12 ggplot2 Visualizations in R

While R has become one of the world's leading languages for statistical and data analysis [1, ch.1], its plots are rarely of high-enough quality for publication (see previous chapter). Enter Hadley Wickam's ggplot2, an aesthetically pleasing and logical approach to data visualization based on the **layered grammar of graphics** (see Section 5.4). In this chapter, we introduce ggplot2's **basic elements**, and present some examples illustrating how it is used in practice.

12.1 Basics of ggplot2's Grammar

Four graphical systems are frequently used with R.

1. The base graphics system, written by R. Ihaka, is included in every R installation.[1]
2. The grid graphics system, written by Paul Murrell in 2011, is implemented through the grid package, which offers a lower-level alternative to the standard graphics system. The user can create arbitrary rectangular regions on graphics devices, define coordinate systems for each region, and use a rich set of drawing primitives to control the arrangement and appearance of graphic elements.[2]
3. The lattice package, written by D. Sarkar in 2008, implements trellis graphs, as outlined by W.S. Cleveland [122]. Basically, trellis graphs display the distribution of a variable or the relationship between variables, separately for each level of one or more other variables. Built using the grid package, the lattice package has grown beyond the original approach to visualizing multivariate data and now provides a comprehensive alternative system for creating statistical graphics in R.
4. Finally, the ggplot2 package, written by H. Wickham [123], provides a system for creating graphs based on the grammar of graphics described by L. Wilkinson [54] and expanded by Wickham [55]. The intention of the ggplot2 package is to provide a comprehensive, grammar-based system for generating graphs in a unified and coherent manner, allowing users to create new and innovative data visualizations. The power of this approach has led to ggplot2 becoming one of the most common R data visualization tool.

1: The graphs produced in Section 11, *Basic Visualizations in R*, rely on base graphics functions.

2: This flexibility makes grid a valuable tool for software developers. But the grid package doesn't provide functions for producing statistical graphics or complete plots. As a result, it is rarely used directly by data analysts and won't be discussed further (see Dr. Murrell's Grid website).

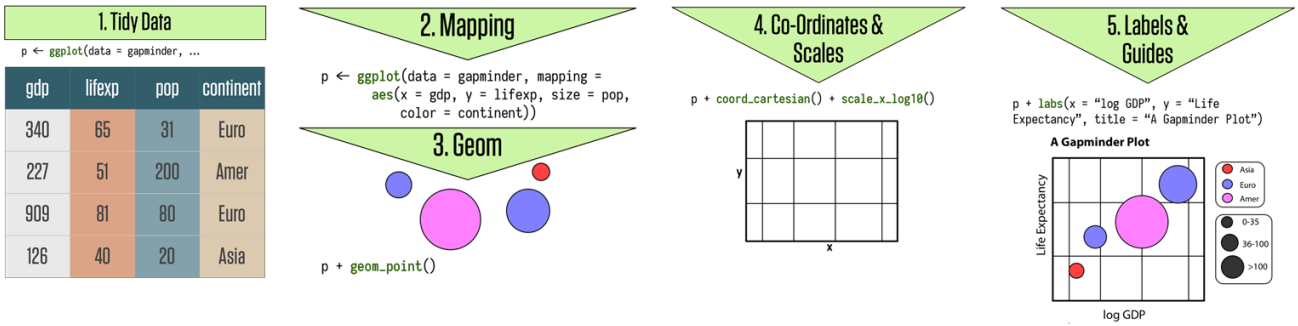


Figure 12.1: Schematics of the grammar of `ggplot2` graphics [124].

Access to the four systems differs: they are all included in the base installation, except for `ggplot2`, and they must all be explicitly loaded, except for the `base` graphics system.

As we saw previously, visualization involves representing data using various elements, such as lines, shapes, colours, etc.. There is a structured relationship – a **mapping** – between the variables in the data and their representation in the displayed plot. We also saw that not all mappings make sense for all types of variables, and (independently), that some representations are harder to interpret than others.

`ggplot2` provides a set of tools to map data to visual display elements and to specify the desired type of plot, and subsequently to control the fine details of how it will be displayed. Figure 12.1 shows a schematic outline of the process starting from data, at the top, down to a finished plot at the bottom.

The most important aspect of `ggplot2` is the way it can be used to think about the logical structure of the plot. The code allows the user to explicitly state the connections between the variables and the plot elements that are seen on the screen – items such as points, colors, and shapes.

Geometries and Aesthetics

In `ggplot2`, the logical connections between the data and the plot elements are called **aesthetic mappings**, or simply **aesthetics**, referred to as an `aes`. After installing and loading the package, a plot is created by telling the `ggplot()` function what the data is, and how the variables in this data logically map onto the plot's aesthetics.

The next step is to specify what sort of plot is desired (scatterplot, boxplot, bar chart, etc), also known as a `geom` (short for "plot **geom**etry"). Each `geom` is created by a specific function:

- `geom_point()` for scatterplots
- `geom_bar()` for barplots
- `geom_boxplot()` for boxplots,
- and so on.

These two components are combined, literally adding them together in an expression, using the "+" symbol. With these, `ggplot2` has enough information to draw a plot – the other components (see Figure 12.1) provide additional **design elements**.

If no further details are specified, `ggplot2` uses a set of **sensible default parameters**; usually, however, the user will want to be more specific about, say, the scales, the labels of legends and axes, and other guides that can improve the plot readability.

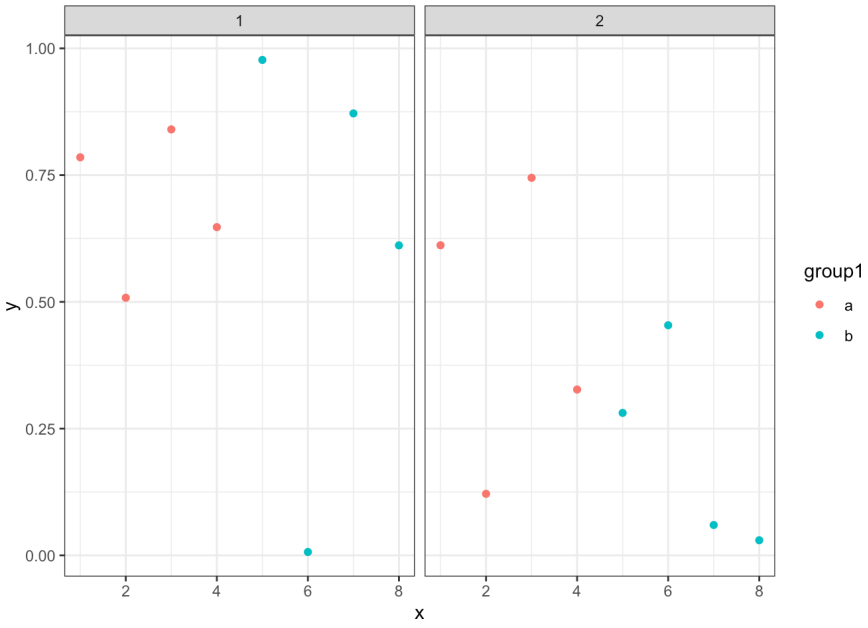
These additional pieces are added to the plot in the same manner as the `geom_function()` component, with specific arguments, again using the "+" symbol. Plots are built systematically in this manner, **piece by piece**.

Let's look at some illustrative `ggplot2` code:

```
library(ggplot2)
theme_set(theme_bw()) # built-in minimalist theme
```

We create an artificial dataset.

```
d <- data.frame(x = c(1:8, 1:8),
            y = runif(16),
            group1 = rep(gl(2, 4, labels = c("a", "b")), 2),
            group2 = gl(2, 8))
head(d)
ggplot(data=d) +
    geom_point(aes(x, y, colour = group1)) +
    facet_grid(~group2)
```



What is going on here? This basic display call contains the following elements:

- `ggplot()`: creates a plotting object and specifies the data;
- `geom_point()`: selects a scatter plot as the "geometry" (this is called a "geom" in `ggplot2` parlance);
- `aes()`: specifies the "aesthetic" chart elements – a legend is automatically created;
- `facet_grid()`: specifies the "faceting" or panel layout of the chart.

Other components include **statistics**, **scales**, and **annotation** options. At a bare minimum, charts require a **dataset**, some **aesthetics**, and a **geometry**, combined, as above, with "+" symbols.

This non-standard approach has the advantage of allowing `ggplot2` plots to be proper `R` objects, which can modified, inspected, and re-used (and they are compatible with the `tidyverse` and pipeline operations).

`ggplot2`'s main plotting functions are `qplot()` and `ggplot()`; `qplot()` is short for "quick plot" and is meant to mimic the format of base R's `plot()`; it requires less syntax for many common tasks, but has limitations – it's essentially a **wrapper** for `ggplot()`, which is not itself that complicated to use. We will focus on this latter function.

Types of `geoms`

Whereas `ggplot()` specifies the data source and variables to be plotted, the various `geom` functions specify how these variables are to be visually represented (using points, bars, lines, and shaded regions).

There are currently 35+ available geometries. The tables below list the more common ones, along with frequently used options (most of the graphs shown in this report can be created using those `geoms`).

Table 12.1: Common `ggplot2` geometries and options

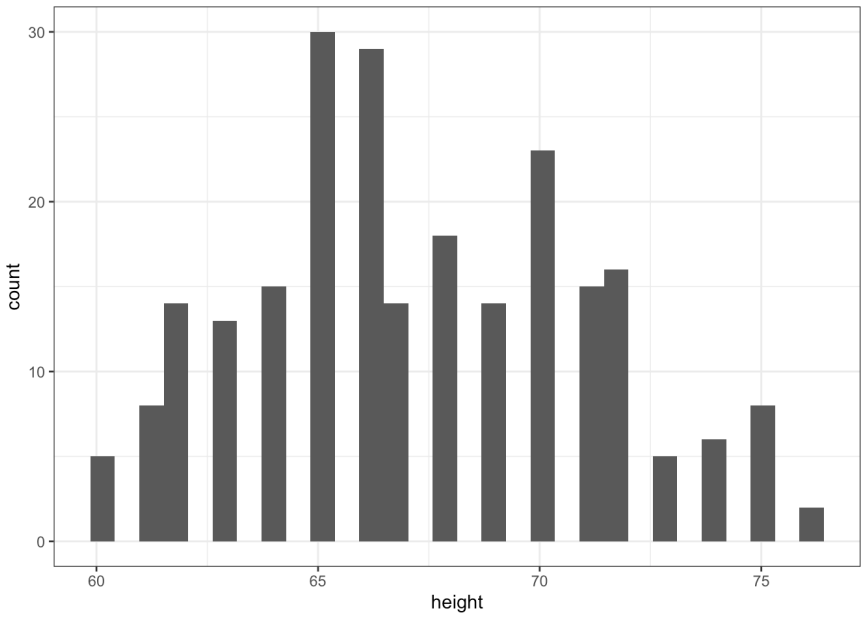
Function	Geometries	Options
`geom_bar()`	bar chart	`color`, `fill`, `alpha`
`geom_boxplot()`	boxplot	`color`, `fill`, `alpha`, `notch`, `width`
`geom_density()`	density plot	`color`, `fill`, `alpha`, `linetype`
`geom_histogram()`	histogram	`color`, `fill`, `alpha`, `linetype`, `binwidth`
`geom_hline()`	horizontal lines	`color`, `alpha`, `linetype`, `size`
`geom_line()`	jittered points	`color`, `size`, `alpha`, `shape`
`geom_jitter()`	line graph	`color`, `alpha`, `linetype`, `size`
`geom_point()`	scatterplot	`color`, `alpha`, shape, `size`
`geom_rug()`	rug plot	`color`, `side`
`geom_smooth()`	fitted line	`method`, `formula`, `color`, `fill`, `linetype`, `size`
`geom_text()`	text annotations	many; see the help for this function
`geom_violin()`	violin plot	`color`, `fill`, `alpha`, `linetype`
`geom_vline()`	vertical lines	`color`, `alpha`, `linetype`, `size`

Table 12.2: Common `ggplot2` geometries options

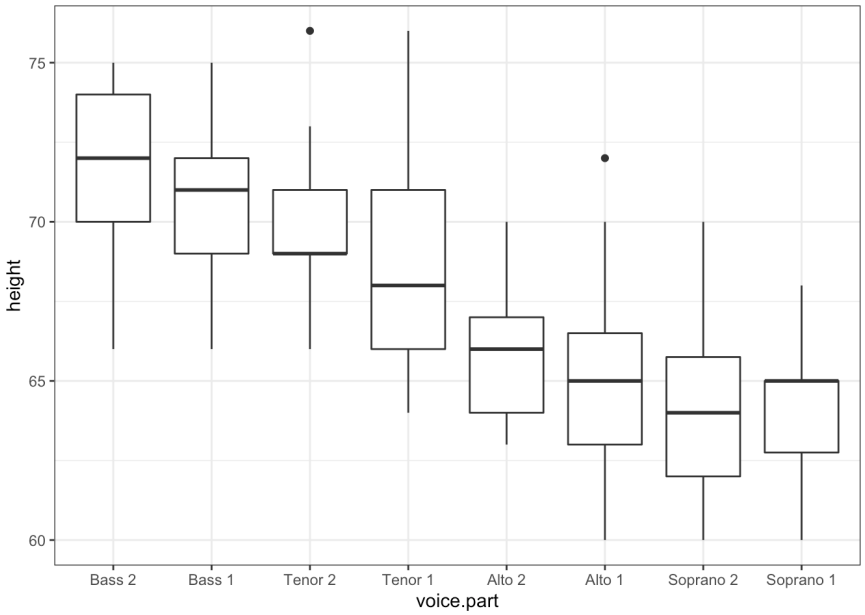
Option	Specifies
`color`	colour of points, lines, and borders around filled regions
`fill`	colour of filled areas such as bars and density regions
`alpha`	transparency of colors, ranging from 0 (fully transparent) to 1 (opaque)
`linetype`	pattern for lines (1 = solid, 2 = dashed, 3 = dotted, 4 = dotdash, 5 = longdash, 6 = twodash)
`size`	point size and line width
`shape`	point shapes (same as pch, with 0 = open square, 1 = open circle, 2 = open triangle, and so on)
`position`	position of plotted objects such as bars and points; for bars, `dodge` places grouped bar charts side by side, `stacked`, vertically stacks grouped bar charts, and `fill`, vertically stacks grouped bar charts and standardizes their heights to be equal; for points, `jitter` reduces point overlap
`binwidth`	bin width for histograms
`notch`	indicates whether boxplots should be notched (TRUE/FALSE)
`sides`	placement of rug plots on the graph (`b` = bottom, `l` = left, `t` = top, `r` = right, `bl` = both bottom and left, and so on)
`width`	width of boxplots

As an example, the next bit of code produces a histogram of the heights of singers in the 1979 edition of the New York Choral Society (Figure and a display of height by voice part for the same data.

```
library(ggplot2)
data(singer, package="lattice")
ggplot(singer, aes(x=height)) + geom_histogram()
```



```
ggplot(singer, aes(x=voice.part, y=height)) + geom_boxplot()
```



From the second of those (the boxplots), it appears that basses tend to be taller and sopranos tend to be shorter. Although the singers' gender was not recorded, it accounts for much of the variation seen in the diagram.

Note that only the `x` variable (height) was specified when creating the histogram, but that both the `x` (voice part) and the `y` (height) variables were specified for the boxplot – indeed, `geom_histogram()` defaults to counts on the $y-$axis when no `y` variable is specified.[3]

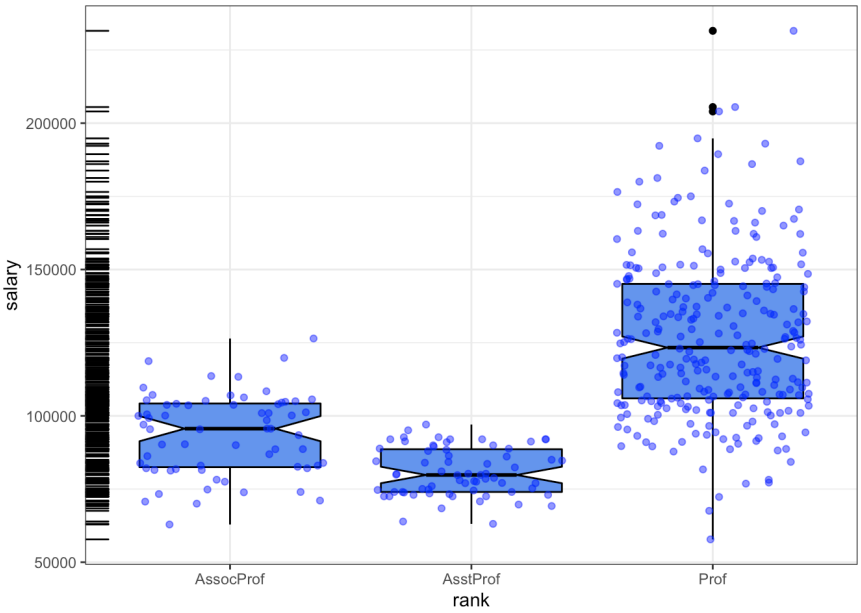
3: Each function's documentation contains details and additional examples, but there's a lot of value to be found in playing around with data in order to determine the function's behaviour.

We examine the use of some of these options using the `Salaries` dataset, which contains information regarding the salaries of university professors collected during the 2008–2009 academic year.

```
Salaries = read.csv("Salaries.csv", head=TRUE)
```

Variables include `rank` (AsstProf, AssocProf, Prof), `sex` (Female, Male), `yrs.since.phd` (obvious), `yrs.service` (ditto), and `salary` (nine-month salary in US dollars).

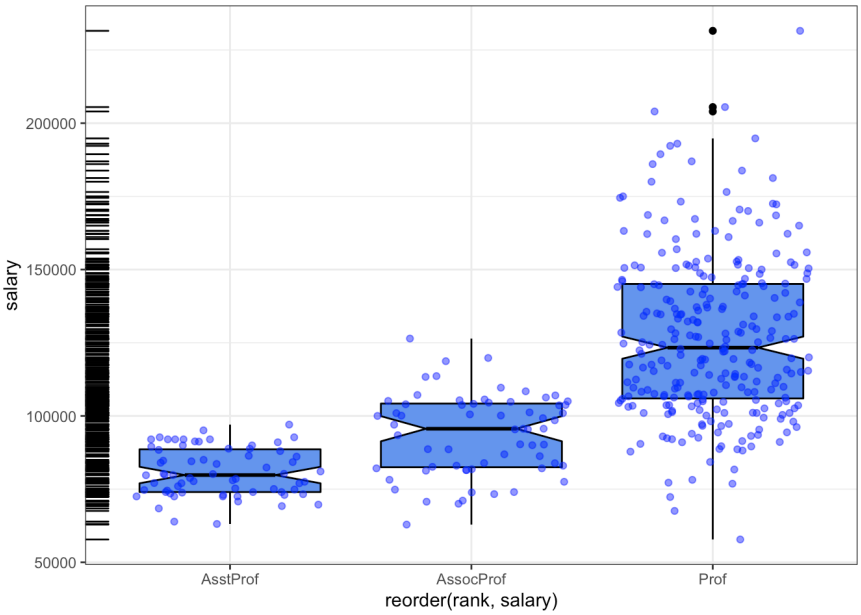
```
library(ggplot2)
ggplot(Salaries, aes(x=rank, y=salary)) +
       geom_boxplot(fill="cornflowerblue", color="black",
                    notch=TRUE) +
       geom_point(position="jitter", color="blue",
                  alpha=.5) +
       geom_rug(sides="l", color="black")
```



The `rank` is out of order;[4] as the salary usually increases with the rank, they can be re-ordered as follows:

4: The progression should run from assistant to associate to regular professor.

```
ggplot(Salaries, aes(x=reorder(rank, salary), y=salary)) +
       geom_boxplot(fill="cornflowerblue",color="black",
                    notch=TRUE) +
       geom_point(position="jitter", color="blue",
                  alpha=.5) +
       geom_rug(sides="l", color="black")
```



The chart displays notched boxplots of salary by academic rank. The actual observations (teachers) are **overlaid** and given some transparency so they don't obscure the boxplots.

They are also **jittered** to reduce their overlap. Finally, a rug plot is provided on the left to indicate the general spread of salaries. We see that the salaries of assistant, associate, and full professors differ significantly from each other (there is no overlap in the notches).

Additionally, the variance in salaries increases with greater rank, with a larger range of salaries for full professors. In fact, at least one full professor earns less than all assistant professors. There are also three full professors whose salaries are so large as to make them **outliers** (as indicated by the black dots in the boxplot to the right).

All in all, we have managed to extract a fair amount of insight from this dataset *via* a fairly simple chart (and a fairly simple `ggplot2` procedure).

More About aes

Aesthetics refer to the displayed attributes of the data. They map the data to an attribute (such as the size or shape of a marker) and generate an appropriate legend. Aesthetics are specified with the `aes()` function.

The aesthetics available for `geom_point()`, as an example, are:

- `x`
- `y`
- `alpha`
- `color`
- `fill`
- `shape`
- `size`

`ggplot()` tries to accommodate the user who has never "suffered" through base graphics before by using intuitive arguments like `color`, `size`, and `linetype`, but `ggplot()` also accepts arguments such as `col`, `cex`, and `lty`.

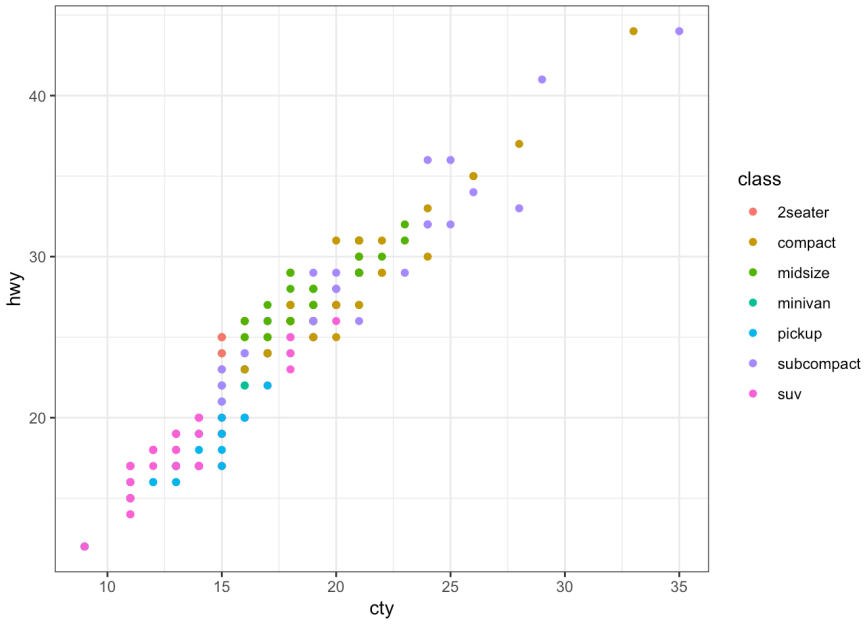
The `ggplot2` documentation explains what aesthetic options exist for each geom (they're generally self-explanatory).

Aesthetics can be specified within the data function or within a `geom`; if they're specified **within** the data function call then they apply to all specified `geoms` in the call.

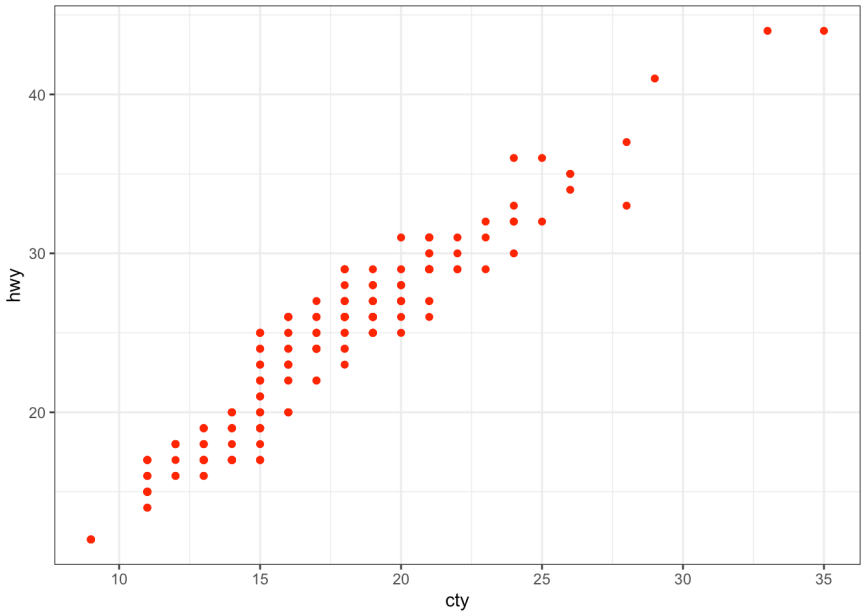
Note the important difference between specifying characteristics (like colour and shape) **inside** and **outside** the `aes()` function: those inside it are assigned characteristics **automatically**, based on the data. The characteristics defined outside the `aes()` function are **not mapped to the data**.

The following example, using the `mpg` dataset, illustrates the difference.

```
ggplot(mpg, aes(cty, hwy)) +
       geom_point(aes(colour = class))
```




```
ggplot(mpg, aes(cty, hwy)) +
       geom_point(colour = "red")
```



That is all there is to it! (well, not entirely, as we will see in the next section... but it's close enough).

12.2 ggplot2 Miscellenea

A few concepts will help take the basic ggplot2 charts to the next level.

Facets

In ggplot2, **small multiples**[5] are referred to as **facets**, implemented as:

- facet_wrap()
- facet_grid()

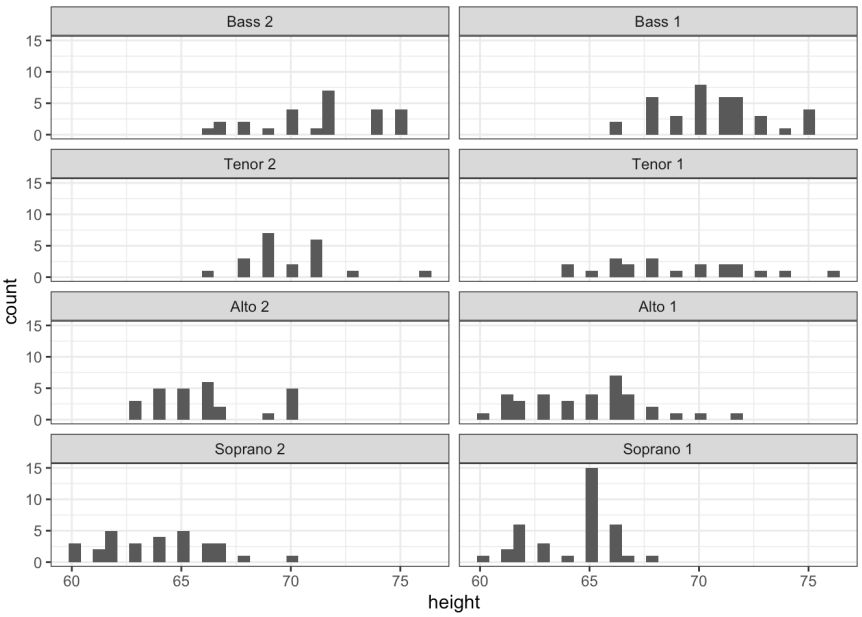
The former plots the panels in the order of the factor levels – when the end of a row is reached, the display wraps to the next one.[6] The grid layout facet_grid() produces a grid with explicit x and y positions; if there are no observations in some of the factor levels, it produces an **empty plot**.

By default, the panels all share the same x and y axes. Note, however, that the various $y-$axes are allowed to vary *via* facet_wrap(scales = "free_y"), and that all axes are allowed to vary *via* facet_wrap(scales = free).

To specify the data frame columns that are mapped to the rows and columns of the facets, separate them with a tilde. Usually, only a row or a column is fed to facet_wrap() (what happens if both are fed to that component?).

Going back to the choral example, a faceted graph can be produced using the following code:

```
data(singer, package="lattice")
library(ggplot2)
ggplot(data=singer, aes(x=height)) + geom_histogram() +
       facet_wrap(~voice.part, nrow=4)
```



5: The same chart, but plotted for various subsets of the data.

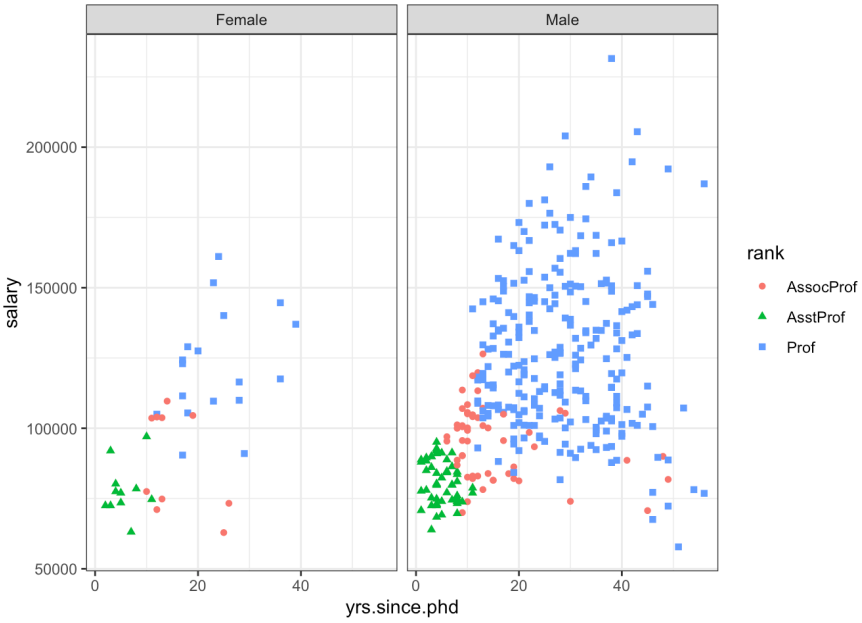
6: The number of columns and rows can be specified with nrow and ncol.

The resulting plot displays the distribution of singer heights by voice part; separating the height distribution into their own small, side-by-side plots makes them **easier to compare**.

As a second example, we re-visit the `Salaries` dataset – there is quite an interesting insight linking `salary`, `sex` and `yrs.since.phd`.[7]

7: We forego the `library(ggplot2)` call from this point on in the interest of readability.

```
ggplot(Salaries, aes(x=yrs.since.phd, y=salary, color=rank,
                     shape=rank)) +
       geom_point() + facet_grid(.~sex)
```



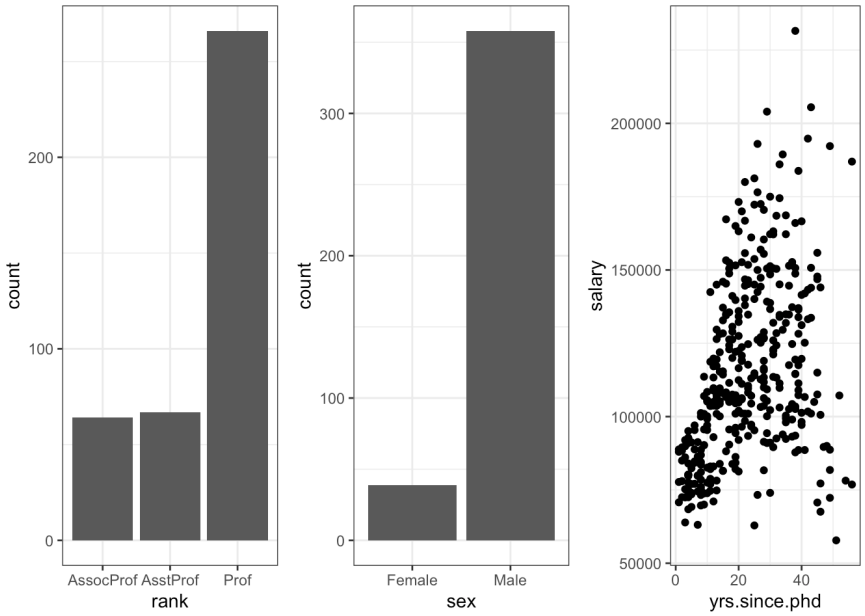
Multiple Graphs

In basic `R`, the graphic parameter `mfrow` and the base function `layout()` are used to combine two or more base graphs into a single plot. This approach will not work with plots created with the `ggplot2` package, however.

The easiest way to place multiple `ggplot2` graphs in a single figure is to use the `grid.arrange()` function found in the `gridExtra` package.

The following chunk of code places three `ggplot2` charts based on the `Salaries` dataset onto a single graph.

```
p1 <- ggplot(data=Salaries, aes(x=rank)) + geom_bar()
p2 <- ggplot(data=Salaries, aes(x=sex)) + geom_bar()
p3 <- ggplot(data=Salaries, aes(x=yrs.since.phd, y=salary)) +
        geom_point()

gridExtra::grid.arrange(p1, p2, p3, ncol=3)
```



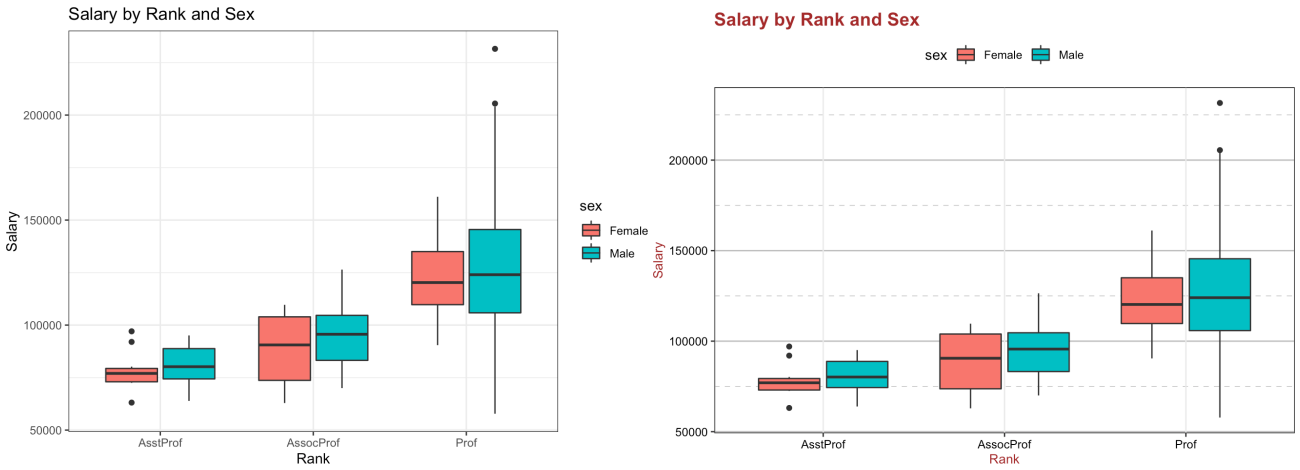
8: Note the difference between faceting and multiple graphs: faceting creates an array of plots based on one or more categorical variables, but the components of a multiple graph could be completely **independent** plots arranged into a single display.

Each graph is saved as an object and then arranged into a **single plot** *via* `grid.arrange()`.[8]

Themes

Themes allow the user to control the overall appearance of `ggplot2` charts; `theme()` options are used to change fonts, backgrounds, colours, gridlines, and more. They can be used once or saved and applied to multiple charts.

```
mytheme <- theme(plot.title=element_text(face="bold",
                  size=14, color="brown"),
    axis.title=element_text(size=10, color="brown"),
    axis.text=element_text(size=9, color="black"),
    panel.background=element_rect(fill="white",color="black"),
    panel.grid.major.y=element_line(color="grey",linetype=1),
    panel.grid.minor.y=element_line(color="grey",linetype=2),
    panel.grid.minor.x=element_blank(),legend.position="top")

ggplot(Salaries, aes(x=reorder(rank,salary), y=salary,
                     fill=sex)) +
    geom_boxplot() +
    labs(title="Salary by Rank and Sex",x="Rank",y="Salary")

ggplot(Salaries, aes(x=reorder(rank,salary), y=salary,
                     fill=sex)) +
  geom_boxplot() +
  labs(title="Salary by Rank and Sex",x="Rank",y="Salary") +
  mytheme
```



Adding `+ mytheme` to the plotting statement generates the second graph:

- plot titles are printed in brown 14-point bold;
- axis titles in brown 10pt;
- axis labels in black 9pt;
- the plot area should have a white fill and black borders;
- major horizontal grids should be solid grey lines;
- minor horizontal grids should be dashed grey lines;
- vertical grids should be suppressed, and
- the legend should appear at the top of the graph.

The `theme()` function allows great control over the look of the finished product (consult `help(theme)` to learn more about these options).

Tidy Data

`ggplot2` is compatible with the **`tidyverse`** [125]. Social scientists will likely be familiar with the distinction between **wide data** and **long data**:

- in a **long** format table,[9] every column represents a different (conceptual) variables, and every row represents an observation,
- in a **wide** format table, some variables are spread out across multiple columns, perhaps along some other characteristic such as the year, say.

9: Also called a "tall" dataset.

Consider, for instance, the `WorldPhones` dataset, one of `R`'s built-in dataset:

Year	N.Amer	Europe	Asia	S.Amer	Oceania	Africa	Mid.Amer
1951	45939	21574	2876	1815	1646	89	555
1956	60423	29990	4708	2568	2366	1411	733
1957	64721	32510	5230	2695	2526	1546	773
1958	68484	35218	6662	2845	2691	1663	836
1959	71799	37598	6856	3000	2868	1769	911
1960	76036	40341	8220	3145	3054	1905	1008
1961	79831	43173	9053	3338	3224	2005	1076

This dataset records the number of telephones, in thousands, on each continent for several years in the 1950s and 1960s. Each column represents a different continent, and each row represents a different year.

This **wide** format seems like a reasonable way to store data, but suppose that we want to compare increases in phone usage between continents, with time on the horizontal axis. In that case, each point on the plot is going to represent a continent during one year – there are seven observations in each row, which makes it difficult to plot using `ggplot2`.

Fortunately, the `tidyverse` provides an easy way to convert this wide dataset into a **long** dataset, by **melting** the data. This can be achieved by loading the third-party package called *reshape2*.[10] The `WorldPhones` dataset can now be melted from a wide to a long dataset *via* the `melt()` function. Let's assign the new melted data to an object called `WorldPhones.m`.[11]

10: Note that this is not the only way to do so, see [1, sec 1.4].

11: Where the `m` reminds us that the data has been melted.

```
WorldPhones.m = reshape2::melt(WorldPhones)
str(WorldPhones.m)
head(WorldPhones.m)
```

```
'data.frame':   49 obs. of  3 variables:
 $ Var1 : int  1951 1956 1957 1958 1959 1960 1961 1951 1956 1957 ...
 $ Var2 : Factor w/ 7 levels "N.Amer","Europe",..: 1 1 1 1 1 1 1 2 2 2 ...
 $ value: num  45939 60423 64721 68484 71799 ...

  Var1   Var2 value
1 1951 N.Amer 45939
2 1956 N.Amer 60423
3 1957 N.Amer 64721
4 1958 N.Amer 68484
5 1959 N.Amer 71799
6 1960 N.Amer 76036
```

Note that while there were originally 7 columns, there are now only 3:

- `Var1` represents the year;
- `Var2` the continent, and
- `value` the number of phones.

Every data cell – every observation – every number of phones per year per continent – in the original dataset now has its own row in the melted dataset.

In 1951, in North America, for instance, there were 45,939,000 phones, which is the same value as in the original unmelted data – the data has not changed, it has just been **reshaped**.

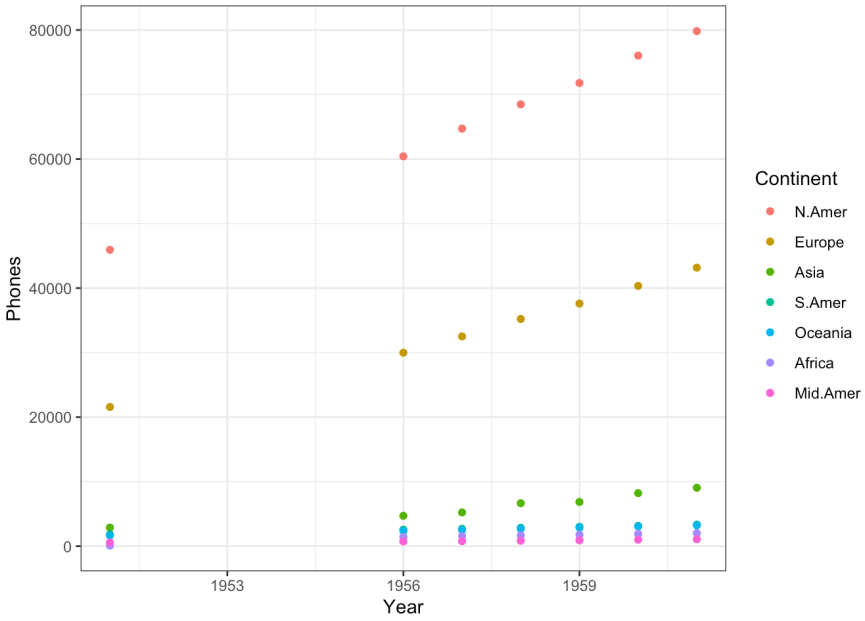
Changing the column names might make the data more intuitive to read:

```
colnames(WorldPhones.m) = c("Year", "Continent", "Phones")
head(WorldPhones.m)
```

```
  Year Continent Phones
1 1951    N.Amer  45939
2 1956    N.Amer  60423
3 1957    N.Amer  64721
4 1958    N.Amer  68484
5 1959    N.Amer  71799
6 1960    N.Amer  76036
```

Now that the data has been melted into a long dataset, it is easy to create a plot with `ggplot2`, with the usual steps of a `ggplot()` call, but with `WorldPhones.m` instead of `WorldPhones`:

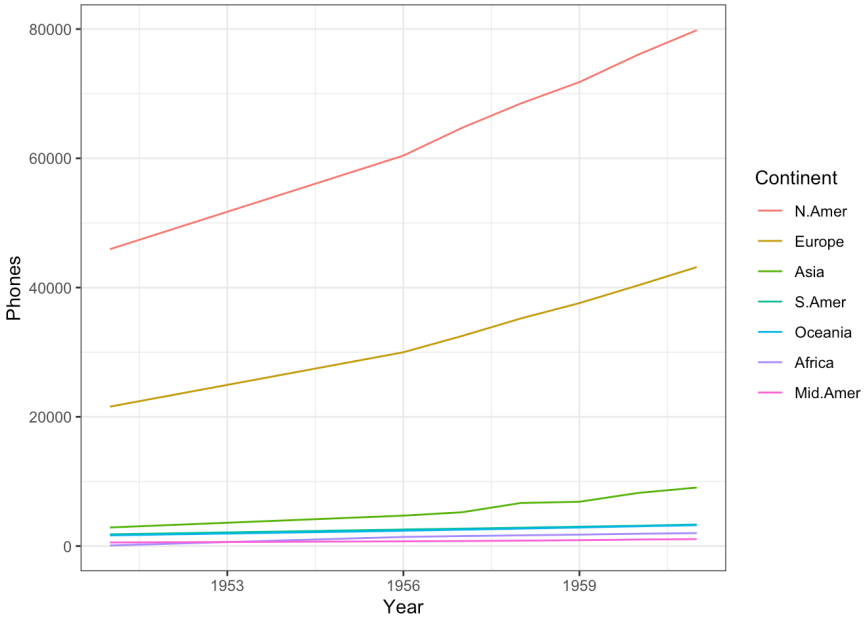
```
ggplot(WorldPhones.m, aes(x=Year, y=Phones,
                          color=Continent)) +
       geom_point()
```



We place `Year` on the $x-$axis, in order to see how the numbers change over time, while `Phones` (the variable of interest) is displayed on the $y-$axis. The `Continent` factor is represented with colour. A scatterplot is obtained by adding a `geom_point()` layer.

We can also show trends over time, by drawing lines between points for each continent. This only require a change to `geom_line()`.

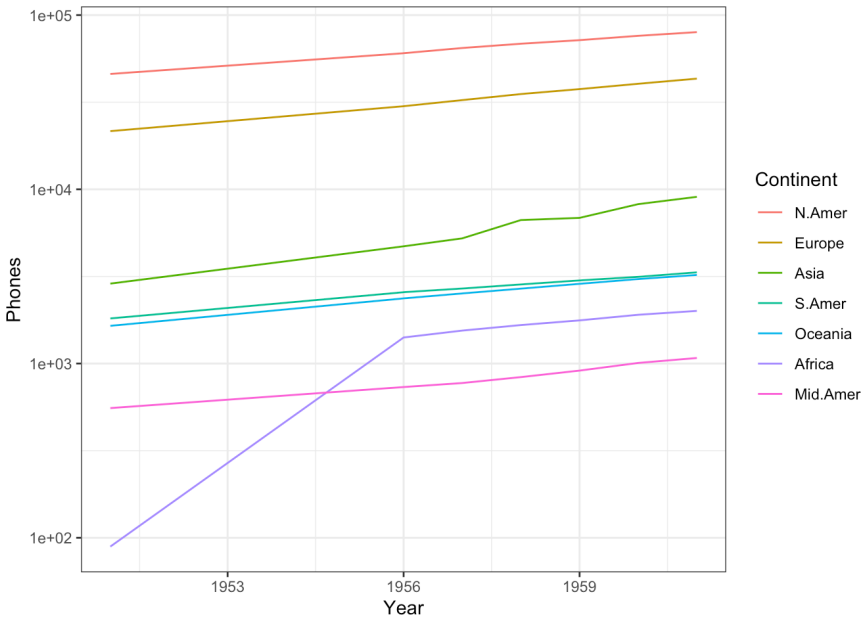
```
ggplot(WorldPhones.m, aes(x=Year, y=Phones,
                          color=Continent)) +
       geom_line()
```



Incidentally, one might expect the number of phones to increase exponentially over time, rather than linearly.[12] When that is the case, it can be a good idea to plot the vertical axis on a **logarithmic scale**.

12: A fair number of observations are clustered at the bottom of the chart.

```
ggplot(WorldPhones.m, aes(x=Year, y=Phones,
                          color=Continent)) +
       geom_line() + scale_y_log10()
```



Most of the phone trends still look linear, and the lower values are spotted more easily; for example, it is now clear that Africa has overtaken Central America by 1956.

Note how easy it was to build this plot once the data was in the long format: one row for every point – that is, every combination of year and continent – on the graph.

Saving Graphs

Plots might look great on the screen, but they typically have to be embedded in other documents (Markdown, LaTeX, Word, etc.). They must first be saved in an appropriate format, with a specific resolution and size.

Default size settings can be saved within a `.Rmd` document by declaring them in the first chunk of code:

```
knitr::opts_chunk$set(fig.width=8, fig.height=5)
```

would tell `knitr` to produce 8 in. $\times$ 5 in. charts.

Saving charts is quite convenient with `ggsave()`: options include which plot to save, where to save it, and in what format. For instance,

```
myplot <- ggplot(data=mtcars, aes(x=mpg)) + geom_histogram()
ggsave(file="mygraph.png", plot=myplot, width=5, height=4)
```

saves the `myplot` object as a 5-inch by 4-inch `.png` file named `mygraph.png` in the current working directory. The available formats include `.ps`, `.tex`, `.jpeg`, `.pdf`, `.jpg`, `.tiff`, `.png`, `.bmp`, `.svg`, or `.wmf` (the latter only being available on Windows machines).

Without the `plot=` option, the most recently created graph is saved. For instance, the following code would save the `mtcars` plot (the last plot before the call) to the current working directory (see the `ggsave()` helf file for additional details):

```
ggplot(data=mtcars, aes(x=mpg)) + geom_histogram()
ggsave(file="mygraph.pdf")
```

Summary

While `ggplot2` and the `tidyverse` have proven popular and user-friendly, they do come with some drawbacks, however: the `ggplot2` and *tidyverse* design teams have fairly strong opinions about how data should be visualized and processed. As a result, it can sometimes be difficult to produce charts that go against their design ideals.

In the same vein, some package updates have been known not to **preserve the functionality** of working code, sending the analysts scurrying to figure how the new functions work, which can cause problems with legacy code.[13] Still, the **versatility** and overall **simplicity** of `ggplot2` cannot be overstated.

13: Although that can prove fairly annoying, it is a really good idea for analysts to maintain and update their code regularly.

The definitive `ggplot2` reference is Wickham, Navarro, and Lin Pedersen's ggplot2: Elegant Graphics for Data Analysis [123]; it contains explanations and examples (some of which we borrowed from), as well as the underlying theory behind `ggplot2`. Other useful examples and starting points can also be found in [124, 126].

The `ggplot2` action flow is always the same: start with data in a table, map the display variables to various **aesthetics** (position, colour, shape, etc.), and select one or more **geometries** to draw the graph. This is accomplished in the code by first creating an object with the basic data and mappings information, and then by adding or layering additional information as needed.

Once this general way of thinking about plots is understood (especially the aesthetic mapping part), the drawing process is simplified significantly. There is no need to think about how to draw particular shapes or colours in the chart; the many (self-explanatory) `geom_` functions do all the heavy lifting.

Similarly, learning how to use new `geoms` is easier when they are viewed as ways to display specific aesthetic mappings.

12.3 Examples

In this section, we provide a copious number of examples; some of them also highlight various aspects of `ggplot2` that we did not touch upon in the preceding explanations.

The vast majority of these examples have been modified from already existing references; we have strived to cite the references when the required information was still extent.[14]

14: Please contact us if you discover missing or mis-attributed references.

Algae Bloom Data

This example is adapted off of L. Torgo's excellent Data Mining with R Learning with Case Studies, Second Edition [31].[15]

15: We explored one of its subsets in Section 2.1.

The ability to monitor and perform early forecasts of various river algae blooms is crucial to control the ecological harm they can cause.

The dataset which is used to train the learning model consists of:

- chemical properties of various water samples of European rivers
- the quantity of seven algae in each of the samples, and
- the characteristics of the collection process for each sample.

It is available in the `algae_blooms.csv` file, or in Torgo's `DMwR` package.[16]

16: Which was not available from CRAN anymore as of publication.

```
algae_blooms<-read.csv("algae_blooms.csv",sep=",",header=TRUE)
```

We get a sense for the data's structure by calling the `str()` function.[17]

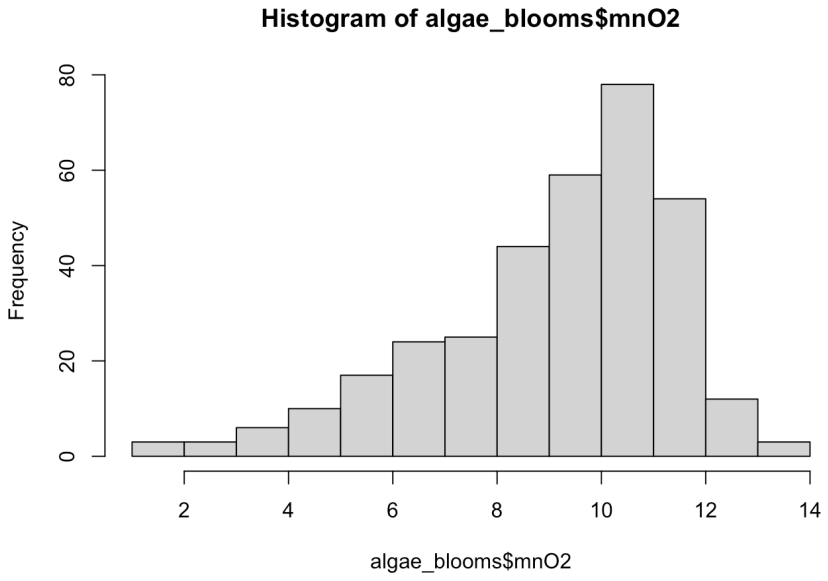
17: Evidently, `algae_blooms` is a data frame with 340 observations of 18 variables each.

```
str(algae_blooms)
```

```
'data.frame':   340 obs. of  18 variables:
 $ season: chr  "winter" "spring" "autumn" "spring" ...
 $ size  : chr  "small" "small" "small" "small" ...
 $ speed : chr  "medium" "medium" "medium" "medium" ...
 $ mxPH  : num  8 8.35 8.1 8.07 8.06 8.25 8.15 8.05 8.7 7.93 ...
 $ mnO2  : num  9.8 8 11.4 4.8 9 13.1 10.3 10.6 3.4 9.9 ...
 $ Cl    : num  60.8 57.8 40 77.4 55.4 ...
 $ NO3   : num  6.24 1.29 5.33 2.3 10.42 ...
 $ NH4   : num  578 370 346.7 98.2 233.7 ...
 $ oPO4  : num  105 428.8 125.7 61.2 58.2 ...
 $ PO4   : num  170 558.8 187.1 138.7 97.6 ...
 $ Chla  : num  50 1.3 15.6 1.4 10.5 ...
 $ a1    : num  0 1.4 3.3 3.1 9.2 15.1 2.4 18.2 25.4 17 ...
 $ a2    : num  0 7.6 53.6 41 2.9 14.6 1.2 1.6 5.4 0 ...
 $ a3    : num  0 4.8 1.9 18.9 7.5 1.4 3.2 0 2.5 0 ...
 $ a4    : num  0 1.9 0 0 0 0 3.9 0 0 2.9 ...
 $ a5    : num  34.2 6.7 0 1.4 7.5 22.5 5.8 5.5 0 0 ...
 $ a6    : num  8.3 0 0 0 4.1 12.6 6.8 8.7 0 0 ...
 $ a7    : num  0 2.1 9.7 1.4 1 2.9 0 0 0 1.7 ...
```

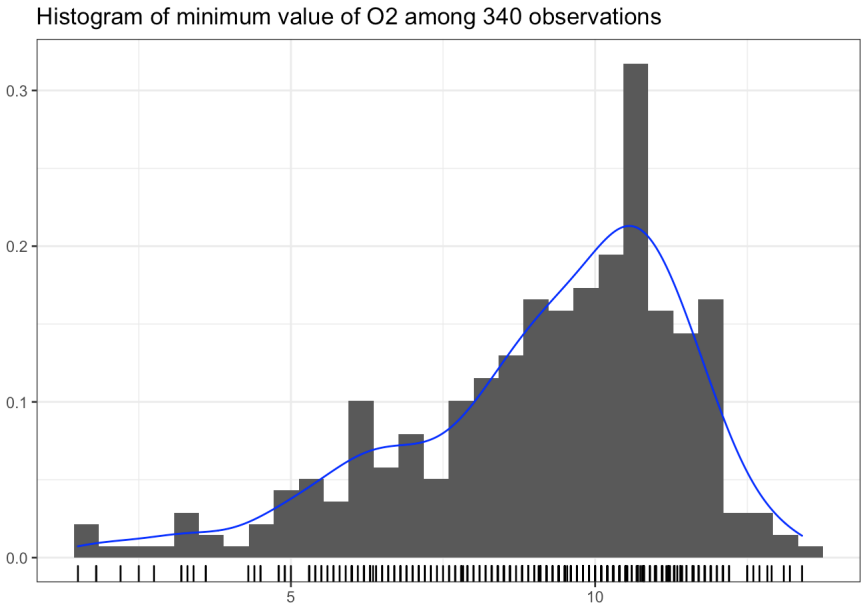
We have seen that basic histograms can be constructed with the `hist()` function. For instance, the histogram of `mnO2` measurements is:

```
hist(algae_blooms$mnO2)
```



Let's spruce up this histogram with `ggplot2`.

```
library(ggplot2)
ggplot(algae_blooms,aes(x=mnO2)) +
    geom_histogram(aes(y=..density..)) +
    geom_density(color="blue") +
    geom_rug() +
    ggtitle("Histogram of mnO2 among 340 observations") +
    xlab("") +
    ylab("")
```

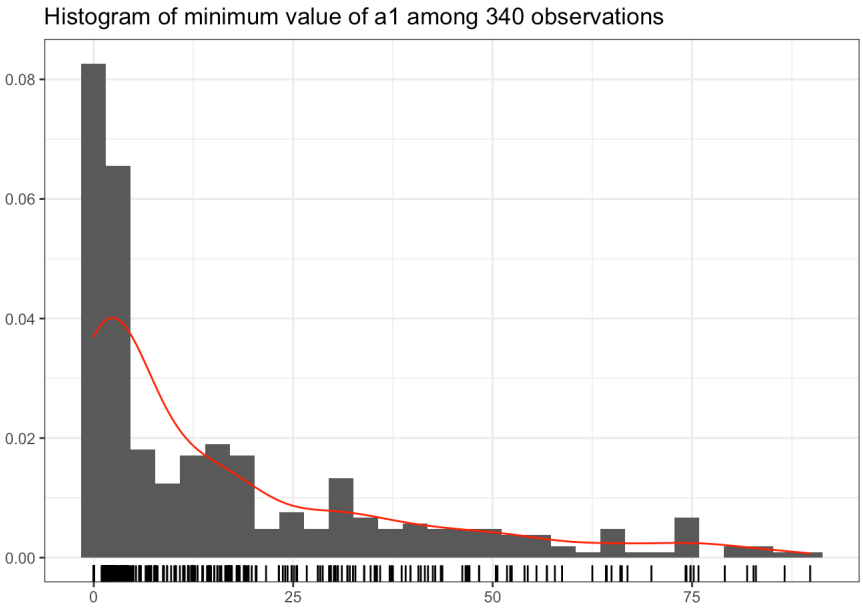


In a nutshell, the code above:

- plots `mnO2` from the `algae_blooms` dataset ...
- as a histogram, where the vertical axis is the density ...
- on which will be layered a blue density curve ...
- and a rug (or comb) chart showing where the observations actually fall...
- with a title ...
- no x axis label ...
- and no y axis label.

We can do the same for `a1`.

```
ggplot(algae_blooms,aes(x=a1)) +
    geom_histogram(aes(y=..density..)) +
    geom_density(color="red") +
    geom_rug() +
    ggtitle("Histogram of a1 among 340 observations") +
    xlab("") + ylab("")
```

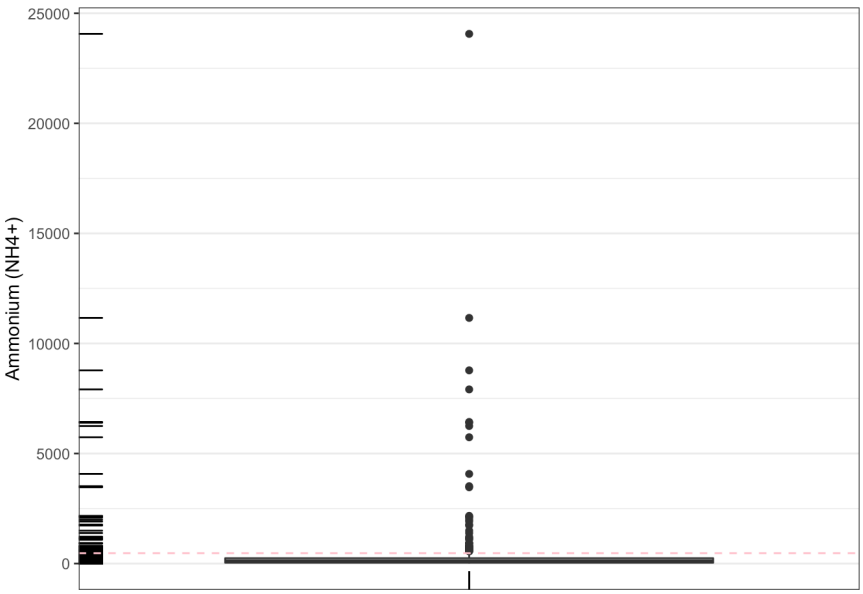


Due to the pronounced skew in both instances, we see that the normal distribution is not a good fit for either of `mn02` or `a1`.

Now let's take a look at some plots involving `NH4`.[18]

18: We plot `NH4` from the `algae_blooms`, as a boxplot with a rug on which the true values are shown and a horizontal line showing where the mean value of `NH4` falls.

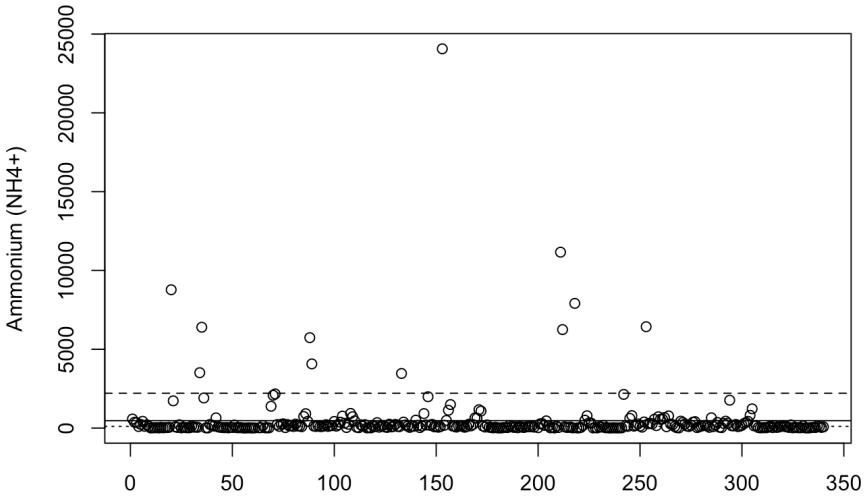
```
ggplot(algae_blooms,aes(x=factor(0),y=NH4)) +
    geom_boxplot() +
    geom_rug() +
    geom_hline(aes(yintercept=mean(algae_blooms$NH4,
           na.rm=TRUE)), linetype=2, colour="pink") +
    ylab("Ammonium (NH4+)") +
    xlab("") +
    scale_x_discrete(breaks=NULL)
```



We can't really see the structure because of the suspected outliers.

Let us take a look at the distribution from another angle: we display the scatter plot of NH4 against the observation number, add a **solid line** at the mean value of NH4, a dashed line at the mean + sd value of NH4, and a tight dashed line at the median value of NH4.

```
plot(algae_blooms$NH4, xlab="", ylab="Ammonium (NH4+)")
abline(h=mean(algae_blooms$NH4, na.rm=TRUE), lty=1)
abline(h=mean(algae_blooms$NH4, na.rm=TRUE) +
          sd(algae_blooms$NH4, na.rm=TRUE), lty=2)
abline(h=median(algae_blooms$NH4, na.rm=TRUE), lty=3)
```

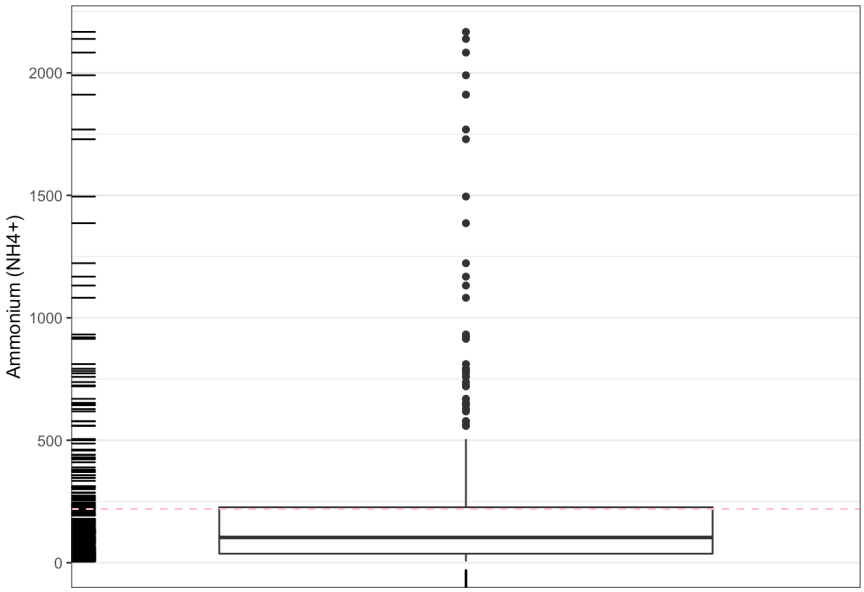


Only a small number of values find themselves above the 3000 threshold – might these be **outliers**?

If we want to only keep the observations that have values of NH4 below 3000 (roughly all values below the long dashed line above), we obtain the following boxplot.[19]

19: Whether this is actually a good strategy or not is a discussion for another time.

```
ggplot(algae_blooms[-which(algae_blooms$NH4>3000),],
       aes(x=factor(0),y=NH4)) +
    geom_boxplot() +
    geom_rug() +
    geom_hline(aes(yintercept = mean(algae_blooms[
        -which(algae_blooms$NH4>3000),8],
         na.rm=TRUE)), linetype=2, colour="pink") +
    ylab("Ammonium (NH4+)") +
    xlab("") +
    scale_x_discrete(breaks=NULL)
```

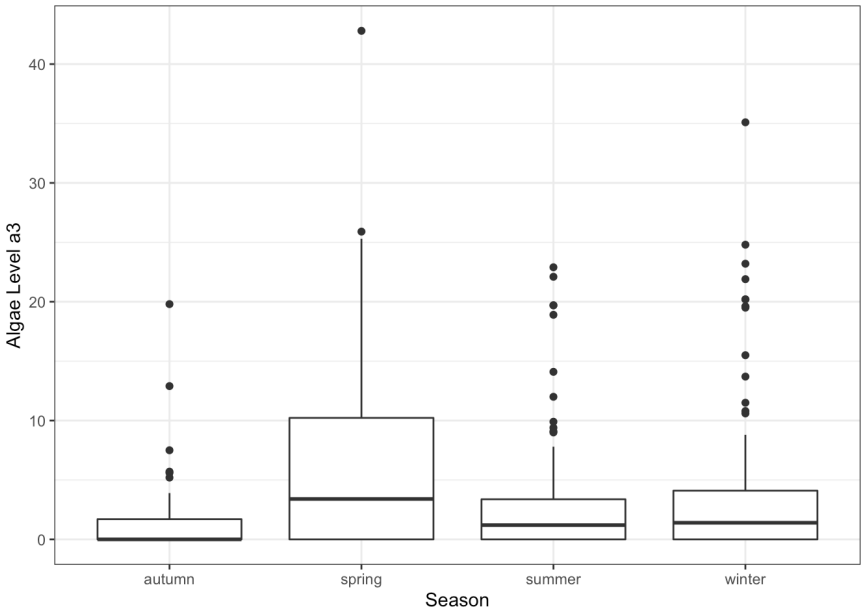


It is a bit better than the previous boxplot, to be sure (the box structure has expanded, at the very least), but there still seems to be a few outlying.[20]

20: Perhaps that is to be expected? How could we find out? [1]

Now we take a look at some of the algae levels: we plot `a3` by `season` in a series of boxplots.

```
ggplot(algae_blooms,aes(x=season,y=a3)) +
    geom_boxplot() +
    xlab("Season") +
    ylab("Algae Level a3")
```



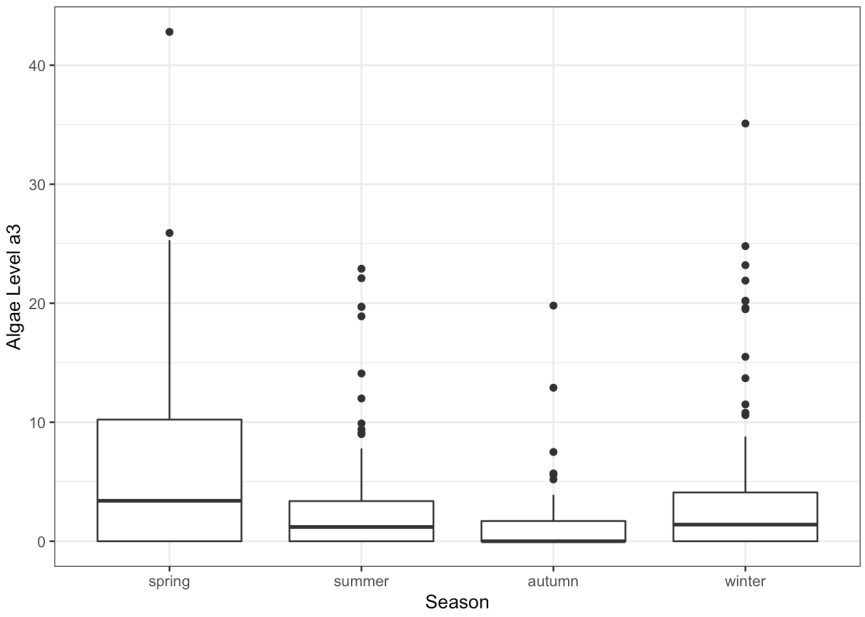
We can re-arrange the factors' order, but it requires a bit of fancy footwork using the `forcats`'library `fct_relevel()` function, and `dplyr`'s `mutate()`.

```
library(forcats)
library(dplyr)
algae_blooms = mutate(algae_blooms,
        # factors should appear in the desired order
        size=fct_relevel(size,c("small","medium","large")),
        speed=fct_relevel(speed,c("low","medium","high")),
        season=fct_relevel(season,c("spring","summer",
                                    "autumn","winter")))
```

Note the difference:[21]

21: A cyclic seasonal pattern is evident.

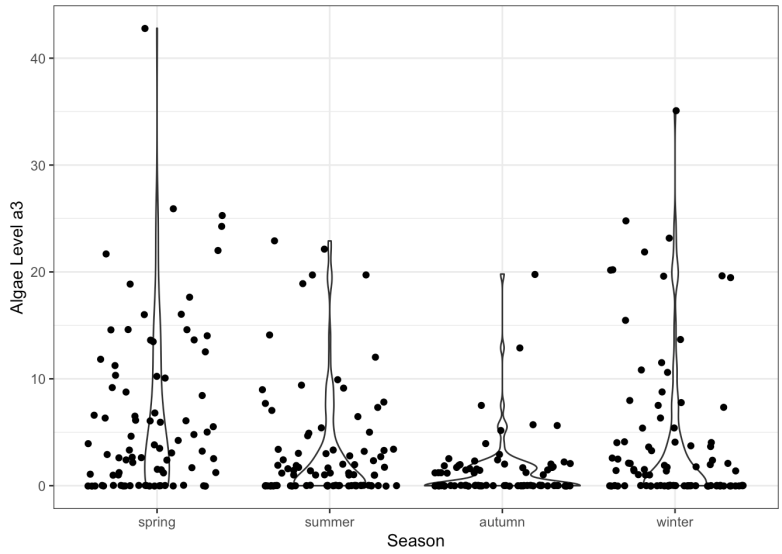
```
ggplot(algae_blooms,aes(x=season,y=a3)) +
    geom_boxplot() +
    xlab("Season") +
    ylab("Algae Level a3")
```



Violin plots are cousins of boxplots. Can we use them to get a bit more insight on the `a3` trend, say?[22]

22: What happens if the `jitter` option is turned off?

```
ggplot(algae_blooms,aes(x=season,y=a3)) +
    geom_violin() +
    geom_jitter() +
    xlab("Season") +
    ylab("Algae Level a3")
```



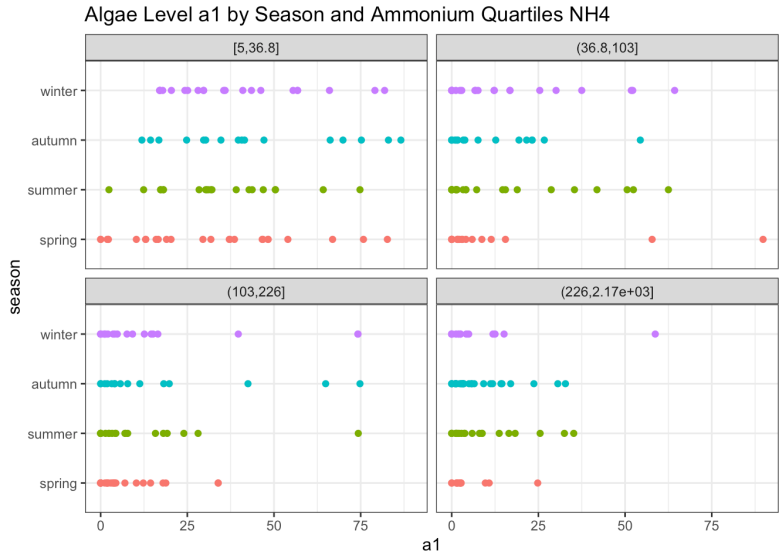
We can now take a look at possible interactions for `NH4`< 3000 and `season`, binning the observations with respect to the **quartiles**.[23]

23: We use the `dplyr` **pipeline operator** `|>` (sometimes written as `%>%`; see [1, sec1.4]).

```
library(dplyr)
f.NH4.data <- filter(algae_blooms,!is.na(NH4)) |>
    filter(NH4<3000) |>  mutate(q.NH4=cut(NH4,quantile(NH4,
           c(0,0.25,0.5,0.75,1)), include.lowest=TRUE))
```

The faceted chart is shown below – is there anything of interest in the chart?

```
ggplot(f.NH4.data,aes(x=a1,y=season,color=season)) +
    geom_point() + facet_wrap(~q.NH4) + guides(color=FALSE) +
    ggtitle("Algae Level a1 by Season and NH4 Quartiles")
```



Gapminder Chart

The `Gapminder` dataset is available in R. Irizarry's `dslabs` package. We'll show how to produce a chart such as the one in Figure 1.4.

```
gapminder_ds <- dslabs::gapminder # for the dataset
library(tidyverse)    # to access ggplot2 and dplyr
library(wesanderson)  # for the colour palette
library(ggrepel)      # for country names on chart
```

We start by getting a summary of the available data in the `dslabs` package, in particular the available years.

```
summary(gapminder_ds)
```

```
  country           year          infant_mortality life_expectancy
Albania   :   57   Min.   :1960   Min.   :  1.50   Min.   :13.20
Algeria   :   57   1st Qu.:1974   1st Qu.: 16.00   1st Qu.:57.50
Angola    :   57   Median :1988   Median : 41.50   Median :67.54
Antigua   :   57   Mean   :1988   Mean   : 55.31   Mean   :64.81
Argentina :   57   3rd Qu.:2002   3rd Qu.: 85.10   3rd Qu.:73.00
Armenia   :   57   Max.   :2016   Max.   :276.90   Max.   :83.90
(Other)   :10203                  NA's   :1453

  fertility       population             gdp               continent
Min.   :0.840   Min.   :3.124e+04   Min.   :4.040e+07   Africa  :2907
1st Qu.:2.200   1st Qu.:1.333e+06   1st Qu.:1.846e+09   Americas:2052
Median :3.750   Median :5.009e+06   Median :7.794e+09   Asia    :2679
Mean   :4.084   Mean   :2.701e+07   Mean   :1.480e+11   Europe  :2223
3rd Qu.:6.000   3rd Qu.:1.523e+07   3rd Qu.:5.540e+10   Oceania : 684
Max.   :9.220   Max.   :1.376e+09   Max.   :1.174e+13
NA's   :187     NA's   :185         NA's   :2972

            region
Western Asia   :1026
Eastern Africa : 912
Western Africa : 912
Caribbean      : 741
South America  : 684
Southern Europe: 684
(Other)        :5586
```

Preparing the chart for 2012 would be a nice symmetry (see Figure 1.4), but the version of the data that we have does not contain all the required information for that year, so we will pick 2009 instead, while setting the possibility of **changing the year** if required.

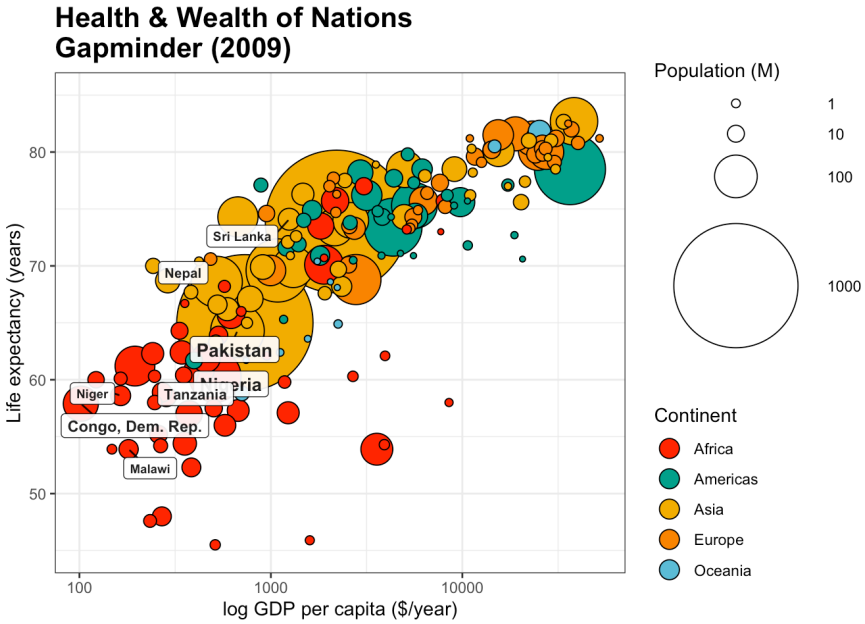
```
yr <- 2009
chart_title <- paste("Health & Wealth of Nations
                     \nGapminder (",yr,")",sep="")
```

Due to lack of space, we will not be able to label all the countries in the chart; instead, we label only 20 of them, with the probability that a name is selected proportional to the country populations.

```
# sort the countries by inverse population
gapminder_ds <- gapminder_ds |>
  dplyr::arrange(year, dplyr::desc(population))

# pick how many countries will have their names labelled
num_countries <- 20

# prepare the data for the selected year
f.gapminder <- gapminder_ds |>
  filter(year==yr) |>
  mutate(pop_m = population/1e6, gdppc=gdp/population)

weights <- f.gapminder$pop_m/sum(f.gapminder$pop_m)
p <- sample(nrow(f.gapminder), num_countries, prob = weights)

f.gapminder$country_display <- ifelse(
         ifelse(1:nrow(f.gapminder) %in% p, TRUE,FALSE),
         as.character(f.gapminder$country),"")
```

The chart is then produced by the code below, using the Darjeeling1 colour palette from the `wesanderson` package.

```
f.gapminder |>
  ggplot(aes(x = gdppc, y=life_expectancy, size=pop_m)) +
  geom_point(aes(fill=continent), pch=21) +
  scale_fill_manual(values=wes_palette(n=5, name="Darjeeling1")) +
  scale_x_log10() +
  geom_label_repel(aes(label=country_display, size=sqrt(pop_m/pi)),
    alpha=0.9, fontface="bold", show.legend=FALSE,
    min.segment.length = unit(0, 'lines')) +
  ggtitle(chart_title) +
  theme(plot.title = element_text(size=14, face="bold")) +
  xlab('log GDP per capita ($/year)') +
  ylab('Life expectancy (years)') + ylim(45,85) +
  scale_size_continuous(range=c(1,40), limits = c(0, 1500),
    breaks = c(1,10,100,1000), labels = c("1","10","100","1000")) +
  guides(fill=guide_legend(override.aes = list(size=5))) +
  labs(fill="Continent", size="Population (M)") +
  theme_bw() +
  theme(plot.title = element_text(size=16, face="bold"))
```

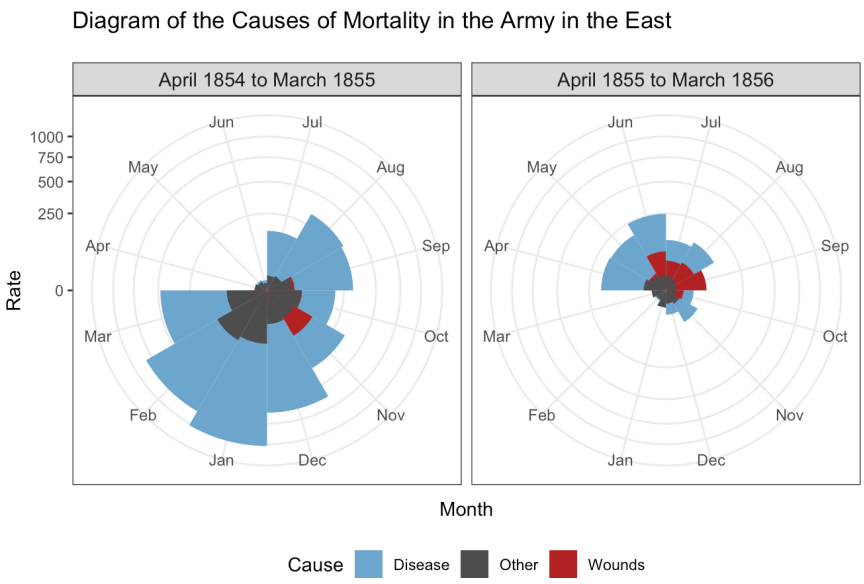


Florence Nightingale's Causes of Mortality

Nightingale's celebrated rose charts (see Figure 1.1) can also be re-created using `ggplot2` (with a big assist to N. Saunders' tutorial).[24]

24: We always assume that the `tidyverse` package has been loaded from this point on (to have access to all `ggplot2` and `dplyr` functions.

```
library(HistData) # to get access to the Nightingale dataset

Nightingale |>
  select(Date, Month, Year, contains("rate")) |>
  pivot_longer(cols=4:6, names_to="Cause", values_to="Rate") |>
  mutate(Cause = gsub(".rate", "", Cause),
    period = ifelse(Date <= as.Date("1855-03-01"),
    "April 1854 to March 1855", "April 1855 to March 1856"),
    Month = fct_relevel(Month, "Jul", "Aug", "Sep", "Oct",
    "Nov", "Dec", "Jan", "Feb", "Mar", "Apr", "May", "Jun")) |>
  ggplot(aes(Month, Rate)) +
  geom_col(aes(fill=Cause), width=1, position="identity") +
  coord_polar() + facet_wrap(~period) +
  scale_fill_manual(values=c("skyblue3", "grey30",
  "firebrick")) +
  scale_y_sqrt() + theme_bw() +
  theme(axis.text.x = element_text(size = 9),
        strip.text = element_text(size = 11),
        legend.position = "bottom",
        plot.margin = unit(c(10, 10, 10, 10), "pt"),
        plot.title = element_text(vjust = 5)) +
  ggtitle("Diagram of the Causes of Mortality in the
                                      Army in the East")
```



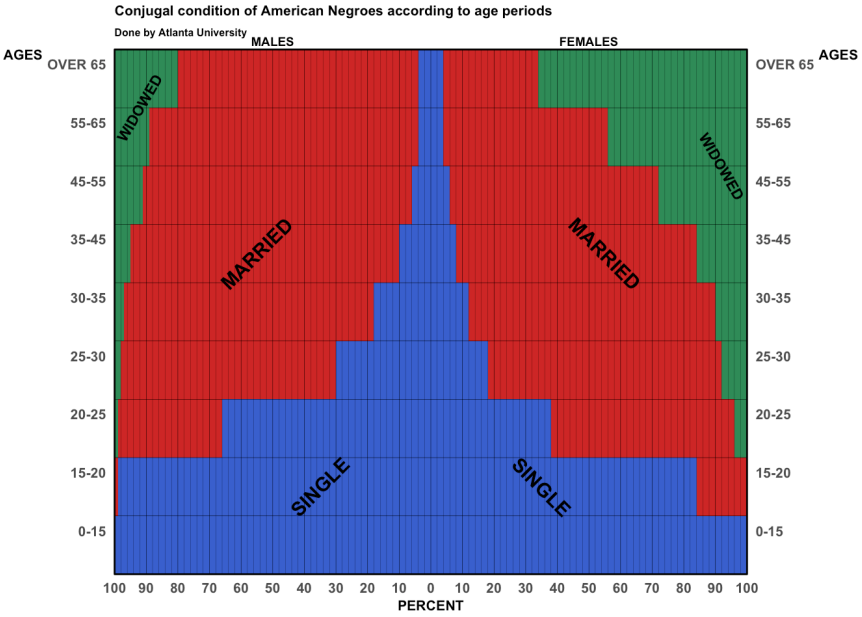
W.E.B. Du Bois' Conjugal Status Chart

We follow statswithmatt's tutorial to recreate another W.E.B. Du Bois classic chart [5].[25]

25: For the historical examples, it would be a great idea to take the time to explore the data before trying to plot it.

```
# creating the data
gender <- c("female", "male")
status <- c("single", "widowed", "married")
age_bins <- c("0-15", "15-20", "20-25", "25-30", "30-35",
  "35-45", "45-55", "55-65", "OVER 65")

marital <- expand.grid(age_bins, gender, status)
names(marital) <- c("age", "gender", "status")
marital$pct <- c(100, 84, 38, 18, 12, 8, 6, 4, 4, 100, 99,
  66, 30, 18, 10, 6, 4, 4, 0, 0, 4, 8, 10, 16, 28, 44, 66,
  0, 0, 1, 2, 3, 5, 9, 11, 20, 0, 16, 58, 74, 78, 76, 66,
  52, 30, 0, 1, 33, 68, 79, 85, 85, 85, 76)

marital$status <- factor(marital$status,levels = c("widowed",
    "married", "single"))
marital$age_numeric <- as.numeric(marital$age)

# creating the chart
ppmsca_33915 <- ggplot(data=marital, mapping = aes(
    x = age_numeric, y = ifelse(gender == "male", -pct, pct),
    fill=status)) +
  geom_bar(stat = "identity", width = 1) +
  scale_x_continuous(breaks = (1:9) + 0.5, labels = age_bins,
```

```
      expand = c(0, 0), sec.axis = dup_axis()) +
  scale_y_continuous(breaks = seq(-100, 100, by = 10),
      labels = abs, expand = c(0, 0),
      minor_breaks = seq(-100, 100, by = 2)) +
  scale_fill_manual(values=c("seagreen4", "firebrick3",
  "royalblue3"),
    labels = c("WIDOWED", "MARRIED", "SINGLE")) +
  labs(title = "Conjugal condition of American Negroes
                according to age periods",
    subtitle = "Done by Atlanta University", x = "AGES",
                y = "PERCENT") +
  coord_flip(clip = "off")


# annotating the chart
ppmsca_33915 + annotate("text",label = rep(c("SINGLE",
       "MARRIED", "WIDOWED"), each = 2),
    y = c(-35, 35, -55, 55, -92, 92),
    angle = c(45, -45, 45, -45, 60, -60),
    x = c(2, 2, 6, 6, 8.5, 7.5),
    size = c(4, 4, 4, 4, 3, 3),
    fontface = "bold") +
  annotate("text", label = c("MALES", "FEMALES"),
    y = c(-50, 50), x = Inf,
    vjust = -0.4,size=2.5, fontface = "bold") +
  theme(text = element_text(face = "bold"),
    panel.background = element_blank(),
    plot.title = element_text(size = 8, vjust = 2),
    plot.subtitle = element_text( size = 6, vjust = 2),
    axis.title = element_text(size = 8),
    axis.ticks = element_blank(),
    panel.grid.major = element_line(color = "black",
      size = 0.1),
    panel.grid.minor.x = element_line(color = "black",
      size = 0.05),
    panel.grid.minor.y = element_blank(),
    legend.background = element_blank(),
    legend.position = "none", legend.key = element_blank(),
    panel.ontop = TRUE,
    panel.border = element_rect(fill=NA, color = "black"),
    axis.text.x = element_text(size = 8),
    axis.title.y = element_text(angle = 0, vjust = 1),
    axis.title.y.right = element_text(angle = 0, vjust = 1),
    axis.text.y = element_text(vjust = 2,size=8))
```



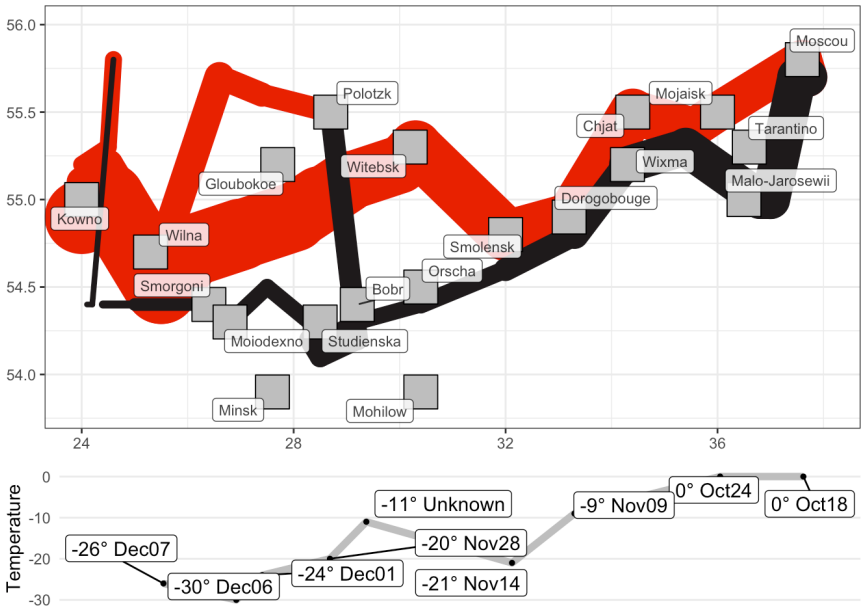
Minard's March to Moscow

We recreate Minard's famous *March to Moscow* chart (see Figure 1.1 and Section 1.4) by following very closely the code provided in M. Friendly's tutorial.[26]

26: We would have had a hard time coming up with this stuff on our own, not going to lie...

```
# getting the data
data(Minard.troops,Minard.cities,Minard.temp,package="HistData")

# required packages
library(ggplot2)
library(scales)        # additional formatting for scales
library(grid)          # combining plots
library(gridExtra)     # combining plots
library(dplyr)         # tidy data manipulations

# the troops/cities upper chart
breaks <- c(1, 2, 3) * 10^5
plot.troops.cities <- Minard.troops |>  ggplot(aes(long, lat)) +
  geom_path(aes(size = survivors, colour = direction,
                group = group), lineend="round") +
  scale_size("Survivors", range = c(0,20),
             breaks=breaks, labels=scales::comma(breaks)) +
  scale_colour_manual("Direction",
                      values=c("#E80000", "#1F1A1B"),
                      labels=c("Advance", "Retreat")) +
  ylim(53.8,56.0) + coord_cartesian(xlim = c(24, 38)) +
  labs(x = NULL, y = NULL) + theme_bw() +
  guides(color = "none",size="none") +
```

```
  geom_point(data=Minard.cities, size=10, pch=22,
             color = "black", fill="gray") +
  geom_label_repel(data=Minard.cities, aes(label = city),
                   size = 3, vjust = 0.5, alpha=0.8)

# replacing a missing value in the temperature data
Minard.temp$date = factor(Minard.temp$date,
  levels=c(levels(Minard.temp$date), "Unknown"))
Minard.temp$date[is.na(Minard.temp$date)] <- "Unknown"

# the temperature lower chart
plot.temp <- Minard.temp |>
  mutate(label = paste0(temp, "° ", date)) |>
  ggplot(aes(long, temp)) +
  geom_path(color="grey", size=2, group=1) +
  geom_point(size=1) +
  geom_label_repel(aes(label=label), size=4) +
  coord_cartesian(xlim = c(24, 38)) +
  labs(x = NULL, y="Temperature") +
  theme_bw() + theme(panel.grid.major.x = element_blank(),
   panel.grid.minor.x = element_blank(),
   panel.grid.minor.y = element_blank(),
   axis.text.x = element_blank(), axis.ticks = element_blank(),
   panel.border = element_blank())

# combining both charts
grid.arrange(plot.troops.cities, plot.temp, nrow=2,
    heights=c(3.5, 1.2))
grid.rect(width = .95, height = .95, gp = gpar(lwd = 0,
    col = "white", fill=NA))
```

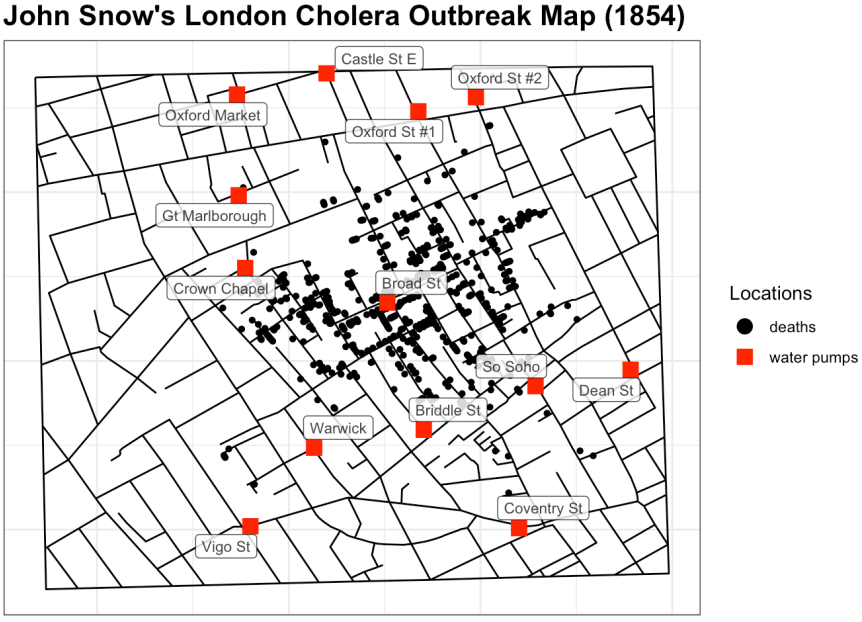


John Snow's Cholera Outbreak Map

We recreate John Snow's historical map of the 1854 London cholera outbreak (adapted from V.B. Lanzetta's R Data Visualization Recipes) [127].[27]

27: The culprit (contaminated pump) is easily identifiable in this version of the chart.

```
# getting the data and required  packages
data(Snow.streets, Snow.deaths, Snow.pumps, package="HistData")
library(ggplot2)
library(ggrepel)

# street map, death locations, water pump locations
ggplot(data=Snow.streets) +
  geom_path(aes(x=x, y=y, group = street)) +
  geom_point(data=Snow.deaths, aes(x=x, y=y,
             colour="black", shape="15")) +
  geom_point(data=Snow.pumps, aes(x=x, y=y,
             colour="red", shape="16"), size=4) +
  scale_colour_manual("Locations", values=c("black","red"),
                      labels=c("deaths","water pumps")) +
  scale_shape_manual("Locations", values=c(16,15),
                      labels=c("deaths","water pumps")) +
  geom_label_repel(data=Snow.pumps, aes(x=x, y=y, label=label),
        colour="black", size=3, vjust=0.5, alpha=0.8) +
  ggtitle("John Snow's London Cholera Outbreak Map (1854)") +
  theme_bw() +
  theme(plot.title = element_text(size=16, face="bold"),
    axis.title.x=element_blank(), axis.text.x=element_blank(),
    axis.ticks.x=element_blank(), axis.title.y=element_blank(),
    axis.text.y=element_blank(), axis.ticks.y=element_blank())
```



Census PUMS Data

The following example is taken from N. Zumel and J. Mount's excellent Practical Data Science with R [128].

The `custdata.tsv` file is derived from U.S. Census PUMS data. The business objective is to predict whether a customer has health insurance. This synthetic dataset contains customer information for individuals whose health insurance status is **known**.

We start by importing the data into a data frame using the `read.delim()` function (to handle the odd file format).

```
df <- read.delim(here::here("data", "custdata.tsv"))
dim(df)
```

```
[1] 1000   11
```

Evidently, there are 1000 observations of 11 variables. The first few observations look like:

```
head(df,5)
```

```
  custid sex is.employed income  marital.stat health.ins
1   2068   F          NA  11300       Married       TRUE
2   2073   F          NA      0       Married       TRUE
3   2848   M        TRUE   4500 Never Married      FALSE
4   5641   M        TRUE  20000 Never Married      FALSE
5   6369   F        TRUE  12000 Never Married       TRUE
              housing.type recent.move num.vehicles age state.of.res
1 Homeowner free and clear       FALSE            2  49     Michigan
2                  Rented        TRUE            3  40      Florida
3                  Rented        TRUE            3  22      Georgia
4    Occupied with no rent       FALSE            0  22   New Mexico
5                  Rented        TRUE            1  31      Florida
```

We obtain a data summary *via* `summary()`.

```
summary(df)
```

```
     custid            sex            is.employed         income
 Min.   :   2068   Length:1000        Mode :logical   Min.   : -8700
 1st Qu.: 345667   Class :character   FALSE:73        1st Qu.: 14600
 Median : 693403   Mode  :character   TRUE :599       Median : 35000
 Mean   : 698500                      NA's :328       Mean   : 53505
 3rd Qu.:1044606                                      3rd Qu.: 67000
 Max.   :1414286                                      Max.   :615000
```

```
marital.stat       health.ins      housing.type       recent.move
Length:1000        Mode :logical   Length:1000        Mode :logical
Class :character   FALSE:159       Class :character   FALSE:820
Mode  :character   TRUE :841       Mode  :character   TRUE :124
                                                      NA's :56

 num.vehicles        age        state.of.res
Min.   :0.000   Min.   :  0.0   Length:1000
1st Qu.:1.000   1st Qu.: 38.0   Class :character
Median :2.000   Median : 50.0   Mode  :character
Mean   :1.916   Mean   : 51.7
3rd Qu.:2.000   3rd Qu.: 64.0
Max.   :6.000   Max.   :146.7
NA's   :56
```

Right off the bat, we see that there are some problems with the data (`NA`s, impossible ranges, etc.). We can also provide the number of `NA`s per variable in an easier-to-read format using the following code block:

```
mv <- colSums(is.na(df))
# cbind(mv)   # cbind to display as column
mv
```

```
     custid sex  is.employed income marital.stat health.ins
          0   0          328      0            0          0
housing.type recent.move num.vehicles age state.of.res
         56          56           56   0            0
```

The fact that three of the variables have the same (relatively high) number of missing values means that it is possible that the same 56 observations have no measurement for `housing.type`, `recent.move`, and `num.vehicles`.[28]

As for the ranges, something is definitely fishy with `income` and `age`:

```
summary(df$income)
summary(df$age)
```

```
  Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
 -8700   14600   35000   53505   67000  615000
  Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
   0.0    38.0    50.0    51.7    64.0   146.7
```

What does it mean for incomes to be negative? For a customer to be 0 years old? Or worse, 146.7?

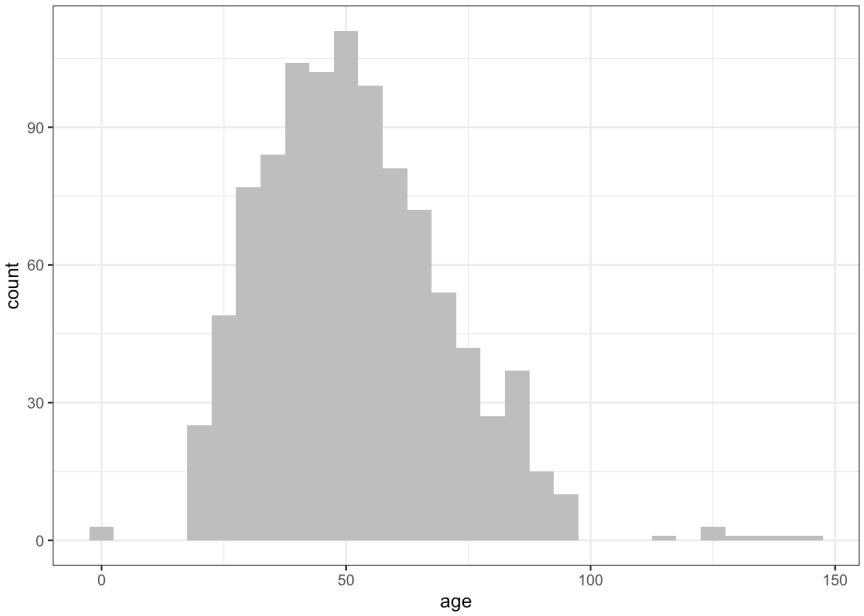
We use `ggplot2` to visually explore the data.[29] We will begin by providing a number of univariate visualizations, starting with the `age` variable.

28: That is not a guarantee, of course. We still need to check (try it!).

29: Recall that:

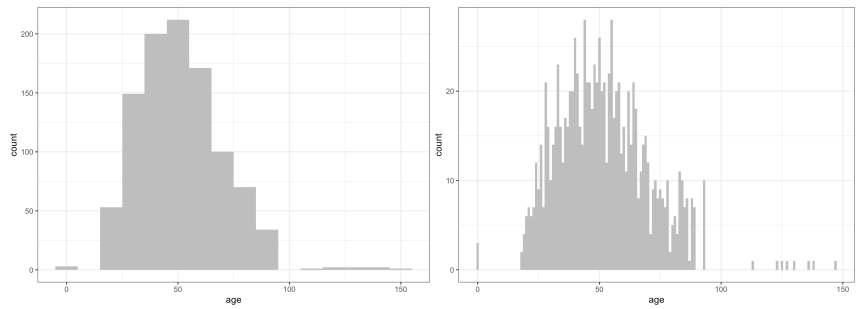
- the `ggplot()` function works only on data frames and/or **tibbles**;
- it does not create a graph, it creates an **object**;
- graphs are produced from **layers**, which are *added* to the object, and
- aesthetics are the **visual elements** of the graph, e.g., the x and y variables, the size of markers, colors, etc.

```
library(ggplot2)
ggplot(df) + geom_histogram(aes(x=age),binwidth=5,fill="gray")
```



What happens if we use different bin widths?

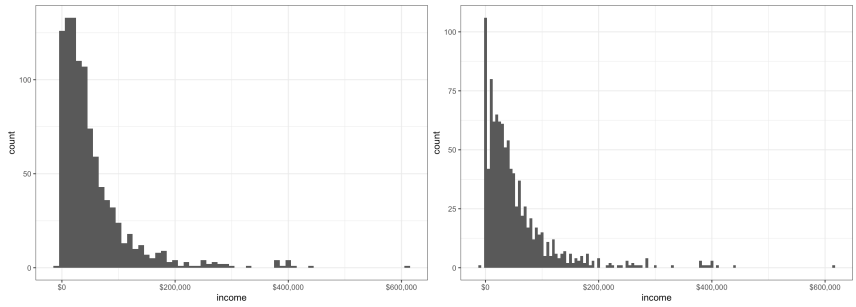
```
ggplot(df) + geom_histogram(aes(x=age),binwidth=10,fill="gray")
ggplot(df) + geom_histogram(aes(x=age),binwidth=1,fill="gray")
```



We definitely seem to find ourselves in a Goldilocks situation.

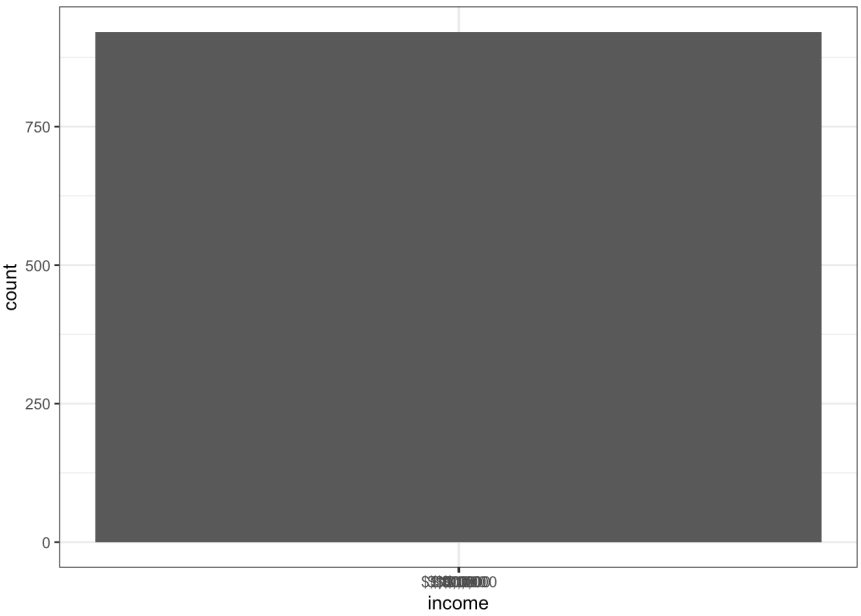
We can also get some (univariate) information about the `income` variable:

```
library(scales)
ggplot(df) + geom_histogram(aes(x=income), binwidth = 10000) +
    scale_x_continuous(labels=dollar)
ggplot(df) + geom_histogram(aes(x=income), binwidth = 5000) +
    scale_x_continuous(labels=dollar)
```



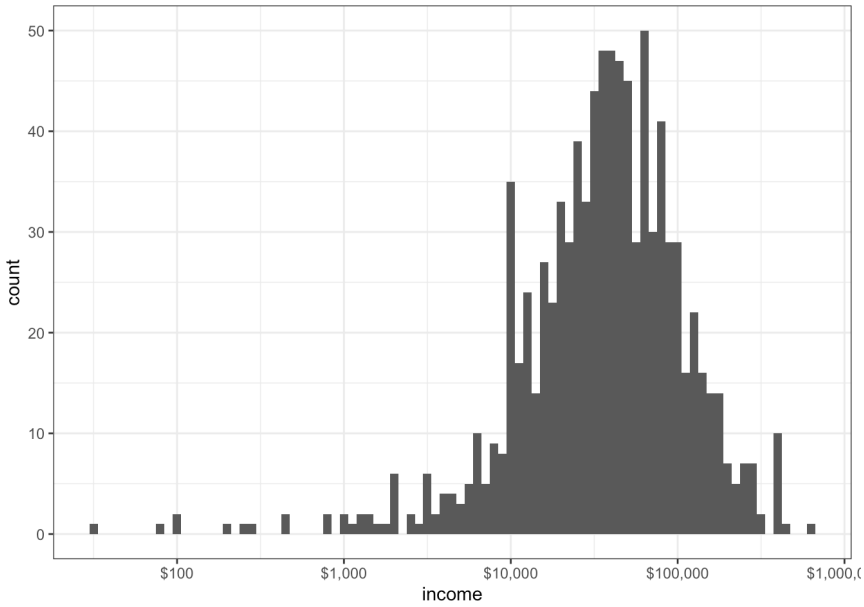
We have already seen that there are negative income values in the dataset. We will restrict the data to those customers with positive income, and display them using a logarithmic scale.

```
df.2 <- subset(df, income > 0)
ggplot(df.2) +
    geom_histogram(aes(x=income), binwidth = 5000) +
    scale_x_log10(breaks=10^(1:6), labels=dollar)
```



Whoa, that's ... quite possible the most useless chart we have ever seen. The problem here is that `binwidth` refers to the powers, not to the raw numbers.

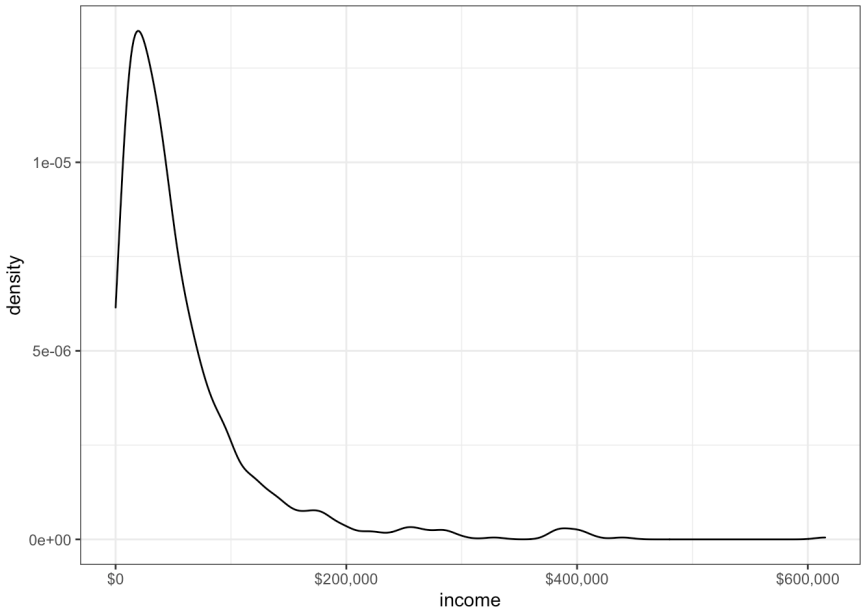
```
ggplot(df.2) +
    geom_histogram(aes(x=income), binwidth = 0.05) +
    scale_x_log10(breaks=10^(1:6), labels=dollar)
```



Much better!

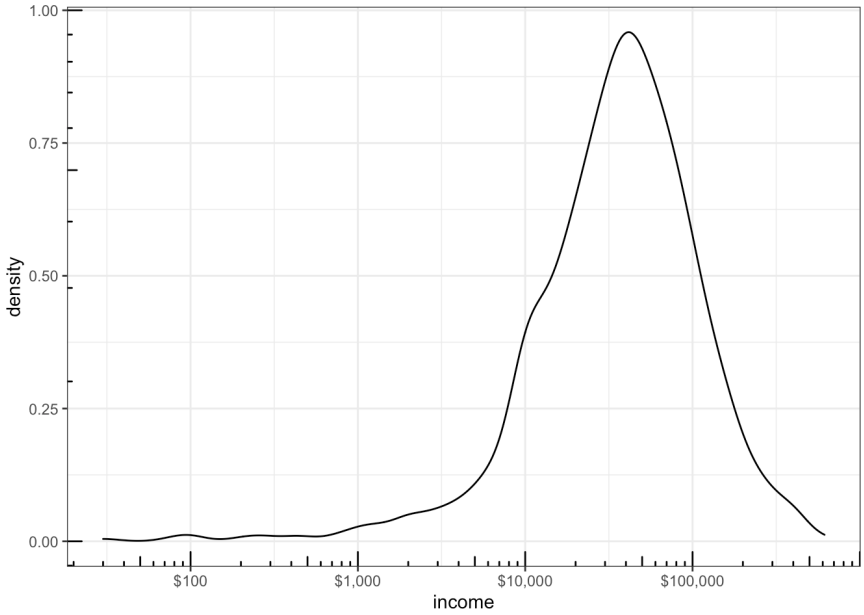
A density plot can also provide an estimate of the probability distribution function.

```
library(scales)
ggplot(df.2) + geom_density(aes(x=income)) +
  scale_x_continuous(labels=dollar)
```



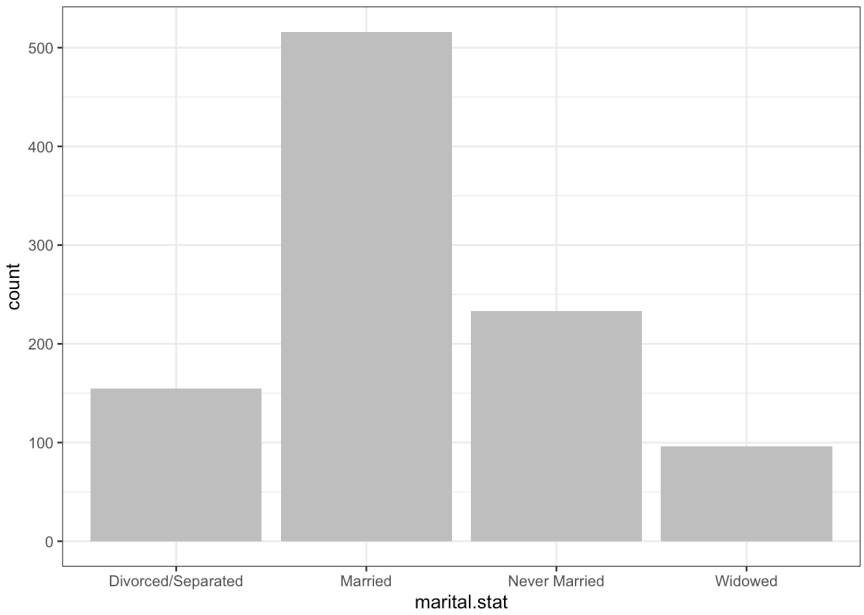
The tail is a bit long/heavy: as before, it might be more illuminating to use a logarithmic scale.

```
ggplot(df.2) + geom_density(aes(x=income)) +
    scale_x_log10(breaks=10^(2:5), labels=dollar) +
    annotation_logticks()
```



What can we say about the distribution of marital status?

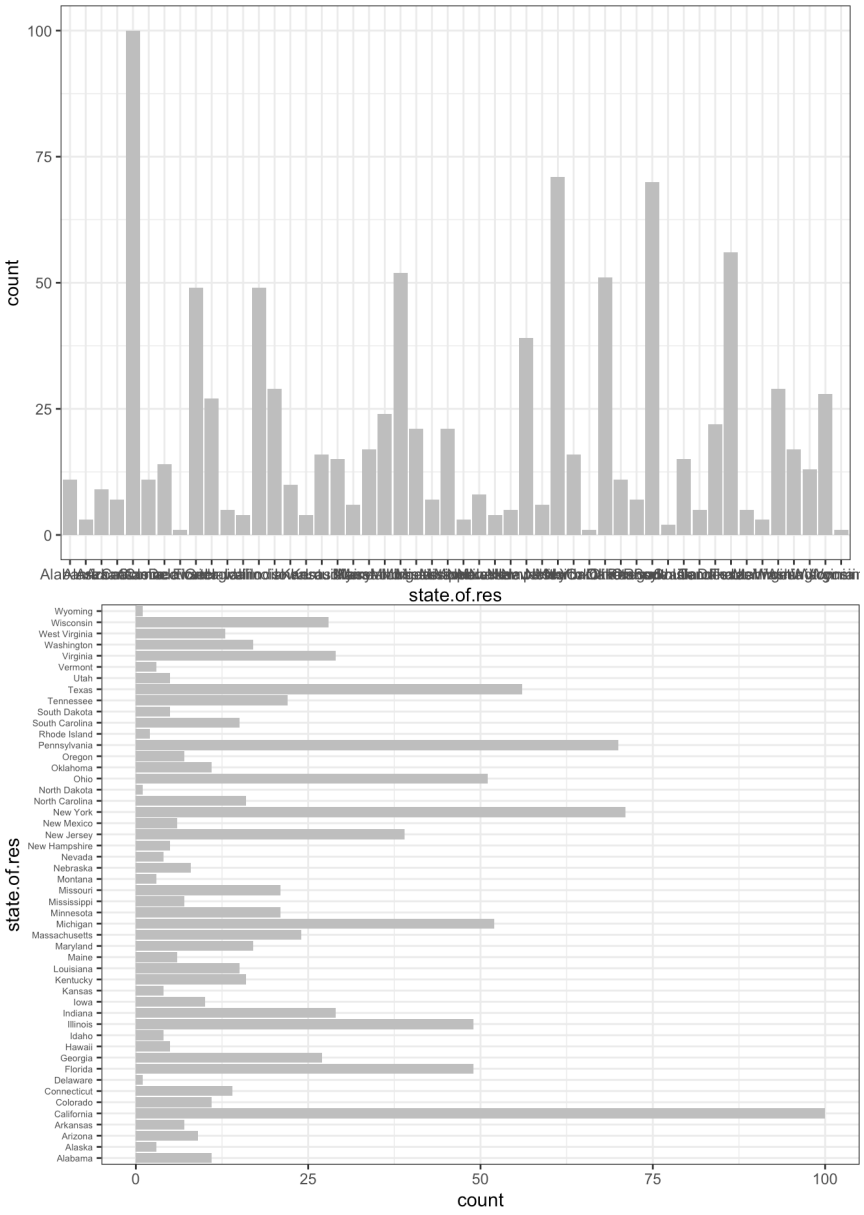
```
ggplot(df) + geom_bar(aes(x=marital.stat), fill="gray")
```



Nothing is too surprising so far (although, as mentioned, something is definitely off with some of the `age` and `income` measurements).

If we try to get information about a variable with 10+ levels (`state.of.res`), we see that the charts can get busy.

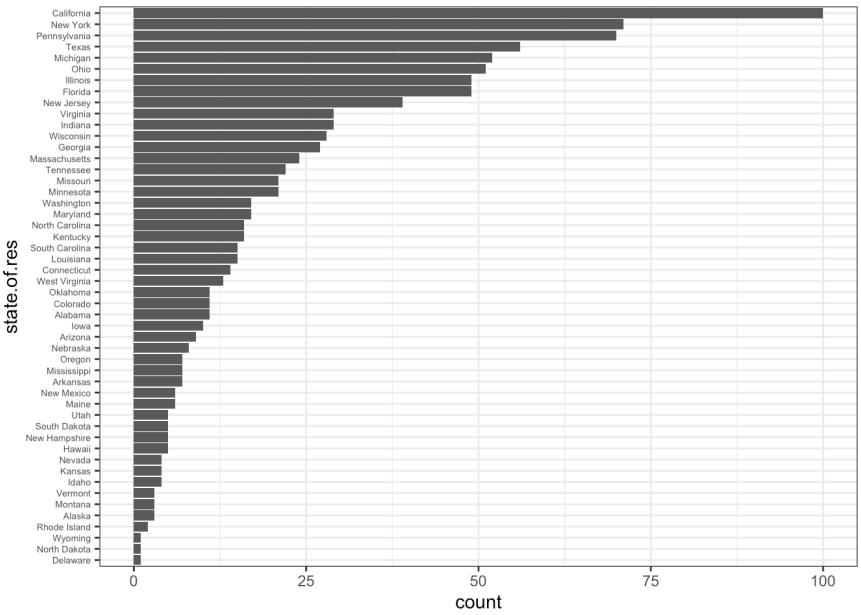
```
ggplot(df) + geom_bar(aes(x=state.of.res), fill="gray")

# same, but with a coordinate flip
and text resizing for readibility
ggplot(df) + geom_bar(aes(x=state.of.res), fill="gray") +
  coord_flip() +
  theme(axis.text.y=element_text(size=rel(0.6)))
```



The flipped chart is clearly easier to read, due to text overlap in the original chart.

The latter displays the states ordered alphabetically; to order according to the number of observations in each state, we first need to modify the data using `transform()`, which actually re-orders the levels for `state.of.res` by population in the dataset (which are presumably representative of the order in the full US population).

```
tbl <- as.data.frame(table(df$state.of.res))
colnames(tbl) <- c("state.of.res","count")
tbl <- transform(tbl,state.of.res=reorder(state.of.res,count))
ggplot(tbl) +
    geom_bar(aes(x=state.of.res, y=count), stat="identity") +
    coord_flip() +
    theme(axis.text.y=element_text(size=rel(0.6)))
```



How can we find the average number of vehicles per customer in each state? For instance, in Delaware and Alaska, it is:

```
with(df,mean(num.vehicles[state.of.res=="Delaware"],na.rm=TRUE))
with(df,mean(num.vehicles[state.of.res=="Alaska"],na.rm=TRUE))
```

```
[1] 2
[1] 2.333333
```

(Note the `na.rm=TRUE` to avoid issues with computations involving observations with no measurement)

We could repeat the process 50 times (once for each state), or we could use either a **split/apply/combine** approach (in `base R`) or a **`tidyverse`** approach (using `plyr`).

```
# split
pieces <- split(df, df$state.of.res)

# apply
result <- lapply(pieces, function(p) data.frame(
    state.of.res=p$state.of.res[[1]],
    state.avg.vehicles=mean(p$num.vehicles, na.rm=TRUE)))

(result <- do.call("rbind", result))
```

state.of.res	**state.avg.vehicles**	state.of.res	**state.avg.vehicles**
Alabama	2.100000	Montana	2.500000
Alaska	2.333333	Nebraska	1.500000
Arizona	1.888889	Nevada	2.000000
Arkansas	1.833333	New Hampshire	1.800000
California	2.098901	New Jersey	1.555556
Colorado	1.636364	New Mexico	2.333333
Connecticut	2.000000	New York	1.928571
Delaware	2.000000	North Carolina	1.666667
Florida	1.866667	North Dakota	3.000000
Georgia	1.708333	Ohio	1.836735
Hawaii	1.750000	Oklahoma	1.818182
Idaho	1.666667	Oregon	2.285714
Illinois	2.183673	Pennsylvania	1.938462
Indiana	2.000000	Rhode Island	2.000000
Iowa	2.000000	South Carolina	1.785714
Kansas	1.750000	South Dakota	1.600000
Kentucky	1.933333	Tennessee	1.571429
Louisiana	1.533333	Texas	1.833333
Maine	2.200000	Utah	1.750000
Maryland	2.750000	Vermont	1.666667
Massachusetts	1.833333	Virginia	1.884615
Michigan	1.843137	Washington	2.235294
Minnesota	2.350000	West Virginia	1.666667
Mississippi	1.500000	Wisconsin	1.692308
Missouri	1.950000	Wyoming	2.000000

The `tidyverse`-like solution is much more elegant, however:

```
library(plyr)
result <- ddply(
    df,                 # dataframe
    "state.of.res",     # split-by variable
    summarize,          # function to apply to each piece
                        # function arguments
    state.avg.vehicles=mean(num.vehicles, na.rm=TRUE)
)
```

When it comes to *univariate* representations:

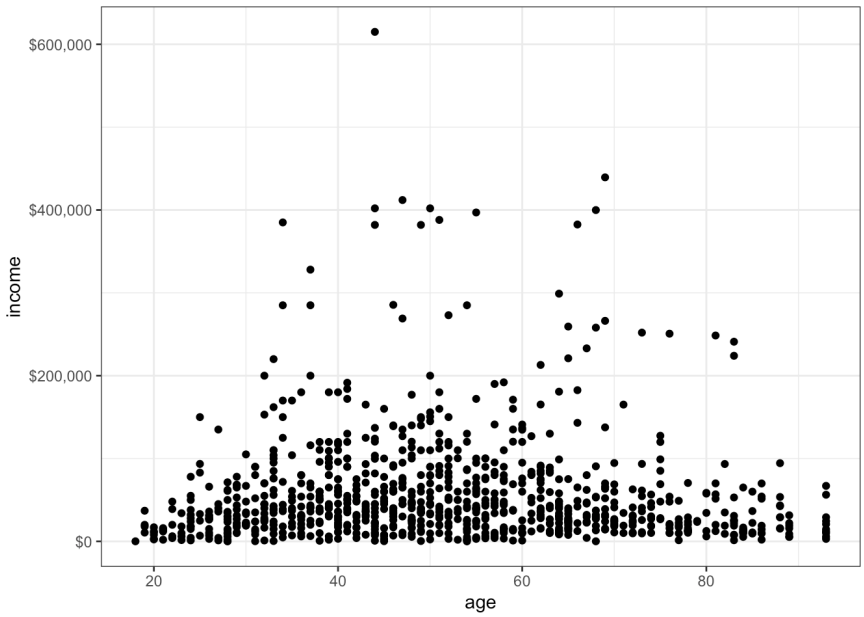
- we may consider using a histogram or density plot to look for outliers or incorrect values in numerical variables,
- which will also give a sense of the distribution – is it symmetric, normal, lognormal, etc;
- but we may consider using a bar chart to compare frequencies for categorical variables.

We can also look at bivariate charts; perhaps one involving `age` and `income`, say. We start by removing the odd observations.

```
df.3 <- with(df, subset(df, age>0 & age < 100 & income > 0))
```

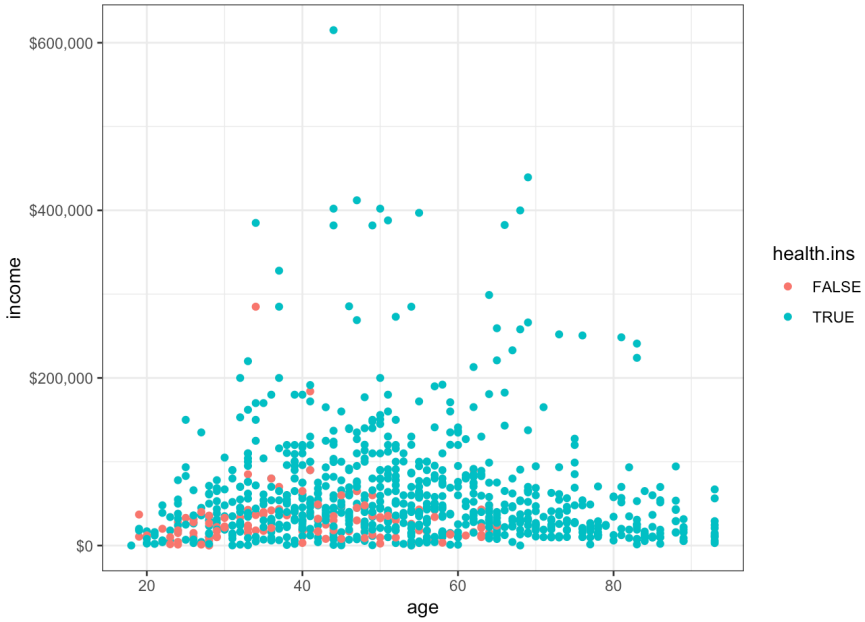
We can prepare a scatterplot:

```
ggplot(df.3, aes(x=age, y=income)) +
  geom_point() +
  scale_y_continuous(labels=dollar)
```



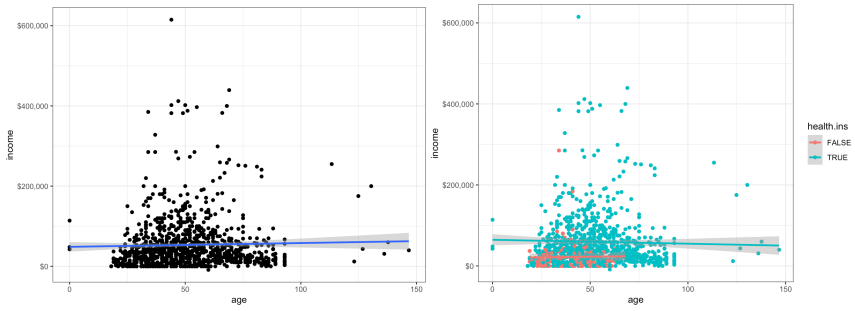
Or colour the dots according to the health insurance status.

```
ggplot(df.3, aes(x=age, y=income, colour = health.ins)) +
  geom_point() +
  scale_y_continuous(labels=dollar)
```



The relationship between `age` and `income` is not linear, so adding the line of best-fit might not provide much in the way of insight, but it can be done nonetheless.

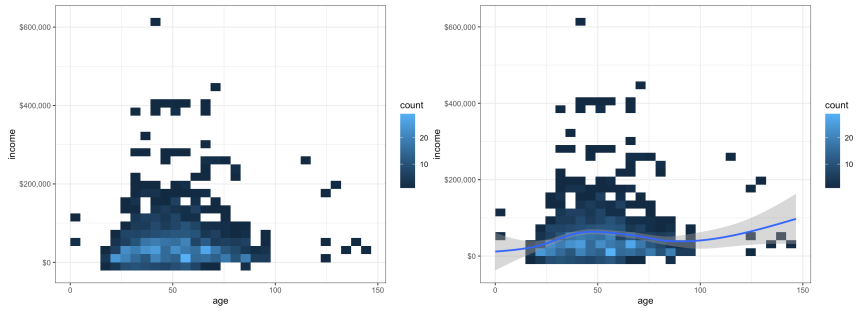
```
ggplot(df, aes(x=age, y=income)) +
  geom_point() +
  geom_smooth(method="lm") +
  scale_y_continuous(labels=dollar)

ggplot(df, aes(x=age, y=income, colour = health.ins)) +
  geom_point() +
  geom_smooth(method="lm") +
  scale_y_continuous(labels=dollar)
```



A heat map (where a cell's colour represents the number of observations in the cell) might be more *à propos*.[30]

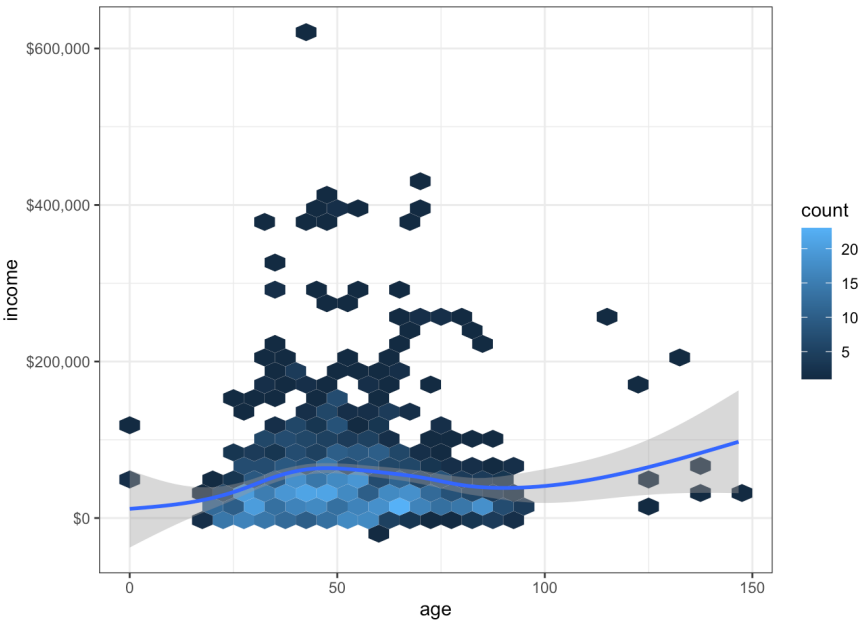
30: Is the smoothing curve a bit too much, here?

```
ggplot(df, aes(x=age, y=income)) +
  geom_bin2d() +
  scale_y_continuous(labels=dollar)

ggplot(df, aes(x=age, y=income)) +
  geom_bin2d() +
  scale_y_continuous(labels=dollar) +
  geom_smooth()
```



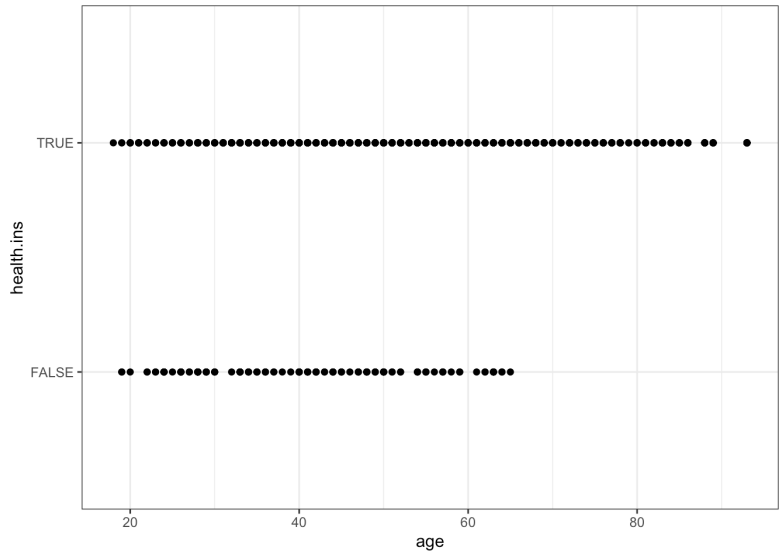
How about a `hexbin` heat map?

```
library(hexbin)
ggplot(df, aes(x=age, y=income)) + geom_hex(binwidth=c(5, 20000)) +
    scale_y_continuous(labels=dollar) + geom_smooth()
```



Other plots can be produced: here is a plot of `health.ins` vs. `age`.

```
ggplot(df.3, aes(x=age, y=health.ins)) + geom_point()
```

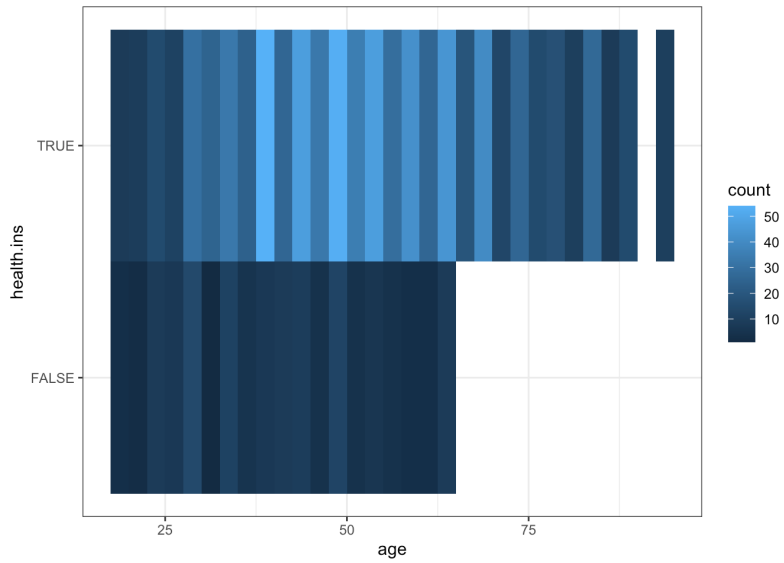


That's not really surprising, is it?[31] It doesn't seem as though there are that many more people with insurance than there are without, but that's because all the observations with the same age are represented by a single dot.

31: As one gets older, one is more likely to get health insurance, we suppose.

A heatmap could incorporate the number of observations into the picture.

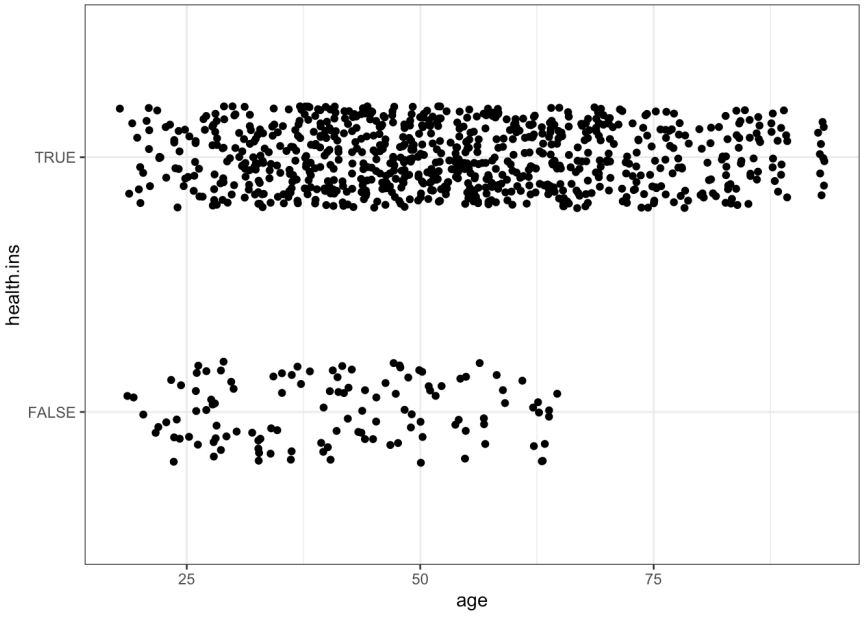
```
ggplot(df.3, aes(x=age, y=health.ins)) +  geom_bin2d()
```



Mmhhh. . . that's not nearly as insightful as could have been expected.

One of the `geoms` can come in handy: `geom_jitter`.

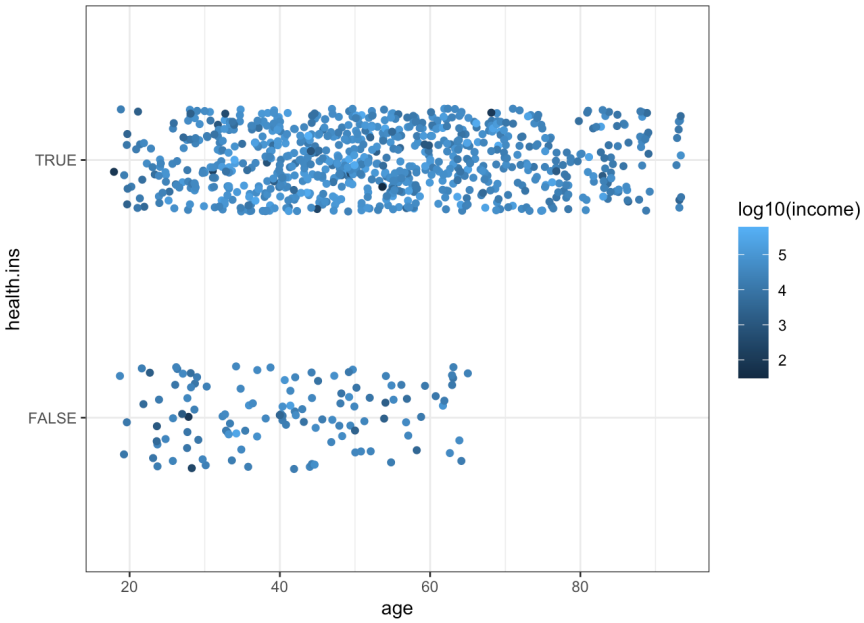
```
ggplot(df.3, aes(x=age, y=health.ins)) +
  geom_jitter(height=0.2)
```



Now we can clearly see that there are substantially fewer customers without life insurance.

Why stop at only 2 variables when we could add `income` to the picture?

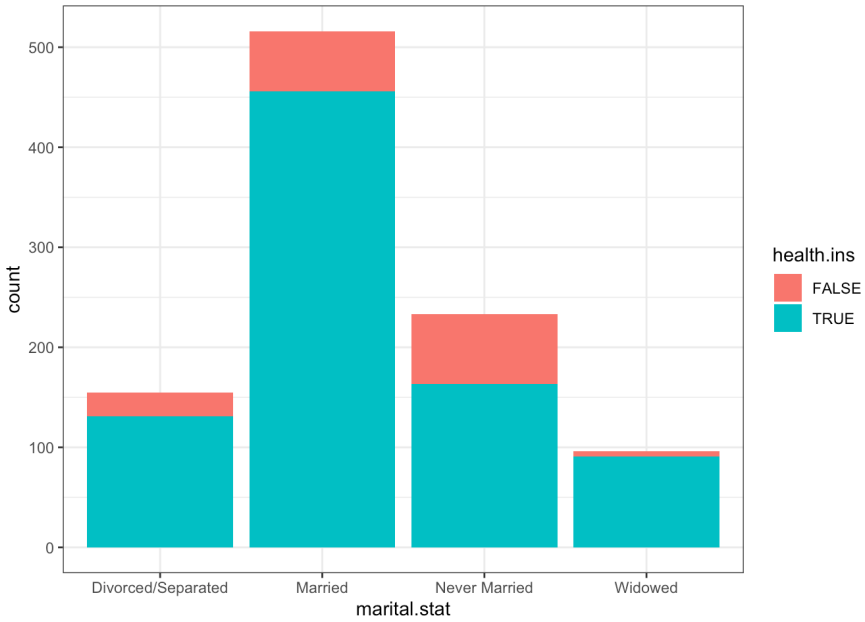
```
ggplot(df.3, aes(x=age, y=health.ins, colour=log10(income))) +
  geom_jitter(height=0.2)
```



Is there anything insightful in there?

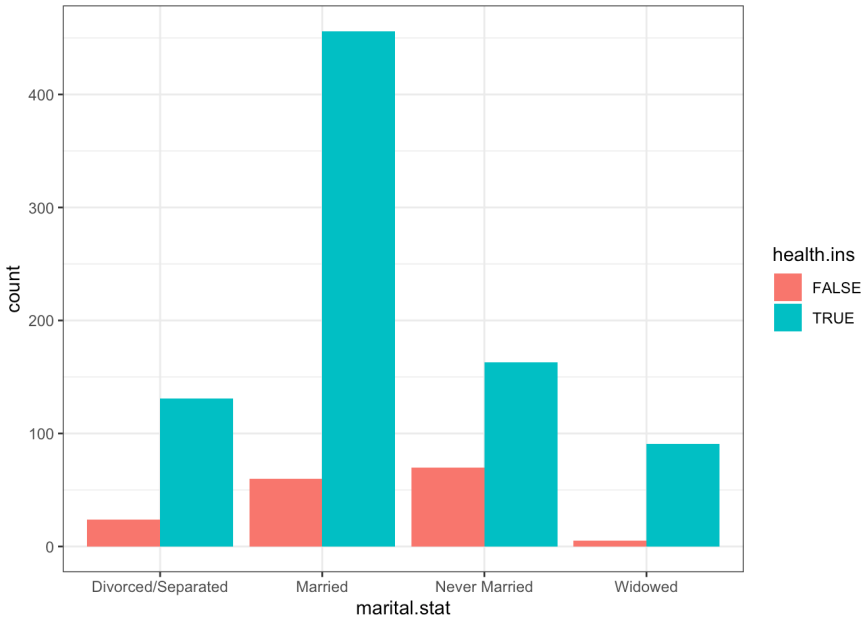
We could also try to link marital status to health insurance status?

```
ggplot(df) + geom_bar(aes(x=marital.stat, fill=health.ins))
```



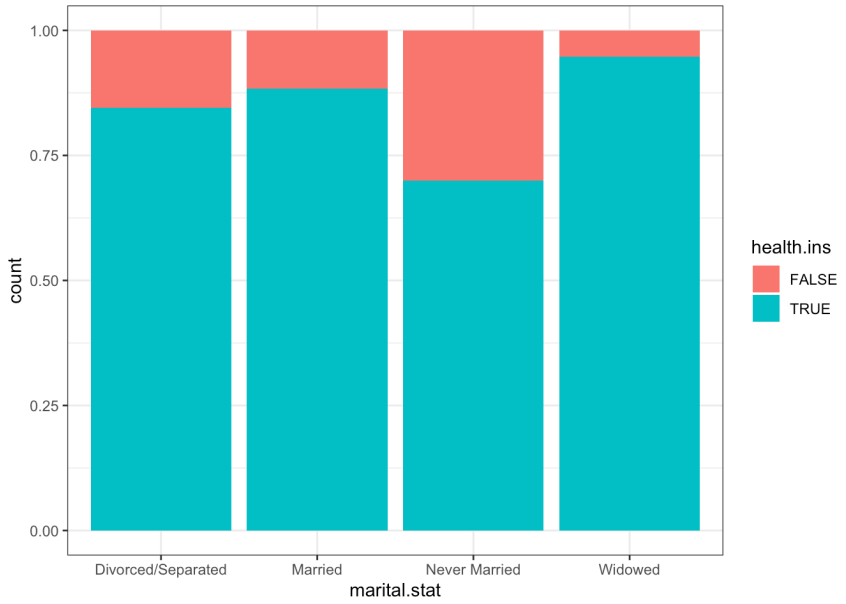
Stacked bar charts are the pie charts of bar charts – it is much better to put the bars side-by-side.

```
ggplot(df) + geom_bar(aes(x=marital.stat, fill=health.ins),
   position="dodge")
```



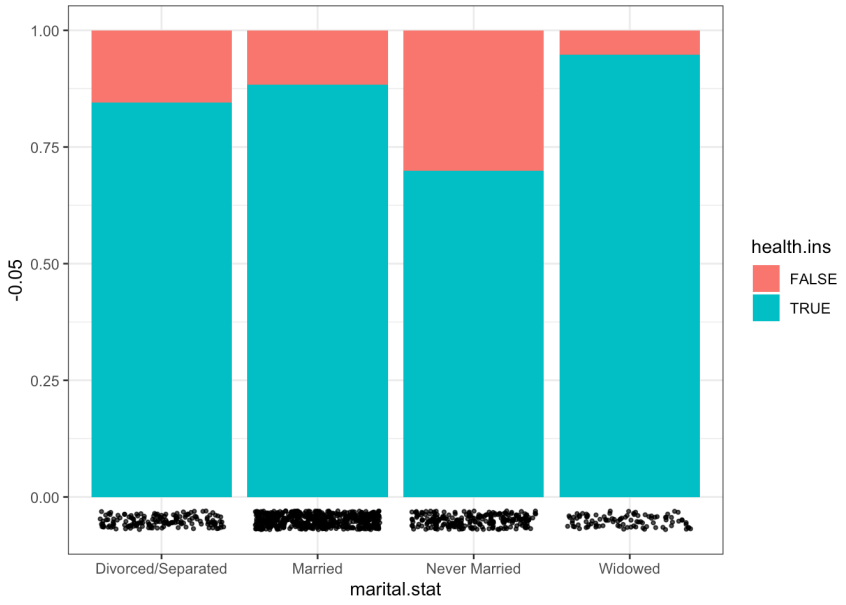
One exception could be made for proportion stacked bar charts:

```
ggplot(df, aes(x=marital.stat)) +
    geom_bar(aes(fill=health.ins), position="fill")
```



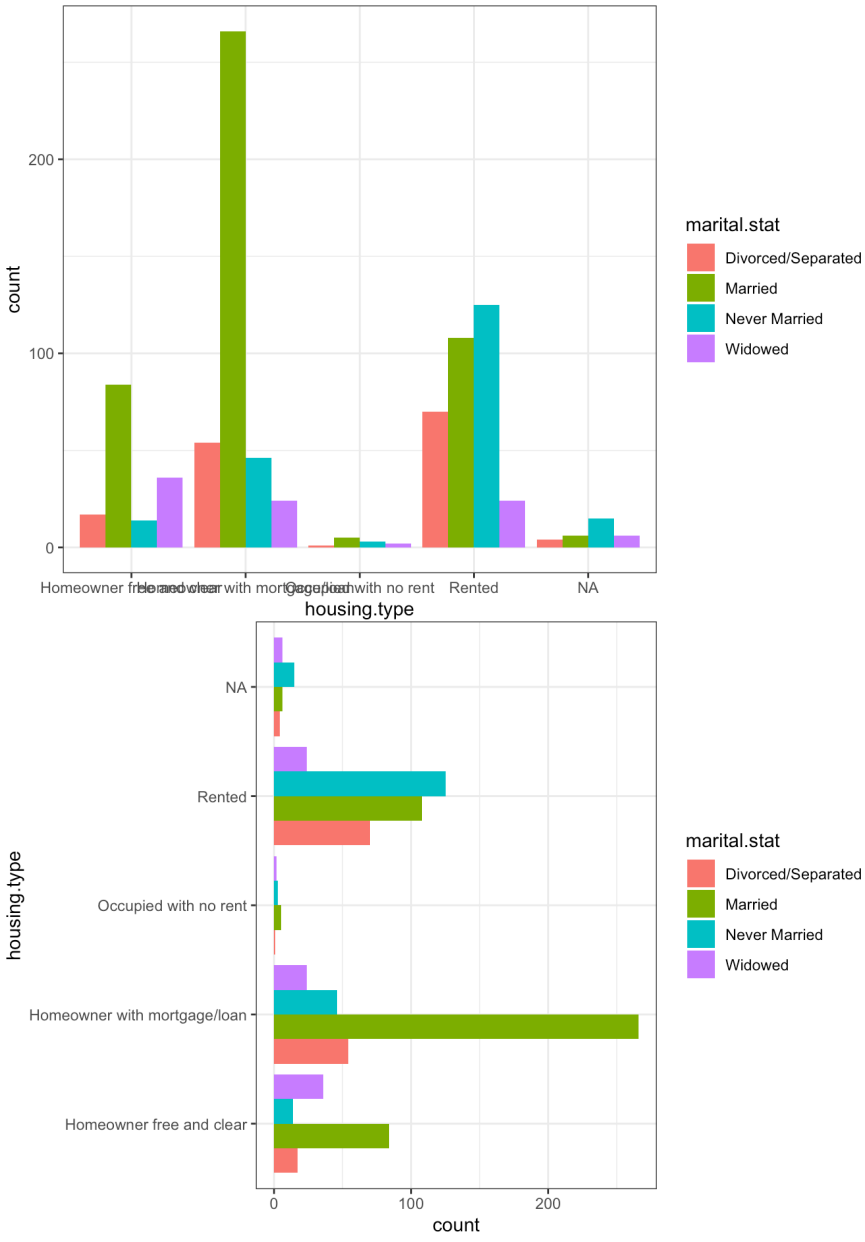
But we do lose the sense of the size of each sub-categories' population. Some jitter functionality comes to the rescue once again!

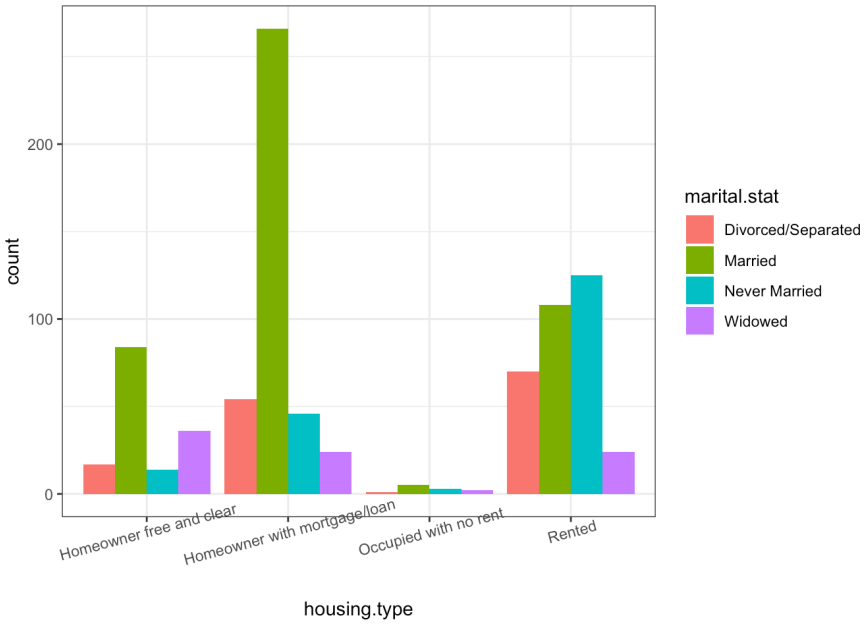
```
last_plot() + geom_point(aes(x=marital.stat, y=-0.05),
   position=position_jitter(h=0.02), size=0.75, alpha=0.75)
```



Might there be a link between housing type and marital status?

```
ggplot(df.3) + geom_bar(aes(housing.type, fill=marital.stat),
position="dodge")

last_plot() + coord_flip()

ggplot(subset(df.3, !is.na(housing.type))) +
   geom_bar(aes(housing.type, fill=marital.stat),
      position="dodge") +
   theme(axis.text.x=element_text(angle=15))
```

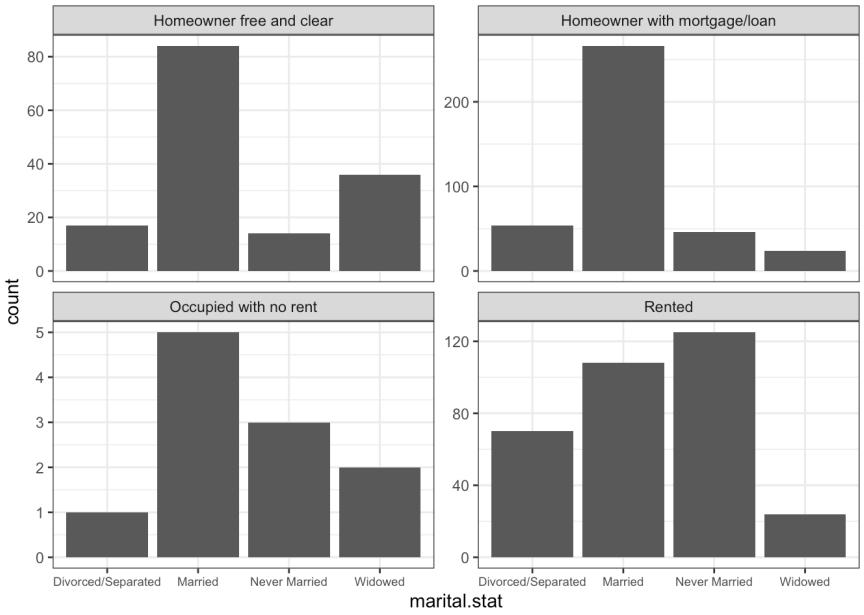




It's easy to see how some fine-tuning can make the charts easier to read (which can only help when it comes to extracting actionable insights).

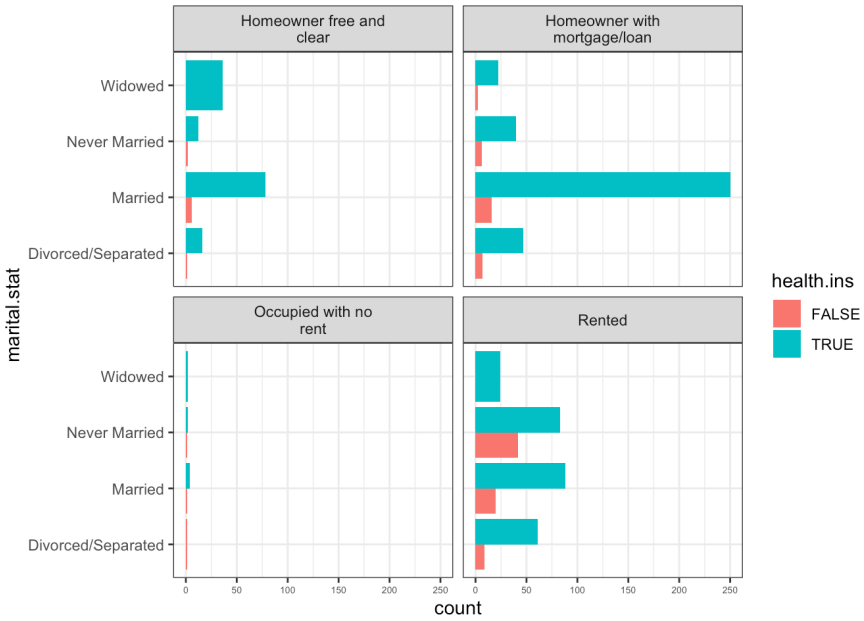
We end our data exploration of by showing how to build a small multiple chart, by `housing.type`:

```
ggplot(subset(df.3, !is.na(housing.type))) +
    geom_bar(aes(marital.stat)) +
    facet_wrap(~housing.type, scales="free_y") +
    theme(axis.text.x=element_text(size=rel(0.8)))
```



Is there any link with with health insurance status?

```
ggplot(subset(df.3, !is.na(housing.type))) +
    geom_bar(aes(marital.stat, fill=health.ins),
             position="dodge") +
    facet_wrap(~housing.type, ncol=2,
       labeller=label_wrap_gen(width=20, multi_line=TRUE)) +
    theme(axis.text.x=element_text(size=rel(0.6)))
    + coord_flip()
```



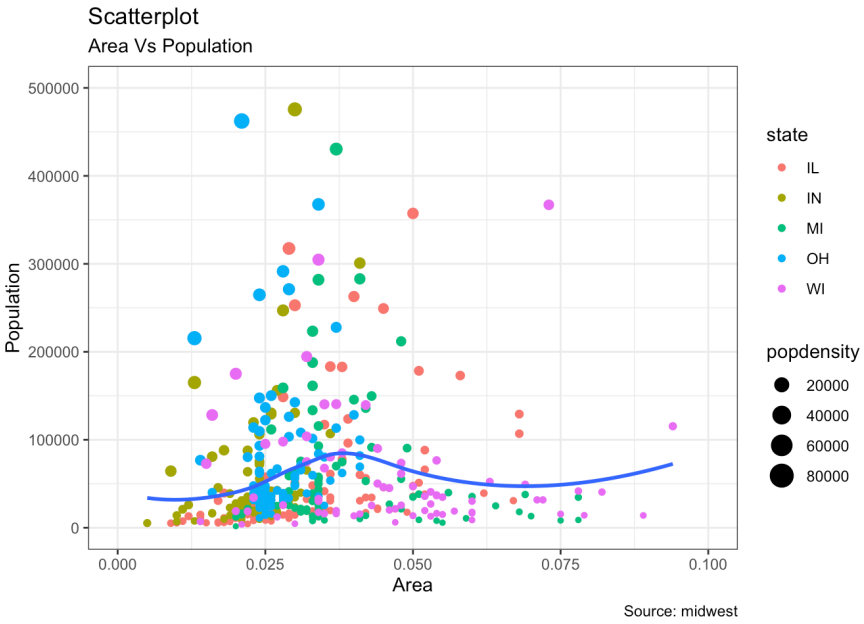
ggplot2 Recipes and Examples

We end with examples showcasing additional functionality.[32]

32: We will not be adding the `ggplot2` and `theme_set` calls in the code chunks anymore; unless otherwise stated, assume that they have been compiled at an earlier stage.

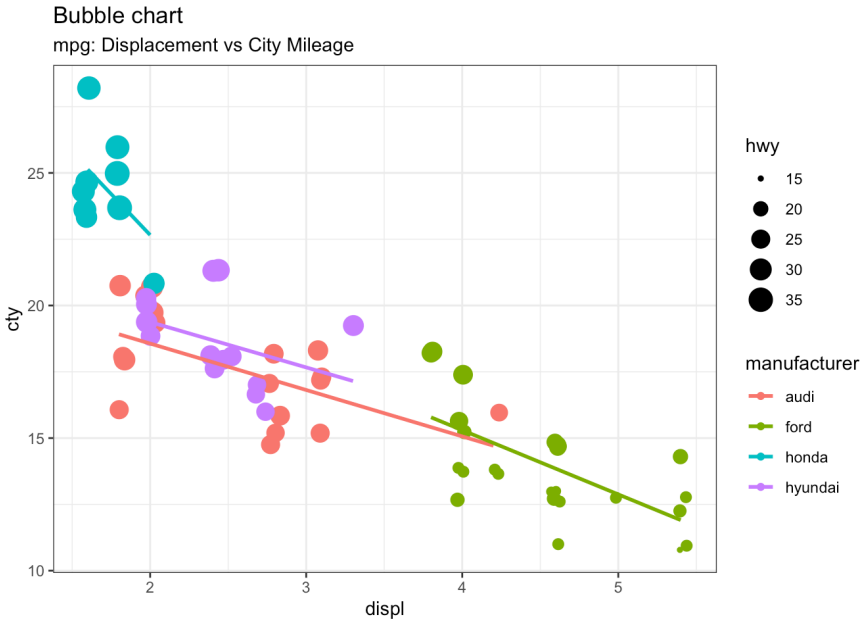
Smoothing Lines

```
options(scipen=999)  # turn-off scientific notation
theme_set(theme_bw())  # pre-set the bw theme.
data("midwest", package = "ggplot2")

ggplot(midwest, aes(x=area, y=poptotal)) +
  geom_point(aes(col=state, size=popdensity)) +
  geom_smooth(method="loess", se=F) +
  xlim(c(0, 0.1)) + ylim(c(0, 500000)) +
  labs(subtitle="Area Vs Population", y="Population", x="Area",
  title="Scatterplot", caption = "Source: midwest")
```



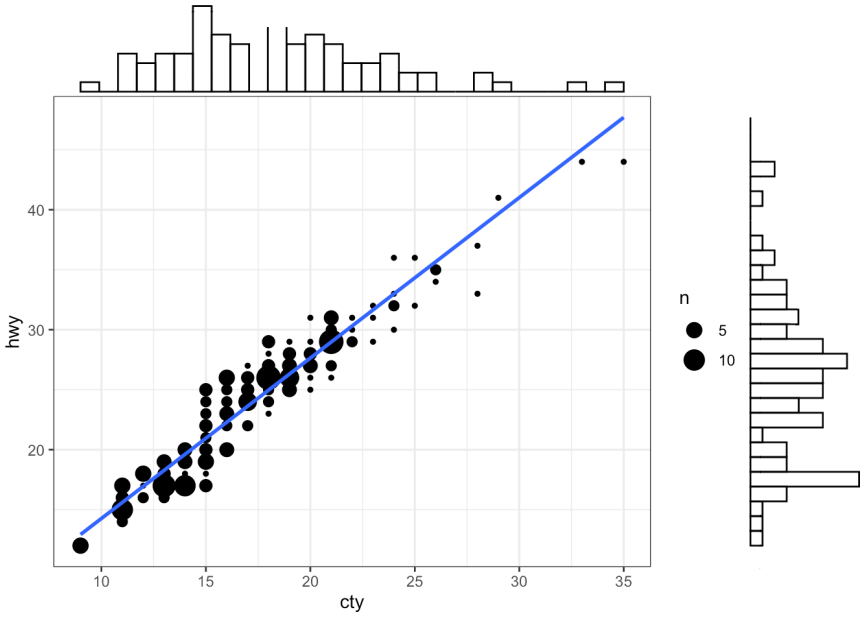
Scatterplots and Jitter Charts

```
data(mpg, package="ggplot2")
mpg_select <- mpg[mpg$manufacturer %in% c("audi", "ford",
                  "honda", "hyundai"), ]

g <- ggplot(mpg_select, aes(displ, cty)) +
  labs(subtitle="mpg: Displacement vs City Mileage",
       title="Bubble chart") +
  geom_jitter(aes(col=manufacturer, size=hwy)) +
  geom_smooth(aes(col=manufacturer), method="lm", se=F)
```



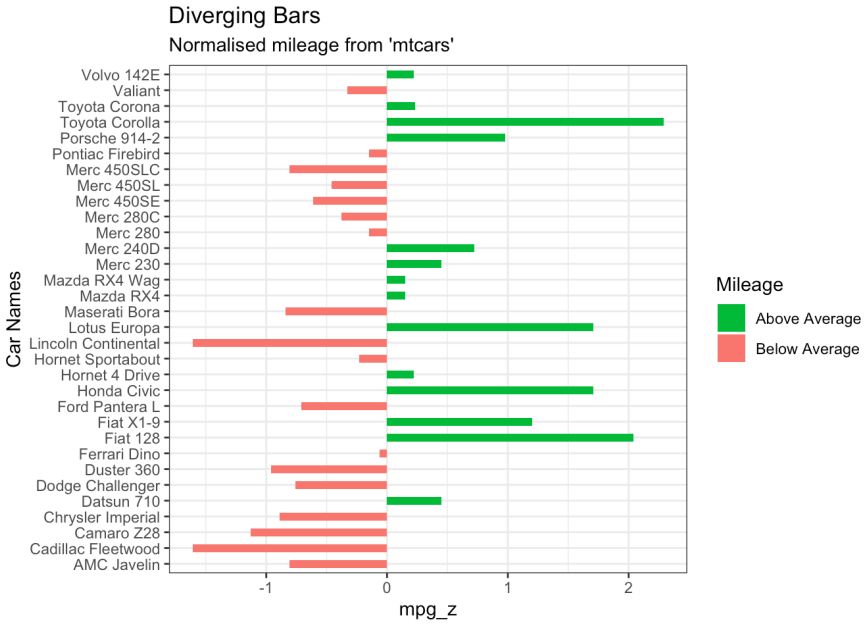
Marginal Distributions

```
library(ggExtra)
data(mpg, package="ggplot2")

mpg_select <- mpg[mpg$hwy >= 35 & mpg$cty > 27, ]
g <- ggplot(mpg, aes(cty, hwy)) + geom_count() +
  geom_smooth(method="lm", se=F)

plot(g)
ggMarginal(g, type = "histogram", fill="transparent")
```



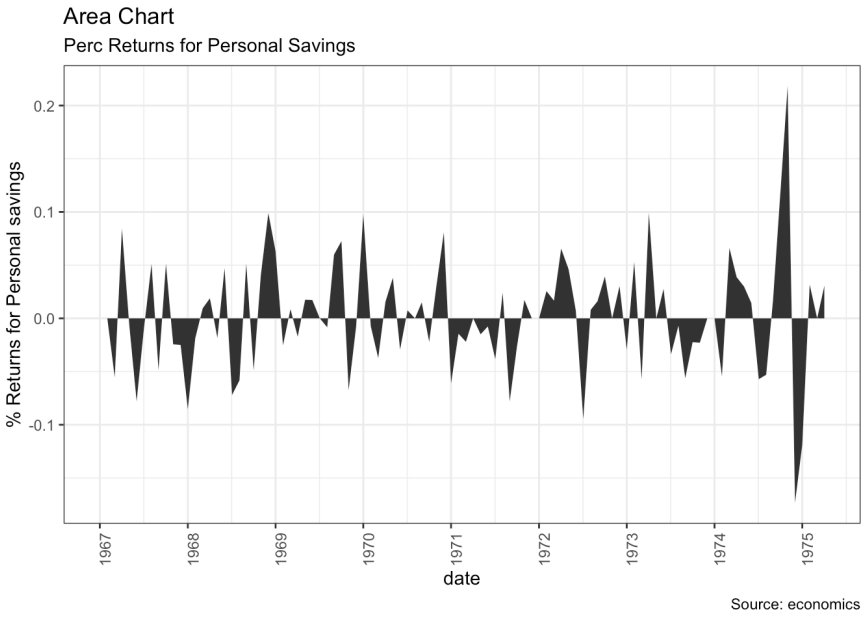
Diverging Bar Charts

```
mtcars_new <- mtcars |>
  tibble::rownames_to_column(var = "car_name") |>
  dplyr::mutate(car_name = as.factor(car_name),
    mpg_z = round(scale(mpg), 2),
    mpg_type = ifelse(mpg_z < 0, "below", "above")) |>
  dplyr::arrange(mpg_z) # sort

# Diverging Barcharts
ggplot(mtcars_new, aes(x= car_name, y=mpg_z, label=mpg_z)) +
  geom_bar(stat='identity', aes(fill=mpg_type), width=.5)  +
  scale_fill_manual(name="Mileage",
    labels = c("Above Average", "Below Average"),
    values=c("above"="#00ba38", "below"="#f8766d")) +
  labs(subtitle="Normalised mileage from 'mtcars'",
    title= "Diverging Bars", x = "Car Names") + coord_flip()
```



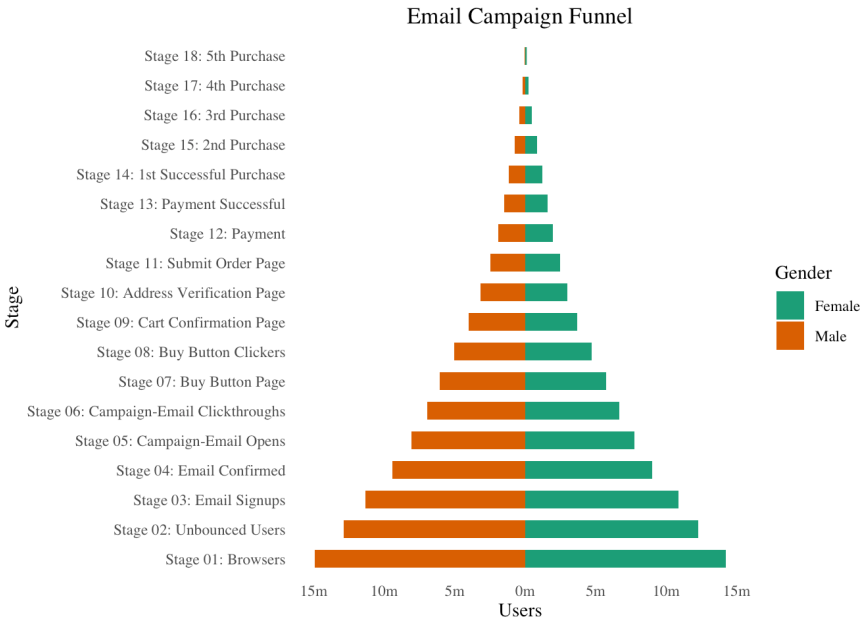
Area Charts

```
library(quantmod)
data("economics", package = "ggplot2")

# Compute % Returns
economics$returns_perc <- c(0, diff(economics$psavert) /
     economics$psavert[-length(economics$psavert)])

# Create break points and labels for axis ticks
brks <- economics$date[seq(1, length(economics$date), 12)]
#install.packages("lubridate")
lbls <- lubridate::year(economics$date[seq(1,
    length(economics$date), 12)])

# Plot
ggplot(economics[1:100, ], aes(date, returns_perc)) +
  geom_area() +
  scale_x_date(breaks=brks, labels=lbls) +
  theme(axis.text.x = element_text(angle=90)) +
  labs(title="Area Chart",
       subtitle = "Perc Returns for Personal Savings",
       y="% Returns for Personal savings",
       caption="Source: economics")
```



Funnel Charts

```
library(ggthemes)
library(ggfortify)

# Read data
email_campaign_funnel <- read.csv("https://raw.
      githubusercontent.com/selva86/datasets/
      master/email_campaign_funnel.csv")

# X Axis Breaks and Labels
brks <- seq(-15000000, 15000000, 5000000)
lbls = paste0(as.character(c(seq(15, 0, -5),
                             seq(5, 15, 5))), "m")

# Plot
ggplot(email_campaign_funnel, aes(x = Stage, y = Users,
        fill=Gender)) +
    geom_bar(stat = "identity", width = .6) +
    scale_y_continuous(breaks = brks,
        labels = lbls) +
    coord_flip() +
    labs(title="Email Campaign Funnel") +
    theme_tufte() +  # Tufte theme from ggfortify
    theme(plot.title = element_text(hjust = .5),
        axis.ticks = element_blank()) +
    scale_fill_brewer(palette = "Dark2")
```

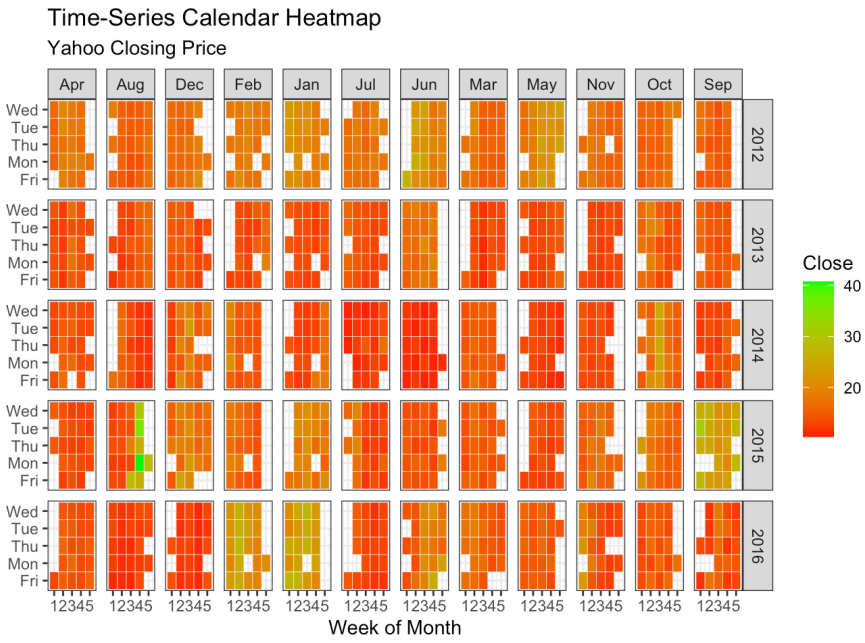


Calendar Heatmaps

```
library(plyr)
library(scales)
library(zoo)

df <- read.csv("https://raw.githubusercontent.com/selva86/
       datasets/master/yahoo.csv")
df$date <- as.Date(df$date)  # format date
df <- df[df$year >= 2012, ]  # filter reqd years

# Create Month/Week
df$yearmonth <- as.yearmon(df$date)
df$yearmonthf <- factor(df$yearmonth)
df <- ddply(df,.(yearmonthf), transform,
    monthweek=1+week-min(week))  # compute week number of month
df <- df[, c("year", "yearmonthf", "monthf", "week",
       "monthweek", "weekdayf", "VIX.Close")]
head(df)
```

```
  year yearmonthf monthf week monthweek weekdayf VIX.Close
1 2012   Jan 2012    Jan    1         1      Tue     22.97
2 2012   Jan 2012    Jan    1         1      Wed     22.22
3 2012   Jan 2012    Jan    1         1      Thu     21.48
4 2012   Jan 2012    Jan    1         1      Fri     20.63
5 2012   Jan 2012    Jan    2         2      Mon     21.07
6 2012   Jan 2012    Jan    2         2      Tue     20.69
```

```
# Plot
ggplot(df, aes(monthweek, weekdayf, fill=VIX.Close)) +
  geom_tile(colour = "white") +
  facet_grid(year~monthf) +
  scale_fill_gradient(low="red", high="green") +
  labs(x="Week of Month",
       y="",
       title = "Time-Series Calendar Heatmap",
       subtitle="Yahoo Closing Price",
       fill="Close")
```

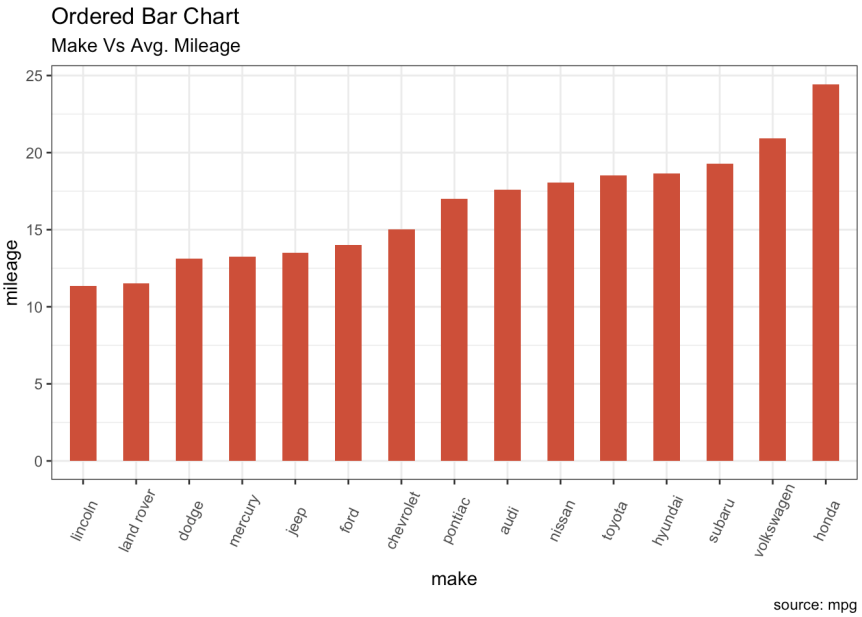


Ordered Bar Charts

```
# Prepare data: group mean city mileage by manufacturer.
cty_mpg <- aggregate(mpg$cty, by=list(mpg$manufacturer), FUN=mean)
colnames(cty_mpg) <- c("make", "mileage")
cty_mpg <- cty_mpg[order(cty_mpg$mileage), ]
cty_mpg$make <- factor(cty_mpg$make, levels = cty_mpg$make)
head(cty_mpg, 4)
```

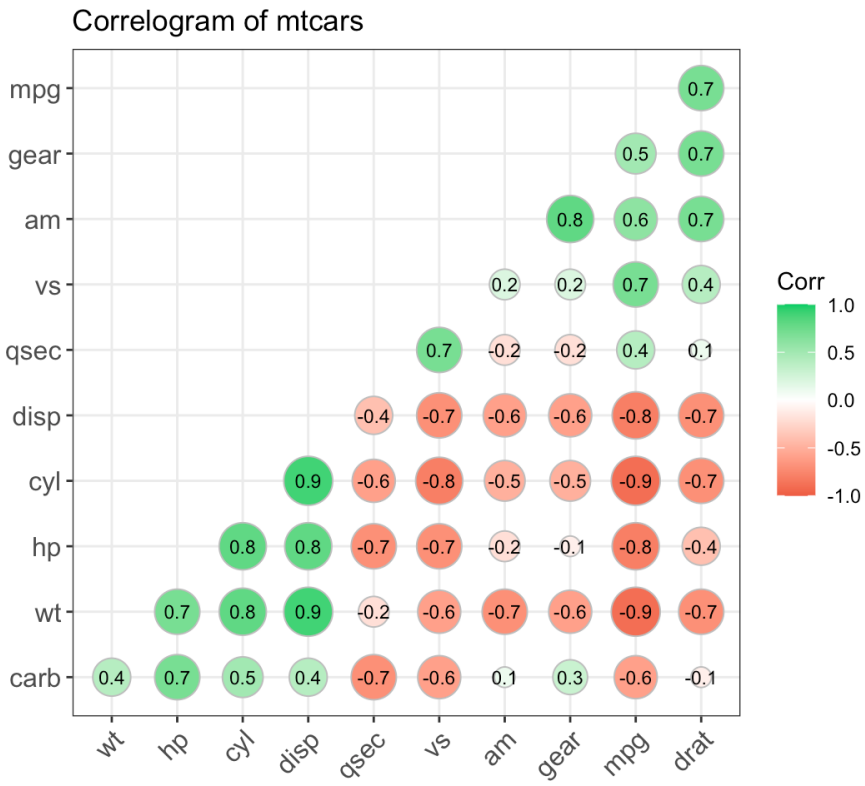
```
         make  mileage
9     lincoln 11.33333
8  land rover 11.50000
3       dodge 13.13514
10    mercury 13.25000
```

```
# Draw plot
ggplot(cty_mpg, aes(x=make, y=mileage)) +
  geom_bar(stat="identity", width=.5, fill="tomato3") +
  labs(title="Ordered Bar Chart",
       subtitle="Make Vs Avg. Mileage",
       caption="source: mpg") +
  theme(axis.text.x = element_text(angle=65, vjust=0.6))
```



Correlograms

```
library(ggcorrplot)

# Correlation matrix
corr <- round(cor(mtcars), 1)

# Plot
ggcorrplot(corr, hc.order = TRUE,
           type = "lower",
           lab = TRUE,
           lab_size = 3,
           method="circle",
           colors = c("tomato2", "white", "springgreen3"),
           title="Correlogram of mtcars",
           ggtheme=theme_bw)
```



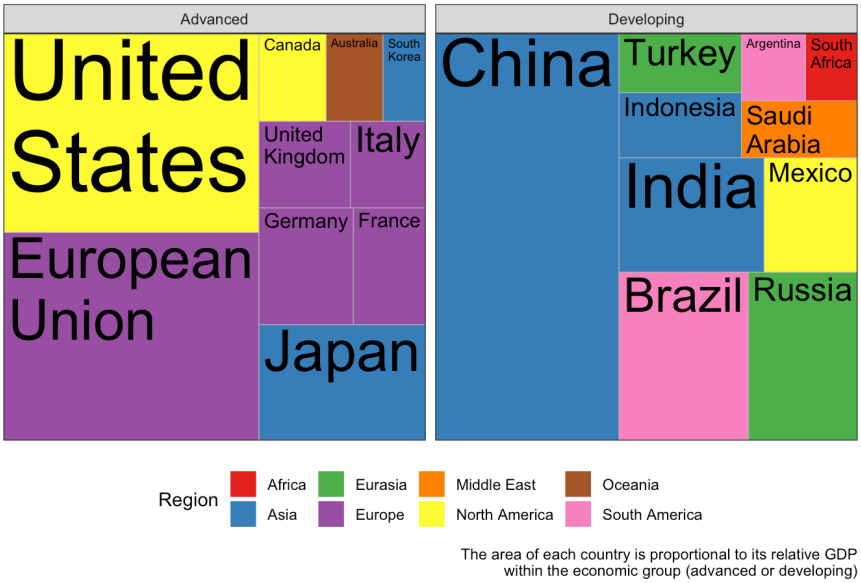
Treemaps

```
library(devtools)
#devtools::install_github("wilkox/treemapify")
library(treemapify)
data(G20)
head(G20)
```

```
         region       country gdp_mil_usd   hdi
1        Africa  South Africa      384315 0.629
2 North America United States    15684750 0.937
3 North America        Canada     1819081 0.911
4 North America        Mexico     1177116 0.775
5 South America        Brazil     2395968 0.730
6 South America     Argentina      474954 0.811

  econ_classification hemisphere
1          Developing   Southern
2            Advanced   Northern
3            Advanced   Northern
4          Developing   Northern
5          Developing   Southern
6          Developing   Southern
```

```
ggplot(G20, aes(area = gdp_mil_usd, fill=region,
     label = country)) +
  geom_treemap() +
  geom_treemap_text(grow = T, reflow = T, colour = "black") +
  facet_wrap( ~ econ_classification) +
  scale_fill_brewer(palette = "Set1") +
  theme(legend.position = "bottom") +
  labs(
    title = "The G-20 major economies",
    caption = "The area of each country is proportional
        to its relative GDP
 within the economic group (advanced or developing)",
    fill="Region"
  )
```

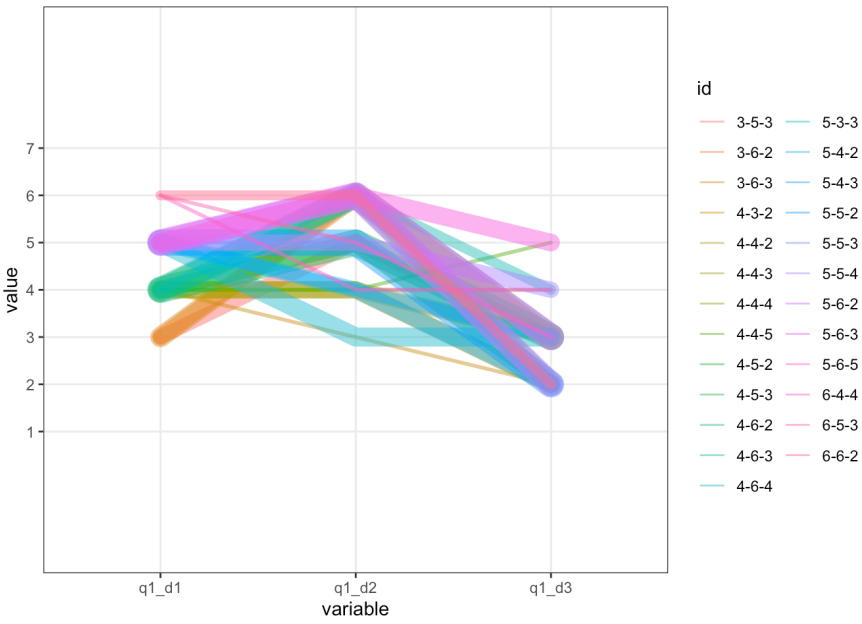
The G-20 major economies



Parallel Coordinates

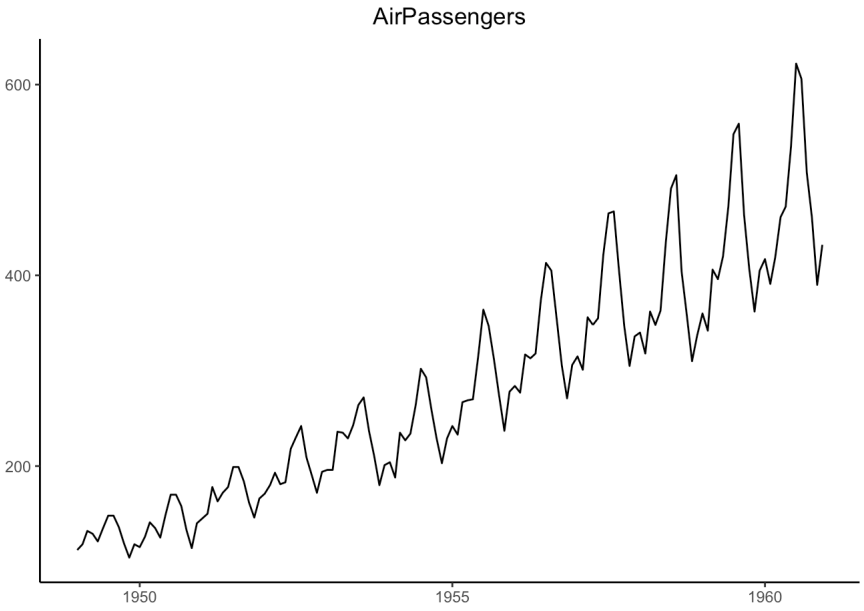
```
library(dplyr)
library(triangle)
set.seed(0)

q1_d1 <- round(rtriangle(1000, 1, 7, 5))
q1_d2 <- round(rtriangle(1000, 1, 7, 6))
q1_d3 <- round(rtriangle(1000, 1, 7, 2))
df <- data.frame(q1_d1 = factor(q1_d1), q1_d2 = factor(q1_d2),
         q1_d3 =  factor(q1_d3))

# group by combinations and count
df_grouped <- df |> group_by(q1_d1, q1_d2, q1_d3) |> count()
```

```
# set an id string that denotes the value combination
df_grouped <- df_grouped |> mutate(id = factor(paste(q1_d1,
       q1_d2, q1_d3, sep = '-')))

order.freq <- order(df_grouped[,4],decreasing=TRUE)

# sort by count and select top rows
df_grouped <- df_grouped[order.freq[1:25],]

library(reshape2)
# create long format
df_pcp <- melt(df_grouped, id.vars = c('id', 'freq'))
df_pcp$value <- factor(df_pcp$value)

y_levels <- levels(factor(1:7))
ggplot(df_pcp, aes(x = variable, y = value, group = id)) +
  geom_path(aes(size = freq, color = id),
            alpha = 0.5,
            lineend = 'round', linejoin = 'round') +
  scale_y_discrete(limits = y_levels, expand = c(0.5, 0)) +
  scale_size(breaks = NULL, range = c(1, 7))
```

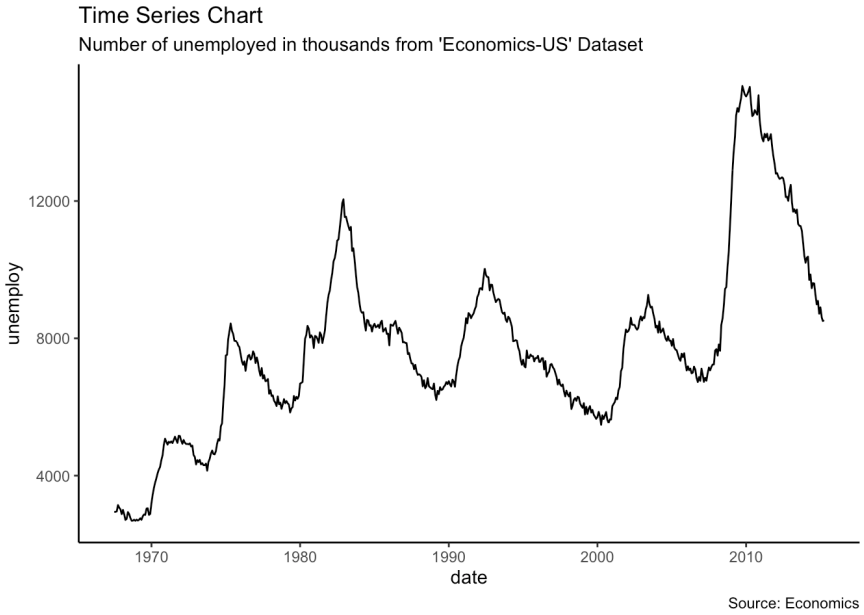


Time Series and Variants

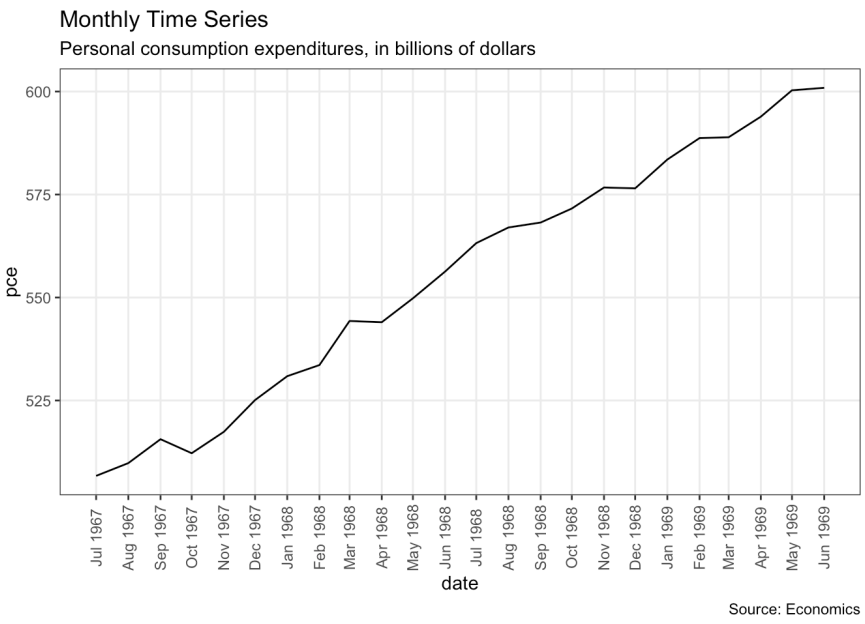
```
library(ggfortify)
theme_set(theme_classic())

autoplot(AirPassengers) + labs(title="AirPassengers") +
  theme(plot.title = element_text(hjust=0.5))
```




```
theme_set(theme_classic())

ggplot(economics, aes(x=date)) +
  geom_line(aes(y=unemploy)) +
  labs(title="Time Series Chart",
       subtitle="Number of unemployed in thousands from
                 'Economics-US' Dataset",
       caption="Source: Economics",
       y="unemploy")
```

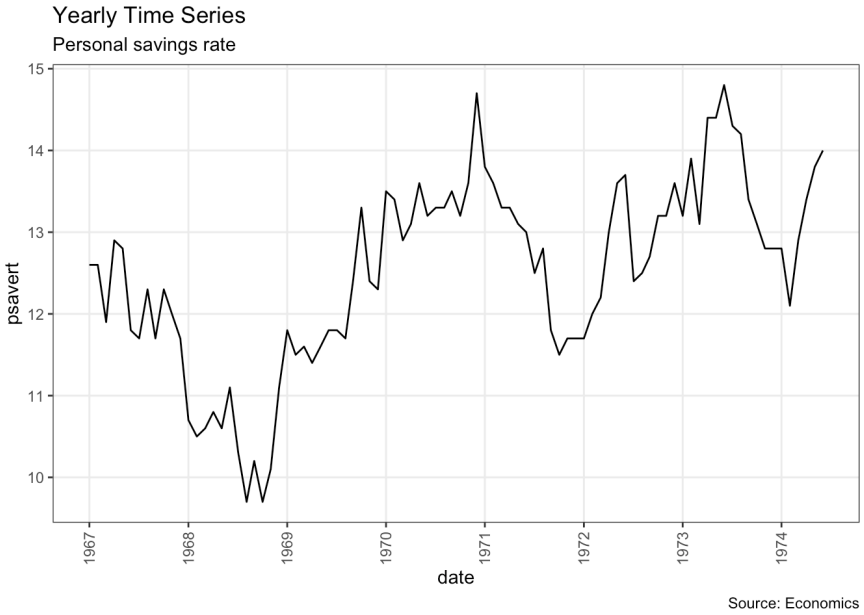


```
library(lubridate)

economics_m <- economics[1:24, ]

# labels and breaks for X axis text
lbls <- paste0(month.abb[month(economics_m$date)], " ",
       lubridate::year(economics_m$date))
brks <- economics_m$date

# plot
ggplot(economics_m, aes(x=date)) +
  geom_line(aes(y=pce)) +
  labs(title="Monthly Time Series",
       subtitle="Personal consumption expenditures, in
                billions of dollars",
       caption="Source: Economics", y="pce") +
  scale_x_date(labels = lbls, breaks = brks) +
  theme(axis.text.x = element_text(angle = 90, vjust=0.5),
        panel.grid.minor = element_blank())
```



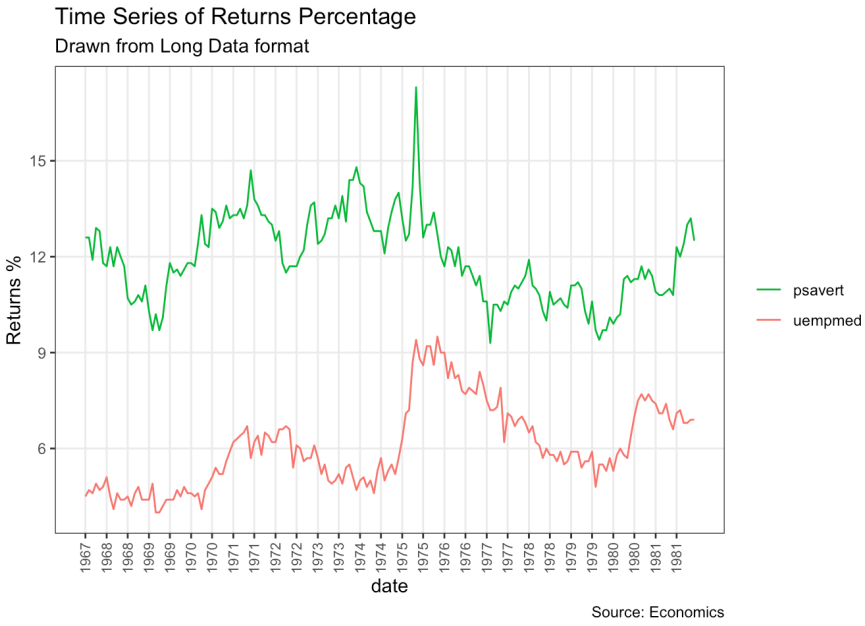

```
library(lubridate)

economics_y <- economics[1:90, ]

# labels and breaks for X axis text
brks <- economics_y$date[seq(1, length(economics_y$date),12)]
lbls <- lubridate::year(brks)

# plot
```

```
ggplot(economics_y, aes(x=date)) +
  geom_line(aes(y=psavert)) +
  labs(title="Yearly Time Series",
       subtitle="Personal savings rate",
       caption="Source: Economics",
       y="psavert") +
  scale_x_date(labels = lbls, breaks = brks) +
  theme(axis.text.x = element_text(angle = 90, vjust=0.5),
        panel.grid.minor = element_blank())
```

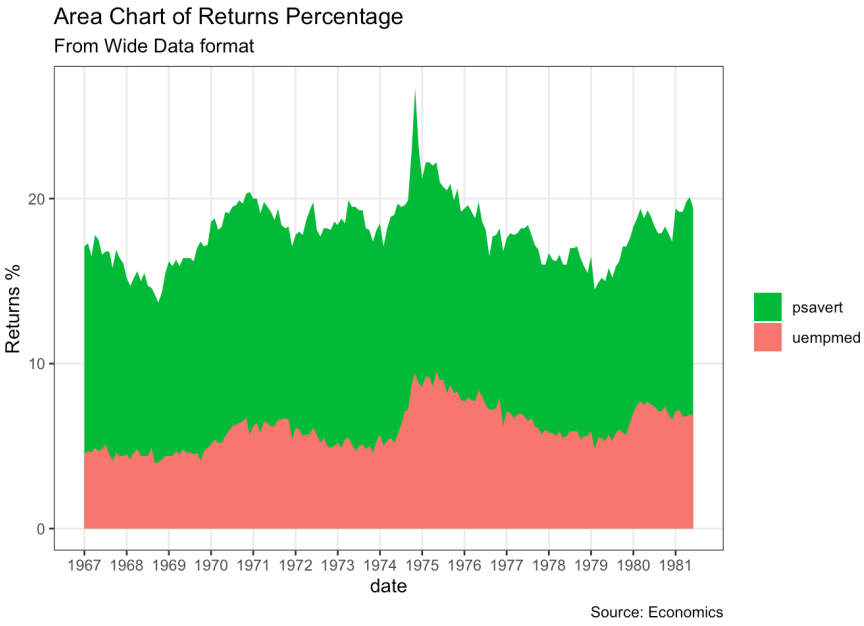



```
data(economics_long, package = "ggplot2")
head(economics_long)

library(lubridate)
df <- economics_long[economics_long$variable %in% c("psavert",
                                  "uempmed"), ]
df <- df[lubridate::year(df$date) %in% c(1967:1981), ]

# labels and breaks for X axis text
brks <- df$date[seq(1, length(df$date), 12)]
lbls <- lubridate::year(brks)

# plot
ggplot(df,aes(x=date)) + geom_line(aes(y=value,col=variable)) +
  labs(title="Time Series of Returns Percentage",
       subtitle="Drawn from Long Data format",
       caption="Source: Economics",
       y="Returns %", color=NULL) +
  scale_x_date(labels = lbls, breaks = brks) +
```

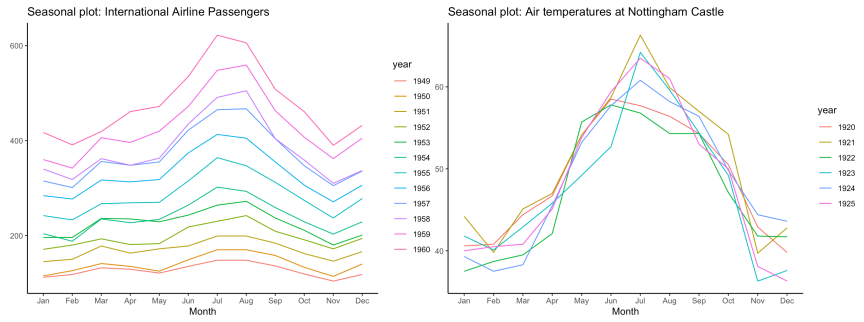
```
  scale_color_manual(labels = c("psavert", "uempmed"),
                     values=c("psavert"="#00ba38",
                              "uempmed"="#f8766d")) +
  theme(axis.text.x = element_text(angle = 90, vjust=0.5,
      size = 8), panel.grid.minor = element_blank())
```




```
library(lubridate)

df <- economics[, c("date", "psavert", "uempmed")]
df <- df[lubridate::year(df$date) %in% c(1967:1981), ]

# labels and breaks for X axis text
brks <- df$date[seq(1, length(df$date), 12)]
lbls <- lubridate::year(brks)

# plot
ggplot(df, aes(x=date)) +
  geom_area(aes(y=psavert+uempmed, fill="psavert")) +
  geom_area(aes(y=uempmed, fill="uempmed")) +
  labs(title="Area Chart of Returns Percentage",
       subtitle="From Wide Data format",
       caption="Source: Economics",
       y="Returns %") +
  scale_x_date(labels = lbls, breaks = brks) +
  scale_fill_manual(name="", values=c("psavert"="#00ba38",
           "uempmed"="#f8766d")) +
  theme(panel.grid.minor = element_blank())
```



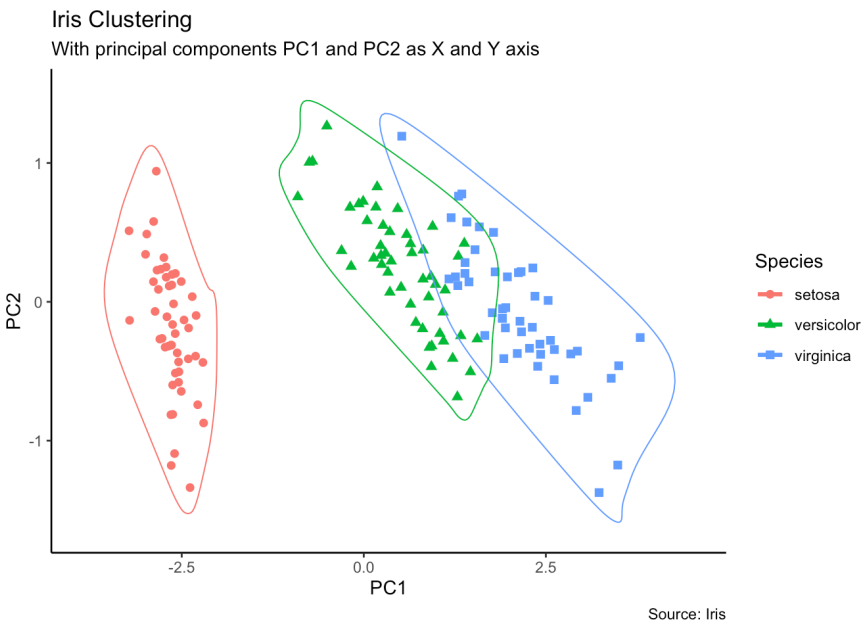

```
library(forecast)
theme_set(theme_classic())

# Subset data
small <- window(nottem, start=c(1920, 1), end=c(1925, 12))

# Plot
ggseasonplot(AirPassengers) + labs(title="Seasonal plot:
    International Airline Passengers")
ggseasonplot(small) + labs(title="Seasonal plot: Air
    temperatures at Nottingham Castle")
```



Clusters

```
# devtools::install_github("hrbrmstr/ggalt")
library(ggalt)
library(ggfortify)
theme_set(theme_classic())
```

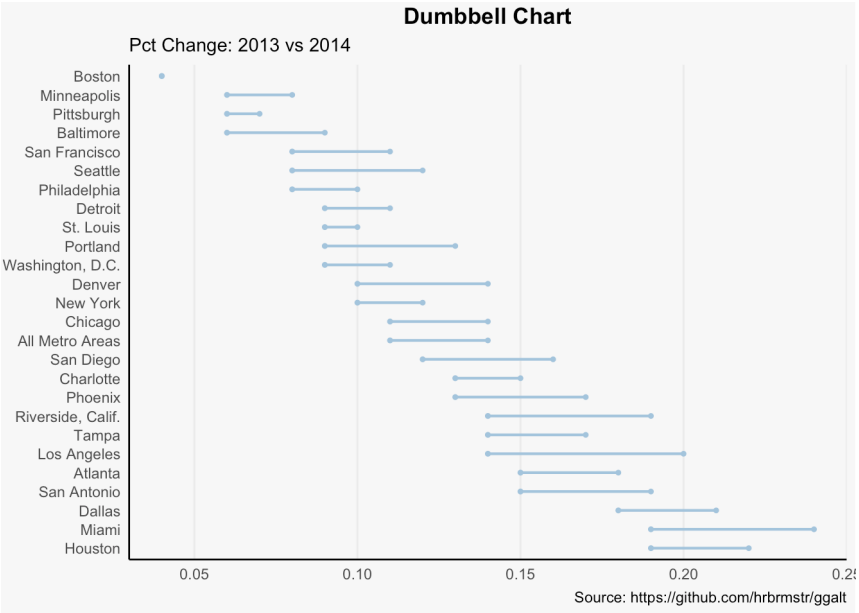
```
# Compute data with principal components
df <- iris[c(1, 2, 3, 4)]
pca_mod <- prcomp(df)  # compute principal components
# Data frame of principal components -
df_pc <- data.frame(pca_mod$x, Species=iris$Species)
df_pc_vir <- df_pc[df_pc$Species == "virginica", ]
df_pc_set <- df_pc[df_pc$Species == "setosa", ]
df_pc_ver <- df_pc[df_pc$Species == "versicolor", ]

# Plot
ggplot(df_pc, aes(PC1, PC2, col=Species)) +
  geom_point(aes(shape=Species), size=2) +
  labs(title="Iris Clustering",
       subtitle="With principal components PC1 and PC2
                 as X and Y axis",
       caption="Source: Iris") +
  coord_cartesian(xlim=1.2*c(min(df_pc$PC1),max(df_pc$PC1)),
                  ylim=1.2*c(min(df_pc$PC2),max(df_pc$PC2))) +
  geom_encircle(data=df_pc_vir, aes(x=PC1, y=PC2)) +
  geom_encircle(data=df_pc_set, aes(x=PC1, y=PC2)) +
  geom_encircle(data=df_pc_ver, aes(x=PC1, y=PC2))
```



Dumbbell Charts

```
# devtools::install_github("hrbrmstr/ggalt")
library(ggalt)
theme_set(theme_classic())

health <- read.csv("https://raw.githubusercontent.com/
        selva86/datasets/master/health.csv")
```

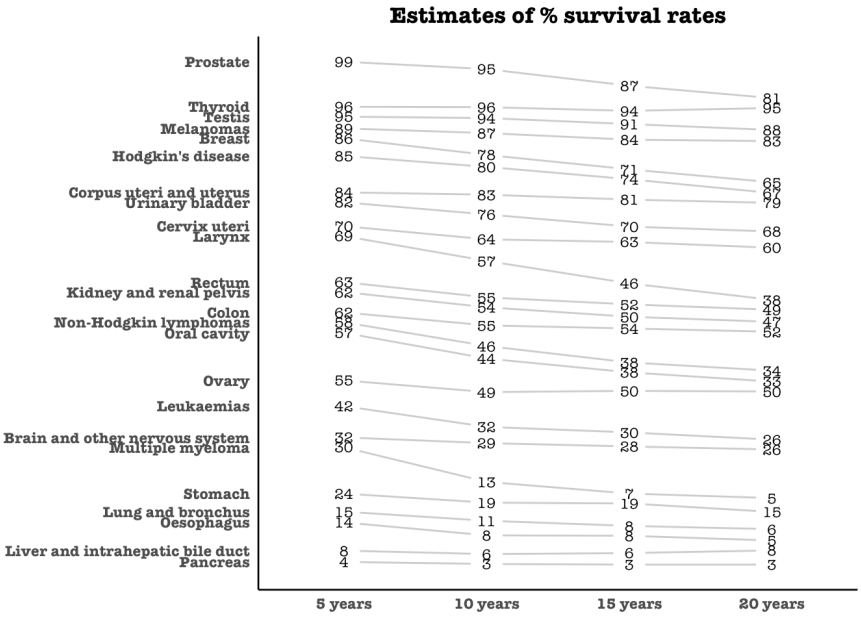
```
# for right ordering of the dumbells
health$Area <- factor(health$Area,
    levels=as.character(health$Area))

# health$Area <- factor(health$Area)
gg <- ggplot(health, aes(x=pct_2013, xend=pct_2014, y=Area,
    group=Area)) +
    geom_dumbbell(color="#a3c4dc",
                  size=0.75,
                  point.colour.l="#0e668b") +
    scale_x_continuous(label=waiver()) +
    labs(x=NULL,
         y=NULL,
         title="Dumbbell Chart",
         subtitle="Pct Change: 2013 vs 2014",
         caption="Source: https://github.com/hrbrmstr/ggalt") +
    theme(plot.title = element_text(hjust=0.5, face="bold"),
          plot.background=element_rect(fill="#f7f7f7"),
          panel.background=element_rect(fill="#f7f7f7"),
          panel.grid.minor=element_blank(),
          panel.grid.major.y=element_blank(),
          panel.grid.major.x=element_line(),
          axis.ticks=element_blank(),
          legend.position="top",
          panel.border=element_blank())
plot(gg)
```



Slope Charts

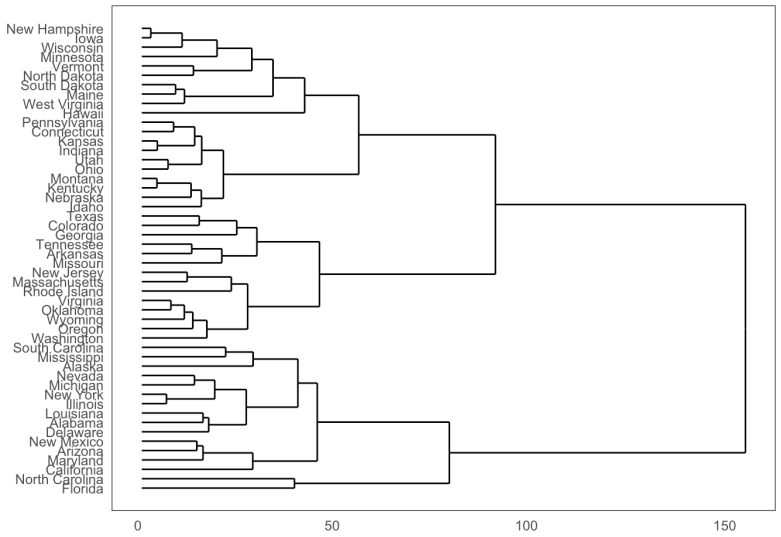
```
library(dplyr)
theme_set(theme_classic())
source_df <- read.csv("https://raw.githubusercontent.com/
    jkeirstead/r-slopegraph/master/cancer_survival_rates.csv")

# Define functions
tufte_sort <- function(df, x="year", y="value", group="group",
        method="tufte", min.space=0.05) {
    ## First rename the columns for consistency
    ids <- match(c(x, y, group), names(df))
    df <- df[,ids]
    names(df) <- c("x", "y", "group")

    ## Expand grid so all combinations have a value
    tmp <- expand.grid(x=unique(df$x), group=unique(df$group))
    tmp <- merge(df, tmp, all.y=TRUE)
    df <- mutate(tmp, y=ifelse(is.na(y), 0, y))

    ## Cast into a matrix shape and arrange by first column
    require(reshape2)
    tmp <- dcast(df, group ~ x, value.var="y")
    ord <- order(tmp[,2])
    tmp <- tmp[ord,]
    min.space <- min.space*diff(range(tmp[,-1]))
    yshift <- numeric(nrow(tmp))
    for (i in 2:nrow(tmp)) {
      mat <- as.matrix(tmp[(i-1):i, -1])
      d.min <- min(diff(mat))
      yshift[i] <- ifelse(d.min < min.space, min.space-d.min,0)
    }

    tmp <- cbind(tmp, yshift=cumsum(yshift))
    scale <- 1
    tmp <- melt(tmp,id=c("group","yshift"), variable.name="x",
                value.name="y")
    tmp <- transform(tmp, ypos=y + scale*yshift)
    return(tmp)
}

plot_slopegraph <- function(df) {
    ylabs <- subset(df, x==head(x,1))$group
    yvals <- subset(df, x==head(x,1))$ypos
    fontSize <- 3
    gg <- ggplot(df,aes(x=x,y=ypos)) +
      geom_line(aes(group=group),colour="grey80") +
      geom_point(colour="white",size=8) +
      geom_text(aes(label=y), size=fontSize) +
```

```
      scale_y_continuous(name="", breaks=yvals, labels=ylabs)
    return(gg)
}

## Prepare data
df <- tufte_sort(source_df,
                 x="year",
                 y="value",
                 group="group",
                 method="tufte",
                 min.space=0.05)

df <- transform(df,
                x=factor(x, levels=c(5,10,15,20),
                            labels=c("5 years","10 years",
                                     "15 years","20 years")),
                y=round(y))

## Plot
plot_slopegraph(df) + labs(title="Estimates of % survival rates") +
                theme(axis.title=element_blank(),
                          axis.ticks = element_blank(),
                          plot.title = element_text(hjust=0.5,
                              family = "American Typewriter",
                              face="bold"),
                          axis.text = element_text(family =
                              "American Typewriter",
                              face="bold"))
```



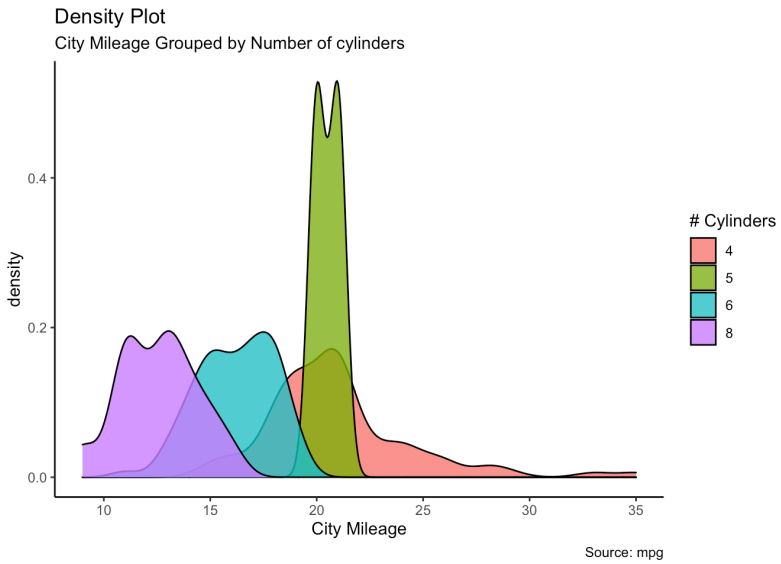
Dendrograms

```
library("ggdendro")
hc <- hclust(dist(USArrests), "ave")  # hierarchical clust.
ggdendrogram(hc, rotate = TRUE,size=2)
```



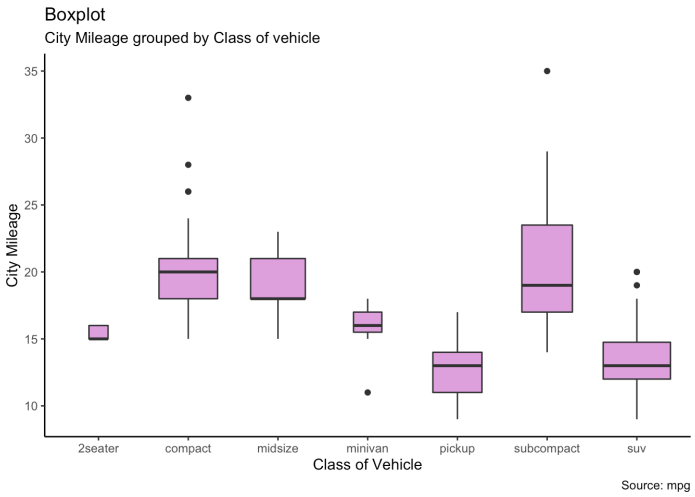
Density Plots

```
theme_set(theme_classic())
ggplot(mpg, aes(cty)) + geom_density(aes(fill=factor(cyl)),
  alpha=0.8) + labs(title="Density Plot",
  subtitle="City Mileage Grouped by Number of cylinders",
  caption="Source: mpg", x="City Mileage", fill="# Cylinders")
```



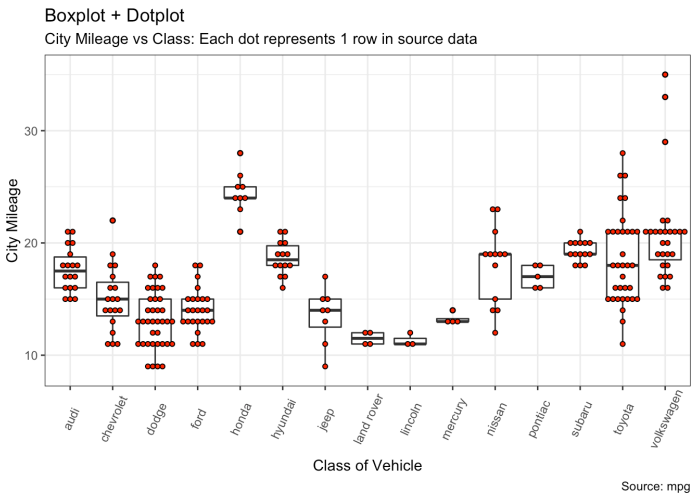
Boxplots

```
theme_set(theme_classic())
ggplot(mpg, aes(class, cty)) + geom_boxplot(varwidth=T,
  fill="plum") + labs(title="Boxplot",
   subtitle="City Mileage grouped by Class of vehicle",
   caption="Source: mpg", x="Class of Vehicle", y="City Mileage")
```



Boxplots and Dotplots

```
theme_set(theme_bw())
ggplot(mpg, aes(manufacturer, cty)) + geom_boxplot() +
  geom_dotplot(binaxis='y', stackdir='center',
               dotsize=.5, fill="red") +
  theme(axis.text.x = element_text(angle=65, vjust=0.6)) +
  labs(title="Boxplot + Dotplot", subtitle="City Mileage vs
    Class: Each dot represents 1 row in source data",
  caption="Source: mpg",x="Class of Vehicle",y="City Mileage")
```



Waffle Charts

```
var <- mpg$class  # the categorical data
nrows <- 10
df <- expand.grid(y = 1:nrows, x = 1:nrows)
(categ_table <- round(table(var)*((nrows*nrows)/(length(var)))))
```

```
  2seater compact midsize minivan pickup subcompact suv
        2      20      18       5     14         15  26
```

```
df$category <- factor(rep(names(categ_table), categ_table))

ggplot(df,aes(x=x,y=y,fill=category)) +
  geom_tile(color="black", size=0.5) +
  scale_x_continuous(expand=c(0,0)) +
  scale_y_continuous(expand = c(0, 0), trans = 'reverse') +
  scale_fill_brewer(palette = "Set3") +
  labs(title="Waffle Chart", subtitle="'Class' of vehicles",
  caption="Source: mpg") +
  plot.title = element_text(size = rel(1.2)),
    legend.position = "right",
  axis.text = element_blank(),
  axis.title = element_blank(),
  axis.ticks = element_blank(),
  legend.title = element_blank())
```