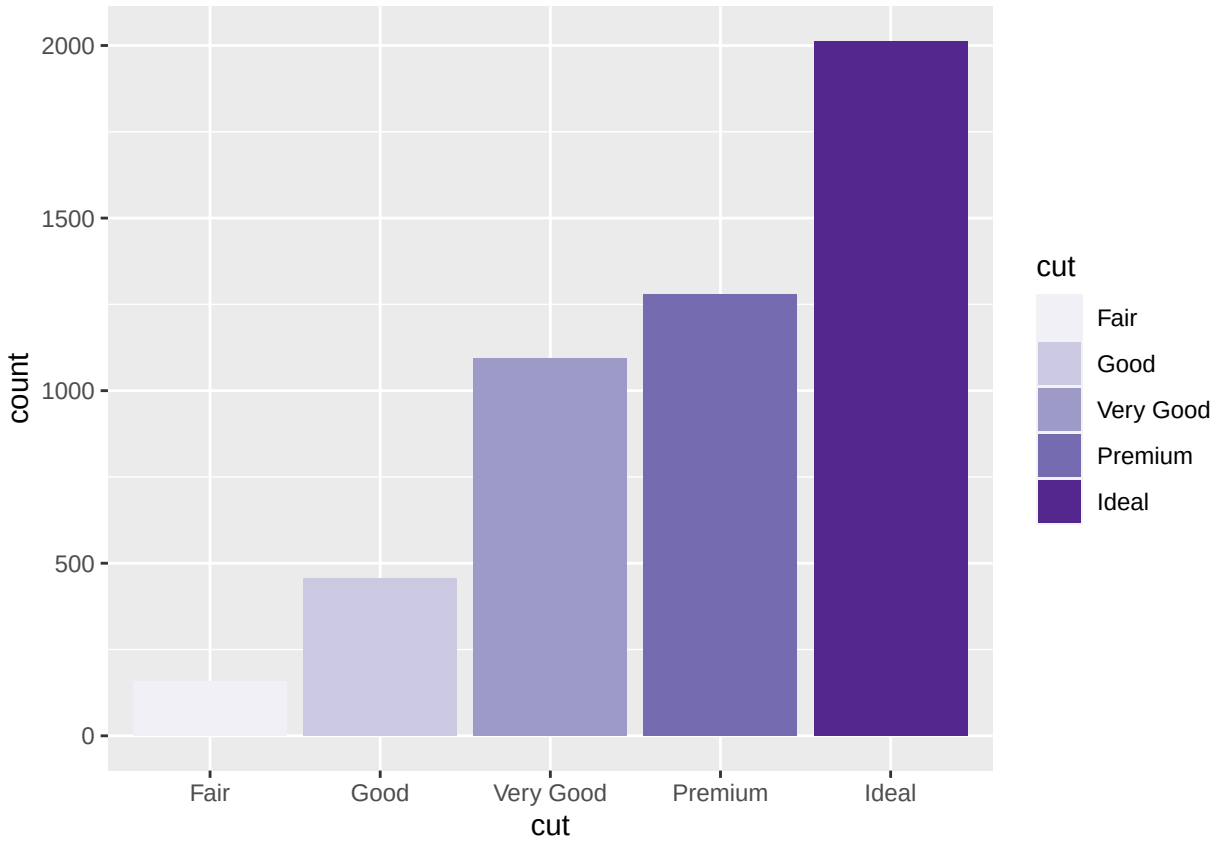
— color in a barplot

```
p1 <- ggplot(diamonds2)+aes(x=cut)+geom_bar(aes(fill=cut))
p1
```



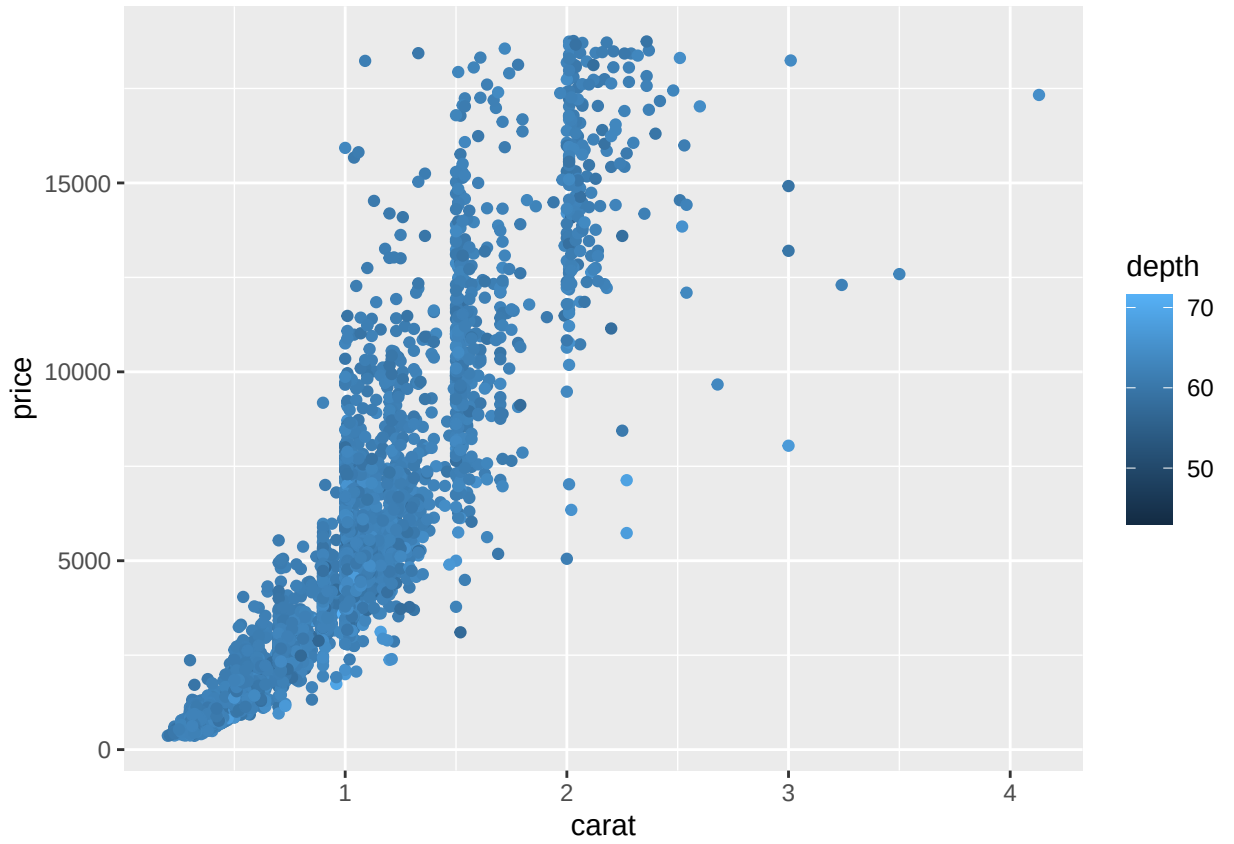
We change colors by using the palette **Purples** :

```
p1+scale_fill_brewer(palette="Purples")
```



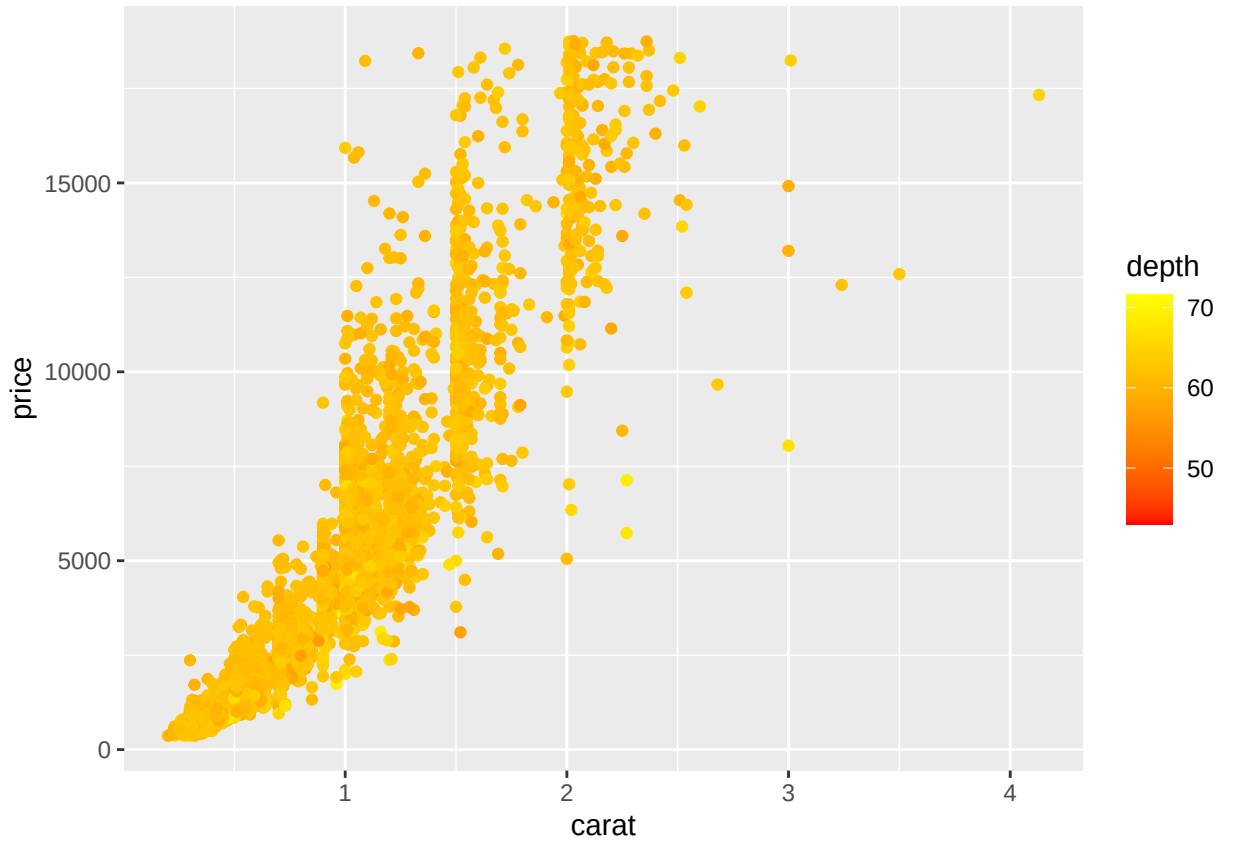
— Gradient color for a scatter plot :

```
p2 <- ggplot(diamonds2)+aes(x=carat,y=price)+geom_point(aes(color=depth))
p2
```



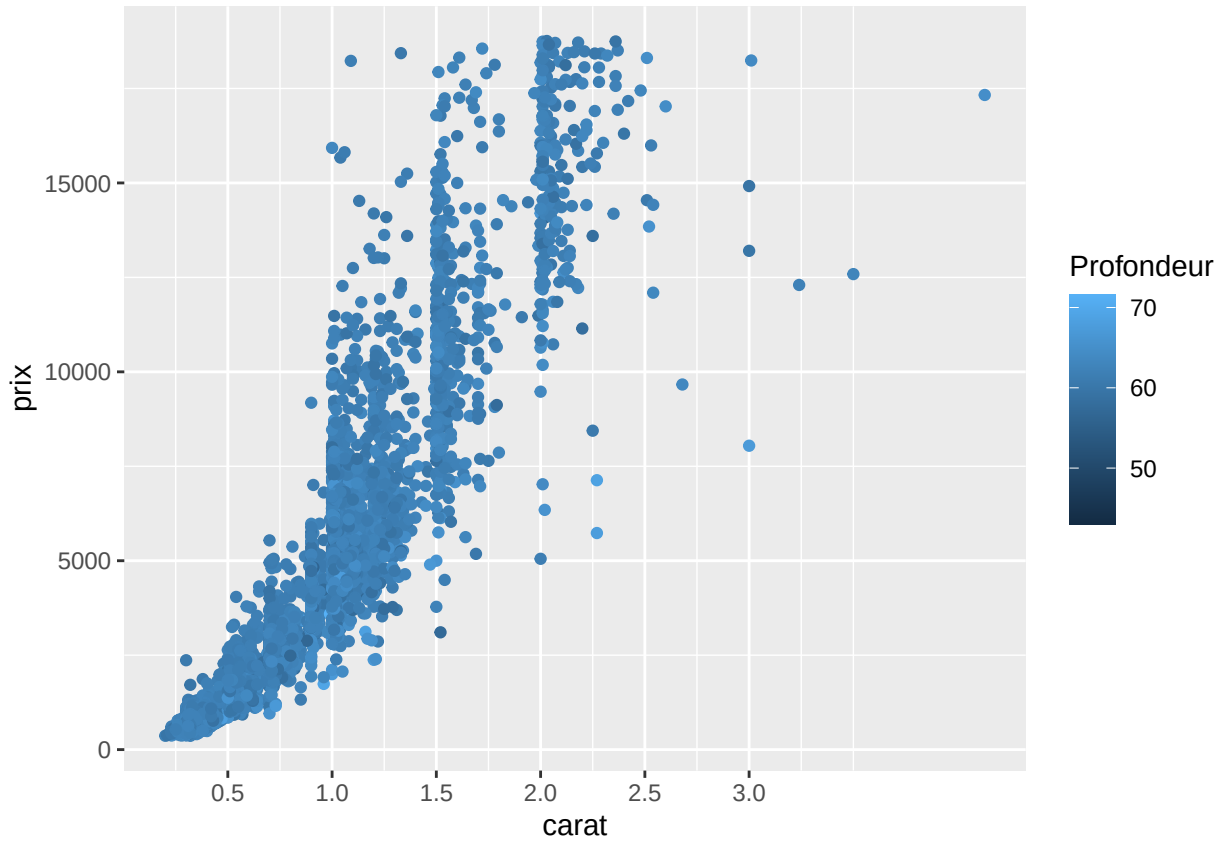
We change the gradient color

```
p2+scale_color_gradient(low="red",high="yellow")
```



— Change on the axis

```
p2+scale_x_continuous(breaks=seq(0.5,3,by=0.5))+scale_y_continuous(name="prix")+scale_color_gradient("P
```



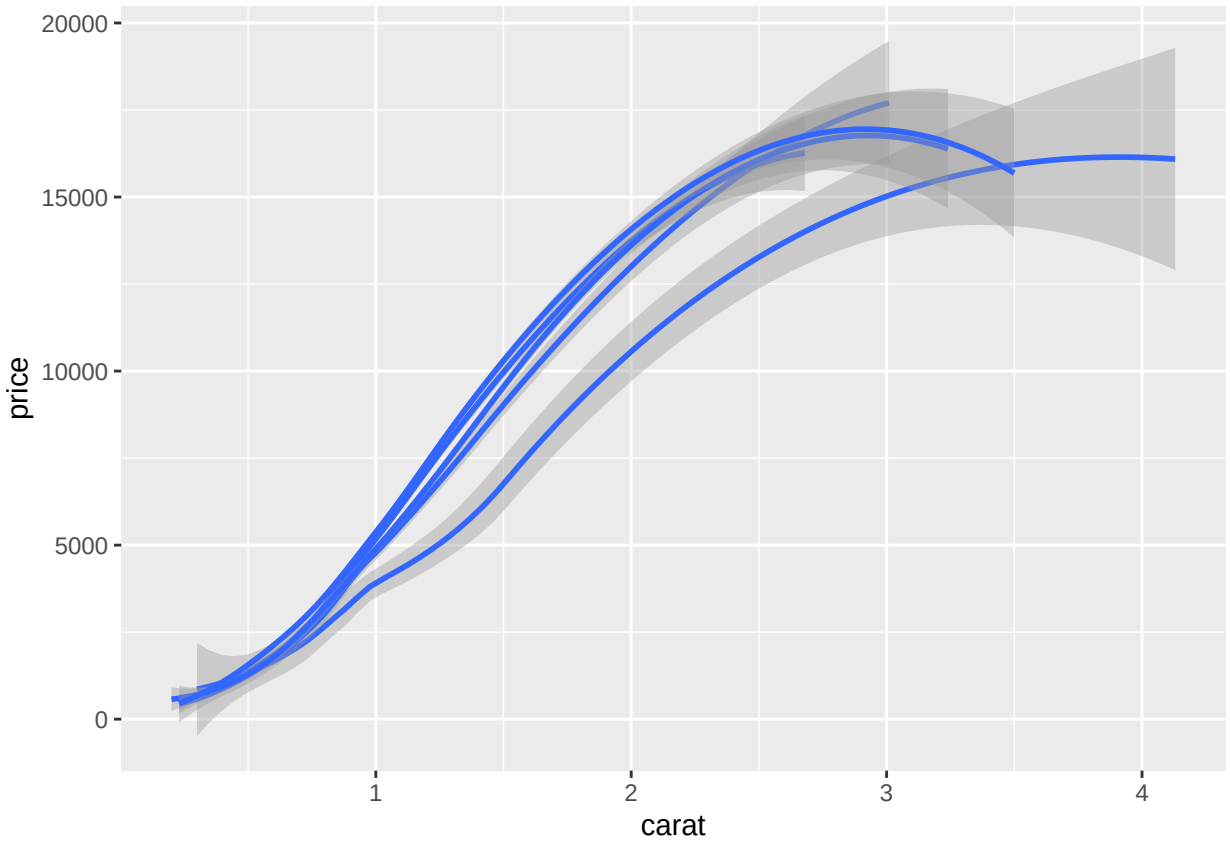
1.2.6 Group and facets

ggplot allows to make representations for subgroup of individuals. We can proceed in two ways :

— to represent subgroup on the same graph => *group* in **aes**
— to represent subgroup on the different graphs => **facets**

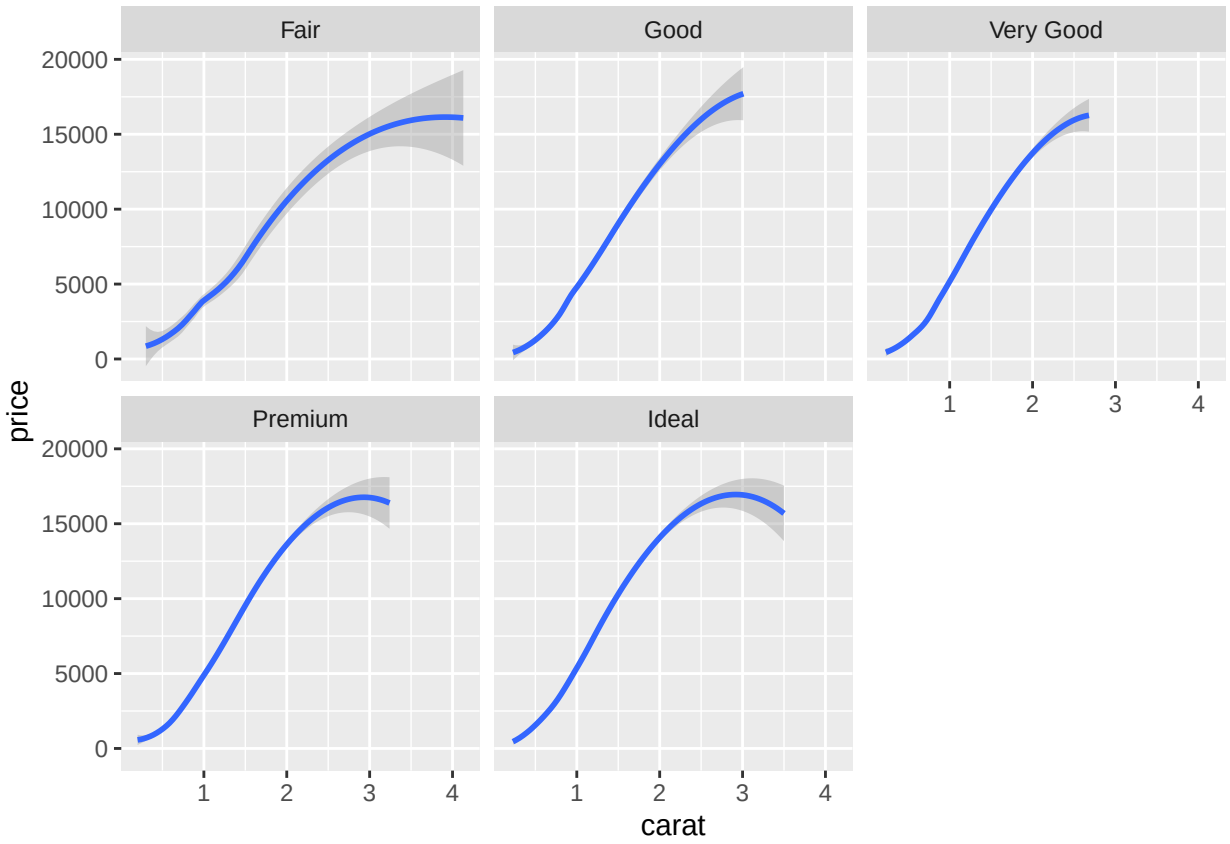
We represent (on the same graph) the smoother **price vs carat** for each modality of *cut* with

```
ggplot(diamonds2)+aes(x=carat,y=price,group=cut)+
  geom_smooth(method="loess")
```

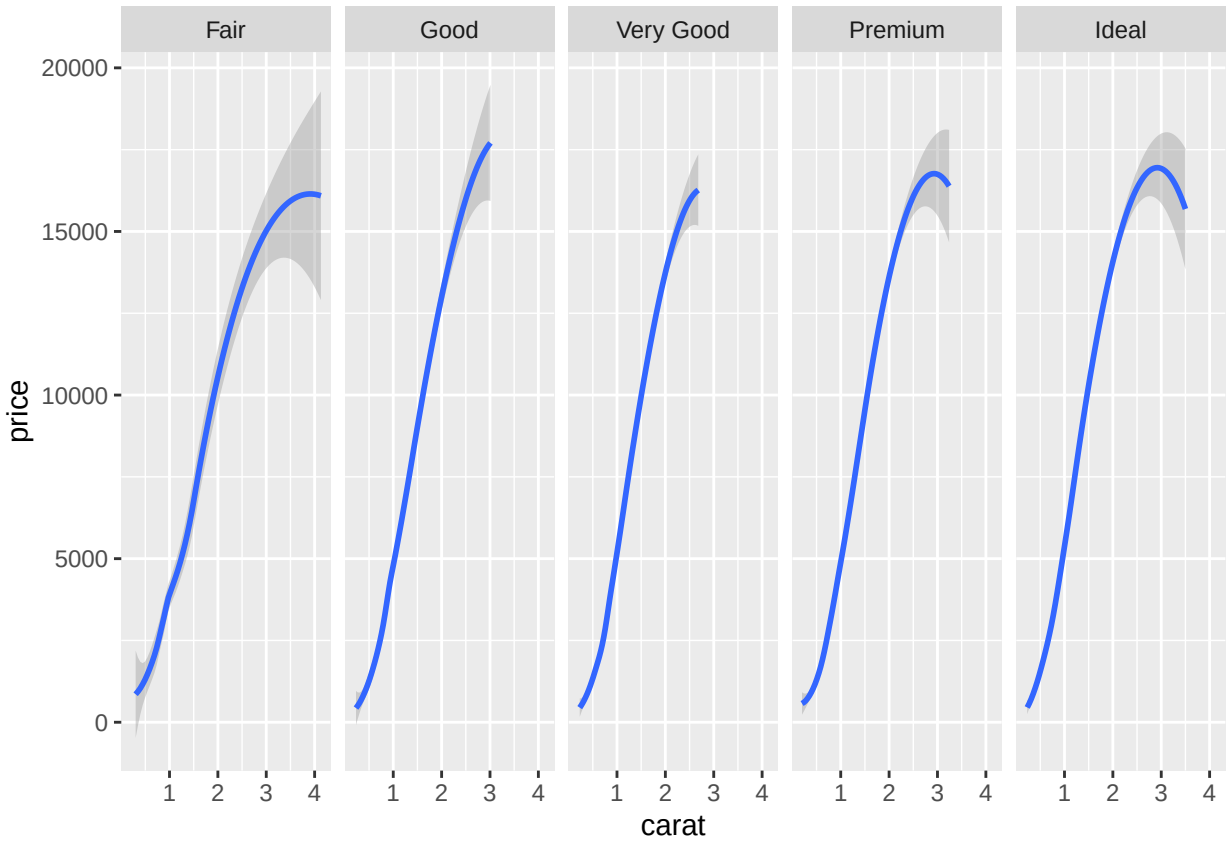


To obtain the representation on many graphs, we use

```
ggplot(diamonds2)+aes(x=carat,y=price)+
  geom_smooth(method="loess")+facet_wrap(~cut)
```

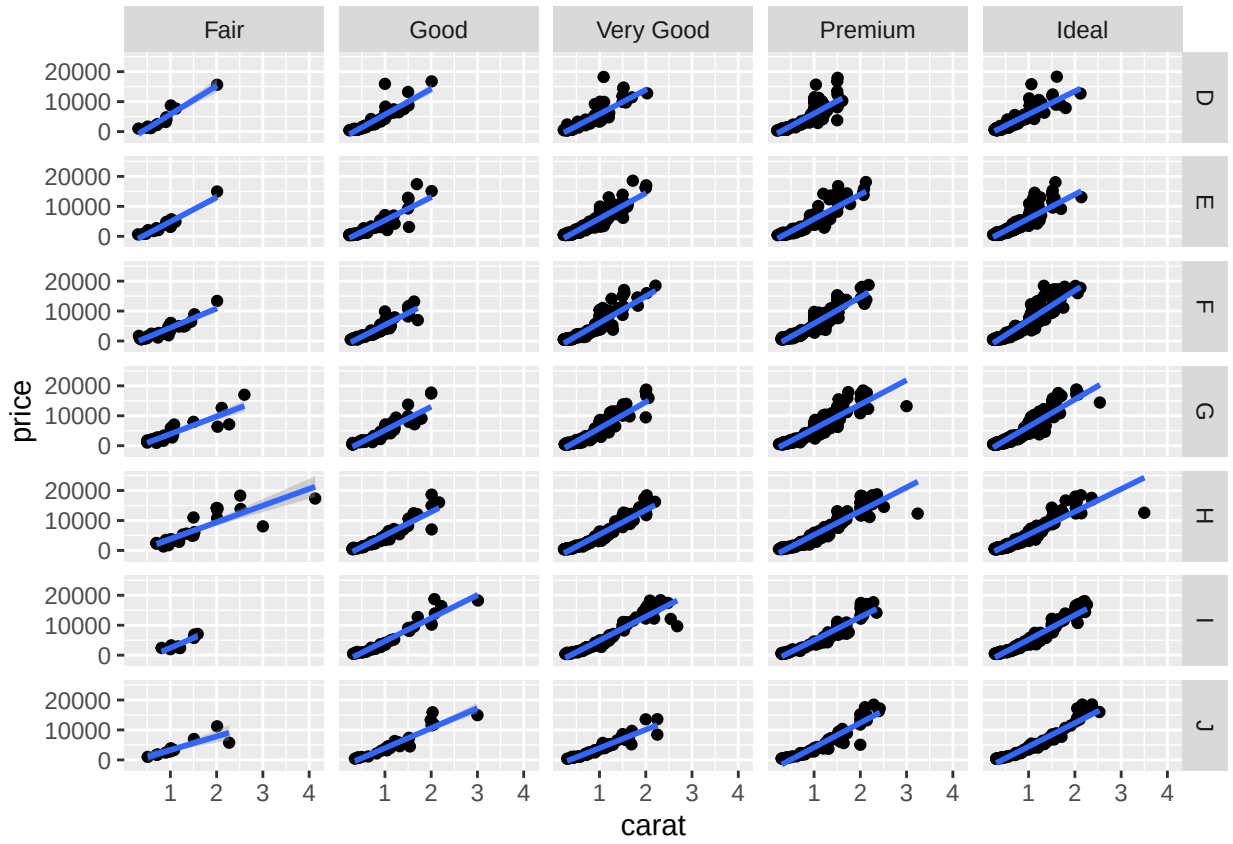



```
ggplot(diamonds2)+aes(x=carat,y=price)+
  geom_smooth(method="loess")+facet_wrap(~cut,nrow=1)
```

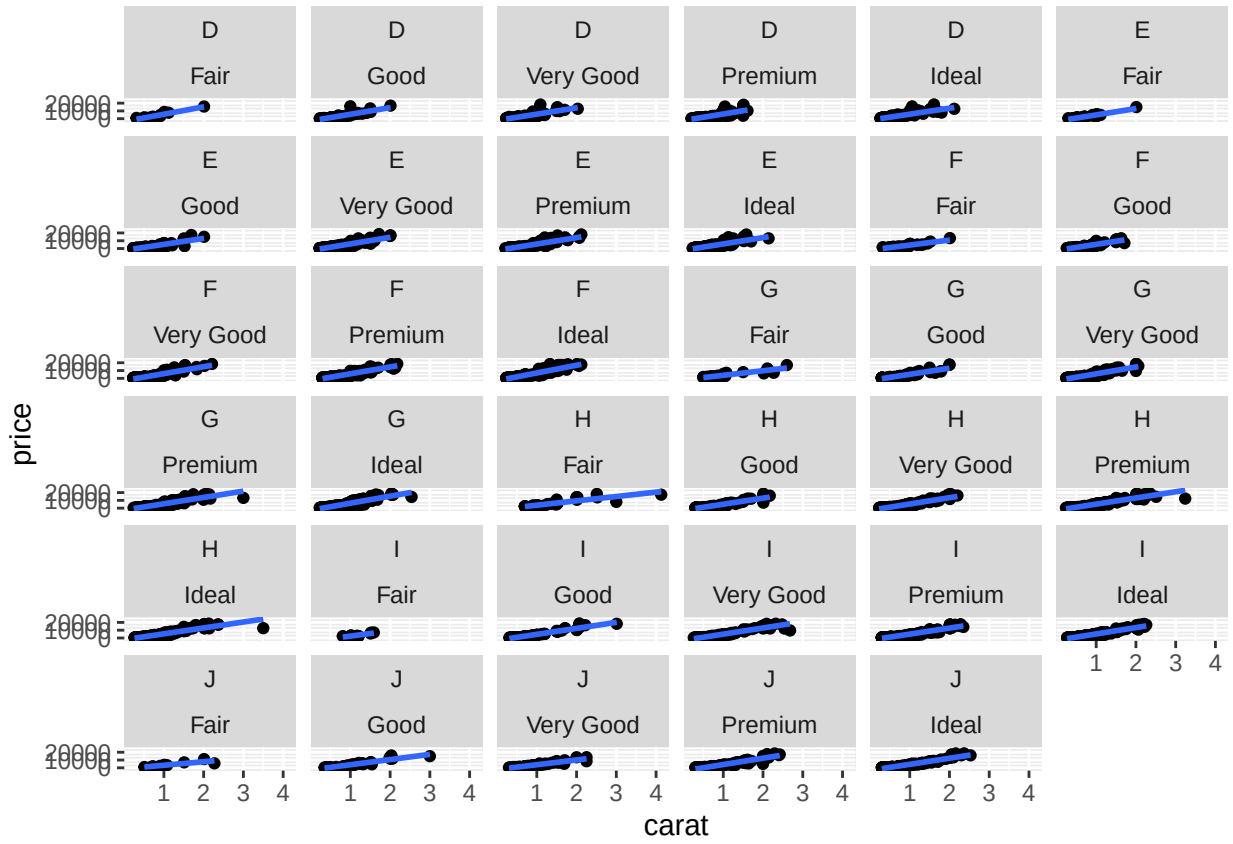


`facet_grid` and `facet_wrap` do the same job but split the screen in different ways :

```
ggplot(diamonds2)+aes(x=carat,y=price)+geom_point()+
  geom_smooth(method="lm")+facet_grid(color~cut)
```




```
ggplot(diamonds2)+aes(x=carat,y=price)+geom_point()+
  geom_smooth(method="lm")+facet_wrap(color~cut)
```



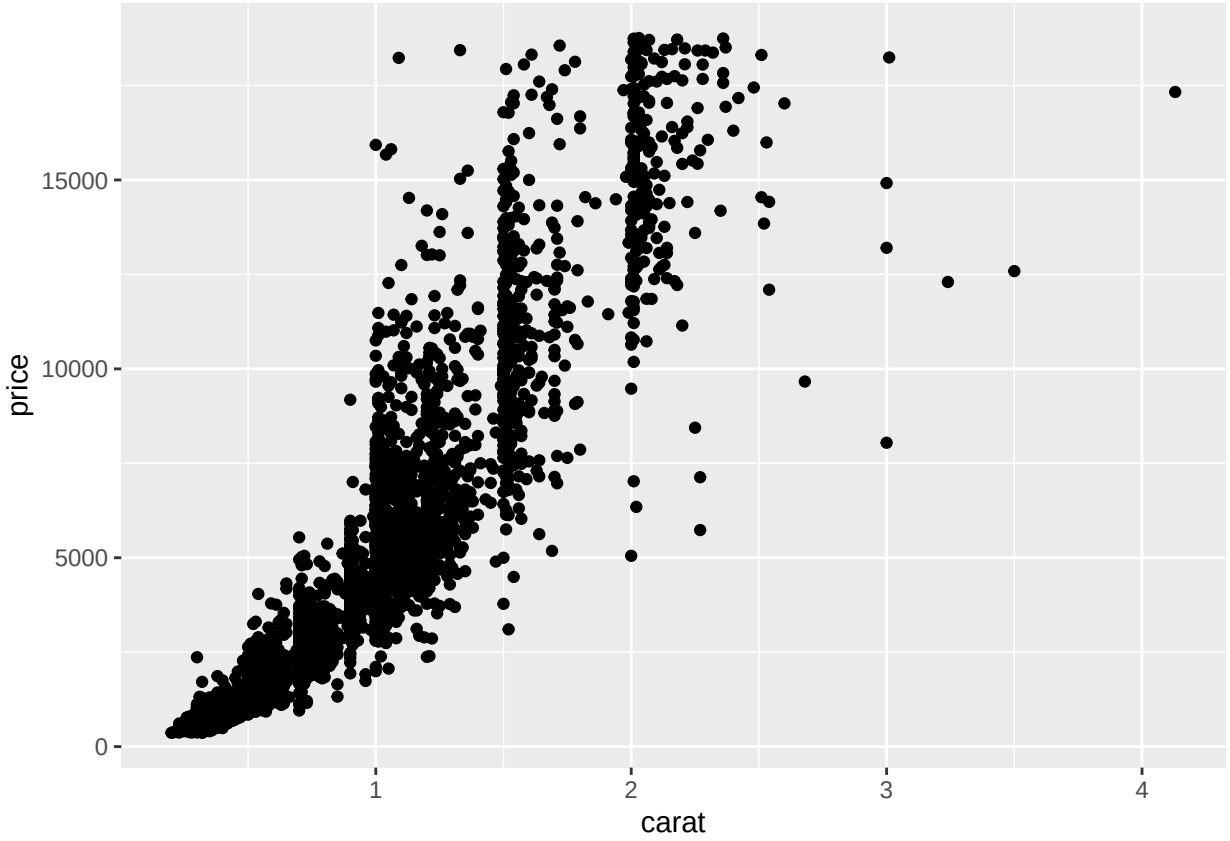
1.3 Complements

Syntax for **ggplot** is defined according to the following scheme :

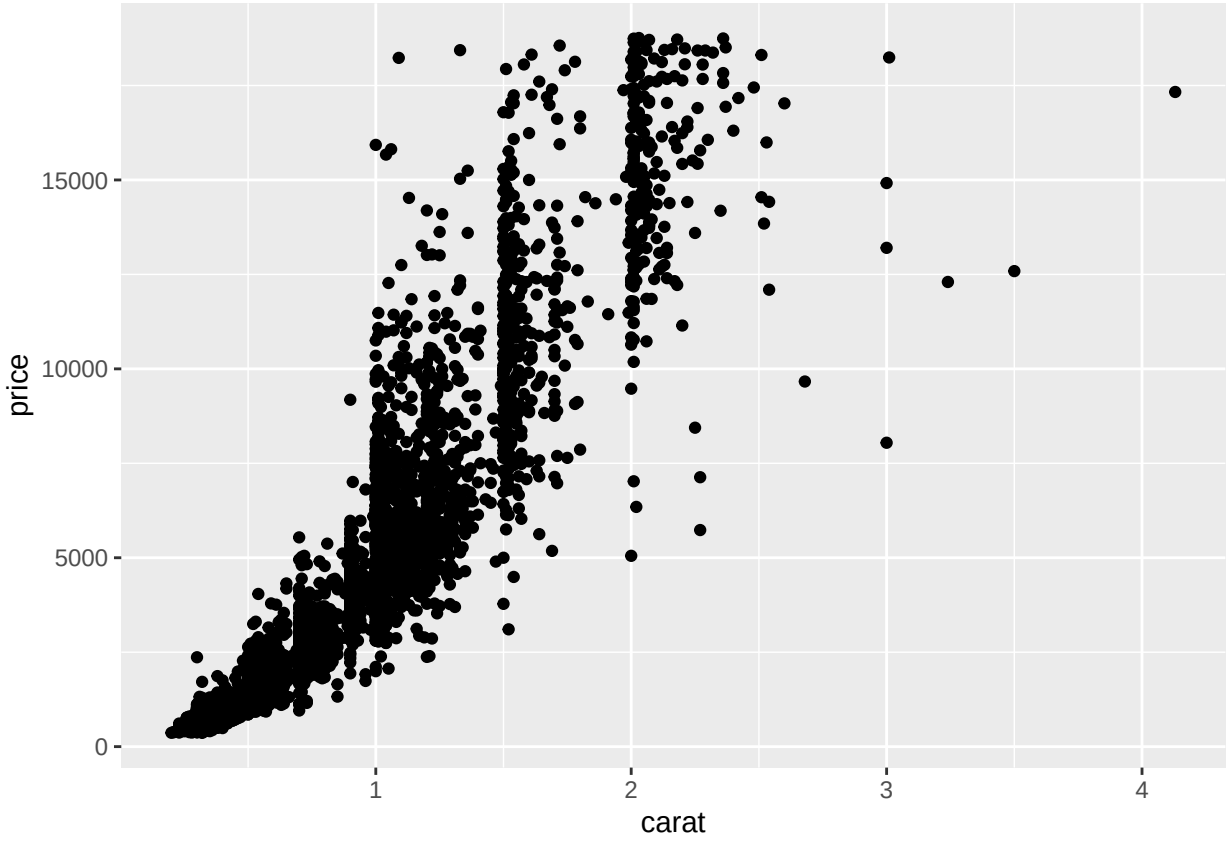
```
ggplot()+aes()+geom_()+scale_()
```

It is really flexible : for instance **aes** could also be specified in **ggplot** or in **geom__**

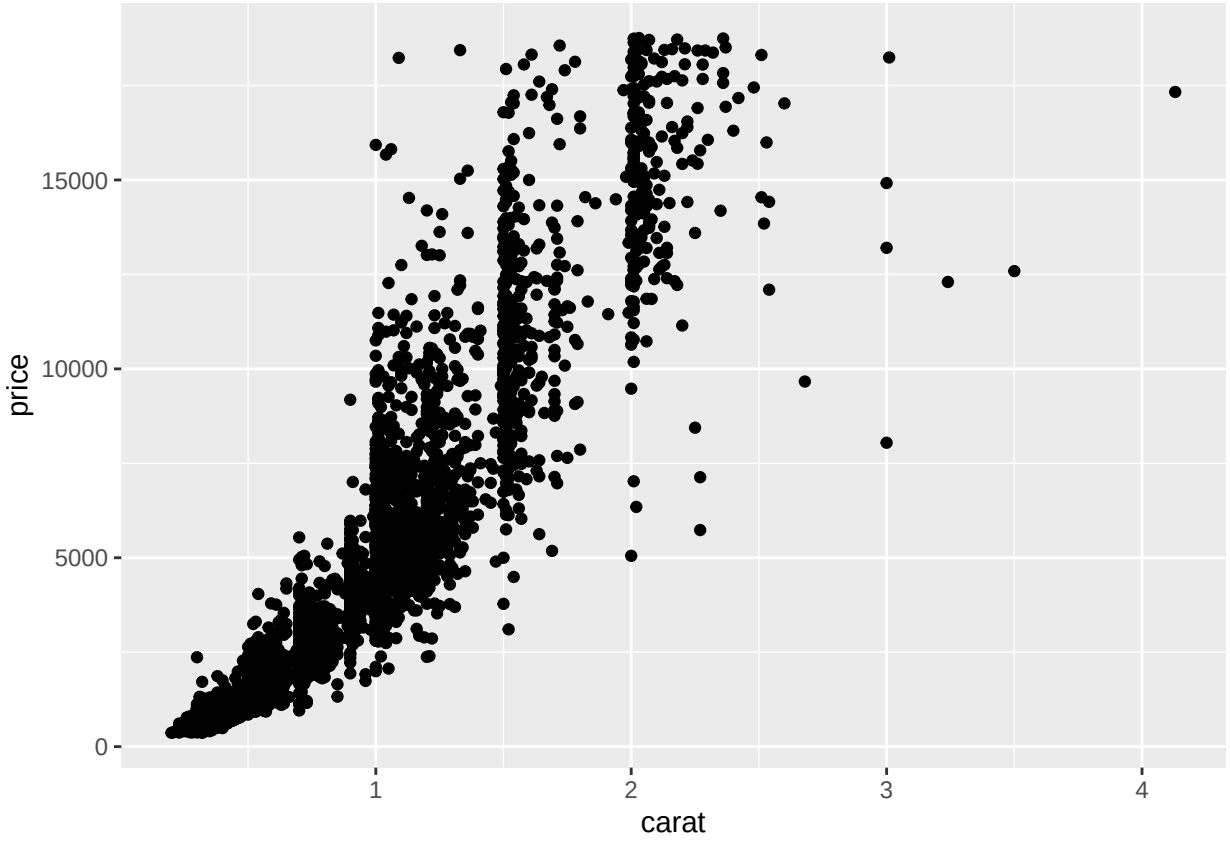
```
ggplot(diamonds2)+aes(x=carat,y=price)+geom_point()
```




```
ggplot(diamonds2,aes(x=carat,y=price))+geom_point()
```



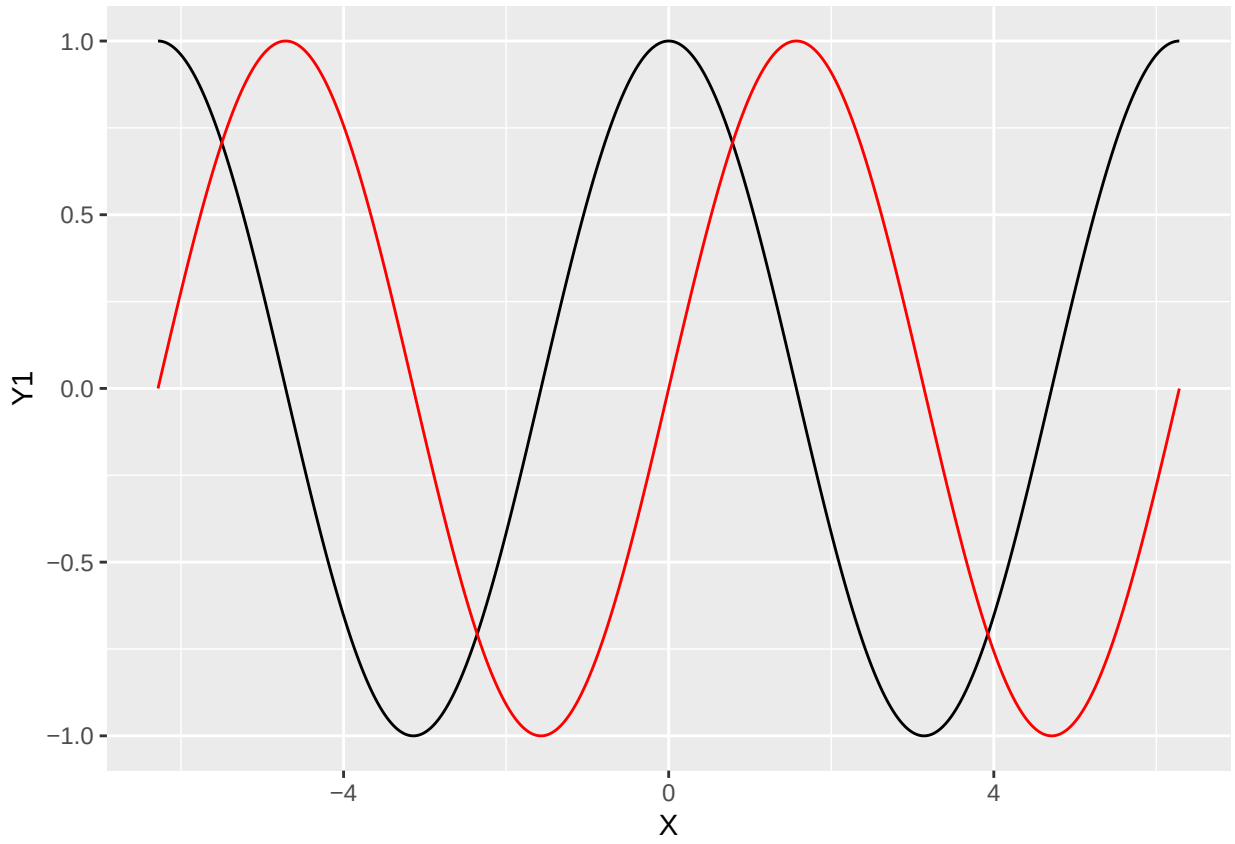

```
ggplot(diamonds2)+geom_point(aes(x=carat,y=price))
```



It could be very useful when we want to use different **aes** in the **geom_**

We can also build a chart from many dataset :

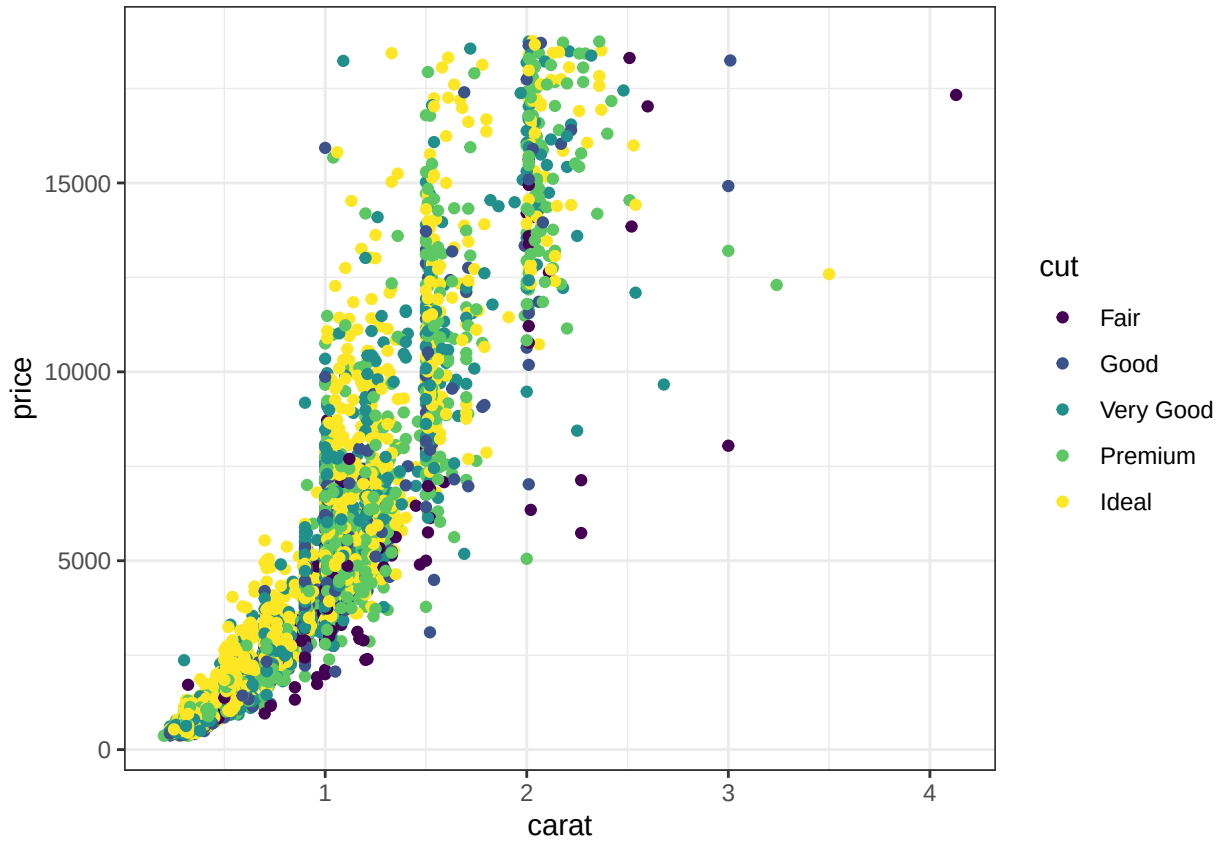
```
X <- seq(-2*pi,2*pi,by=0.001)
Y1 <- cos(X)
Y2 <- sin(X)
donnees1 <- data.frame(X,Y1)
donnees2 <- data.frame(X,Y2)
ggplot(donnees1)+geom_line(aes(x=X,y=Y1))+
  geom_line(data=donnees2,aes(x=X,y=Y2),color="red")
```



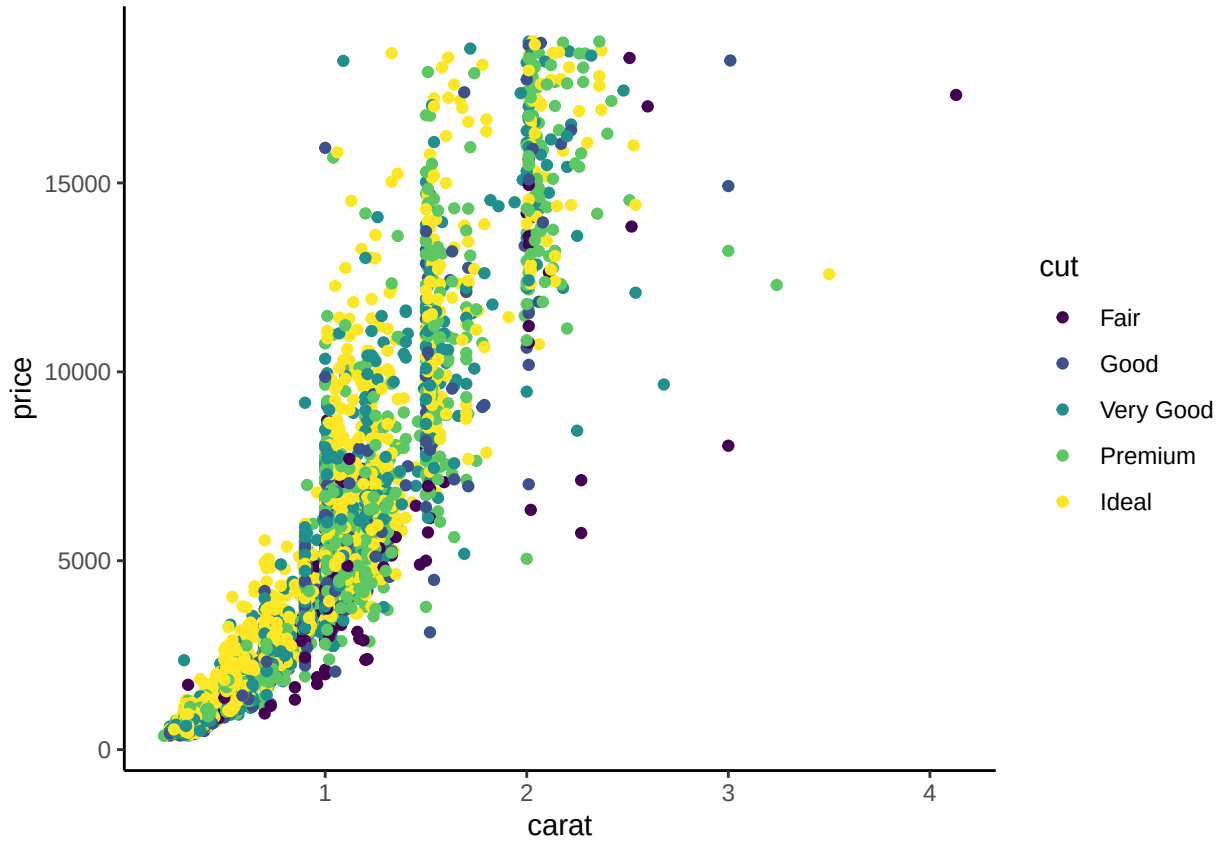
Many other functions are proposed by **ggplot** :

— **ggtitle** to add a title.
— **ggsave** ta save a graph.
— **theme_** to change the theme of the graph.

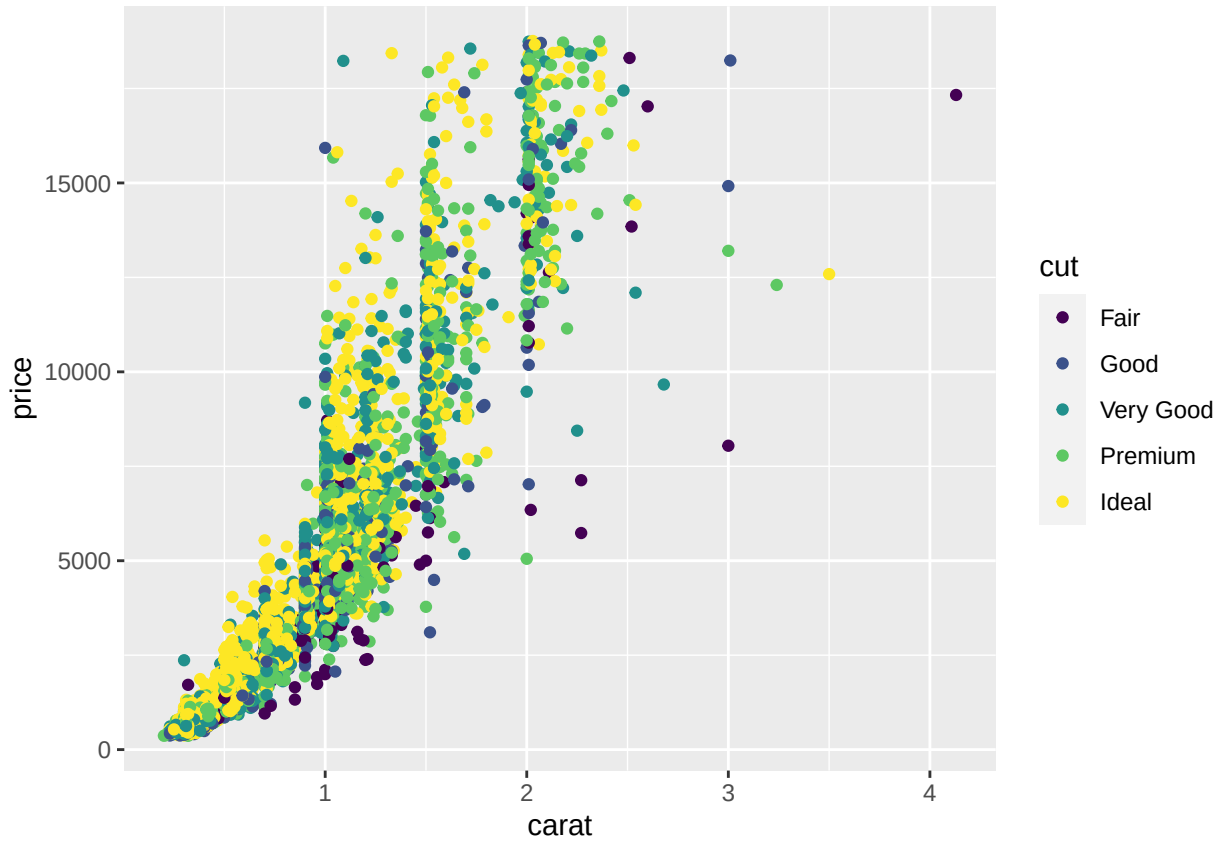
```
p <- ggplot(diamonds2)+aes(x=carat,y=price,color=cut)+geom_point()
p+theme_bw()
```



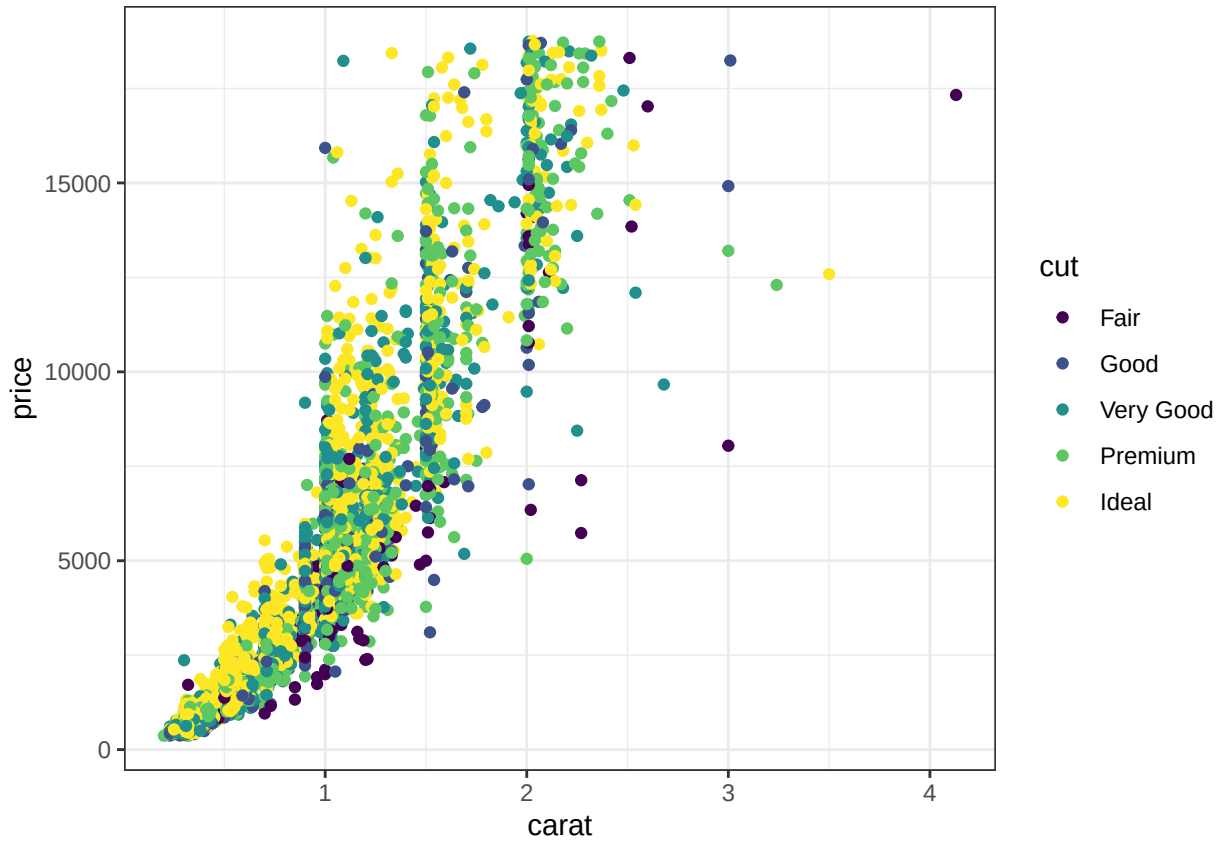

```
p+theme_classic()
```


price
15000
10000
5000
0
1
2
3
4
carat
cut
Fair
Good
Very Good
Premium
Ideal

```
p+theme_grey()
```


price
15000
10000
5000
0
1
2
3
4
carat
cut
Fair
Good
Very Good
Premium
Ideal

```
p+theme_bw()
```



Many other themes are available in the **ggtheme** package. The function `set_theme` can be used to change the default theme in a **markdown document**.

1.4 Some exercises

Exercise 1.9 (Cosine and sine functions...)**.**

1. Draw the sine and cosine functions on the same graph. You first have to use two datasets (one for the sine function, the other for the cosine function).
2. Do the same with one dataset and 2 `geom_line`.
3. Do the same with one dataset and 1 `geom_line`. Hint : use the **pivot_longer** function from the **tidyverse** package.
4. Draw the two functions on two different graphs (use **facet_wrap**).
5. Do the same with the function **grid.arrange** from the package **gridExtra**.

Exercise 1.10 (Classical representations for a dataset)**.**

We consider the **mtcars** dataset :

```
data(mtcars)
summary(mtcars)
      mpg             cyl             disp
 Min.   :10.40   Min.   :4.000   Min.   : 71.1
 1st Qu.:15.43   1st Qu.:4.000   1st Qu.:120.8
 Median :19.20   Median :6.000   Median :196.3
 Mean   :20.09   Mean   :6.188   Mean   :230.7
 3rd Qu.:22.80   3rd Qu.:8.000   3rd Qu.:326.0
 Max.   :33.90   Max.   :8.000   Max.   :472.0
```

```
       hp             drat             wt
 Min.   : 52.0   Min.   :2.760   Min.   :1.513
 1st Qu.: 96.5   1st Qu.:3.080   1st Qu.:2.581
 Median :123.0   Median :3.695   Median :3.325
 Mean   :146.7   Mean   :3.597   Mean   :3.217
 3rd Qu.:180.0   3rd Qu.:3.920   3rd Qu.:3.610
 Max.   :335.0   Max.   :4.930   Max.   :5.424
      qsec             vs              am
 Min.   :14.50   Min.   :0.0000   Min.   :0.0000
 1st Qu.:16.89   1st Qu.:0.0000   1st Qu.:0.0000
 Median :17.71   Median :0.0000   Median :0.0000
 Mean   :17.85   Mean   :0.4375   Mean   :0.4062
 3rd Qu.:18.90   3rd Qu.:1.0000   3rd Qu.:1.0000
 Max.   :22.90   Max.   :1.0000   Max.   :1.0000
      gear            carb
 Min.   :3.000   Min.   :1.000
 1st Qu.:3.000   1st Qu.:2.000
 Median :4.000   Median :2.000
 Mean   :3.688   Mean   :2.812
 3rd Qu.:4.000   3rd Qu.:4.000
 Max.   :5.000   Max.   :8.000
```

1. Draw the histogram of `mpg` (use many number of bins).
2. Always for the histogram, represent the density on the y-axis.
3. Draw the barplot of `cyl`.
4. Draw the scatter plot `disp vs mpg` with one color for each value of `cyl`.
5. Add the linear smoothers, one linear smoother for each value of `cyl`.

Exercise 1.11 (Residuals for a simple regression model)**.**

1. Simulate a sample $(x_i, y_i), i = 1, \dots, 100$ according to the linear model

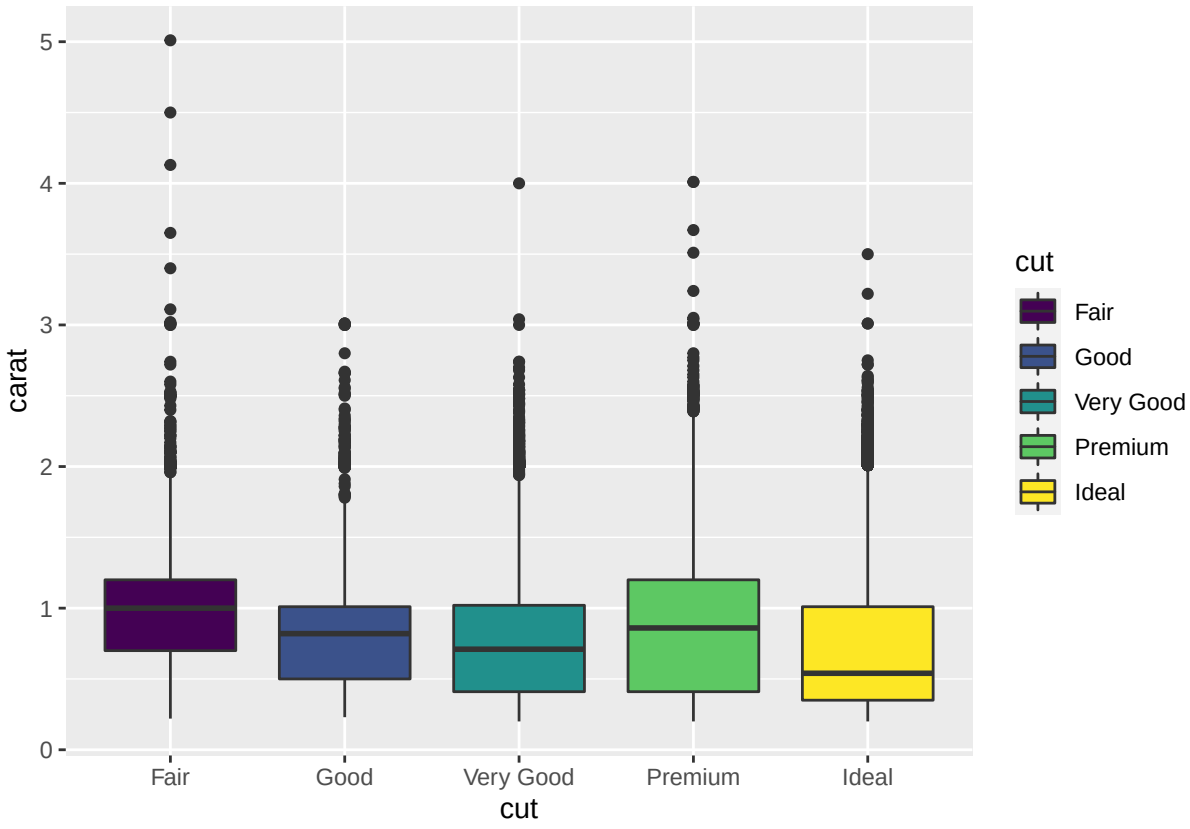
$$y_i = 3 + x_i + \varepsilon_i$$

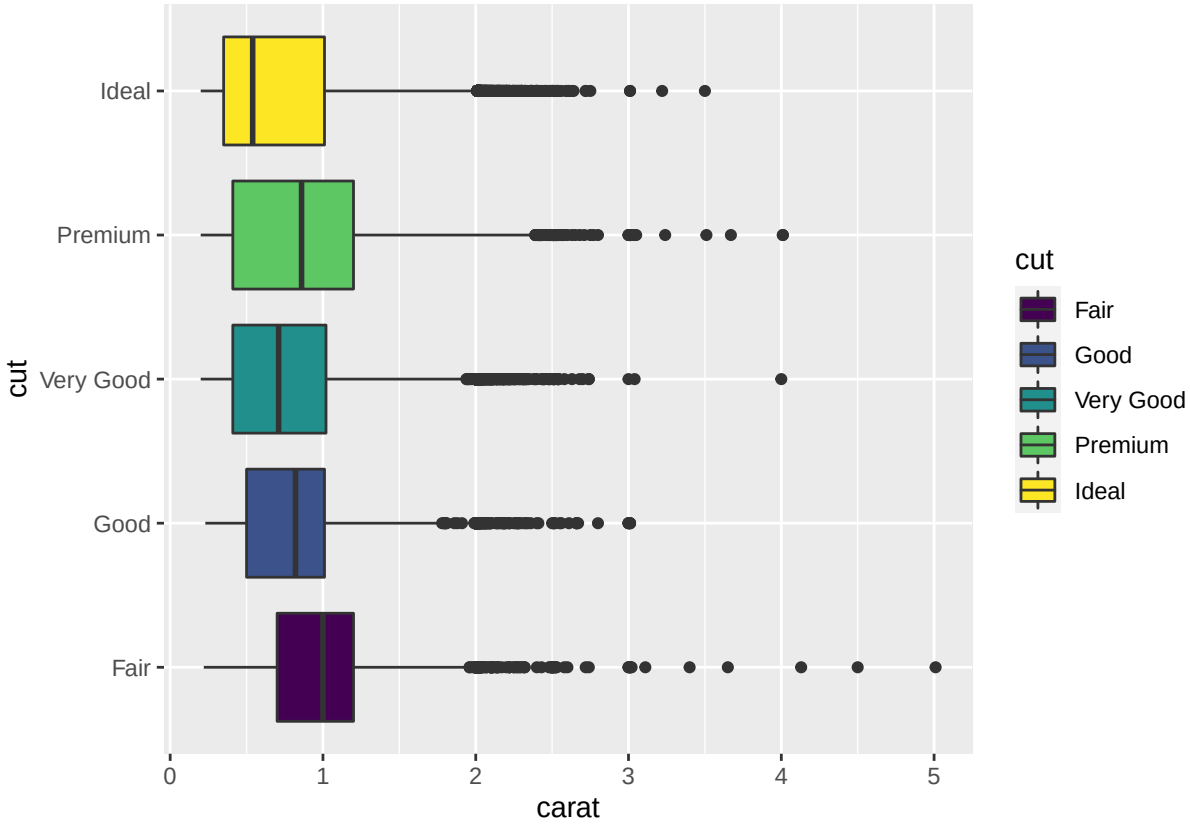
   where the x_i's are i.i.d. with uniform distribution over $[0, 1]$ and ε_i's are gaussian $N(0, 0.2^2)$ (use **runif** and **rnorm**)
2. Draw the scatter plot **y vs x** and add the linear smoother.
3. Draw the residuals : add a vertical line from each point to the linear smoother (use **geom_segment**).

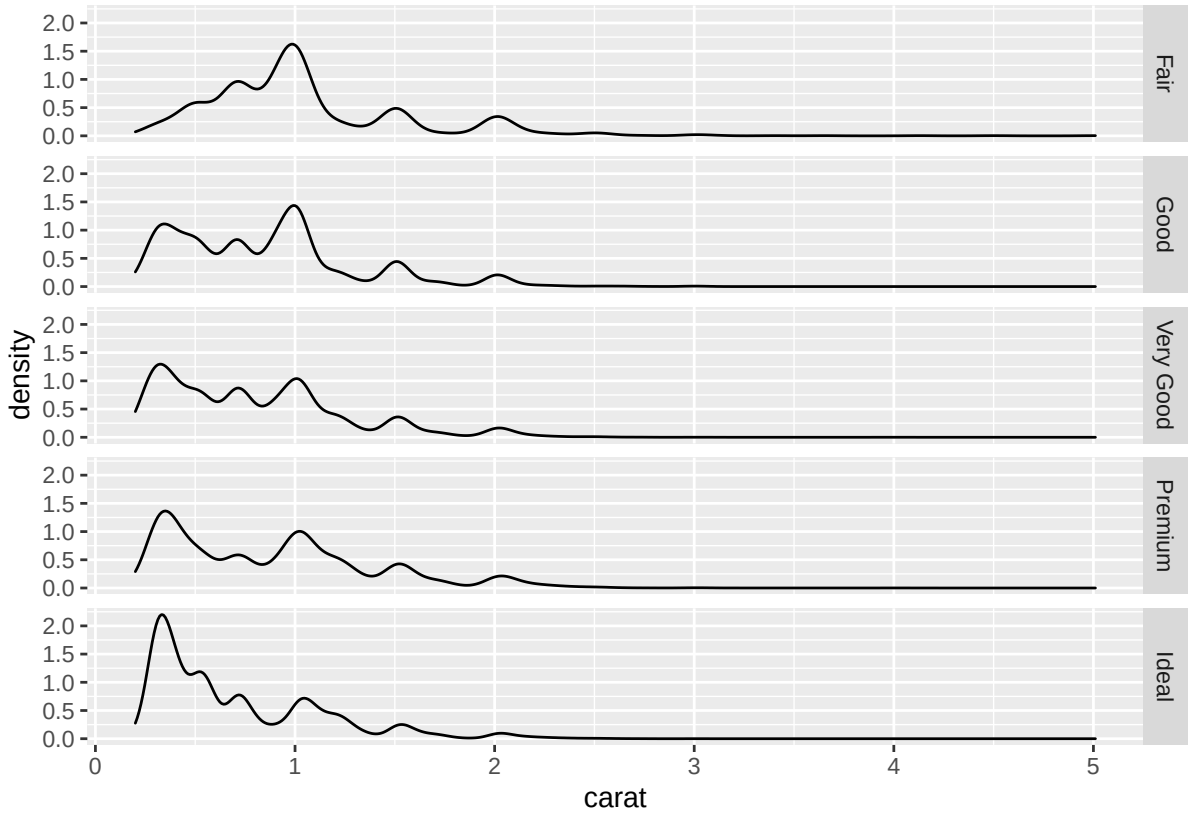
Exercise 1.12 (Challenge)**.**

We consider the **diamonds** dataset.

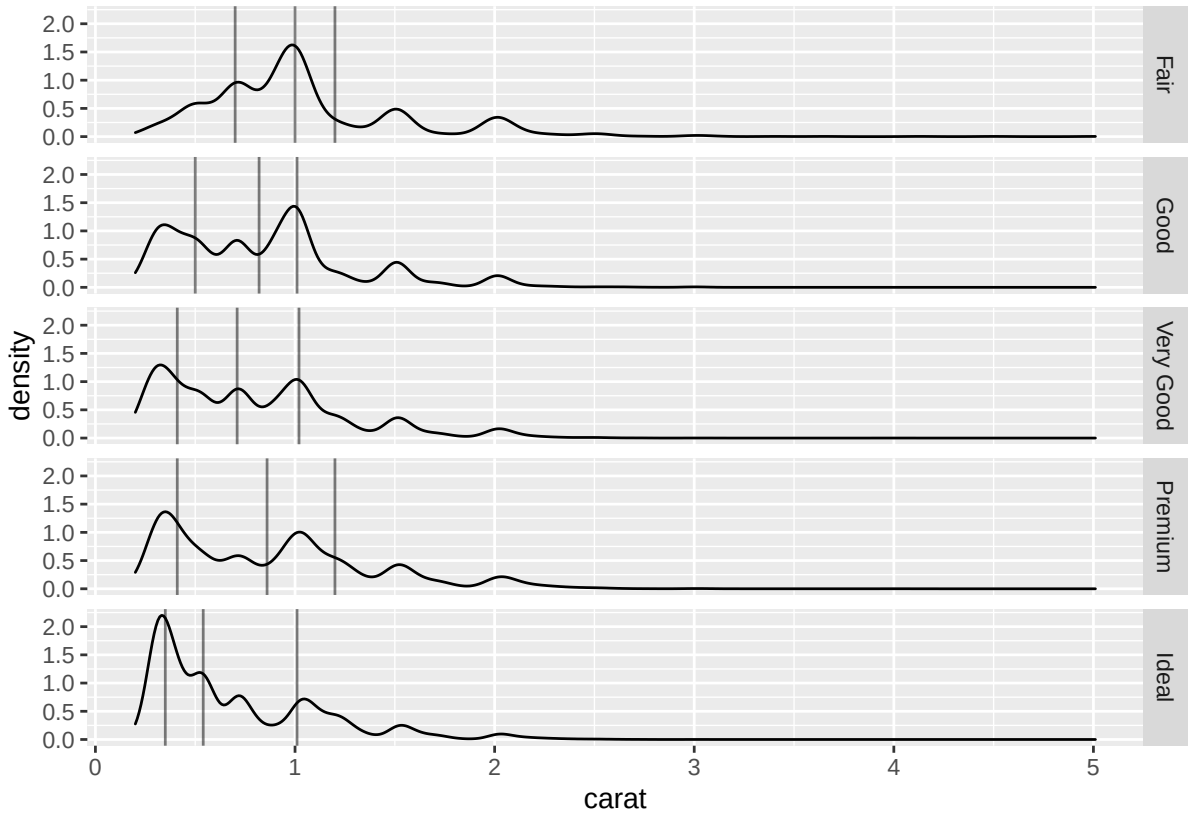
1. Draw the following graphs (use **coord_flip** for the second one).


carat
5
4
3
2
1
0
Fair
Good
Very Good
Premium
Ideal
cut
cut
Fair
Good
Very Good
Premium
Ideal

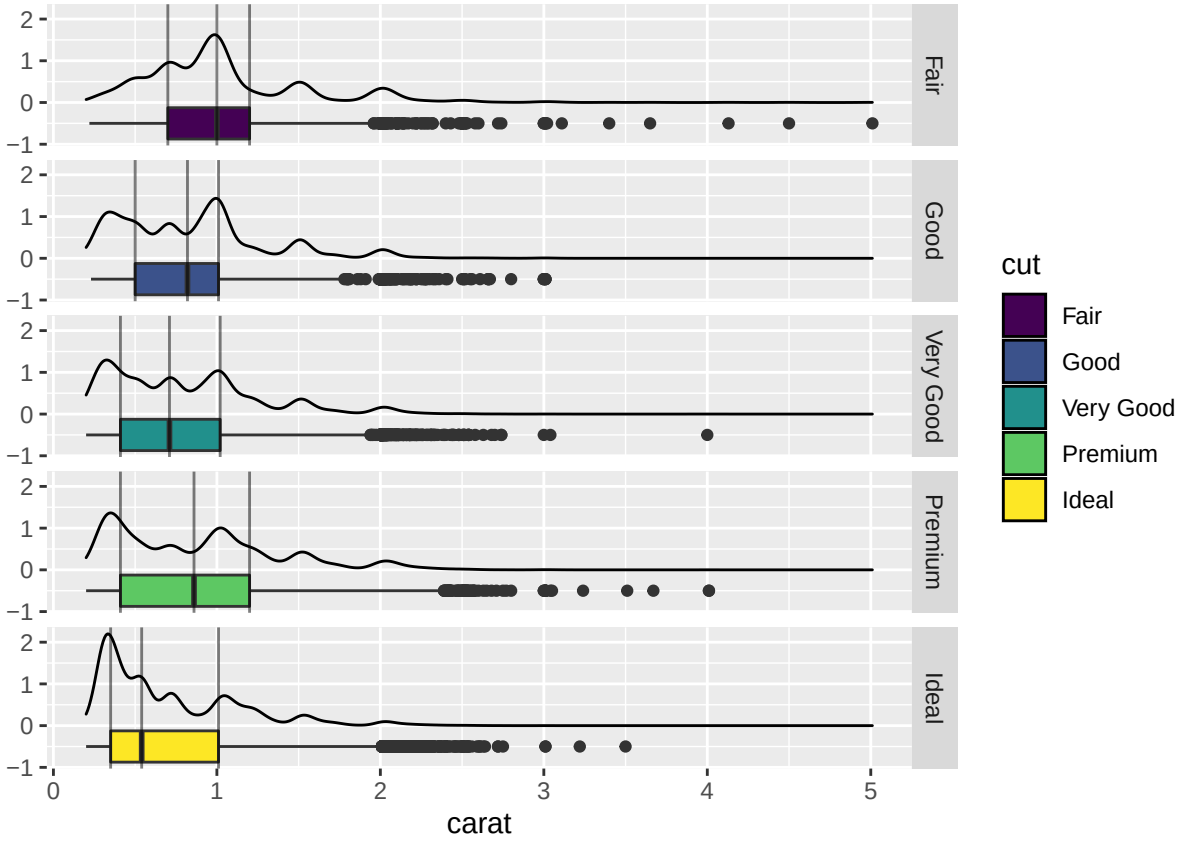

cut
Ideal
Premium
Very Good
Good
Fair
0
1
2
3
4
5
carat
cut
Fair
Good
Very Good
Premium
Ideal



2. Add on the third graph a vertical line for the quartiles of the variable **carat** (for each value of **cut**).



3. Add a horizontal boxplot under each graph (use the **ggstance** package) to obtain the following chart :



2 Mapping with R

Many datasets contains informations about location. It is natural to use map to visualize these data. We can differentiate two kind of maps :

— **static map** : to be exported in **pdf** or **png** format, usefull to publish report ;
— **dynamic** or **interactive** map : to be exported in **html** format for instance. We can visualize these maps in a web browser. We can use some and add information when we click on the map.

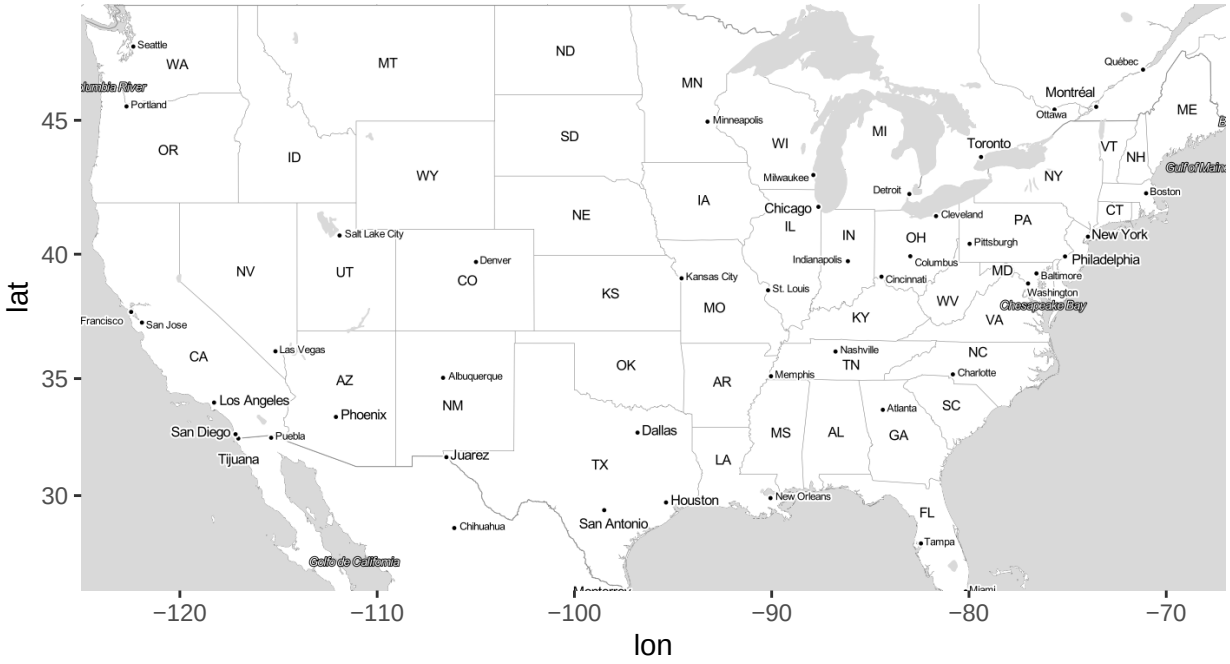
We can build map with many **R** packages. In this chapter, we present `ggmap` and `sf` for static map and `leaflet` for dynamici map.

2.1 ggmap package

We show in this part how to get background map and add informations from a dataset with `ggmap` package. For more details, we refer to this article

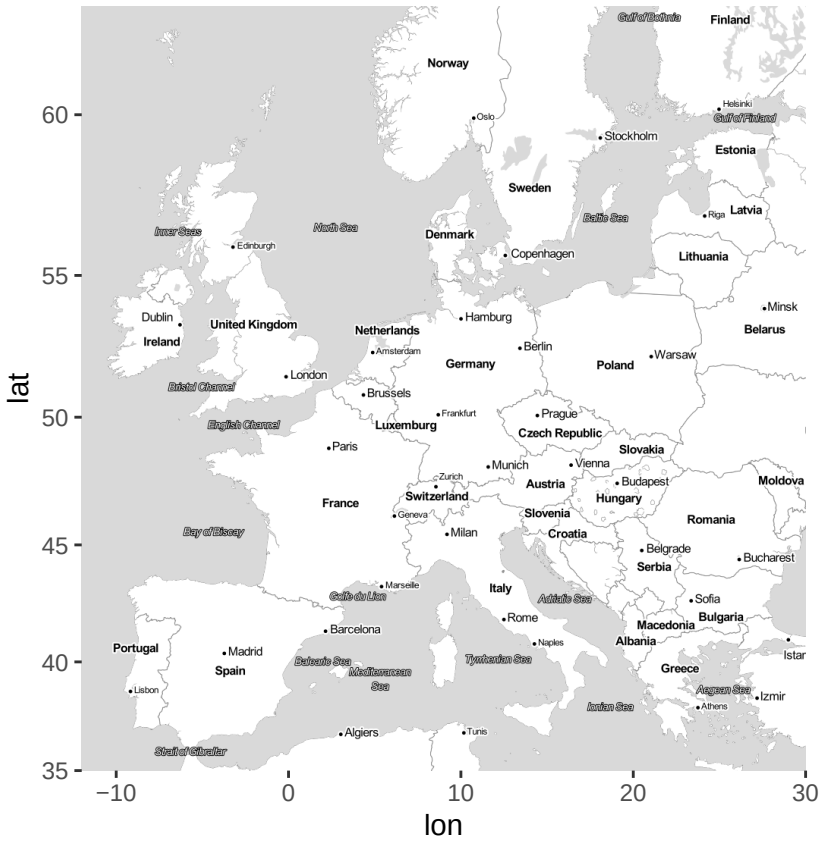
It is quite easy to download background map, for instance

```
library(ggmap)
us <- c(left = -125, bottom = 25.75, right = -67, top = 49)
map <- get_stamenmap(us, zoom = 5, maptype = "toner-lite")
ggmap(map)
```



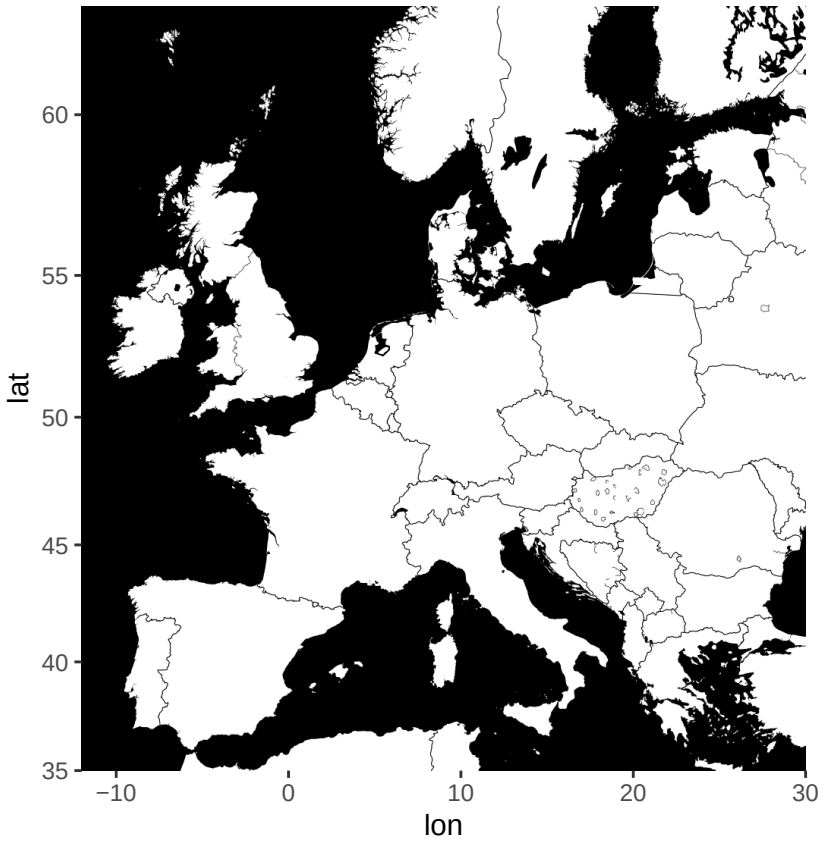
For Europe we can use

```
europe <- c(left = -12, bottom = 35, right = 30, top = 63)
get_stamenmap(europe, zoom = 5,"toner-lite") %>% ggmap()
```



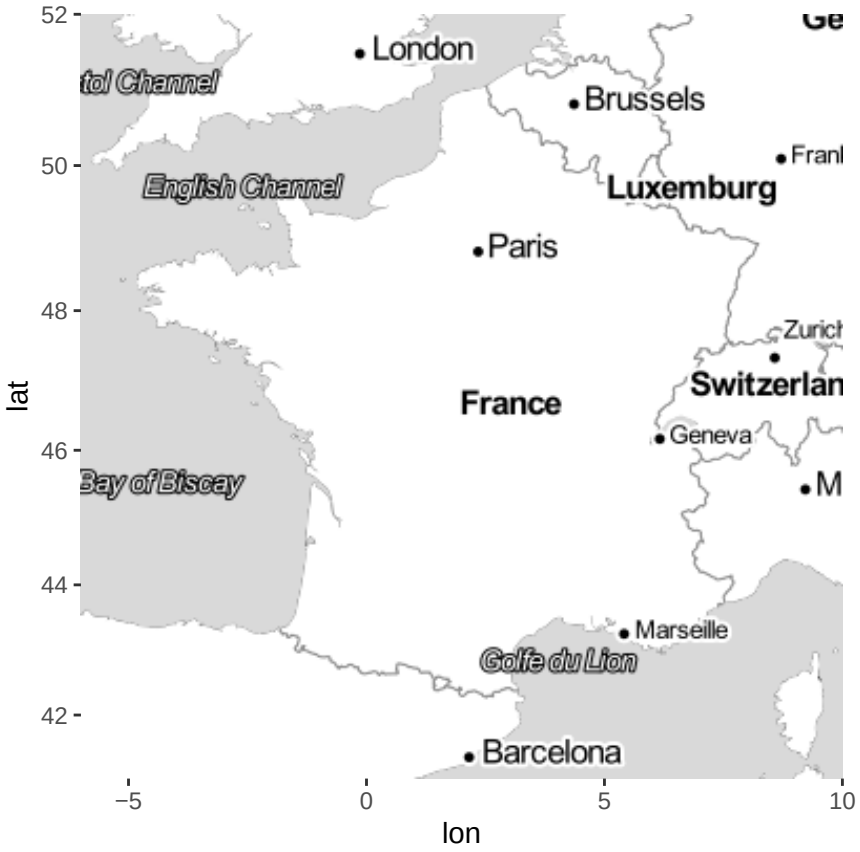
We can change the type f the background map On peut également changer le fond de carte

```
get_stamenmap(europe, zoom = 5,"toner-background") %>% ggmap()
```



Here is an example for France

```
fr <- c(left = -6, bottom = 41, right = 10, top = 52)
get_stamenmap(fr, zoom = 5,"toner-lite") %>% ggmap()
```



`geocode` function from `ggmap` made it possible to get latitudes and longitudes from a location. An **API** is now needed to use it (we could have to pay). We propose to use the following function instead :

```
if (!(require(jsonlite))) install.packages("jsonlite")
mygeocode <- function(adresses){
# adresses est un vecteur contenant toutes les adresses sous forme de chaine de caracteres
  nominatim_osm <- function(address = NULL){
    ## details: http://wiki.openstreetmap.org/wiki/Nominatim
    ## fonction nominatim_osm proposée par D.Kisler
    if(suppressWarnings(is.null(address)))  return(data.frame())
    tryCatch(
      d <- jsonlite::fromJSON(
        gsub('\\@addr\\@', gsub('\\s+', '\\%20', address),
             'http://nominatim.openstreetmap.org/search/@addr@?format=json&addressdetails=0&limit=1')
      ), error = function(c) return(data.frame())
    )
    if(length(d) == 0) return(data.frame())
    return(c(as.numeric(d$lon), as.numeric(d$lat)))
  }
  tableau <- t(sapply(adresses,nominatim_osm))
  colnames(tableau) <- c("lon","lat")
  return(tableau)
}
```

We can get latitudes and longitudes with

```
mygeocode("the white house")
                     lon     lat
```

```
the white house -77.03655 38.8977
mygeocode("Paris")
           lon     lat
Paris 2.351462 48.8567
mygeocode("Rennes")
            lon      lat
Rennes -1.68002 48.11134
```

Exercise 2.1 (Population sizes in France)**.**

1. Find latitudes and longitudes for Paris, Lyon and Marseille and represent these cities on a map (you can use a dot).
2. File **villes_fr.csv** contains population sizes for 30 cities in France. Visualize with a point these cities. We will use different point sizes in term of the populations sizes in 2014.

2.2 Maps with contours, shapefile format

`ggmpap` makes it easy to download background map and to add informations through `gplot` functions. However, it is more difficult to take into account of contours (boundaries for countries or department…). We propose here an introduction to the **sf** package. It allows to create "advanced" maps, by managing boundaries through specific objects. Moreover we can manage many coordinate systmes with this package. Recall that earth is not flat… But we usually visualize a map in 2D. We thus have to make projections in order to visualize locations defined by a coordinate (latitude and longitude for instance). These projections are generally managed by the packages, it is the case of **sf**. We can find documentation on this package at :

— https://statnmap.com/fr/2018-07-14-initiation-a-la-cartographie-avec-sf-et-compagnie/
— in the **vignettes** of the documentation of the package : https://cran.r-project.org/web/packages/sf/index.html

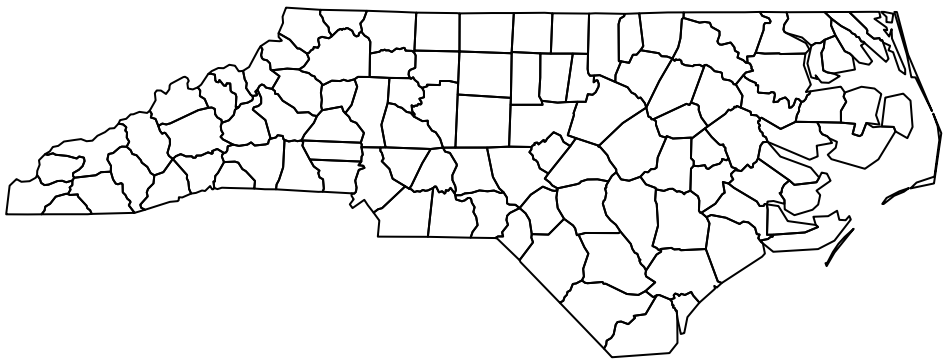
Package **sf** allows to define a new class of **R** objects specific for mapping. Look at the object `nc`

```
library(sf)
nc <- st_read(system.file("shape/nc.shp", package = "sf"), quiet = TRUE)
class(nc)
[1] "sf"         "data.frame"
nc
Simple feature collection with 100 features and 14 fields
geometry type:  MULTIPOLYGON
dimension:      XY
bbox:           xmin: -84.32385 ymin: 33.88199 xmax: -75.45698 ymax: 36.58965
CRS:            4267
First 10 features:
    AREA PERIMETER CNTY_ CNTY_ID        NAME  FIPS FIPSNO
1  0.114     1.442  1825    1825        Ashe 37009  37009
2  0.061     1.231  1827    1827   Alleghany 37005  37005
3  0.143     1.630  1828    1828       Surry 37171  37171
4  0.070     2.968  1831    1831   Currituck 37053  37053
5  0.153     2.206  1832    1832 Northampton 37131  37131
6  0.097     1.670  1833    1833    Hertford 37091  37091
7  0.062     1.547  1834    1834      Camden 37029  37029
8  0.091     1.284  1835    1835       Gates 37073  37073
9  0.118     1.421  1836    1836      Warren 37185  37185
10 0.124     1.428  1837    1837      Stokes 37169  37169
   CRESS_ID BIR74 SID74 NWBIR74 BIR79 SID79 NWBIR79
1         5  1091     1      10  1364     0      19
```

```
2          3   487     0      10   542     3      12
3         86  3188     5     208  3616     6     260
4         27   508     1     123   830     2     145
5         66  1421     9    1066  1606     3    1197
6         46  1452     7     954  1838     5    1237
7         15   286     0     115   350     2     139
8         37   420     0     254   594     2     371
9         93   968     4     748  1190     2     844
10        85  1612     1     160  2038     5     176
                        geometry
1  MULTIPOLYGON (((-81.47276 3...
2  MULTIPOLYGON (((-81.23989 3...
3  MULTIPOLYGON (((-80.45634 3...
4  MULTIPOLYGON (((-76.00897 3...
5  MULTIPOLYGON (((-77.21767 3...
6  MULTIPOLYGON (((-76.74506 3...
7  MULTIPOLYGON (((-76.00897 3...
8  MULTIPOLYGON (((-76.56251 3...
9  MULTIPOLYGON (((-78.30876 3...
10 MULTIPOLYGON (((-80.02567 3...
```

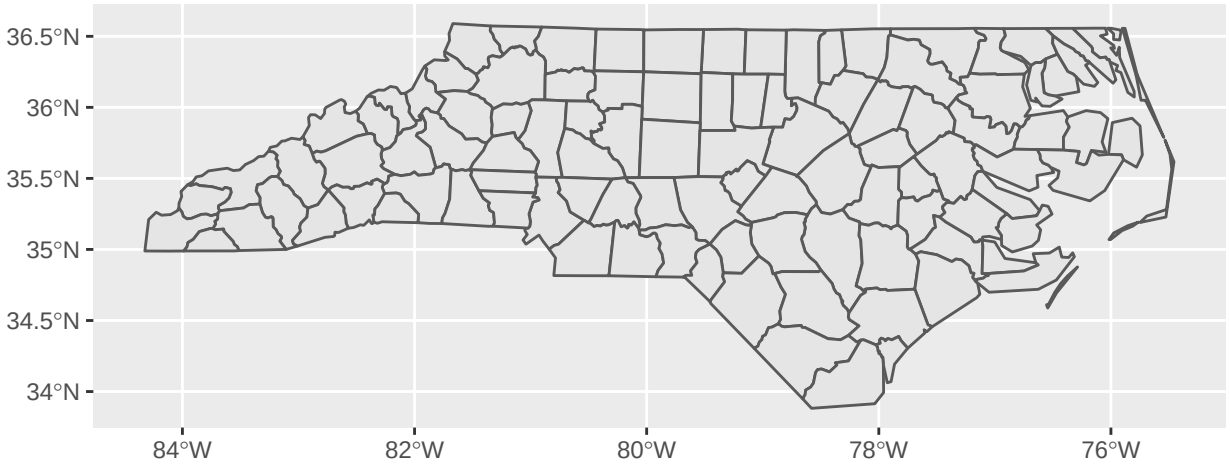
This dataset contains informations about sudden infant death syndrome in North Carolina counties. We observe 2 classes for `nc` : `sf` and `data.frame`. We can manage it as a classical `dataframe`. `sf` class allows to define a particular column (`geometry`) in which we can specify boundaries of the counties with **polygon**. This column makes it easy to plot these boundaries (with polygon) in a map. We can use the classicat `plot` function

```
plot(st_geometry(nc))
```



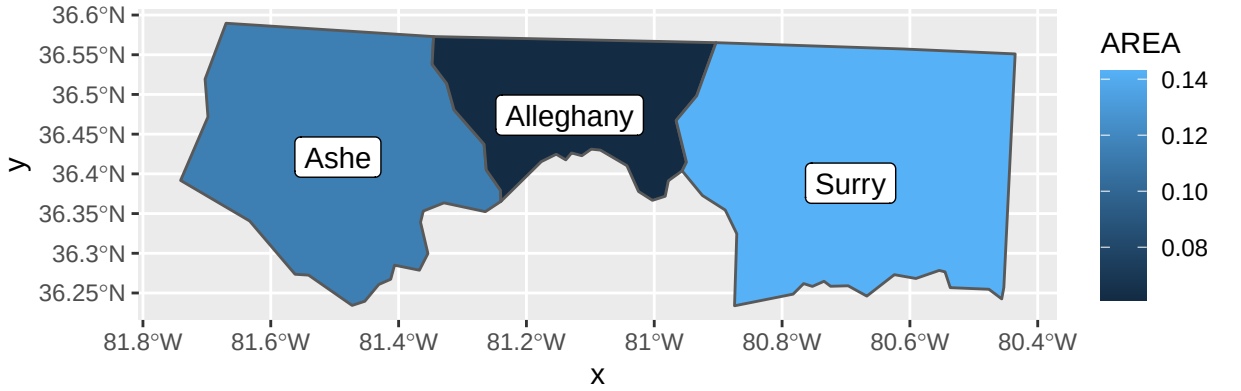
or the `geom_sf` verb if we prefer **ggplot**

```
ggplot(nc)+geom_sf()
```



It is now easy to color counties and to add their names

```
ggplot(nc[1:3,]) + geom_sf(aes(fill = AREA)) + geom_sf_label(aes(label = NAME))
```



`geometry` column of `nc` uses `MULTIPOLYGON`. This allows to represent boundaries. If we want to represent one country by a point, we have to change the format of this column. We can do it as follows :

1. We first compute latitude and longitude for each country :

```
coord.ville.nc <- mygeocode(paste(as.character(nc$NAME),"NC"))
coord.ville.nc <- as.data.frame(coord.ville.nc)
names(coord.ville.nc) <- c("lon","lat")
```

2. We give to these coordinates the format `MULTIPOINT` (**st_multipoint** function)

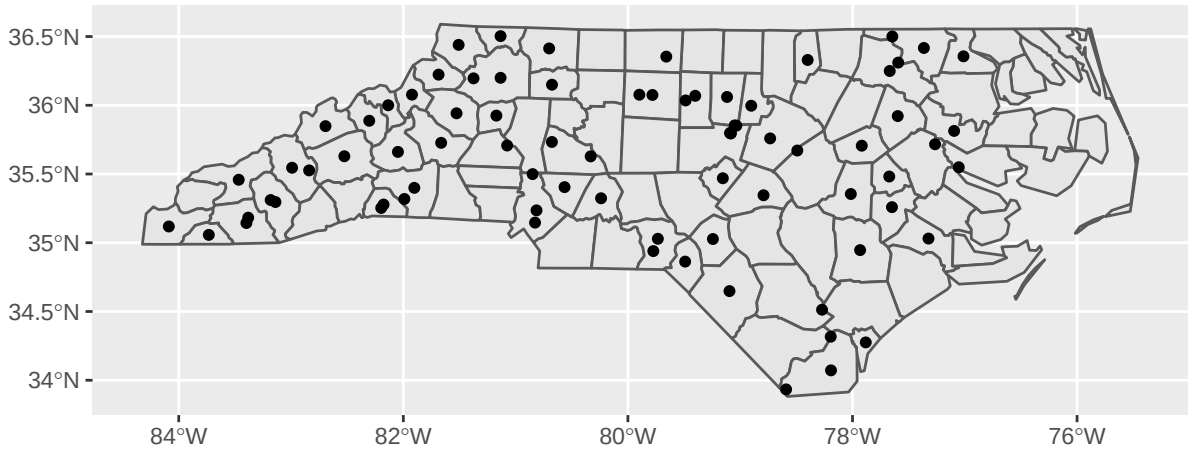
```
coord.ville1.nc <- coord.ville.nc %>%
  filter(lon<=-77 & lon>=-85 & lat>=33 & lat<=37) %>%
  as.matrix() %>% st_multipoint() %>% st_geometry()
coord.ville1.nc <- coord.ville.nc %>%
  filter(lon<=-77 & lon>=-85 & lat>=33 & lat<=37) %>%
  as.matrix() %>% st_multipoint()  %>% st_geometry() %>% st_cast(to="POINT")
coord.ville1.nc
Geometry set for 79 features
geometry type:  POINT
dimension:      XY
bbox:           xmin: -84.08862 ymin: 33.93323 xmax: -77.01151 ymax: 36.503
CRS:            NA
First 5 geometries:
```

3. We indicate that these coordinates correspond to longitudes and latitudes (there exists other coordinate systmes) :

```
st_crs(coord.ville1.nc) <- 4326
```

4. We can now visualize both the boundaries and the counties :

```
ggplot(nc)+geom_sf()+geom_sf(data=coord.ville1.nc)
```

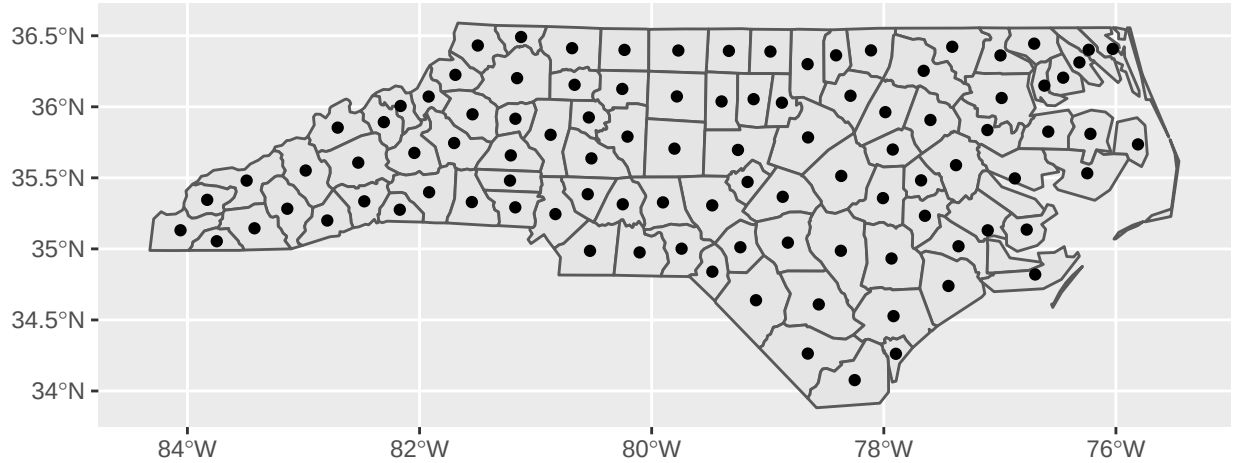


There are many useful functions in **sf** to deal with mapping data, for instance

— `st_distance` to compute (real) distances between coordinates ;
— `st_centroid` to obtain the center of a polygon (or region) ;
— ...

For example we con visualize the centers of the areas identified by the polygons in `nc` with

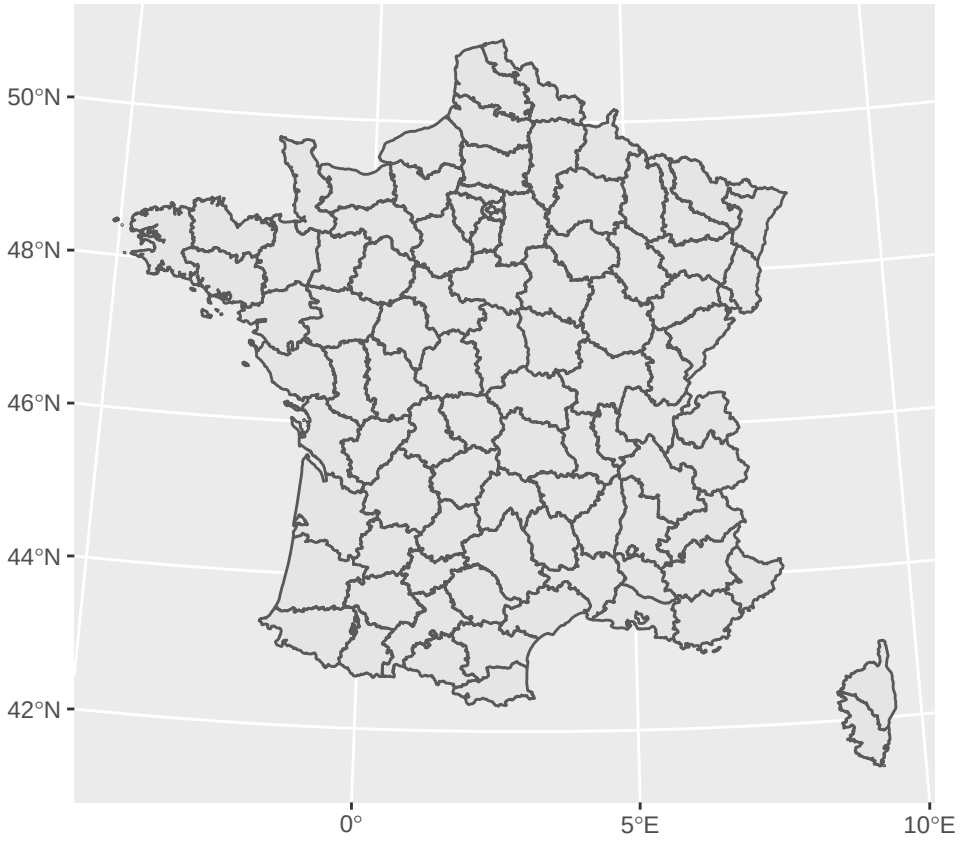
```
nc2 <- nc %>% mutate(centre=st_centroid(nc)$geometry)
ggplot(nc2)+geom_sf()+geom_sf(aes(geometry=centre))
```



Exercise 2.2 (A first map with sf)**.**

We consider the GEOFLAR map proposed by "l'Institut Géographique National" to obtain a shapefile background map of the french departments. This map is available at http : //professionnels.ign.fr/, we can obtain it in the file **dpt.zip** (you have to unzip this file). We can import this map into a R object with

```
dpt <- read_sf("data/dpt")
ggplot(dpt) + geom_sf()
```



Redo the map of exercise 2.1 with this background map.

Exercise 2.3 (Unemployment rates)**.**

We want to visualize differences between unemployment rates in 2006 and 2011. The data are in the file **tauxchomage.csv**. We are interested in variables `TCHOMB1T06` and `TCHOMB1T11`.

1. Read the dataset.
2. Merge this dataset with the one of the department. You can use **inner_join**.
3. Make a comparison between the unemployment rates in 2006 and 2011 (build one map for 2006 and another one for 2011).

2.2.1 Challenge 1 : temperature map with sf

We want to visualize temperatures in france far a given date. Data are available on the website of public data of meteofrance. In particlar, we can obtain temperatures measured in some stations for man dates as well as the locations of these stations.

1. Import the 2 required dataset (you can read those directly on the website). Temperatures are given in Kelvin. Convert them in Celsius (you just have to subtract 273.15).
2. Keep only stations from metropolitan france (remove stations from overseas department). **Hint** : You can keep only stations with longitude between -20 and 25. We call this dataset **station1**. Visualize stations on a french map with boundaries department.
3. Create a dataframe (with **sf** format) which contains temperatures of the stations in one column and a column `geometry` with the coordinate of these stations. We can start with

```
station2 <- station1 %>% select(Longitude,Latitude) %>%
  as.matrix() %>% st_multipoint() %>% st_geometry()
st_crs(station2) <- 4326
station2 <- st_cast(station2, to = "POINT")
```

4. Visualize the stations in the french map. You can color the points (stations) according to the observed temperatures.
5. We obtain coordinates of the centroids of the departments with

   ```
   centro <- st_centroid(dpt$geometry)
   centro <- st_transform(centro,crs=4326)
   ```

   We then deduce distances between these centroids and the stations (here **df** is the **sf** table computed in question 3).

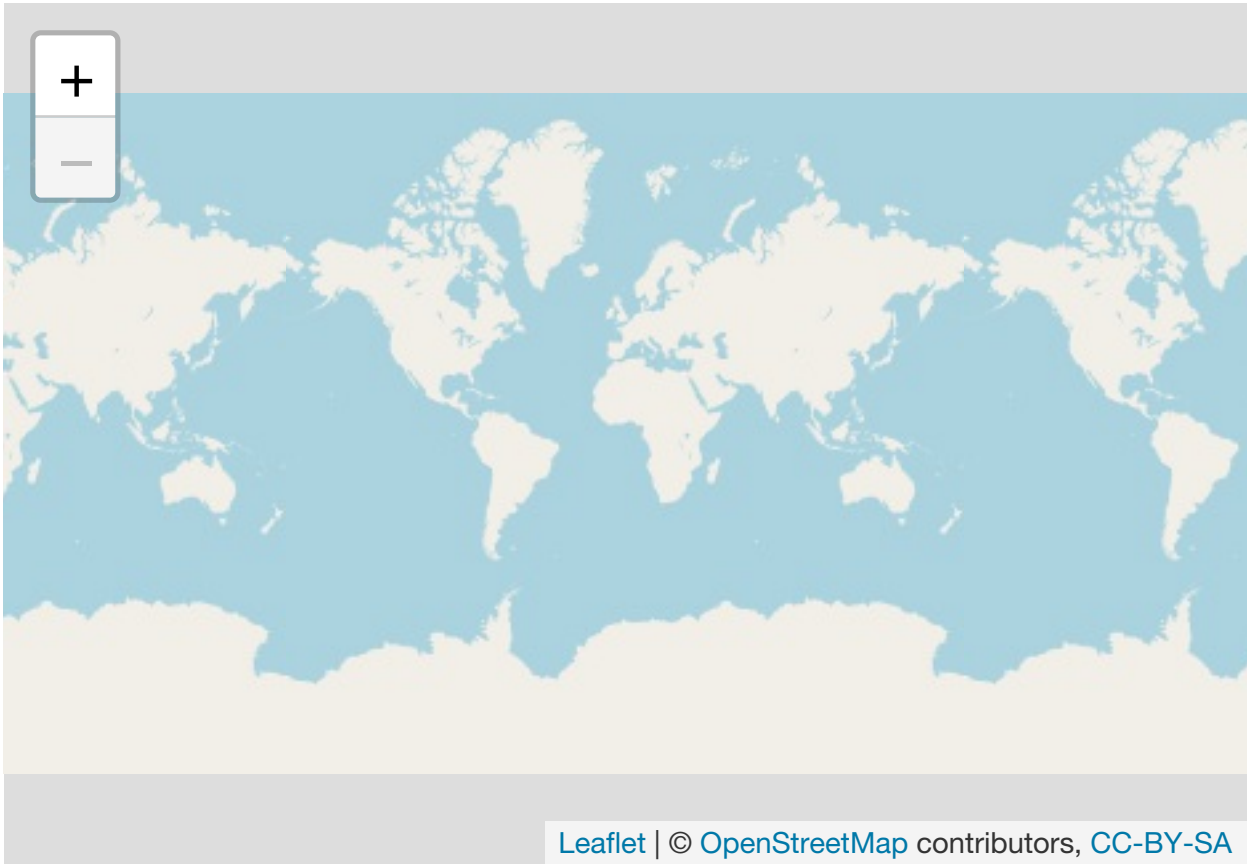
   ```
   DD <- st_distance(df,centro)
   ```

   Predict the temperature in each department with a one nearest neighbour rule.
6. Color departments according to the predicted temperatures. We can use a gradient color from yellow (for low temperatures) to red (for high temperatures).

2.3 Dynamic maps with leaflet

`Leaflet` is a R package which allows to produce interactive maps. You can find informations about this pakage at https://rstudio.github.io/leaflet/. The ideas are quite the same as for `ggmap` and `sf` : maps are defined from many layers. A leaflet background map can be created with

```
library(leaflet)
leaflet() %>% addTiles()
```



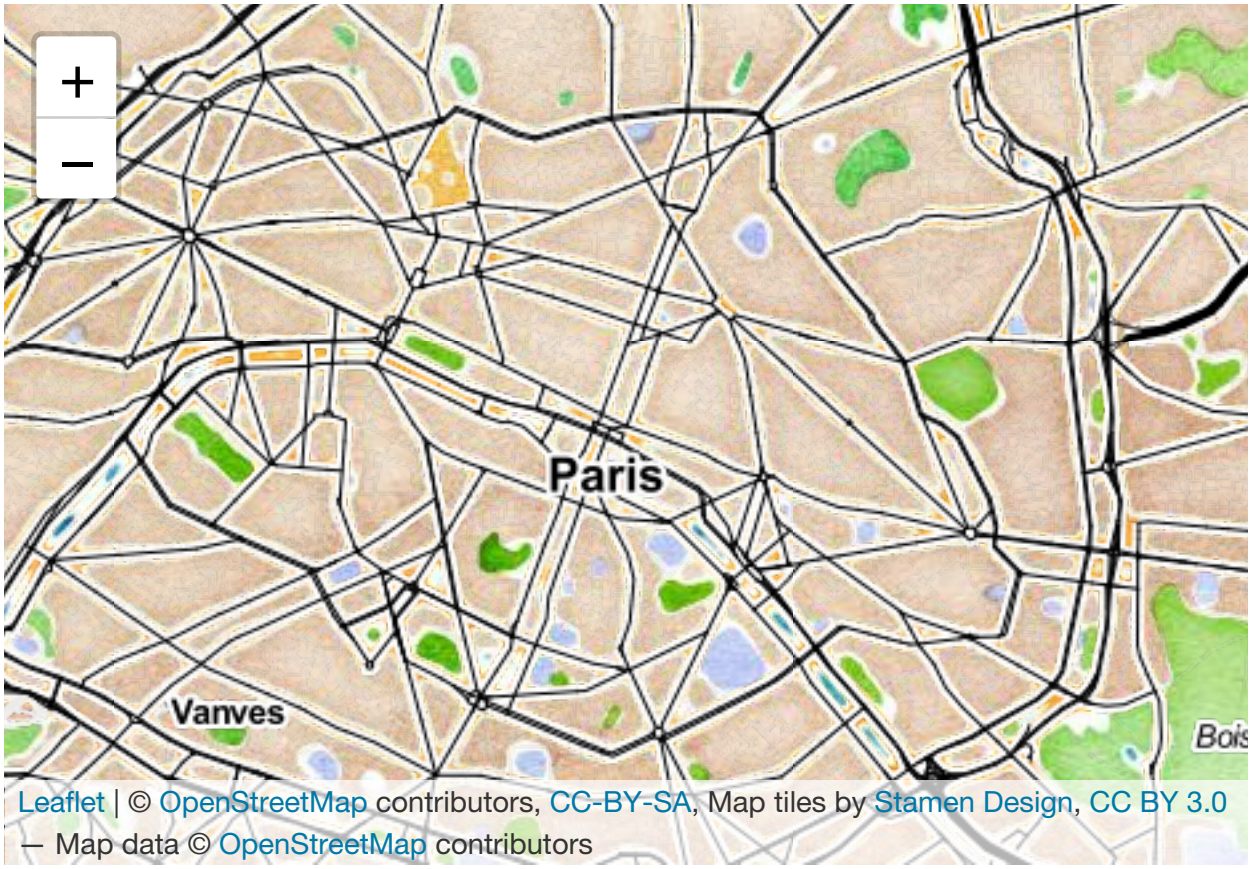
Many formats of background maps are available (some examples here). For instance

```
Paris <- mygeocode("paris")
m2 <- leaflet() %>% setView(lng = Paris[1], lat = Paris[2], zoom = 12) %>%
  addTiles()
m2 %>% addProviderTiles("Stamen.Toner")
```


```
m2 %>% addProviderTiles("Wikimedia")
```

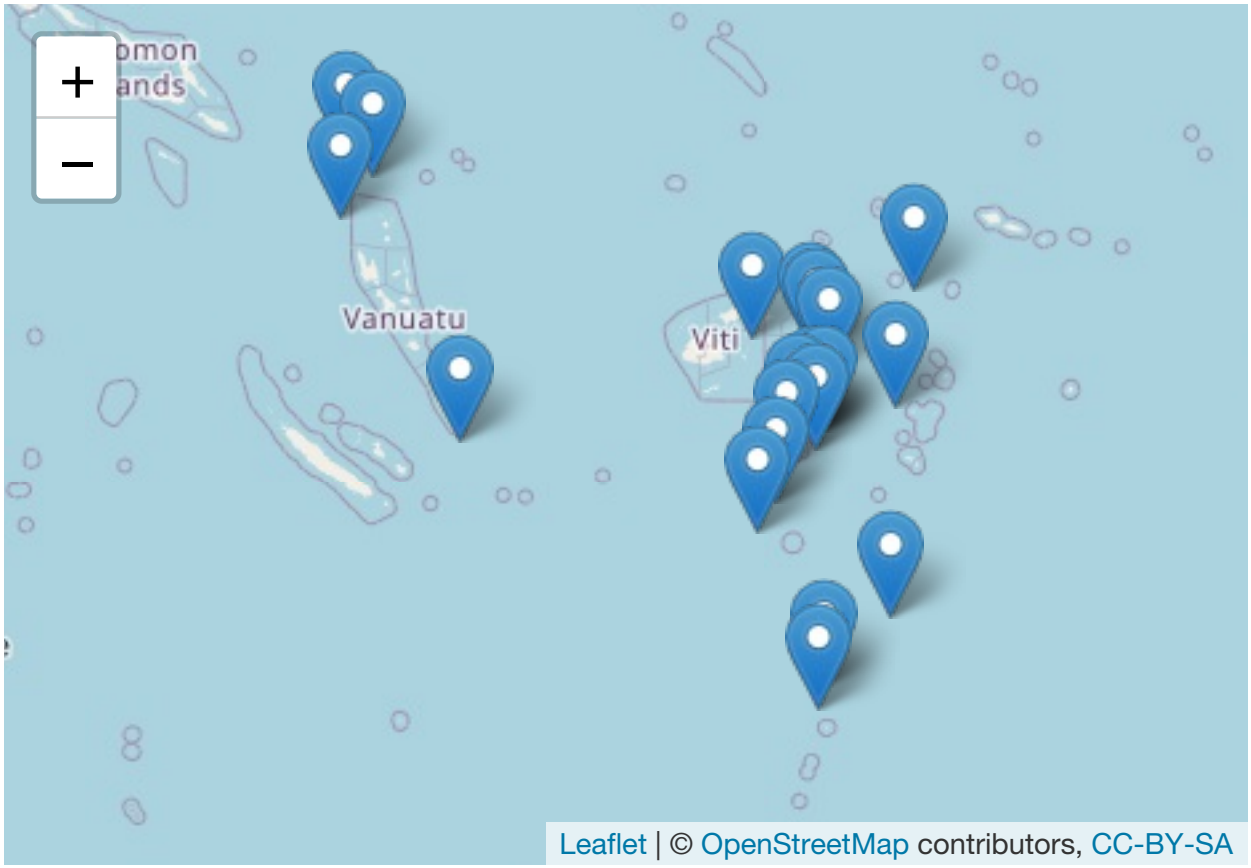

```
m2 %>% addProviderTiles("Esri.NatGeoWorldMap")
```


```
m2 %>%
  addProviderTiles("Stamen.Watercolor") %>%
  addProviderTiles("Stamen.TonerHybrid")
```



We can localize places with markers or circles

```
data(quakes)
leaflet(data = quakes[1:20,]) %>% addTiles() %>%
  addMarkers(~long, ~lat, popup = ~as.character(mag))
```

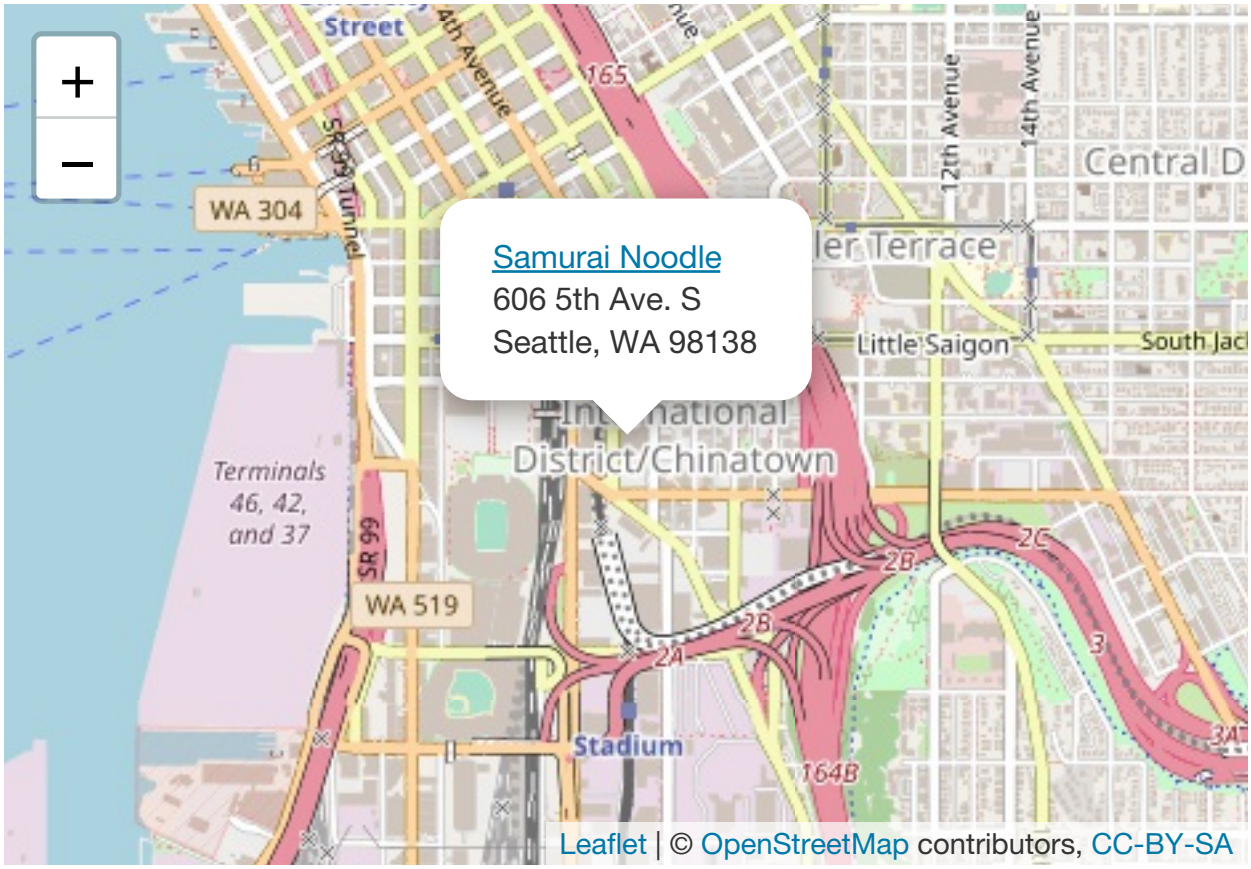


Observe that we have to use the tilda character ~ when we want to use the names of the dataframe to obtain the map.

The dynamic process can be used to add information when we click on a marker (with `popup` option). We can also add **popups** as follows

```
content <- paste(sep = "<br/>",
  "<b><a href='http://www.samurainoodle.com'>Samurai Noodle</a></b>",
  "606 5th Ave. S",
  "Seattle, WA 98138"
)

leaflet() %>% addTiles() %>%
  addPopups(-122.327298, 47.597131, content,
    options = popupOptions(closeButton = FALSE)
  )
```



Exercise 2.4 (Popup with leaflet)**.**

Add a popup on a leaflet map which localize Ensai. We also specify in the popup the website of the school.

2.3.1 Challenge 2 : city bike in Paris

Many cities all over the world provides informations on bike stations. These data are easily available et are updated in real time. Among other, we have informations about the size, the location, the number of available bikes for each stations. We can obtain these data on

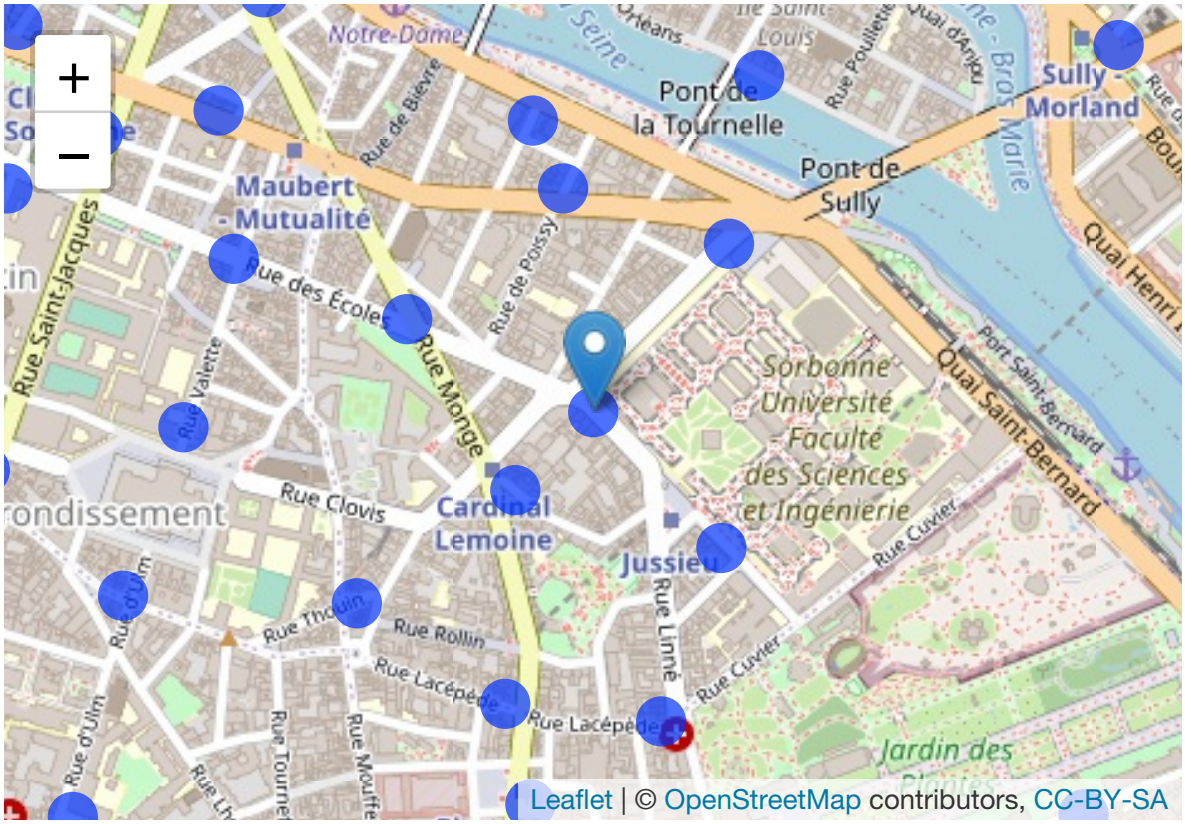
— Decaux
— Open data Paris
— vlstats

1. Import informations onbike stations in Paris fr today : https://opendata.paris.fr/explore/dataset/velib-disponibilite-en-temps-reel/information/. You can use `read_delim` function with `delim=";"`.
2. Describe the dataset.
3. Create variables `latitude` and `longitude` from the column `geo`. You can use the verb **separate** from the `tidyr` package.
4. Visualize the stations on a leaflet background map.
5. Add a popup which indicates the number of available bikes (electric+mecanic) when we click on the station (you can use the **popup** option in the function **addCircleMarkers**).
6. Add the name of the station in the popup.
7. Do the same with different colors to visualize the proportion of available bikes in the station. You can use the color palettes

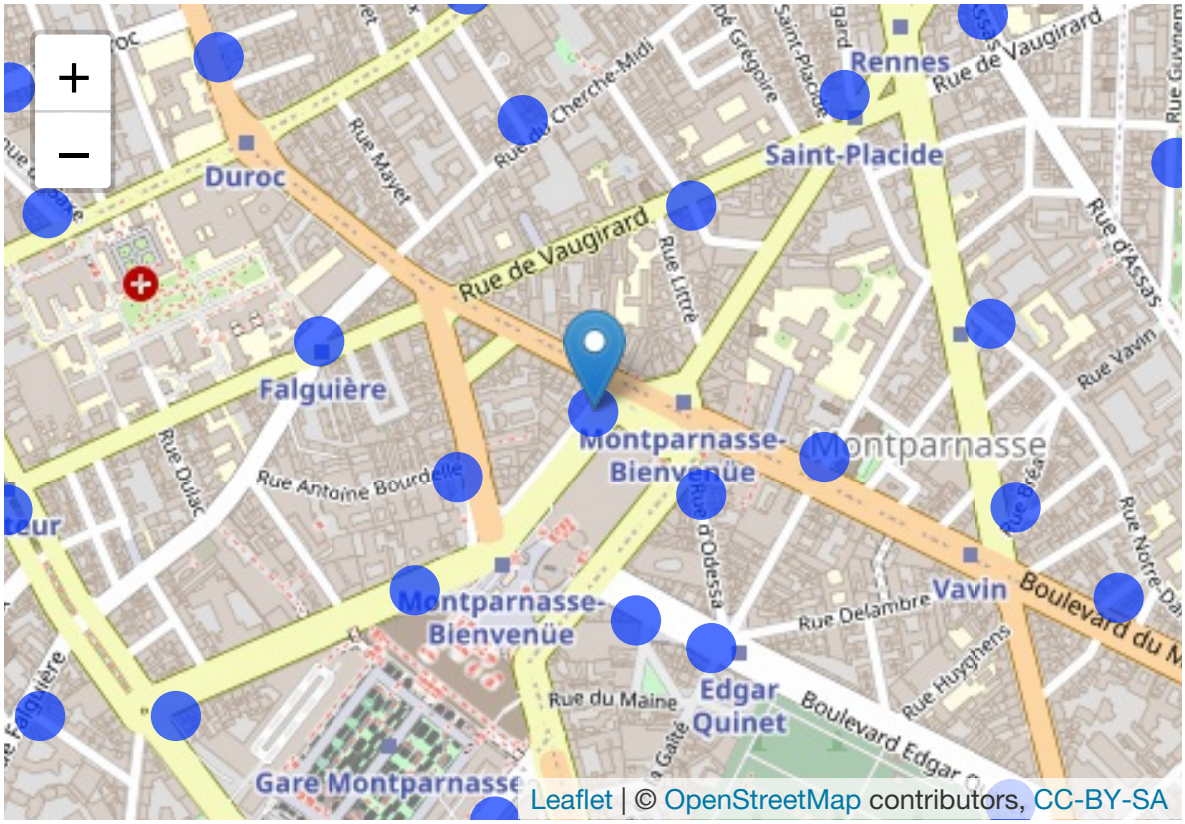
```
ColorPal1 <- colorNumeric(scales::seq_gradient_pal(low = "#132B43", high = "#56B1F7",
                                                   space = "Lab"), domain = c(0,1))
ColorPal2 <- colorNumeric(scales::seq_gradient_pal(low = "red", high = "black",
                                                   space = "Lab"), domain = c(0,1))
```

8. Create a **R** function `local.station` which allows to visualize the closest stations of a given station. For instance

```
local.station("Jussieu - Fossés Saint-Bernard")
```




```
local.station("Gare Montparnasse - Arrivée")
```



2.3.2 Temperature map with leaflet

Exercise 2.5 (Challenge)**.**

Redo the temperature map of the first challenge (see section 2.2.1) with **leaflet**. We will use the table build at the end of the challenge with the function `addPolygons`. We can also add a popup to visualize the name of the department and the predicted temperature when we click on the map.

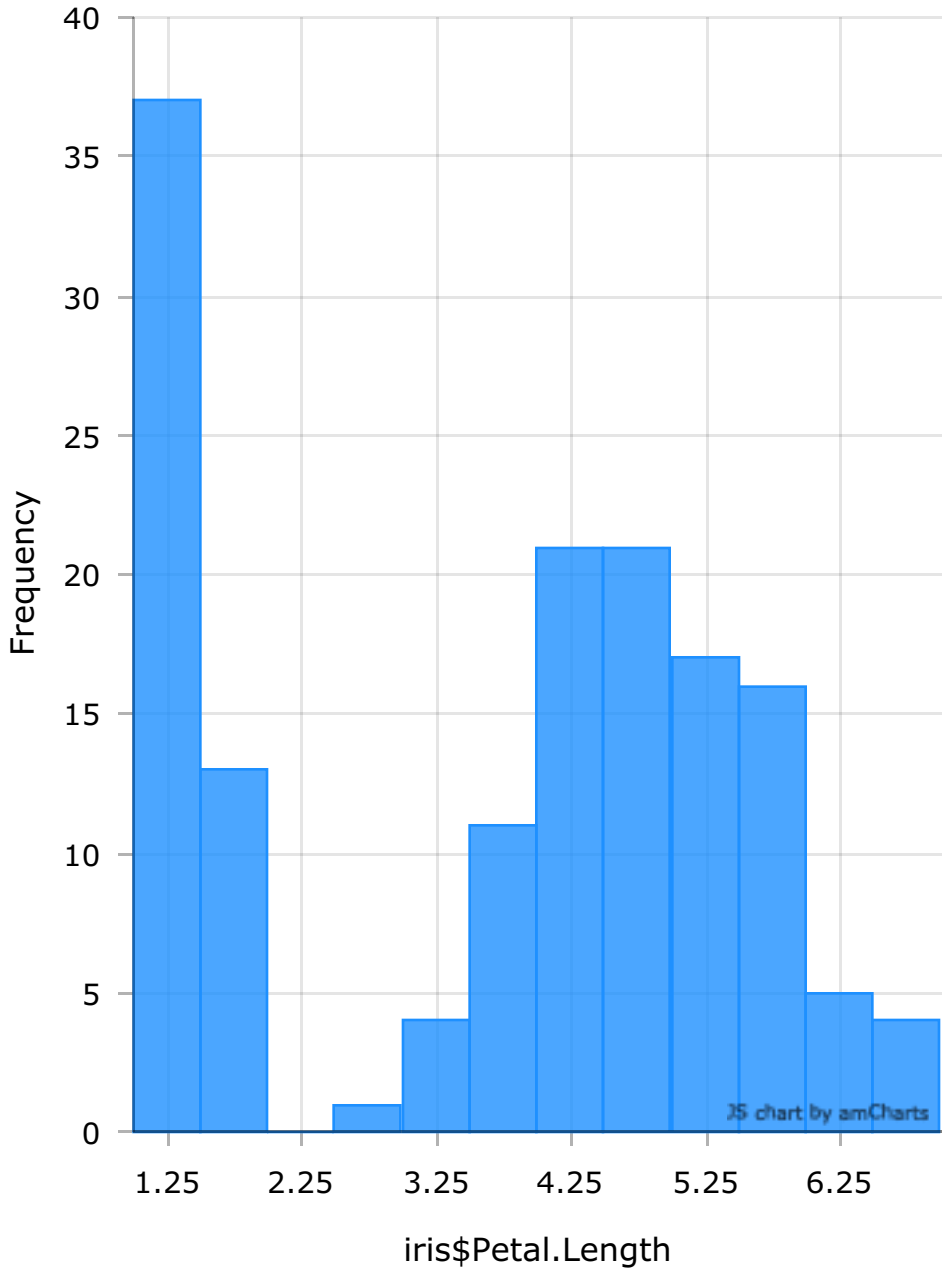
3 Dynamic visualization

As for **leaflet** for mapping, there exists many **R** packages for **dynamic** or **interavtive** visualization. We present some of them in this part.

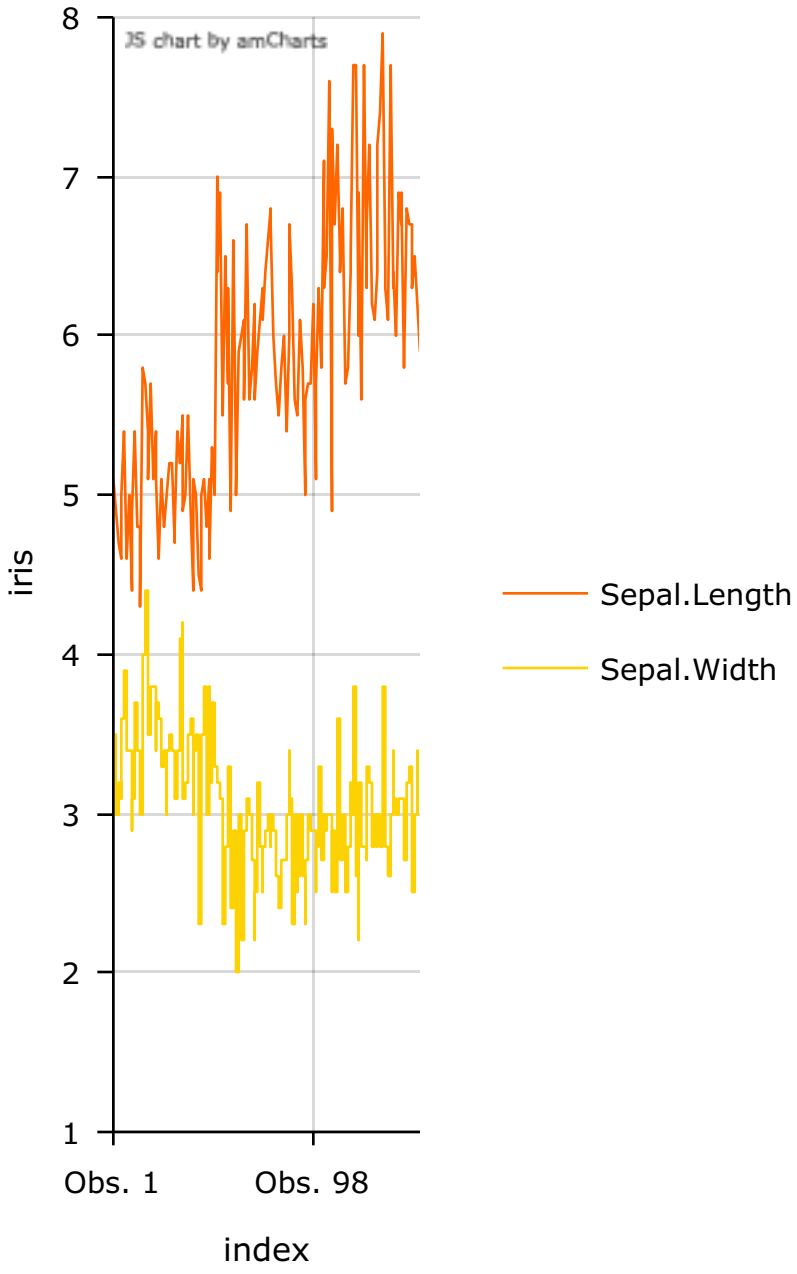
3.1 Classical charts with `rAmCharts` and `plotly`

rAmCharts is user-friendly for standard graphs (scatterplot, times series, histogram…). We just have to use classical **R** functions with the prefix **am**. For instance

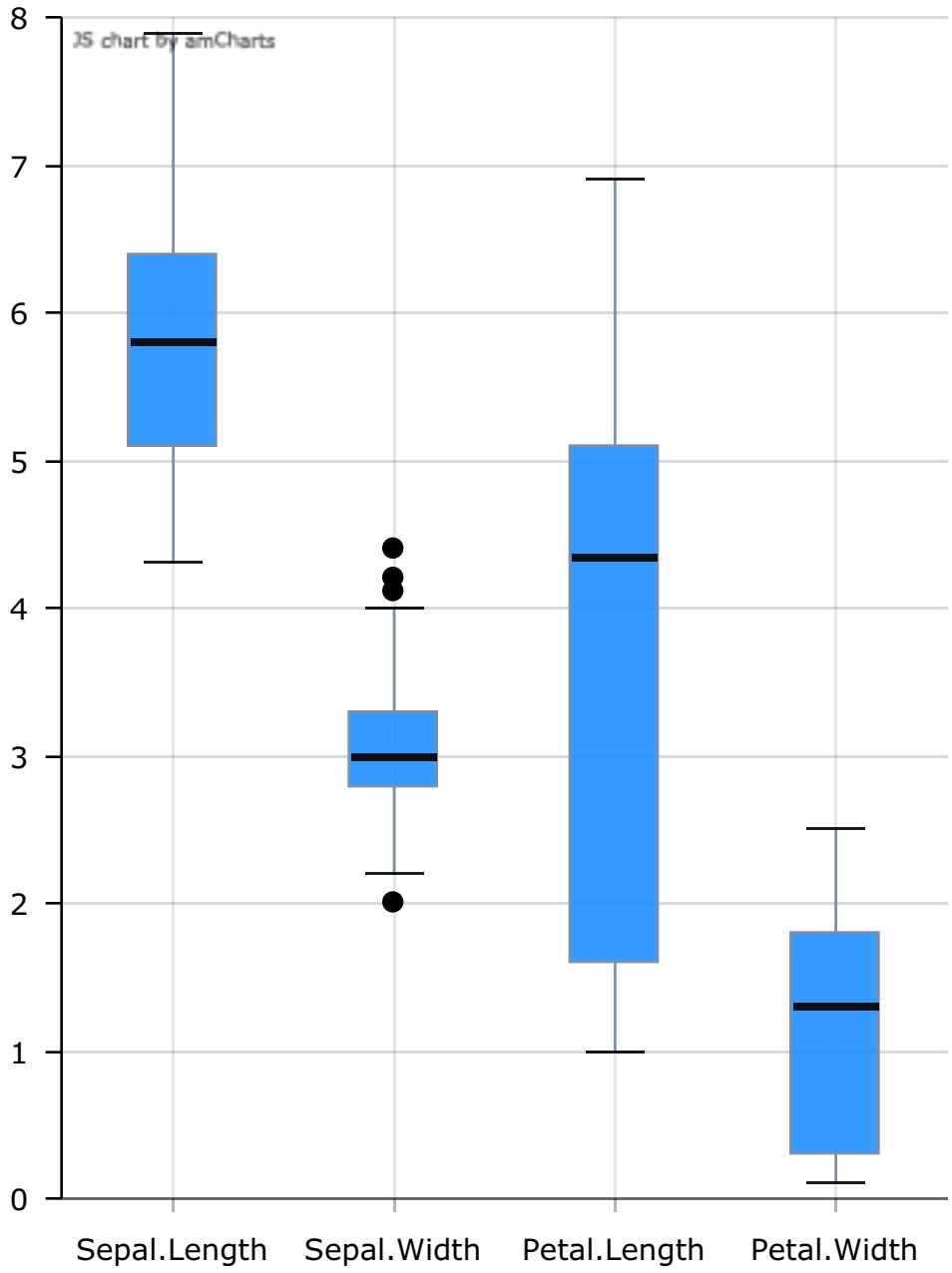
```
library(rAmCharts)
amHist(iris$Petal.Length)
```




```
amPlot(iris, col = colnames(iris)[1:2], type = c("l", "st"),
       zoom = TRUE, legend = TRUE)
```




```
amBoxplot(iris)
```



plotly produces similar things but with a specific syntax. **plotly** commands are expanded into 3 parts :

- dataset and variables (**plot_ly**}) ;
- additional representaions (**add_trace**, **add_markers**…) ;
- options (axis, titles…) (**layout**).

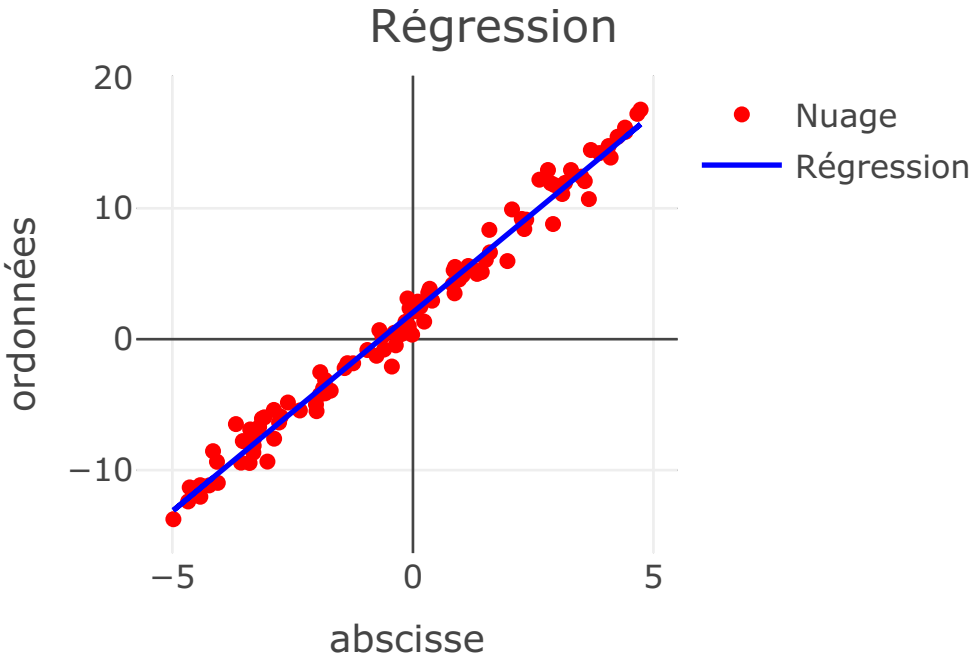
We can find a description for each part at https://plot.ly/r/reference/. As a first chart, we propose to represent a scatterplot with the linear smoother. We start by generating the data and computing the linear model :

```
library(plotly)
n <- 100
```

```
X <- runif(n,-5,5)
Y <- 2+3*X+rnorm(n,0,1)
D <- data.frame(X,Y)
model <- lm(Y~X,data=D)
```

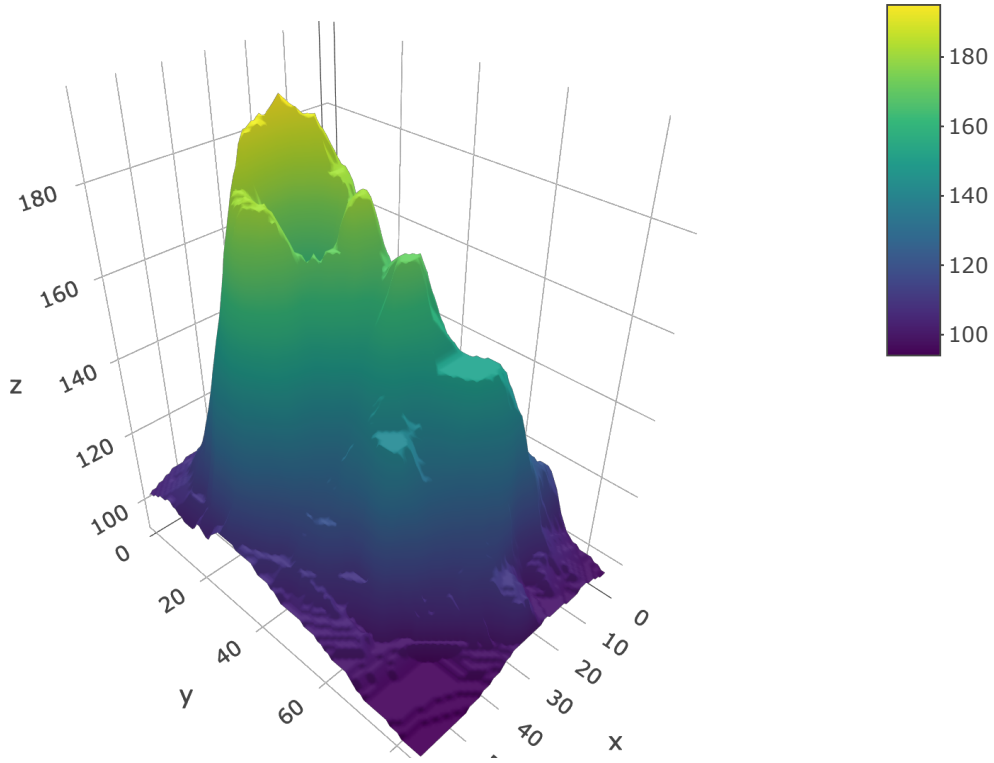
We obtain the required graph with

```
D %>% plot_ly(x=~X,y=~Y) %>%
  add_markers(type="scatter",mode="markers",
              marker=list(color="red"),name="Nuage") %>%
  add_trace(y=fitted(model),type="scatter",mode='lines',
            name="Régression",line=list(color="blue")) %>%
  layout(title="Régression",xaxis=list(title="abscisse"),
         yaxis=list(title="ordonnées"))
```

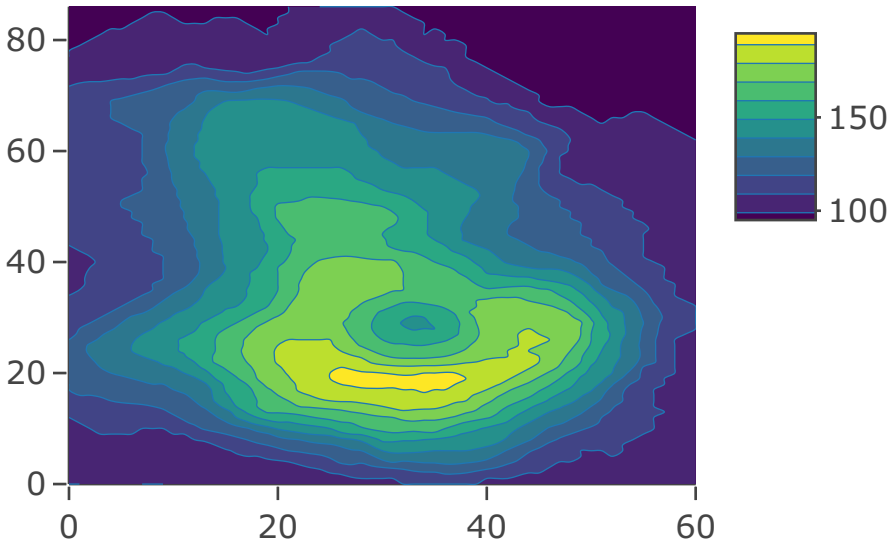


Unlike **ggplot**, we can make 3D with **plotly**. For instance

```
plot_ly(z = volcano, type = "surface")
```

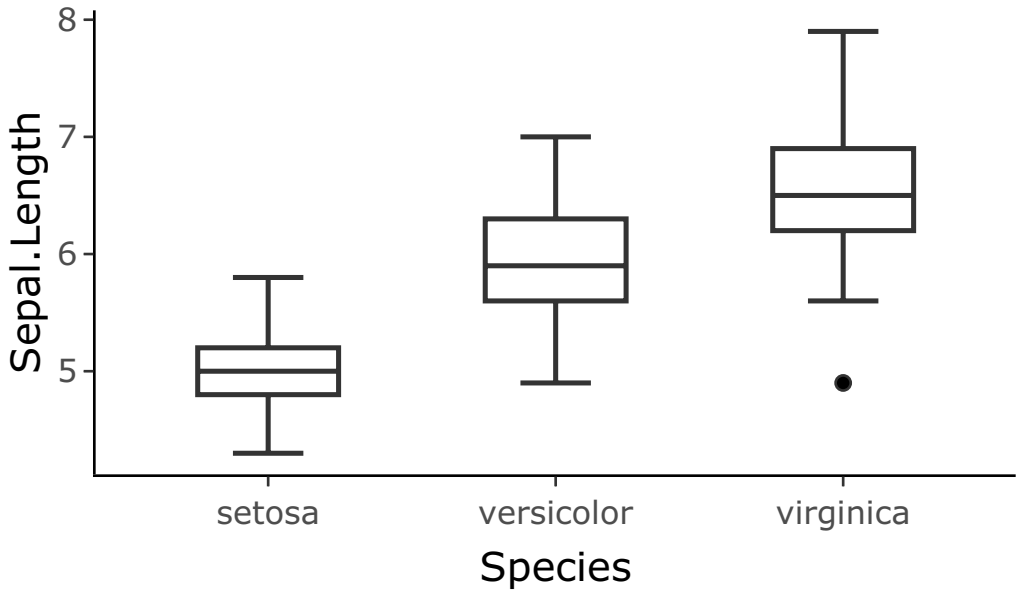



```
plot_ly(z = volcano, type = "contour")
```



We can also convert **ggplot** graph in **plotly** graph with `ggplotly` :

```
p <- ggplot(iris)+aes(x=Species,y=Sepal.Length)+geom_boxplot()+theme_classic()
ggplotly(p)
```



Exercise 3.1 (Basic charts with 'rAmCharts' and 'plotly')**.**

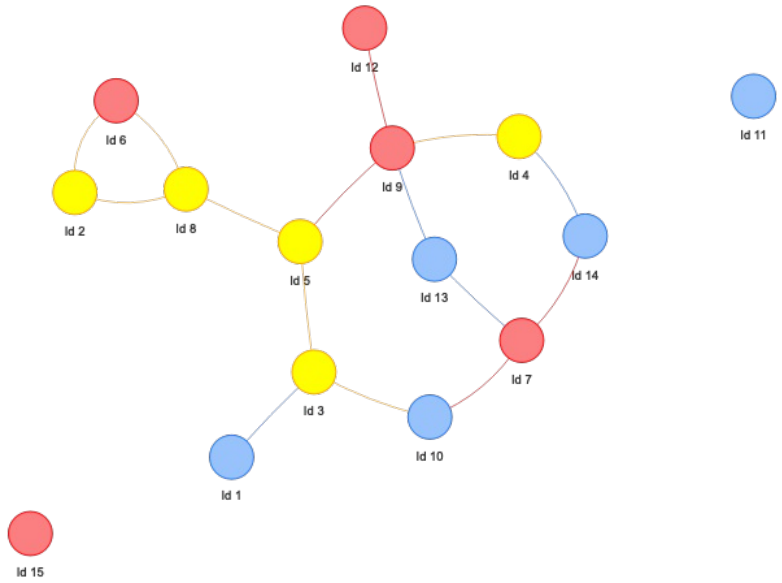
We consider the **iris** dataset. Build the following graph with `rAmCharts` and `plotly`.

1. Scatterplot `Sepal.Length` in term of `Sepal.Width`. Use different colors for each species.
2. Boxplot to visualize the distribution of `Petal.Length` for each species.

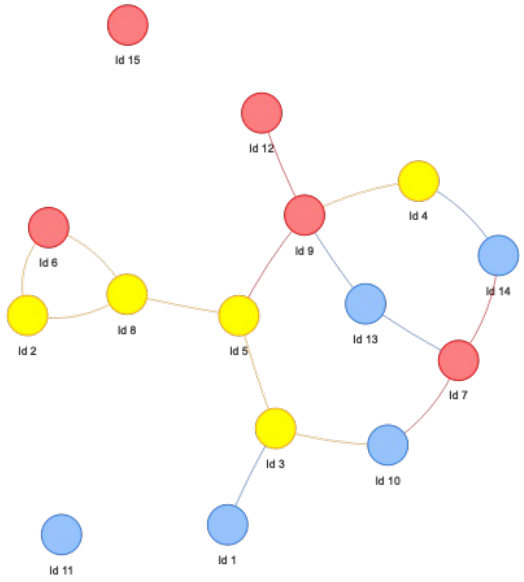
3.2 Graphs to visualize networks with visNetwork

Many datasets can be visualized with graphs, especially when one has to study connexions between individuals. In this case, each individual is represented by a **node** and we use **edges** for the connexions. igraph package proposes static representations for graph. For dynamic graphs, we can use visNetwork. To obtain dynamic graphs, we first hace to specify nodes and edges, for instance

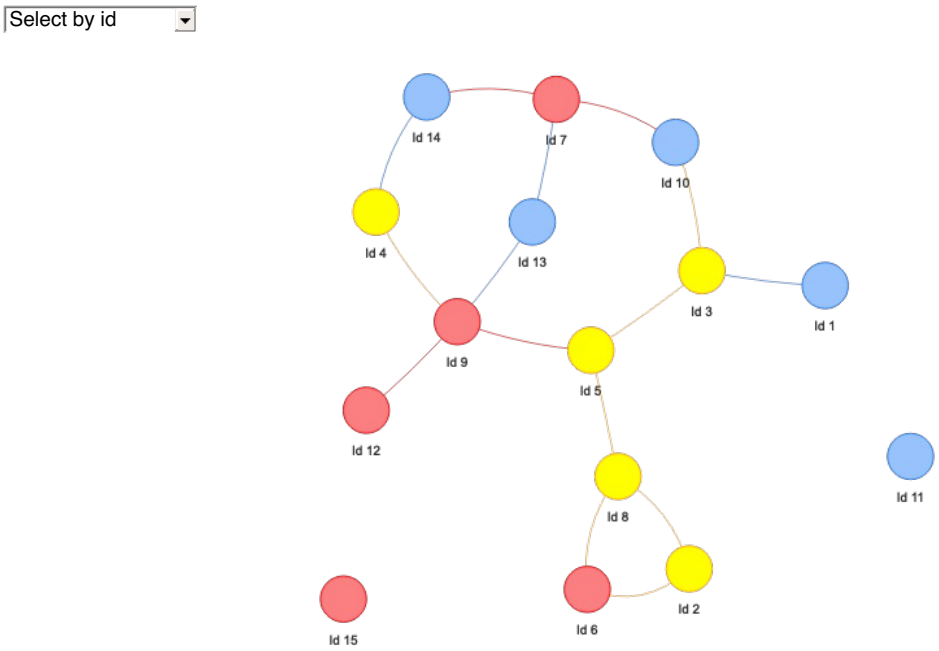
```
nodes <- data.frame(id = 1:15, label = paste("Id", 1:15),
                    group=sample(LETTERS[1:3], 15, replace = TRUE))
edges <- data.frame(from = trunc(runif(15)*(15-1))+1,to = trunc(runif(15)*(15-1))+1)
library(visNetwork)
visNetwork(nodes,edges)
```



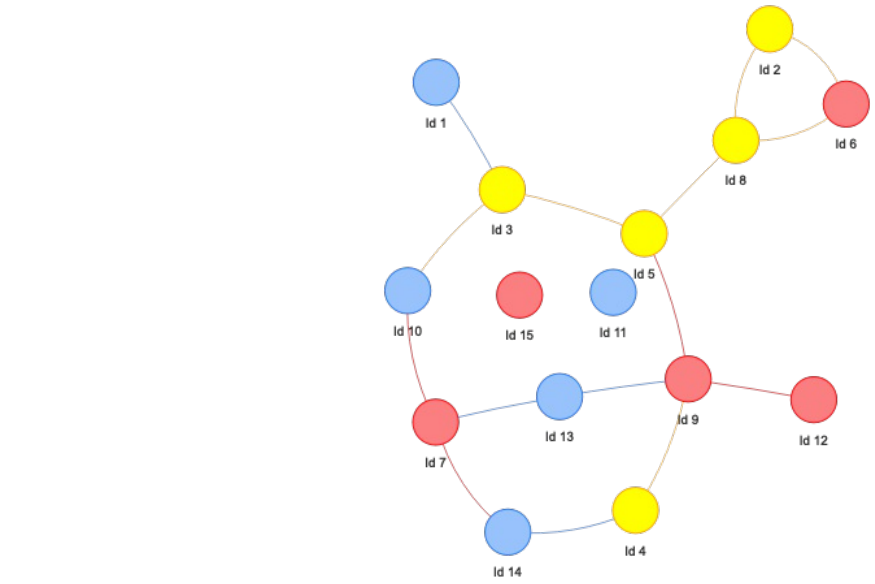

```
visNetwork(nodes, edges) %>% visOptions(highlightNearest = TRUE)
```




```
visNetwork(nodes, edges) %>% visOptions(highlightNearest = TRUE, nodesIdSelection = TRUE)
```




```
visNetwork(nodes, edges) %>% visOptions(selectedBy = "group")
```



Exercise 3.2 (Connexions between medias).

We consider a graph wich rrepresents connexions between medias. Data are available here. We can import them with

```
nodes <- read.csv("data/Dataset1-Media-Example-NODES.csv", header=T, as.is=T)
links <- read.csv("data/Dataset1-Media-Example-EDGES.csv", header=T, as.is=T)
head(nodes)
   id              media media.type type.label
1 s01          NY Times          1  Newspaper
2 s02    Washington Post          1  Newspaper
```

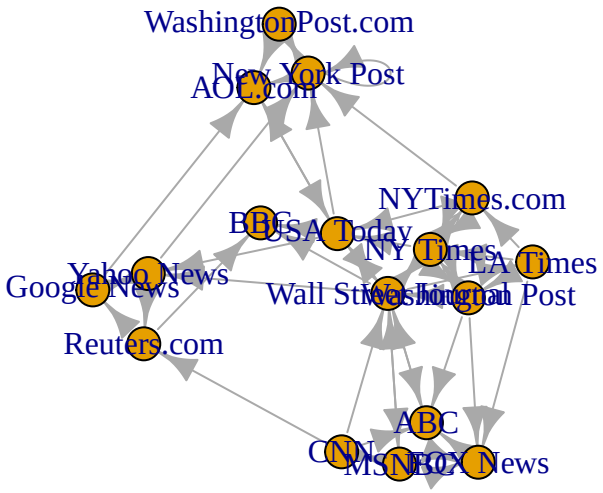
```
3 s03 Wall Street Journal          1  Newspaper
4 s04           USA Today          1  Newspaper
5 s05            LA Times          1  Newspaper
6 s06       New York Post          1  Newspaper
  audience.size
1            20
2            25
3            30
4            32
5            20
6            50
head(links)
  from  to weight      type
1  s01 s02     10 hyperlink
2  s01 s02     12 hyperlink
3  s01 s03     22 hyperlink
4  s01 s04     21 hyperlink
5  s04 s11     22   mention
6  s05 s15     21   mention
```

`nodes` objects représents the nodes (normal) while `links` is for the edges. We can obtain a **graph** object with

```
library(igraph)
media <- graph_from_data_frame(d=links, vertices=nodes, directed=T)
V(media)$name <- nodes$media
```

and we can visualize the (static) graph with a simple `plot` :

```
plot(media)
```



1. Visualize this graph with **VisNetwork**. **Hint** : use **toVisNetworkData**.
2. Add an option which allows to select the type of media (Newspaper, TV or Online).
3. Use different colors for each media.
4. Use arrows with different width in term of the variable **weight**. We can also add the option **visOptions(highlightNearest = TRUE)**.

3.3 Dashboard

Dashboards are very often used in datascience. It is a powerful tool to provide important messages in a dataset and/or a model. We can build dashboard in **R** with the package `flexdashboard`. The syntax is based on **Rmarkdown**, we don't have to learn new tools. We can find a very nice tutorial on this package at https://rmarkdown.rstudio.com/flexdashboard/. You can use this tutorial to make the following exercise.
Exercise 3.3 (A Dashboard for linear models)**.**

We consider the dataset `ozone.txt`. The goal is to explain the maximum daily ozone concentration (variable `maxO3`) by the other variables (information about temperatures, nebulosity, wind…). We wand to make a dashboard to

— visualize the data : the database and two or three graphs about the output variables (`maxO3`) ;
— visualize siple linear models : we choose one input and we obtain the scatterplot and the linear smoother ;
— visualize the full linear model : a summari of the models with some graphs about the residuals ;
— select the inputs in the linear models ;
— …

1. As a first step, we propose to write some simple functions for the dashboard.
   a. We only consider numeric variables. Visualize correlations between the variables with the `corrplot` function of the `corrplot` package.
   b. Draw the histogram of `maxO3` with **ggplot**, **rAmCharts** and **plotly** (use **ggplotly**).
   c. Fit the linear model with output `maxO3` (all the other variables as input). Calculate the Studentized residuals (**rstudent**) and visualize these residuals in term of `maxO3`. You can also add a linear smoother on the graph.
2. We can now start the dashboard. Use **File -> Rmarkdown -> From Template -> Flex Dashboard** dialog to open a script.
   a. Buil a first dashboard which allows to visualize
      — the dataset on a column (use **datatable** function from **DT** package) ;
      — the histogram of `maxO3` aand the correlation matrix on a second column.
   b. Add a second page to visualize simple linear models. We can select the input with **Shiny**, use

```
radioButtons("variable1",
                    label="Choisir la variable explicative",
                    choices=names(df)[-1],
                    selected=list("T9"))
```

      Don't forget to add

```
runtime: shiny
```

      in the header.
   c. Add a page to visualize the full linear model and the graph of residuals defined at question 1.c.
   d. Add a last page for selecting the inputs variables. Here again, you can use **shiny** commands, for instance

```
checkboxGroupInput("variable",
                    label="Choisir la variable",
                    choices=names(df)[-1],
                    selected=list("T9"))
```

      For the selected inputs, we will see in this pages the coefficients of the linear model and the Studentized residuals. The final dashboard may look like

It is available at https://lrouviere.shinyapps.io/dashboard/.