Math 241: Engineering Statistics

S DeRuiter (based on original by R Pruim)

Spring 2015

Contents

0 Where do numbers come from?

Scientists and engineers work with numbers constantly. Physical constants, values for the specific heat index or measures of strength or flexibility of some material, resistance of some component in an electrical device, etc., etc.

Most of these numbers come from some process that generated data, often leading to a calculuation that produced the number.

Thought experiment – How many coins?

Here's a thought experiment for you. Suppose a middle school class has collected a large number of coins in a sack. Before bringing the money to the bank, they would like to estimate how many coins they have (using tools and methods that 6th graders have at their disposal). You've been brought in to consult with them about how they should do this.

1. What method would you suggest? Why?
2. What other methods would be possible? What makes your proposed method better?
3. For your favorite method and others, identify factors that lead the resulting estimate to be different from the exact number of coins in the sack.

Some important terms

estimand/measureand The number we want to know. The "truth." In our example this is the number of coins in the bag. Typically this will be a number that describes some process or population, and typically it will be impossible to know the value exactly.

estimate/measurement The value calculated from our data. This may be as simple as recording a value reported by some device, or it may involve recording multiple values, perhaps of multiple variables, maybe at multiple times, and making some computations with that data.

error The difference between the estimate and the estimand. Because we don't know the estimand exactly, we can't know the error exactly either. But thinking about what the error could be is a big part of understanding the statistical properties of an estimation method. Generally, we want methods where errors tend to be small (so our estimate is "likely to be close to the estimand") and centered around 0 (so we're "right on average").

systematic (component of) error a component of error that makes our estimate biased – in other words, leads the estimate to be either an over- or under-estimate. For example, neglecting the weight of the sack would lead us to overestimate the weight of the coins, and therefore overestimate the number of coins. Another way to express this idea is "a tendency to be off in a certain direction."

random (component of) error a component of error that leads to variability in estimates (but not a particular tendency toward over- or under-estimation). If random errors are larger, there will be more variability in estimates, so we will be less confident that the estimand and estimate are close together – although some estimates may still be very close to the estimand, just by chance.

One of the big questions in statistics is this: *What does our estimate tell us about the estimand?* We will eventually learn techniques for quantifying (and attempting to reduce) the effects of error in our measurements.

1 Graphical Summaries of Data

1.1 Getting Started With RStudio

RStudio is an integrated development environment (IDE) for R, a freely available language and environment for statistical computing and graphics. Both Rand RStudio are freely available for Mac, PC, and Linux.

We have set up an RStudio server on campus, which allows you to run R in a web browser on any computer without installing the software yourself. Your session is restored each time you log in, so you can work on multiple computers without losing your work when you move from one to the other. The RStudio server is the recommended interface for using R and RStudio for this course. You can access the RStudio server via a web browser. (For best results, avoid Internet Explorer.)

If you prefer to install R and RStudio directly on your own computer, you can get R at `<http://cran.r-project.org>` and RStudio at `<http://rstudio.org/>`.

To access the Calvin RStudio server, use the links from our course Moodle site, or connect directly at `http://rstudio.calvin.edu:8787`.

1.1.1 Logging in

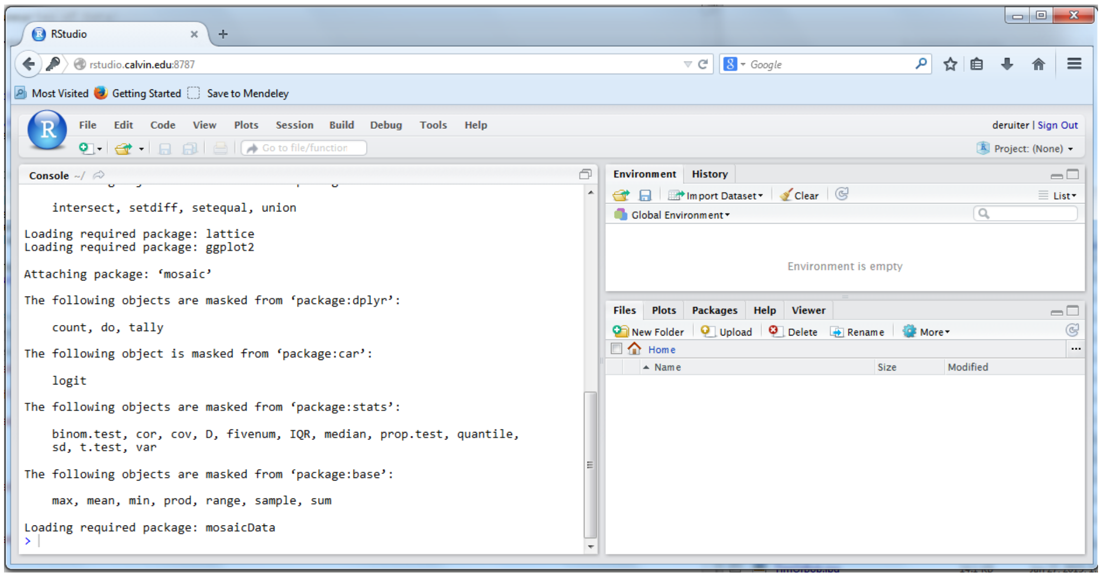
When you navigate to the RStudio server, you will be prompted to login. Your login is your Calvin Gmail address, and your password is the corresponding password. Once you are logged in, you will see something like Figure 1.1.

1.1.2 Using R as a calculator

Notice that RStudio divides its world into four panels. Several of the panels are further subdivided into multiple tabs. The **Console** panel is where we type commands that R will execute.

R can be used as a calculator. Try typing the following commands in the console panel.

```
5 + 3

## [1] 8

15.3 * 23.4
```



```
    intersect, setdiff, setequal, union

Loading required package: lattice
Loading required package: ggplot2

Attaching package: ‘mosaic’

The following objects are masked from ‘package:dplyr’:

    count, do, tally

The following object is masked from ‘package:car’:

    logit

The following objects are masked from ‘package:stats’:

    binom.test, cor, cov, D, fivenum, IQR, median, prop.test, quantile,
    sd, t.test, var

The following objects are masked from ‘package:base’:

    max, mean, min, prod, range, sample, sum

Loading required package: mosaicData
>
```

Figure 1.1: Welcome to RStudio.

```
## [1] 358.02

sqrt(16)

## [1] 4
```

You can save values to named variables for later reuse

```
product = 15.3 * 23.4        # save result
product                      # show the result

## [1] 358.02

product <- 15.3 * 23.4       # <- is assignment operator, same as =
product

## [1] 358.02

15.3 * 23.4 -> newproduct    # -> assigns to the right
newproduct

## [1] 358.02

.5 * product                 # half of the product

## [1] 179.01

log(product)                 # (natural) log of the product
```

```
## [1] 5.880589

log10(product)              # base 10 log of the product

## [1] 2.553907

log(product,base=2)         # base 2 log of the product

## [1] 8.483896
```

The semi-colon can be used to place multiple commands on one line. One frequent use of the semi-colon is to save and print a value all in one line of code:

```
15.3 * 23.4 -> product; product     # save result and show it

## [1] 358.02
```

1.1.3 Loading packages

R is divided up into packages. You can think of the packages as software toolkits designed to do particular jobs. A few of these, known as "base R", are loaded every time you run R, but most have to be selected. This way you only have as much of R as you need. There are two steps to follow before you can use a package in R:

1. Install the package. This operation downloads the relevant files to your computer, and lets R know where they are located. It does *not* give the current R session permission to use the tools contained in the package! The packages you will need for work in this course have already been installed on the Calvin RStudio server. For this course, you will probably not need to install any packages yourself, unless you are using a local copy of R and RStudio installed on your own computer. If you need to install packages, an easy way to do it is to use the **Packages** tab in the lower right panel of RStudio. Just click on **Install** (upper left corner of the **Packages** tab) and then type the name of the package.

2. Load the package. This operation gives the current R session permission to access and use the tools contained in the package. Even if you are using the RStudioserver, you will often need to load required packages at the beginning of each R session. There are several ways to load packages, as detailed below.

In the Packages tab, check the boxes next to the following packages to load them:

- `mosaic` (a package from Project MOSAIC; this should already be loaded)
- `DAAG` (a package that goes with the book *Data Analysis and Graphics*; probably not loaded, check the box to load it.)

You an also load packages by typing, for example

```
require(DAAG)  # loads the DAAG package if it is not already loaded
```

1.1.4 Four Things to Know About R

1. R is case-sensitive

   If you mis-capitalize something in R, it won't do what you want.

2. Functions in R use the following syntax:

   ```
   functionname(argument1, argument2, ...)
   ```

   - The arguments are always *surrounded by (round) parentheses* and *separated by commas.* Some functions (like `data()`) have no required arguments, but you still need the parentheses.
   - If you type a function name without the parentheses, you will see the *code* for that function printed out to the console window – which probably isn't what you want at this point.

3. TAB completion and arrows can improve typing speed and accuracy.

   If you begin typing a command and hit the TAB key, R will show you a list of possible ways to complete the command. If you hit TAB after the opening parenthesis of a function, it will show you the list of arguments it expects. The up and down arrows can be used to retrieve past commands.

4. Hit ESCAPE to break out of a mess.

   If you get into some sort of mess typing (usually indicated by extra '+' signs along the left edge, indicating that R is waiting for more input – perhaps because you have some sort of error in what has gone before), you can hit the escape key to get back to a clean prompt.

1.2 Data in R

1.2.1 Data Frames

Most often, data sets in R are stored in a structure called a **data frame**. A data frame is designed to hold "rectangular data". The people or things being measured or observed are called **observational units** (or subjects or cases when they are people). For measurements collected over time, the observational units would be the individual time-points at which data points were collected. Each observational unit is represented by one row in the data frame. The different pieces of information recorded for each observational unit are stored in separate columns, called **variables**.

1.2.2 Data in Packages

There are a number of data sets built into R and many more that come in various add-on packages.

You can see a list of data sets in a particular package like this:

```
data(mosaic)
```

You can find a longer list of all data sets available in any loaded package using

```
data()
```

1.2.3 The HELPrct data set

The `HELPrct` data frame from the `mosaic` package contains data from the Health Evaluation and Linkage to Primary Care randomized clinical trial. You can find out more about the study and the data in this data frame by typing

```
?HELPrct
```

Among other things, this will tell us something about the subjects (observational units) in this study:

> Eligible subjects were adults, who spoke Spanish or English, reported alcohol, heroin or cocaine as their first or second drug of choice, resided in proximity to the primary care clinic to which they would be referred or were homeless. Patients with established primary care relationships they planned to continue, significant dementia, specific plans to leave the Boston area that would prevent research participation, failure to provide contact information for tracking purposes, or pregnancy were excluded.
>
> Subjects were interviewed at baseline during their detoxification stay and follow-up interviews were undertaken every 6 months for 2 years.

It is often handy to look at the first few rows of a data frame. It will show you the names of the variables and the kind of data in them:

```
head(HELPrct)

##   age anysubstatus anysub cesd d1 daysanysub dayslink drugrisk e2b female    sex g1b
## 1  37            1    yes   49  3        177      225        0  NA      0   male yes
## 2  37            1    yes   30 22          2       NA        0  NA      0   male yes
## 3  26            1    yes   39  0          3      365       20  NA      0   male  no
## 4  39            1    yes   15  2        189      343        0   1      1 female  no
## 5  32            1    yes   39 12          2       57        0   1      0   male  no
## 6  47            1    yes    6  1         31      365        0  NA      1 female  no
##   homeless i1 i2 id indtot linkstatus link       mcs      pcs pss_fr racegrp satreat
## 1   housed 13 26  1     39          1  yes 25.111990 58.41369      0   black      no
## 2 homeless 56 62  2     43         NA <NA> 26.670307 36.03694      1   white      no
## 3   housed  0  0  3     41          0   no  6.762923 74.80633     13   black      no
## 4   housed  5  5  4     28          0   no 43.967880 61.93168     11   white     yes
## 5 homeless 10 13  5     38          1  yes 21.675755 37.34558     10   black      no
## 6   housed  4  4  6     29          0   no 55.508991 46.47521      5   black      no
##   sexrisk substance treat
## 1       4   cocaine   yes
## 2       7   alcohol   yes
## 3       2    heroin    no
## 4       4    heroin    no
## 5       6   cocaine    no
## 6       5   cocaine   yes

dim(HELPrct)

## [1] 453  27
```

The commands and R output above tell us that there are 453 observational units in this data set and 27 variables. That's plenty of variables to get us started with exploration of data.

1.2.4 The KidsFeet data set

Here is another data set in the `mosaic` package:

```
head(KidsFeet)
```

```
##     name birthmonth birthyear length width sex biggerfoot domhand
## 1  David          5        88   24.4   8.4   B          L       R
## 2   Lars         10        87   25.4   8.8   B          L       L
## 3   Zach         12        87   24.5   9.7   B          R       R
## 4   Josh          1        88   25.2   9.8   B          L       R
## 5   Lang          2        88   25.1   8.9   B          L       R
## 6 Scotty          3        88   25.7   9.7   B          R       R
```

1.2.5 The oldfaith data set

A final example data set comes from the `alr3` package. This package is probably not loaded (unless you already loaded it). You can load it from the Packages tab or by typing the command

```
require(alr3)
```

Once you have done that, you will have access to the data set containing information about eruptions of Old Faithful, a geyser in Yellowstone National Park.

```
head(oldfaith)
```

```
##   Duration Interval
## 1      216       79
## 2      108       54
## 3      200       74
## 4      137       62
## 5      272       85
## 6      173       55
```

If you want to know the size of your data set, you can ask it how many rows and columns it has with `nrow()`, `ncol()`, or `dim()`:

```
nrow(oldfaith)
```

```
## [1] 270
```

```
ncol(oldfaith)
```

```
## [1] 2
```

```
dim(oldfaith)
```

```
## [1] 270   2
```

In this case we have 270 observations of each of two variables. In a data frame, the observational units are always in the rows and the variables are always in the columns. If you create data for use in R (or most other statistical packages), you need to make sure your data are also in this shape.

1.2.6 Using your own data

We will postpone for now a discussion about getting your own data into RStudio, but any data you can get into a reasonable format (like csv) can be imported into RStudio pretty easily.

1.3 Graphing the Distribution of One Variable

A **distribution** tells which values a variable takes on, and with what frequency. That is, the distribution answers two questions:

- What values?
- How often?

Several standard statistical graphs can help us see distributions visually.

The general syntax for making a graph or numerical summary of one variable in a data frame is

```
plotname(~variable, data = dataName)
```

In other words, there are three pieces of information we must provide to R in order to get the plot we want:

- The kind of plot (`histogram()`, `bargraph()`, `densityplot()`, `bwplot()`, etc.)
- The name of the variable
- The name of the data frame this variable is a part of.

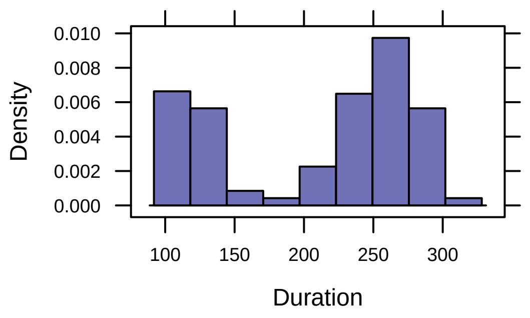
Note: The same syntax works for numerical summaries as well – thanks to the `mosaic` package we can apply the same syntax for `mean()`, `median()`, `sd()`, `var()`, `max()`, `min()`, etc. Later we will use this syntax again to fit linear and nonlinear models to data.

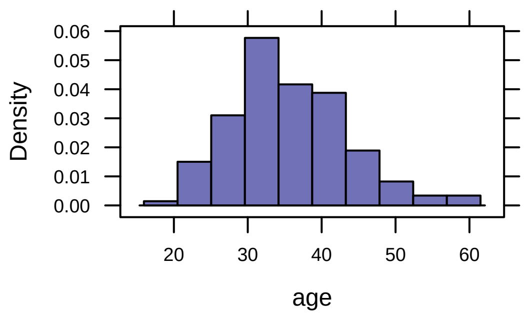
1.3.1 Histograms (and density plots) for quantitative variables

Histograms are a way of displaying the distribution of a quantitative variable.

Here are a couple examples:

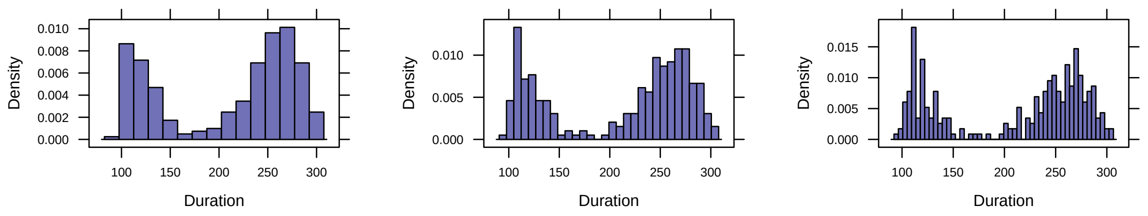
```
histogram(~Duration, data = oldfaith)
histogram(~age, data = HELPrct)
```





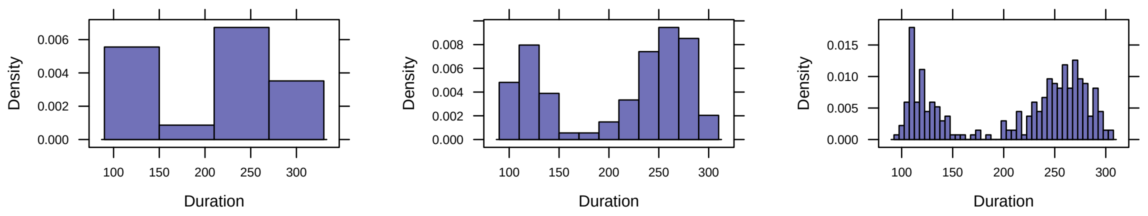
We can control the (approximate) number of bins using the `nint` argument, which may be abbreviated as `n`. The number of bins (and to a lesser extent the positions of the bins) can make a histogram look quite different.

```
histogram(~Duration, data = oldfaith, n = 15)
histogram(~Duration, data = oldfaith, n = 30)
histogram(~Duration, data = oldfaith, n = 50)
```



The `histogram()`[1] function in the `mosaic` package lets you describe the bins in terms of center and width instead of in terms of the number of bins. This is especially nice for count data.

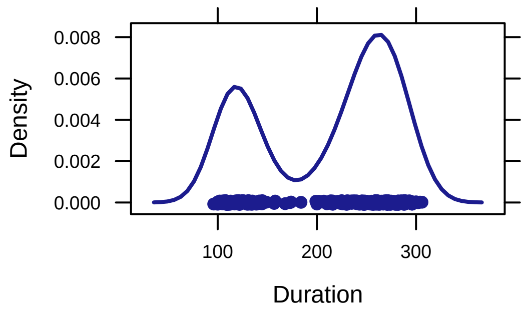
```
histogram(~Duration, data = oldfaith, width = 60)
histogram(~Duration, data = oldfaith, width = 20)
histogram(~Duration, data = oldfaith, width = 5)
```

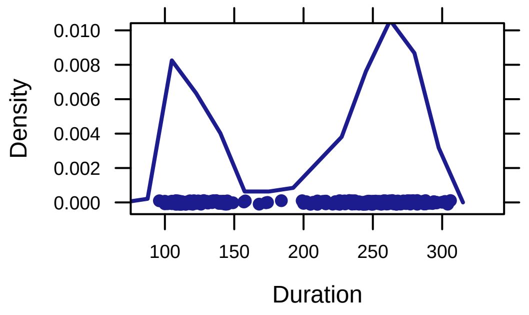


R also provides a "smooth" version called a density plot and a triangular version called a frequency polygon; just change the function name from `histogram()` to `densityplot()` or `freqpolygon()`.

```
densityplot(~Duration, data = oldfaith)
freqpolygon(~Duration, data = oldfaith)
```

[1]The `mosaic` version of the `histogram()` function has some extra features (like the `width` argument) but is otherwise is very similar to regular `histogram()` function in `lattice`.





1.3.2 The shape of a distribution

If we make a histogram of our data, we can describe the overall shape of the distribution. Keep in mind that the shape of a particular histogram may depend on the choice of bins. Choosing too many or too few bins can hide the true shape of the distribution. (When in doubt, compare several histograms with different bin settings before you decide which one provides the most informative summary of the data.)

Here are some words we use to describe shapes of distributions.

symmetric The left and right sides are mirror images of each other.

skewed The distribution stretches out farther in one direction than in the other. (We say the distribution is skewed toward the long tail. So right-skewed (also known as positive-skewed) data have a "fat right tail" – more observations of larger values than of small ones.)

uniform The heights of all the bars are (roughly) the same. (So the data are equally likely to be anywhere within some range.)

unimodal There is one major "bump" where there is a lot of data.

bimodal There are two "bumps".

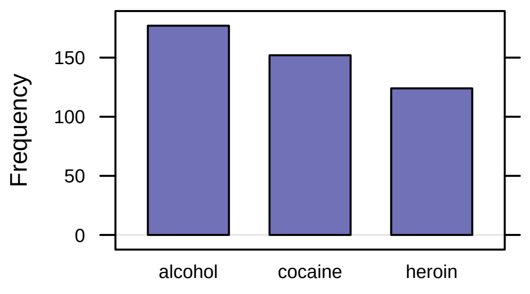
outlier An observation that does not fit the overall pattern of the rest of the data.

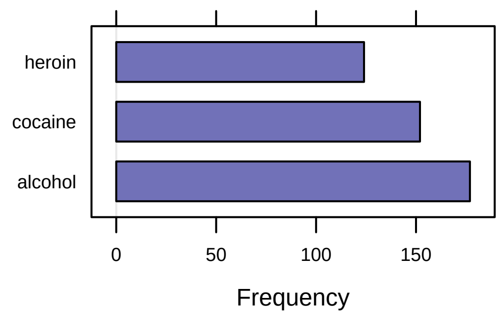
We'll learn about another graph used for quantitative variables (a boxplot, `bwplot()` in R) soon.

1.3.3 Bar graphs for categorical variables

Bar graphs are a way of displaying the distribution of a categorical variable.

```
bargraph(~substance, data = HELPrct)
bargraph(~substance, data = HELPrct, horizontal = TRUE)
```





A side note: we will be unlikely to use pie charts in this course. Many data analysts argue that pie charts are difficult to read and interpret, and often use space ineffectively. Unless you are *sure* there is a good reason to use one, don't.

1.4 Looking at Multiple Variables at Once

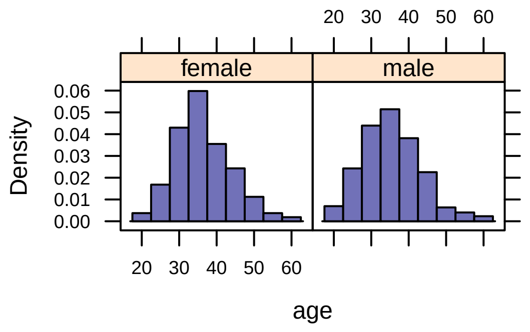
1.4.1 Conditional plots

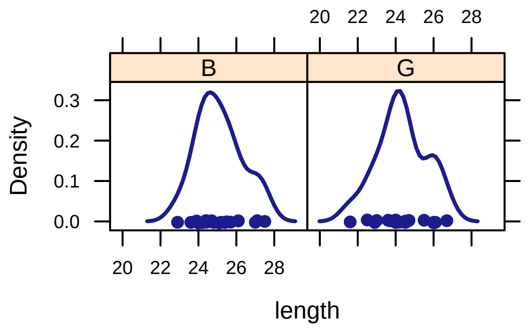
The formula for a `lattice` plot can be extended to create multiple panels based on a "condition", often given by another variable. The general syntax for this becomes

```
plotname(~variable | condition, data = dataName)
```

For example, we might like to see how the ages of men and women compare in the HELP study, or whether the distribution of weights of male mosquitoes is different from the distribution for females.

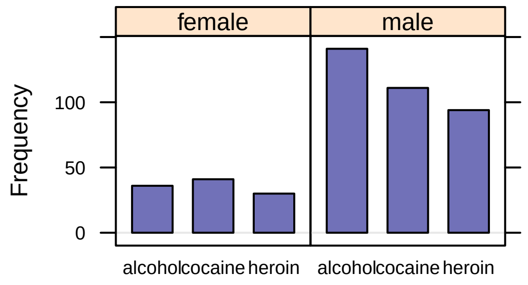
```
histogram(~age | sex, HELPrct, width = 5)
densityplot(~length | sex, KidsFeet)
```





We can do the same thing for bar graphs.

```
bargraph(~substance | sex, data = HELPrct)
```

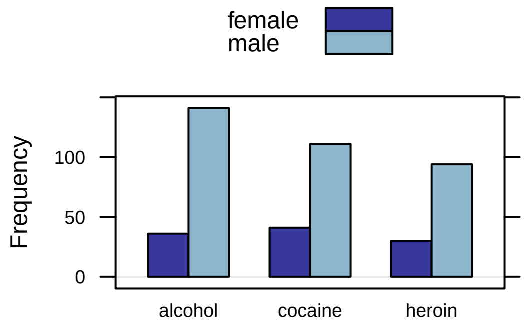


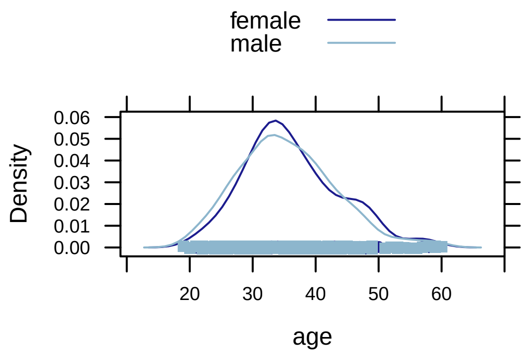
1.4.2 Grouping

Another way to look at multiple groups simultaneously is by using the groups argument. What groups does depends a bit on the type of graph, but it will put the information in one panel rather than multiple panels. Using groups with histogram() doesn't work so well because it is difficult to overlay histograms.[2] Density plots work better when you wish to look at the shapes of several distributions in a single plot panel.

Here are some examples. We use auto.key=TRUE to build a simple legend so we can tell which groups are which.

```
bargraph(~substance, groups = sex, data = HELPrct, auto.key = TRUE)
densityplot(~age, groups = sex, data = HELPrct, auto.key = TRUE)
```

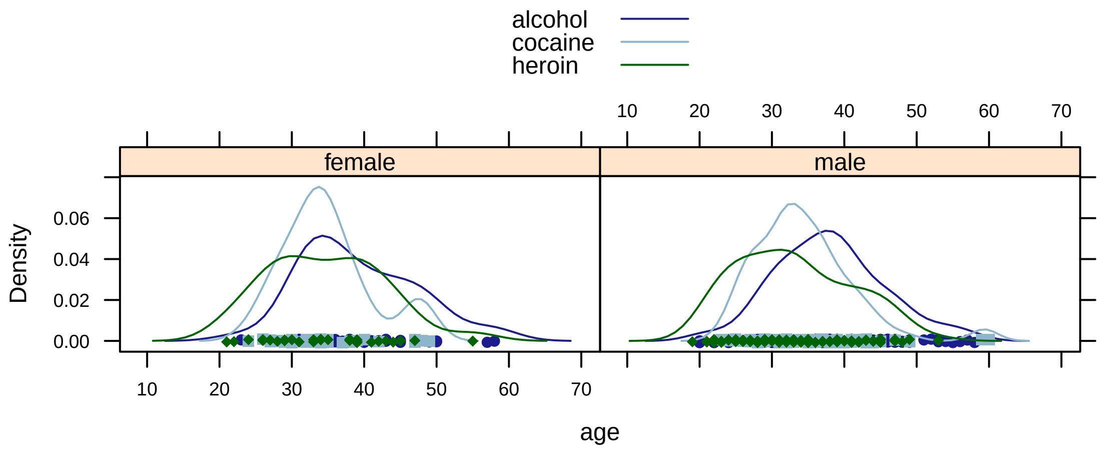




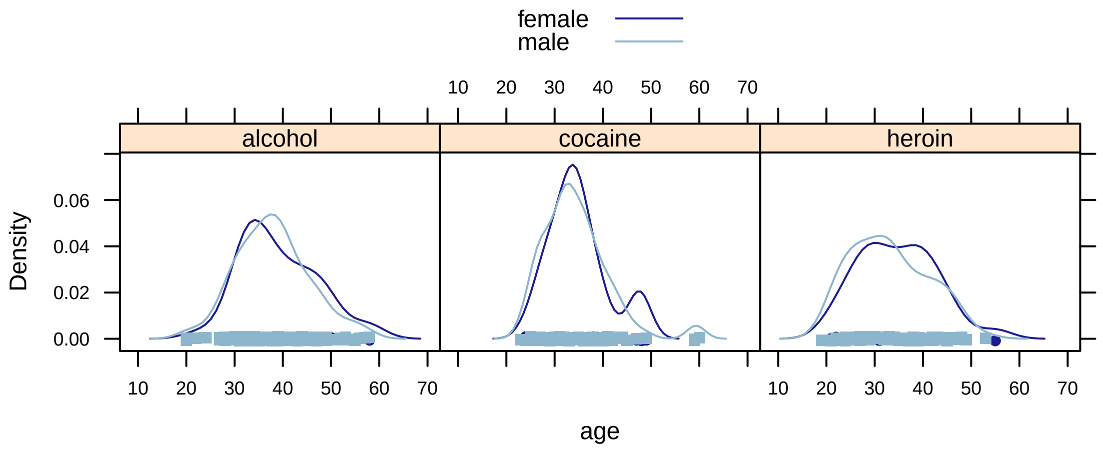
We can even combine grouping and conditioning in the same plot.

```
densityplot(~age | sex, groups = substance, data = HELPrct, auto.key = TRUE)
```

[2]The mosaic function histogram() does do something meaningful with groups in some situations.



```
densityplot(~age | substance, groups = sex, data = HELPrct, auto.key = TRUE, layout = c(3,
    1))
```



This plot shows that for each substance, the age distributions of men and women are quite similar, but that the distributions differ from substance to substance.

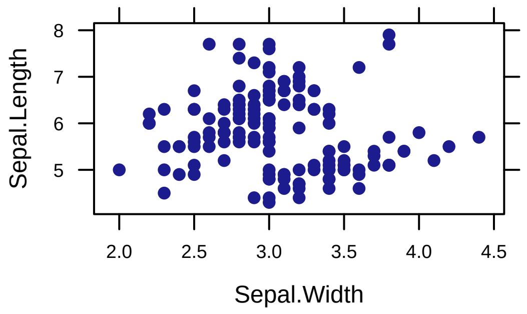
1.4.3 Scatterplots

The most common way to look at two quantitative variables is with a scatter plot. The `lattice` function for this is `xyplot()`, and the basic syntax is

```
xyplot(yvar ~ xvar, data = dataName)
```

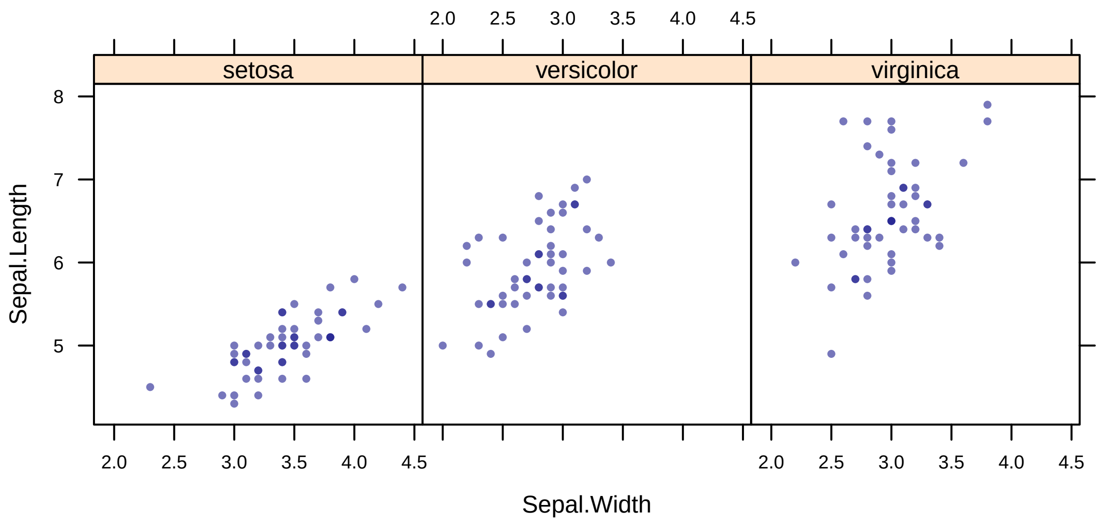
Notice that now we have something on both sides of the ~ since we need to tell R about two variables.

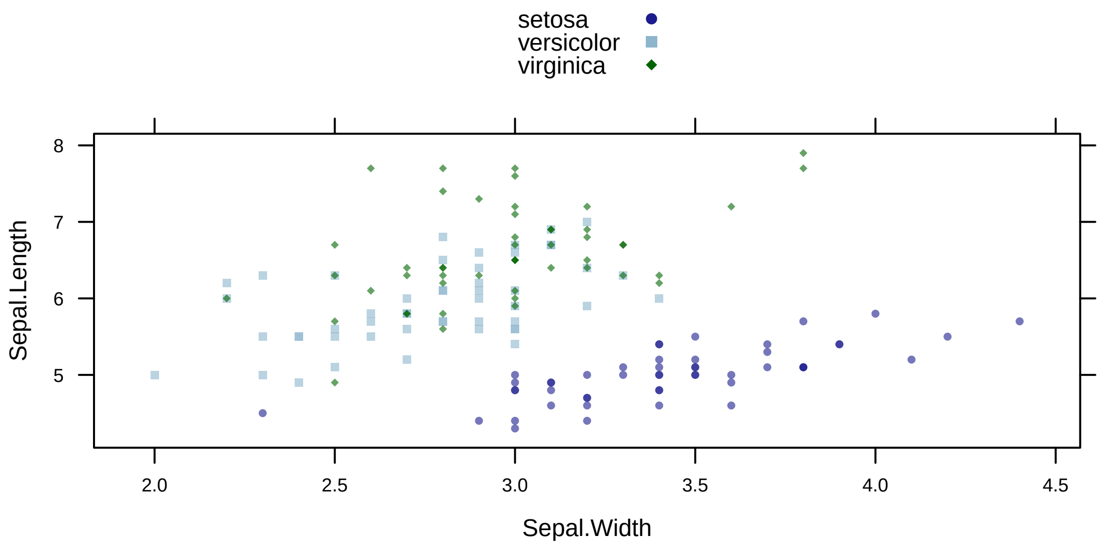
```
head(iris) # data on iris plants


##   Sepal.Length Sepal.Width Petal.Length Petal.Width Species
## 1          5.1         3.5          1.4         0.2  setosa
## 2          4.9         3.0          1.4         0.2  setosa
## 3          4.7         3.2          1.3         0.2  setosa
## 4          4.6         3.1          1.5         0.2  setosa
## 5          5.0         3.6          1.4         0.2  setosa
## 6          5.4         3.9          1.7         0.4  setosa

xyplot( Sepal.Length ~ Sepal.Width, data=iris )
```



Grouping and conditioning work just as before and can be used to see the relationship between sepal length and sepal width broken down by species of iris plant. With large data set, it can be helpful to make the dots semi-transparent so it is easier to see where there are overlaps. This is done with `alpha`. We can also make the dots smaller (or larger) using `cex`.

```
xyplot( Sepal.Length ~ Sepal.Width | Species, data=iris, alpha=.6, cex=.5 )
xyplot( Sepal.Length ~ Sepal.Width, groups = Species, data=iris, alpha=.6, cex=.5,
          auto.key=TRUE )
```





1.5 Exporting Plots

You can save plots to files or copy them to the clipboard using the Export menu in the Plots tab. It is quite simple to copy the plots to the clipboard and then paste them into a Word document, for example. You can even adjust the height and width of the plot first to get it the shape you want.

1.6 Reproducible Research

When starting to learn to use R for data analysis, it may be tempting to work by typing commands into the R console directly, or maybe by copying and pasting commands from some other source (for example, these notes, a website, etc.).

There are many reasons to avoid working this way, including:

- It is tedious, unless there is very little to type, or to copy and paste.
- It is error-prone – it's easy to copy too little or too much, or to grab the wrong thing, or to copy when you want to cut or cut when you want to copy.
- If something changes, you have to start all over.
- You have no record of what you did (unless you are an unusual person who takes detailed notes about everything you copied and pasted, or typed into the R console).

So while copy and paste seems easy and convenient at first, it is not *reproducible*. Reproducible, here, means something that can easily be repeated in exactly the same way (or with some desired modification), because the exact procedure that was followed has been clearly documented in a format that is simple to access. Reproducibility is important when projects are large, when it is important to have record of exactly what was done, or when the same analysis will be applied to multiple data sets (or a data set that is growing over time).

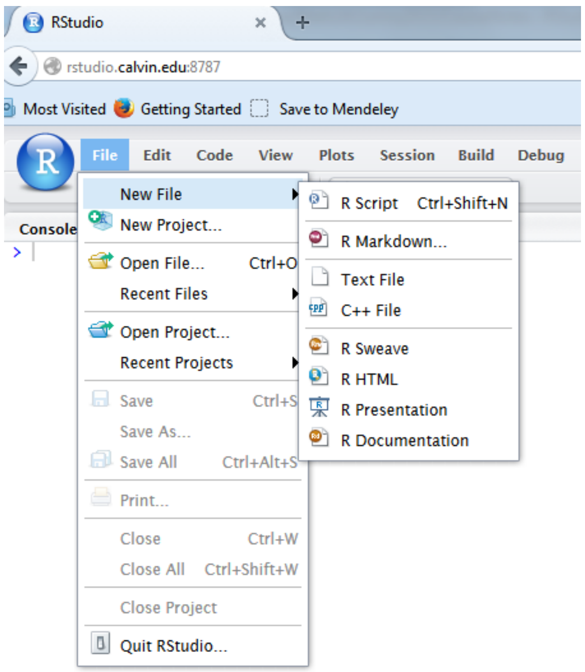
RStudio makes it easy to use techniques of reproducible research to create documents that include text, R commands, R output, and R graphics.

1.6.1 R Markdown

One simple way to do reproducible work is to use a format called R Markdown. Markdown is a simple mark up language that allows for a few basic improvements on plain text (section headers, bulleted lists, numbered lists, bold, italics, etc.) R Markdown adds the ability to mix in the R stuff (R commands and output, including figures). The end product is an HTML file, so it is especially good for producing web documents.[3]

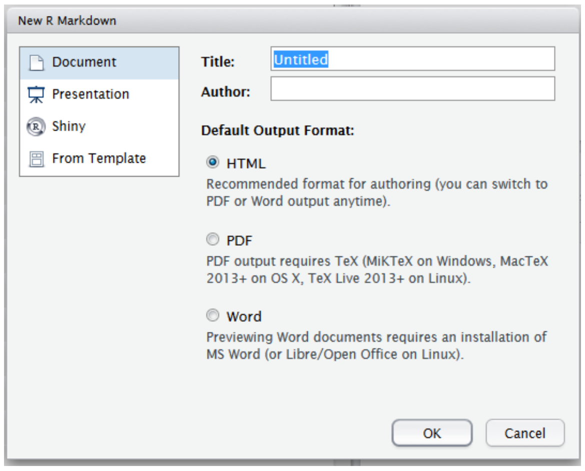
Creating a new document

To create a new R Markdown document in RStudio, go to "File", "New File", then "R Markdown":



A small pop-up window will appear; for current purposes, you can select all the default options (a Document, with HTML output format, with the Title and Author blanks filled in or left blank, as you wish).

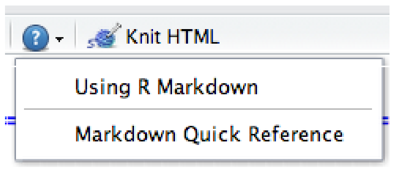
[3]You can actually mix in arbirary HTML and even css, so if you are good at HTML, you can have quite a bit of control over how things look. Here we will focus on the basics.



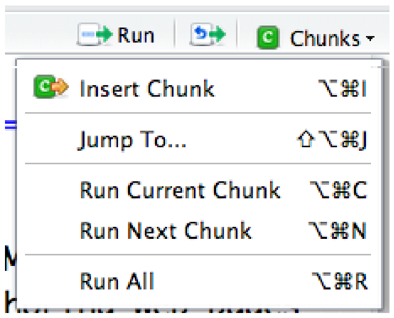
Title: Untitled
Author:
Default Output Format:
[✓ HTML]
Recommended format for authoring (you can switch to PDF or Word output anytime).
PDF
PDF output requires TeX (MiKTeX on Windows, MacTeX 2013+ on OS X, TeX Live 2013+ on Linux).
Word
Previewing Word documents requires an installation of MS Word (or Libre/Open Office on Linux).

When you do this, a file editing pane will open with a template inserted. If you click on “Knit HTML”, RStudio will turn this into an HTML file and display it for you. Give it a try. You will be asked to name your file if you haven’t already done so. If you are using the RStudio server in a browser, then your file will live on the server (“in the cloud”) rather than on your computer.

If you look at the template file you will see that the file has two kinds of sections. Some of this file is just normal text (with some extra symbols to make things bold, add in headings, etc.) You can get a list of all of these mark up options by selecting the “Markdown Quick Reference” in the question mark menu (at the top of the Markdown document in the editing pane).



The second type of section is an R code chunk. These are colored differently to make them easier to see. You can insert a new code chunk by selecting “Insert Chunk” from the “Chunks” menu:



(You can also type ```{r} to begin and ``` to end the code chunk if you would rather type.) You can put any R code in these code chunks and the results (text output or graphics) as well as the R code will be displayed in your HTML file.

In addition to knitting the document to HTML, you can do a number of other things that will make your work more efficient. In the “Chunk” menu, you can choose to run a single chunk or all the chunks. This will execute your commands in the console so you can make sure your R code is working one chunk at a time. There is also a “run” button that allows you to run just one line from within a chunk.

R Markdown files must be self-contained

R Markdown files do not have access to things you have done in your console. (This is good, else your document would change based on things not in the file.) Within each R Markdown file, you must explicitly load data, and require packages *in the R Markdown file* in order to use them. In this class, this means that most of your R Markdown files will have a chunk near the beginning that loads required packages and datasets.

Chunk options

R Markdown provides a number of chunk options that control how R code is processed. You can use them to do things like:

- run the code without displaying it (good for polished reports – your client doesn't want to see the code)
- show the code without running it – mainly useful for demonstration purposes
- control the size and alignment of graphics

You can set default values for the chunk options and you can also override them in individual chunks. See the R Markdown help for more information about chunk options.

The default plots are often bigger than required. The following chunk options are a place to start. They can be adjusted as necessary.

```
require(knitr)
opts_chunk$set(fig.width = 5, fig.height = 2, fig.align = "center", fig.show = "hold")
```

1.6.2 knitr/latex

There is another system that produces PDFs by combining LaTeX and R, using the Rpackage `knitr`. This is the system used to create this document; it gives much more control over document formatting. The quality is good enough for professional publishing. If you already knwow LaTeX, it is very easy to learn. If you don't know LaTeX, then you need to learn the basics of LaTeX to get going, which is not covered in detail here. If you are interested in learning more, consult the documentation for the `knitr` package, or the knitr website.

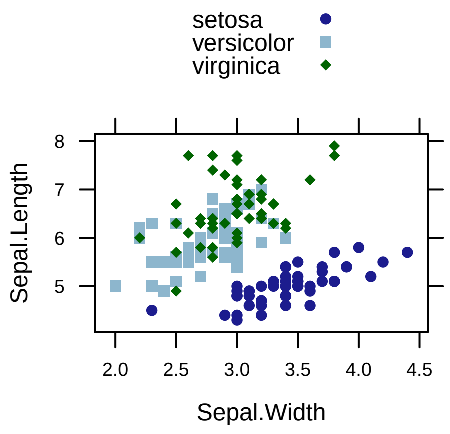
1.7 Customizing Graphics: A Few Bells and Whistles

There are lots of arguments that control the appearance of plots created in R. Here are just a few examples, some of which we have already seen.

1.7.1 auto.key

`auto.key=TRUE` turns on a simple legend for the grouping variable. (There are ways to have more control, if you need it.)

```
xyplot(Sepal.Length ~ Sepal.Width, groups = Species, data = iris, auto.key = TRUE)
```

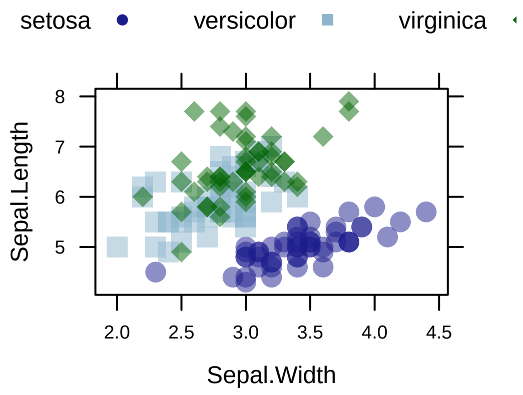


1.7.2 alpha, cex

Sometimes it is nice to have elements of a plot be partly transparent. When such elements overlap, they get darker, showing us where data are "piling up." Setting the `alpha` argument to a value between 0 and 1 controls the degree of transparency: 1 is completely opaque, 0 is invisible. The `cex` argument controls "character expansion" and can be used to make the plotting "characters" larger or smaller by specifying the scaling ratio.

Here is another example using data on 150 iris plants of three species.

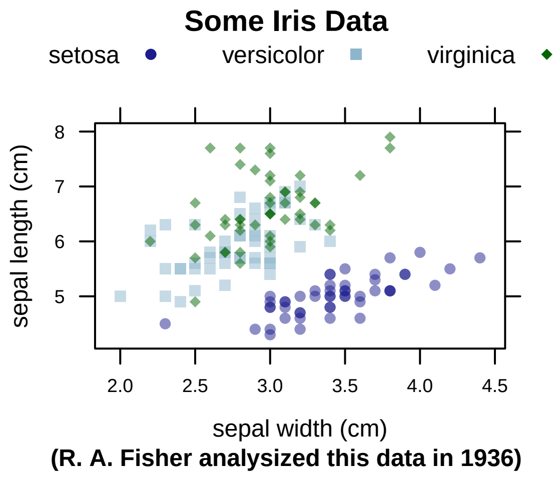
```
xyplot(Sepal.Length ~ Sepal.Width, groups = Species, data = iris, auto.key = list(columns = 3),
    alpha = 0.5, cex = 1.3)
```



main, sub, xlab, ylab

You can add a title or subtitle, or change the default labels of the axes.

```
xyplot(Sepal.Length ~ Sepal.Width, groups = Species, data = iris, main = "Some Iris Data",
    sub = "(R. A. Fisher analyzed this data in 1936)", xlab = "sepal width (cm)", ylab = "sepal length
    alpha = 0.5, auto.key = list(columns = 3))
```



layout

layout can be used to control the arrangement of panels in a multi-panel plot. The format is

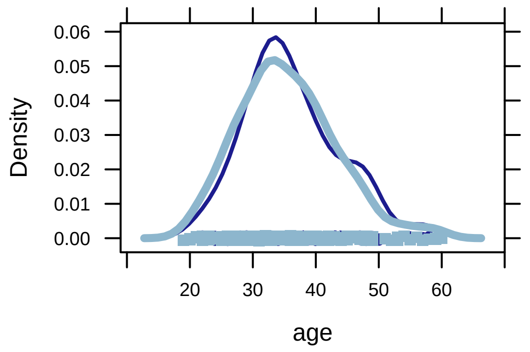
```
layout = c(cols, rows)
```

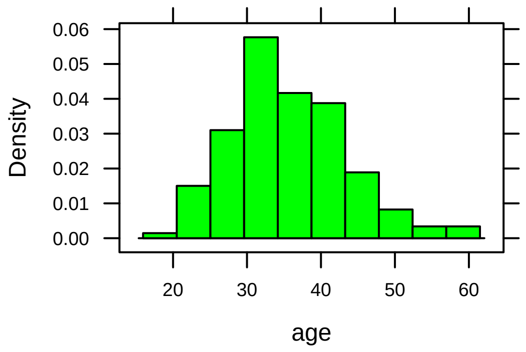
where cols is the number of columns and rows is the number of rows. (Columns first because that is the x-coordinate of the plot.)

lty, lwd, pch, col

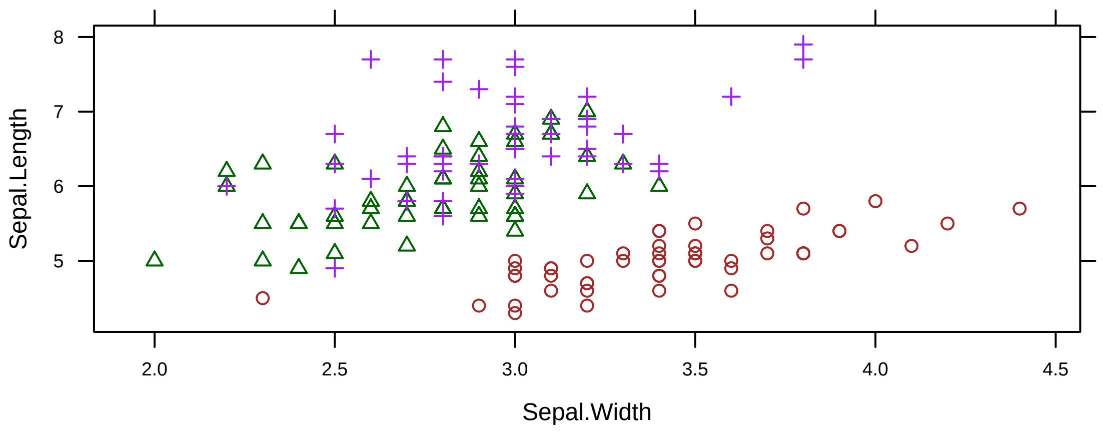
These can be used to change the line type, line width, plot symbol, and color, respectively. To specify multiples (one for each group), use the c() function (to remember this function, remember that "c" is for "concatenate"). An example is below.

```
densityplot(~age, data = HELPrct, groups = sex, lty = 1, lwd = c(2, 4))
histogram(~age, data = HELPrct, col = "green")
```





```
# There are 25 numbered plot symbols
xyplot( Sepal.Length ~ Sepal.Width, data=iris, groups=Species,
        pch=c(1,2,3), col=c('brown', 'darkgreen', 'purple'), cex=.75 )
```



Note: If you change the colors and symbols this way, they will *not* match what is generated in the legend using `auto.key=TRUE`. So it can be better to set these things in a different way if you are using `groups`. See below.

You can see a list of the hundreds of available color names using

```
colors()
```

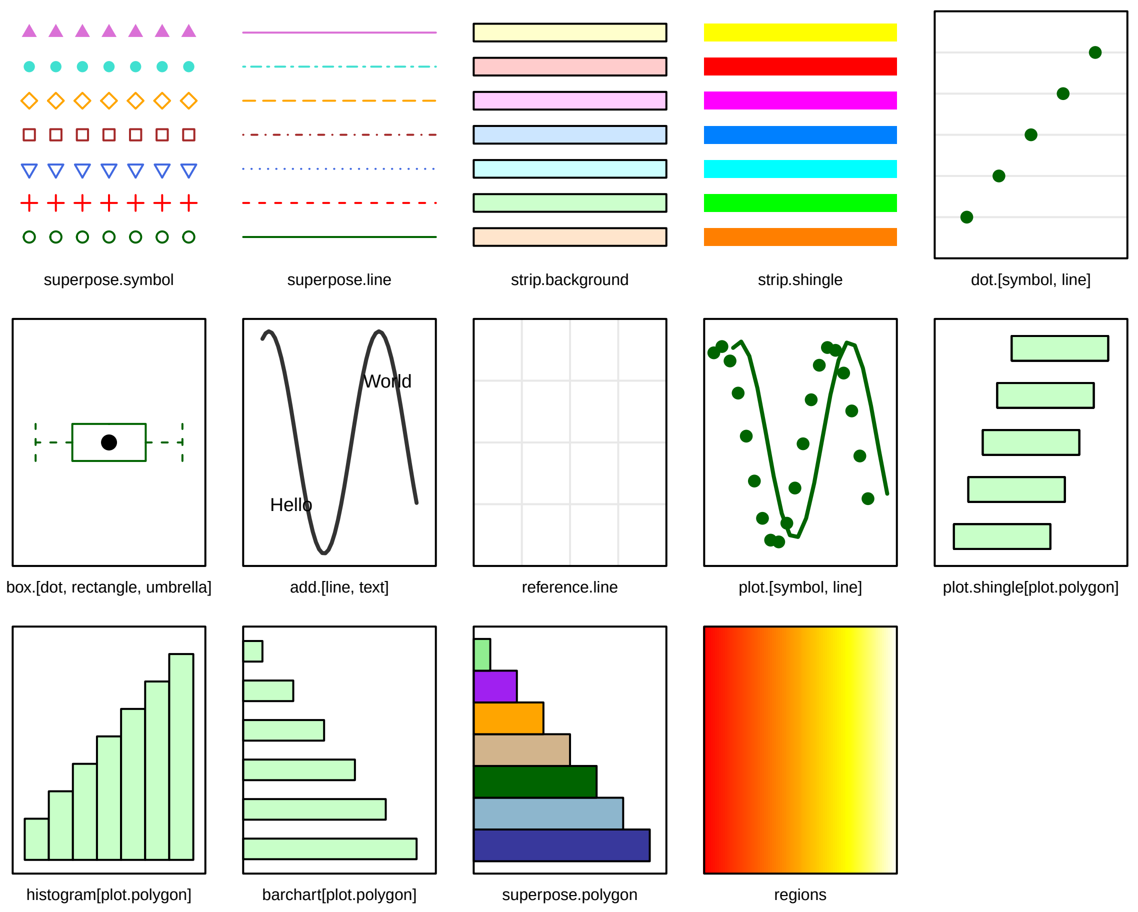
1.7.3 trellis.par.set()

Default settings for lattice graphics are set using `trellis.par.set()`. Don't like the default font sizes? You can change them! For example, change to a 7 point (base) font using

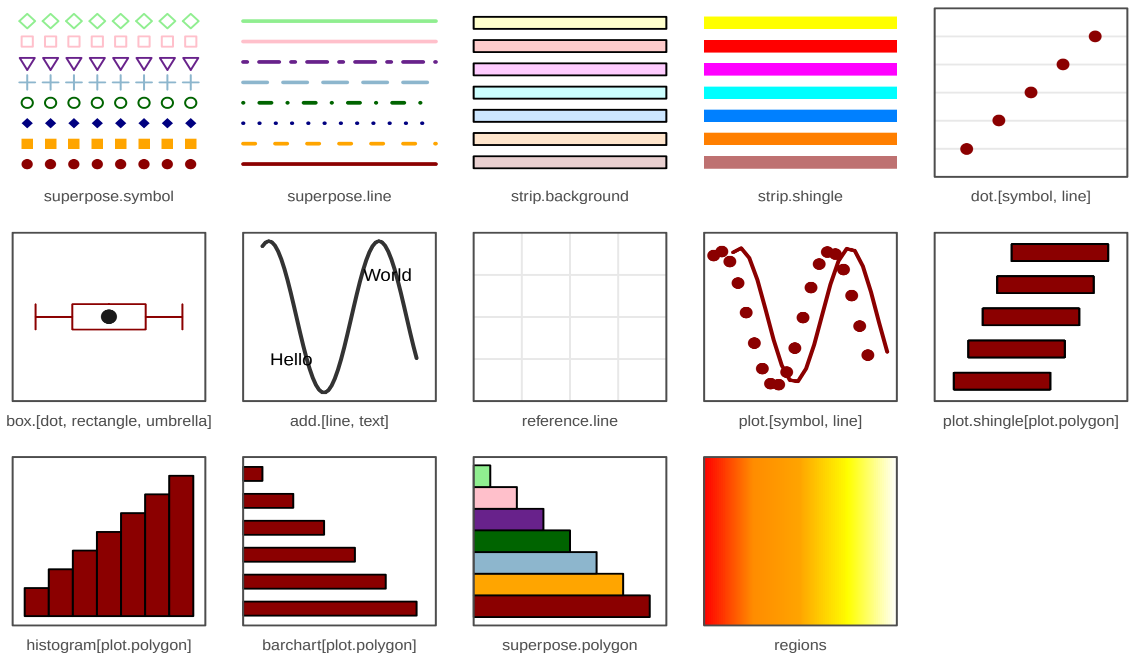
```
trellis.par.set(fontsize = list(text = 7))  # base size for text is 7 point
```

Nearly every feature of a lattice plot can be controlled: fonts, colors, symbols, line thicknesses, colors, etc. Rather than describe them all here, we'll mention only that groups of these settings can be collected into a theme. `show.settings()` will show you what the current theme looks like. Below are a few examples of changing the theme settings, then viewing the results.

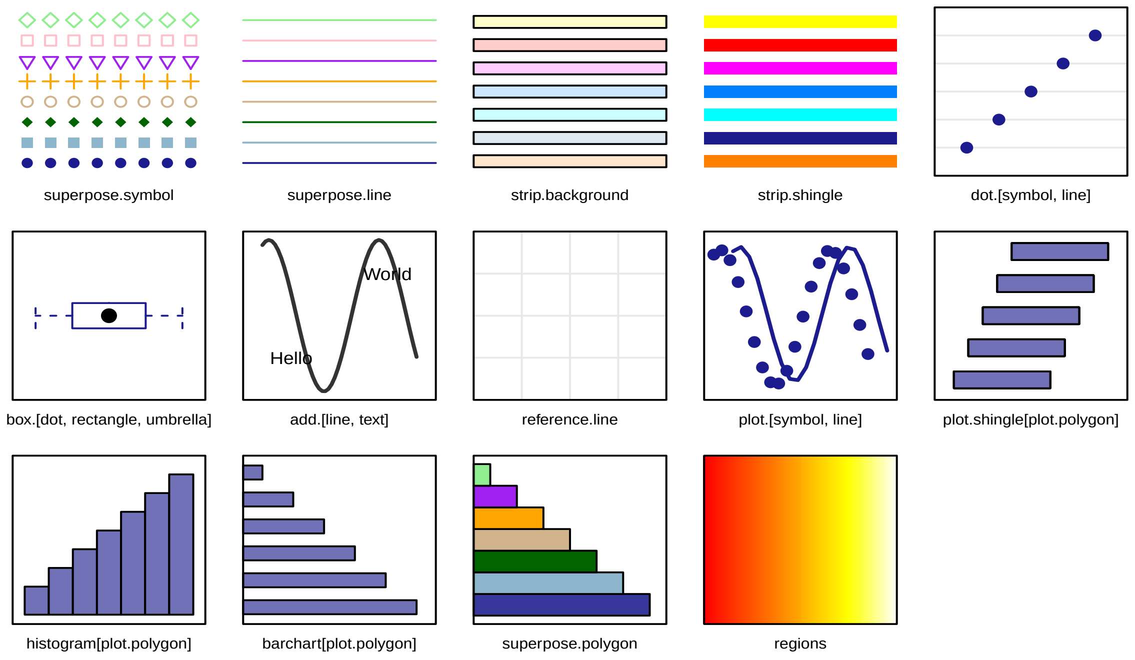
```
trellis.par.set(theme = col.whitebg())  # a theme in the lattice package
show.settings()
```


superpose.symbol
superpose.line
strip.background
strip.shingle
dot.[symbol, line]
box.[dot, rectangle, umbrella]
add.[line, text]
World
Hello
reference.line
plot.[symbol, line]
plot.shingle[plot.polygon]
histogram[plot.polygon]
barchart[plot.polygon]
superpose.polygon
regions

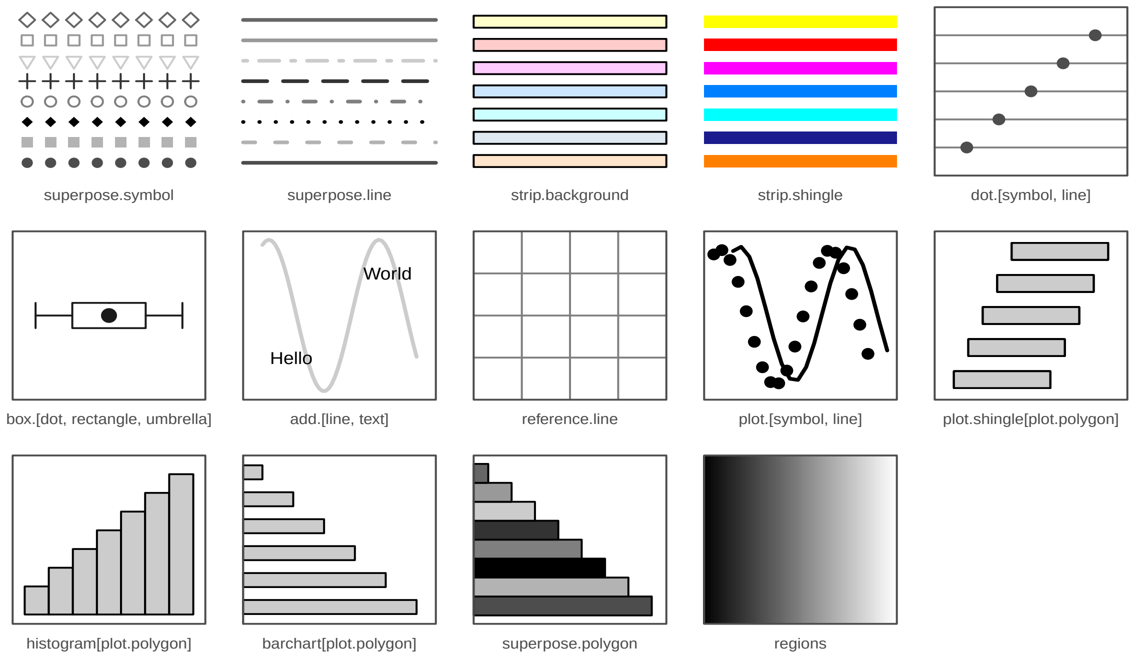
```r
require(abd)
trellis.par.set(theme = col.abd())  # a theme in the abd package
show.settings()
```



```r
trellis.par.set(theme = col.mosaic)  # a theme in the mosaic package
show.settings()
```



```
trellis.par.set(theme = col.mosaic(bw = TRUE))  # a b/w theme in the mosaic package
show.settings()
```



```
trellis.par.set(theme = col.mosaic())  # back to the mosaic theme
trellis.par.set(fontsize = list(text = 9))  # and back to a 10 point font
```

Want to save your settings?

```
# save current settings
mySettings <- trellis.par.get()
# switch to abd defaults
trellis.par.set(theme = col.abd())
# switch back to my saved settings
trellis.par.set(mySettings)
```

1.8 Getting Help in RStudio

1.8.1 The RStudio help system

There are several ways to get RStudio to help you when you forget something. Most objects in packages have help files that you can access by typing something like:

```
?bargraph
?histogram
?HELPrct
```

You can search the help system using

```r
help.search("Grand Rapids")  # Does R know anything about Grand Rapids?
```

This can be useful if you don't know the name of the function or data set you are looking for.

1.8.2 Tab completion

As you type the name of a function in RStudio, you can hit the tab key and it will show you a list of all the ways you could complete that name. After you type the opening parenthesis, if you hit the tab key, you will get a list of all the possible input arguments and (sometimes) some helpful hints about what they are.)

1.8.3 History

If you know you have done something before, but can't remember how, you can search your history. The history tab shows a list of recently executed commands. There is also a search bar to help you find things from longer ago.

1.8.4 Error messages

When things go wrong, R tries to help you out by providing an error message. Typos are probably the most common cause of errors: for example, you might misspell a function or argument name, forget to close a set of parentheses or brackets, or misplace a comma. One common error message is illustrated below.

```r
fred <- 23
frd


## Error in eval(expr, envir, enclos):  object 'frd' not found
```

The object `frd` is not found because it was mistyped. It should have been `fred`. Another common mistake is forgetting to load required packages. If you see an "object not found" message, check your typing and check to make sure that the necessary packages have been loaded. If you get an error and can't make sense of the message, you can try copying and pasting your command and the error message and sending to me in an email.

1.9 Graphical Summaries – Important Ideas

1.9.1 The Most Important Template

The plots we have created have all following a single template

$$\boxed{\texttt{goal}}\ \texttt{(}\ \boxed{\texttt{formula}}\texttt{,}\ \texttt{data =}\ \boxed{\texttt{mydata}}\ \texttt{)}$$

We will see this same template used again for numerical summaries and linear and non-linear modeling as well, so it is is important to master it.

- `goal`: The name of the function generally describes your goal, the thing you want the computer to produce for you. In the case of plotting, it is the name of the plot. When we do numerical summaries it will be the name of the numerical summary (mean, median, etc.).

- `formula`: For plotting, the formula describes which variables are used on the x-axis, the y-axis and for conditioning. The general scheme is

  ```
  y ~ x | z
  ```

  where `z` is the conditioning variable. Sometimes `y` or `z` are missing (but the right-hand side `x` must always be included in a formula).

- `data:` A data frame must be given in which the variables mentioned in the formula can be found. Variables not found there will be looked for in the enclosing environment. Sometimes we will take advantage of this to avoid creating a temporary data frame just to make a quick plot, but generally it is best to have all the information inside a data frame.

1.9.2 Patterns and Deviations from Patterns

The goal of a statistical plot is to help us *see*

- potential patterns in the data, and
- deviations from those patterns.

1.9.3 Different Plots for Different Kinds of Variables

Graphical summaries can help us see the *distribution* of a variable or the *relationships* between two (or more) variables. The type of plot used will depend on the kinds of variables involved. Later, when we do more quantitative statistical analysis, we will see that the analysis we use will also depend on the kinds of variables involved, so this is an important idea.

1.9.4 Side-by-side Plots and Overlays Can Reveal Importance of Additional Factors

The `lattice` graphics plots make it particularly easy to generate plots that divide the data into groups and either produce a panel for each group (using |) or display each group in a different way (different colors or symbols, using the `groups` argument). These plots can reveal the possible influence of additional variables – sometimes called covariates.

1.9.5 Area = (relative) frequency

Many plots are based on the key idea that our eyes are good at comparing areas. Plots that use area (e.g., histograms, mosaic plots, bar charts, pie charts) should always obey this principle

$$\text{Area} = \text{(relative) frequency}$$

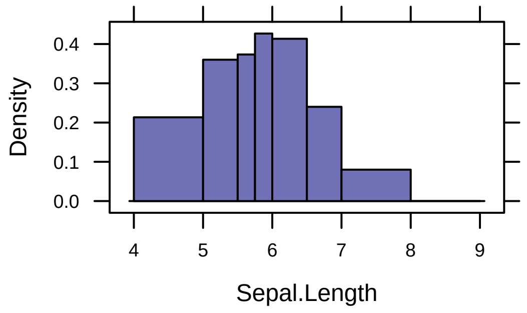
Plots that violate this principle can be deceptive and distort the true nature of the data.

An Example: Histogram with unequal bin widths

It is possible to make histograms with bins that have different widths. But in this case it is important that the height of the bars is chosen so that area (*NOT height*) is proportional to frequency. Using height instead of area would distort the picture.

When unequal bin sizes are specified, `histogram()` by default chooses the density scale:

```
histogram(~Sepal.Length, data = iris, breaks = c(4, 5, 5.5, 5.75, 6, 6.5, 7, 8, 9))
```

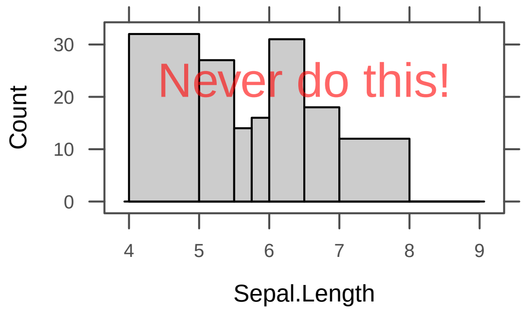


The density scale is important. It tells R to use a scale such that the area (height × width) of the rectangles is equal to the relative frequency. For example, the bar from 5.0 to 5.5 has width $\frac{1}{2}$ and height about 0.36, so the area is 0.18, which means approximately 18% of the sepal lengths are between 5.0 and 5.5.

It would be incorrect to choose `type="count"` or `type="proportion"` since this distorts the picture of the data. Fortunately, R will warn you if you try:

```
histogram(~Sepal.Length, data = iris, breaks = c(4, 5, 5.5, 5.75, 6, 6.5, 7, 8, 9), type = "count")
```

```
## Warning in histogram.formula(~Sepal.Length, data = iris, breaks = c(4, 5, :  type='count' can
be misleading in this context
```



Notice how different this looks. Now the heights are equal to the relative frequency, but this makes the wider bars have too much area.

Exercises

In your answers to these questions, include both the plots and the code you used to make them as well as any required discussion. Once you have obtained a basic plot that satisfies the requirements of the question, feel free to use some of the "bells and whistles" to make the plots even better.

1.1 Create a scatterplot using the two variables in the `oldfaith` data frame. What do we learn about Old Faithful eruptions from this plot?

1.2 Where do the data in the `CPS85` data frame (in the `mosaic` package) come from? What are the observational units? How many are there?

1.3 Choose a quantitative variable that interests you in the `CPS85` data set. Make an appropriate plot and comment on what you see.

1.4 Choose a categorical variable that interests you in the `CPS85` data set. Make an appropriate plot and comment on what you see.

1.5 Create a plot that displays two or more variables from the `CPS85` data. At least one should be quantitative and at least one should be categorical. Comment on what you can learn from your plot.

1.6 Where do the data in the `mpg` data frame (in the `ggplot2` package) come from? What are the observational units? How many are there?

1.7 Choose a quantitative variable that interests you in the `mpg` data set. Make an appropriate plot and comment on what you see.

1.8 Choose a categorical variable that interests you in the `mpg` data set. Make an appropriate plot and comment on what you see.

1.9 Create a plot that displays two or more variables from the `mpg` data. At least one should be quantitative and at least one should be categorical. Comment on what you can learn from your plot.

1.10 The file at `http://www.calvin.edu/~rpruim/data/Fires.csv` is a csv file containing data on wild lands fires in the US over a number of years. You can load this data one of two ways.

- Go to the workspace tab, select Import Data Set, choose From Web URL... and follow the instructions.
- Use the following command in R:

```
Fires <- read.csv("http://www.calvin.edu/~rpruim/data/Fires.csv")
```

You can also use either of these methods to read from a file rather than from a web URL, so this is a good way to get your own data into R.

a) The source for these data claim that data before a certain year should not be compared to data from after that year because the older data were computed a different way and are not considered as reliable. What year is the break point? Use graphs of the data over time to estimate when something changed.

b) You can trim the data to just the subset you want using `subset()`. For example, to get just the subset of years since 1966, you would use

```
Fires2 <- subset(Fires, Year > 1966)
```

Be sure to use a new name for the subset data frame if you want to keep the original data available.

Use `subset()` to create a data set that contains only the data from the new data regime (based on your answer in the previous problem).

c) Using only the data from this smaller set, how would you describe what is happening with fires over time?

1.11 Use R's help system to find out what the `i1` and `i2` variables are in the `HELPrct` data frame. Make histograms for each variable and comment on what you find out. How would you describe the shape of these distributions? Do you see any outliers (observations that don't seem to fit the pattern of the rest of the data)?

1.12 Compare the distributions of `i1` and `i2` among men and women.

1.13 Compare the distributions of `i1` and `i2` among the three `substance` groups.

1.14 The `SnowGR` contains historical data on snowfall in Grand Rapids, MI. The snowfall totals for November and December 2014 were 31 inches and 1 inch, respectively.

a) Create histograms of November and December snowfall totals. How unusual were the snowfall totals we had in 2014?

b) If there is very little snow in December, should we expect to have unusually much or little snow in February? Make a scatter plot comparing December and February historic snowfall totals and comment on what you see there.

Bibliography

Index