Data Visualization in R

L. Torgo

ltorgo@dal.ca

Faculty of Computer Science / Institute for Big Data Analytics
Dalhousie University

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ACADIA UNIVERSITY

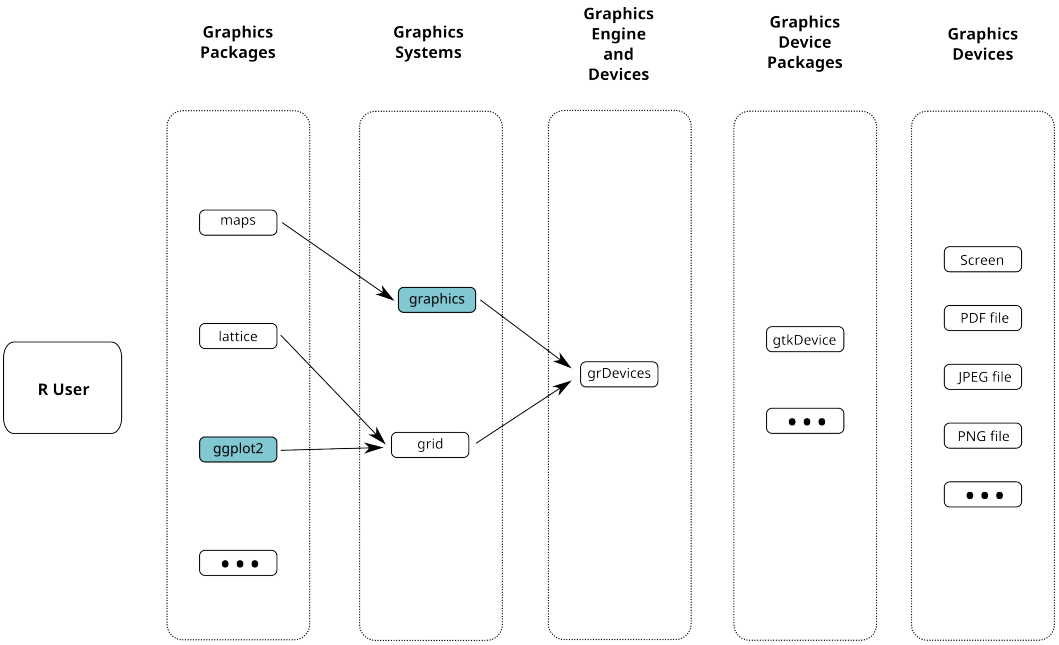
Motivation for Data Visualization

- Humans are outstanding at detecting patterns and structures with their eyes
- Data visualization methods try to explore these capabilities
- In spite of all advantages visualization methods also have several problems, particularly with very large data sets

Outline of what we will learn

- Tools for visualizing amounts
- Tools for visualizing distributions of values
- Tools for visualizing proportions
- Tools for visualizing x-y relationships
- Multivariate visualization tools

R Graphics



Standard Graphics (the `graphics` package)

- R standard graphics, available through package **graphics**, includes several functions that provide standard statistical plots, like:
  - Scatterplots
  - Boxplots
  - Piecharts
  - Barplots
  - etc.
- These graphs can be obtained tyipically by a single function call
  - Example of a scatterplot

```
plot(1:10,sin(1:10))
```

- These graphs can be easily augmented by adding several elements to these graphs (lines, text, etc.)

Graphics Devices

- R graphics functions produce output that depends on the active graphics device
- The default and more frequently used device is the **screen**
- There are many more graphical devices in R, like the **pdf** device, the **jpeg** device, etc.
- The user just needs to open (and in the end close) the graphics output device she/he wants. R takes care of producing the type of output required by the device
- This means that to produce a certain plot on the screen or as a GIF graphics file the R code is exactly the same. You only need to open the target output device before!
- Several devices may be open at the same time, but only one is the active device

A few examples

A scatterplot

```
plot(seq(0,4*pi,0.1),sin(seq(0,4*pi,0.1)))
```

The same but stored on a jpeg file

```
jpeg('exp.jpg')
plot(seq(0,4*pi,0.1),sin(seq(0,4*pi,0.1)))
dev.off()
```

And now as a pdf file

```
pdf('exp.pdf',width=6,height=6)
plot(seq(0,4*pi,0.1),sin(seq(0,4*pi,0.1)))
dev.off()
```

Package `ggplot2`

- Package `ggplot2` implements the ideas created by Wilkinson (2005) on a grammar of graphics
- This grammar is the result of a theoretical study on what is a statistical graphic
- `ggplot2` builds upon this theory by implementing the concept of a layered grammar of graphics (Wickham, 2009)
- The grammar defines a statistical graphic as:
  - a mapping from data into **aesthetic attributes** (color, shape, size, etc.) of **geometric objects** (points, lines, bars, etc.)

L. Wilkinson (2005). The Grammar of Graphics. Springer.

H. Wickham (2009). A layered grammar of graphics. Journal of Computational and Graphical Statistics.

The Basics of the Grammar of Graphics

- Key elements of a statistical graphic:
  - data
  - aesthetic mappings
  - geometric objects
  - statistical transformations
  - scales
  - coordinate system
  - faceting

Aesthetic Mappings

- Controls the relation between data variables and graphic properties
  - map the *Temperature* variable of a data set into the *x coordinate* in a scatter plot
  - map the *Species* of a plant into the *colour* of dots in a graphic
  - map the *Citizenship* of a person into the *shape* of a dot
  - map tje *Age* of a car into the *line width* of lines in a graphic
  - etc.

Geometric Objects / Graphical Elements

- Controls what is shown in the graphics, e.g.
  - show each observation by a point using the aesthetic mappings that map two variables in the data set into the x, y coordinates of the plot
  - etc.

Statistical Transformations

- Allows us to calculate and do statistical analysis over the data in the plot
  - Use the data and approximate it by a regression line on the x, y coordinates
  - Count occurrences of certain values
  - etc.

Scales

- Decide how the data values are mapped into the aesthetics properties
  - A scale defines a one to one mapping between the data values and the values of some aesthetical property

Coordinate System

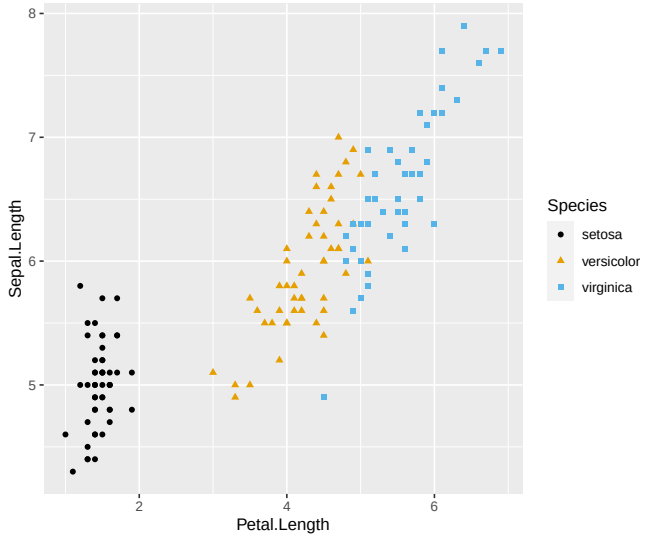
- The coordinate system used to plot the data
  - Cartesian
  - Polar
  - etc.

Faceting

- Split the data into sub-groups and draw sub-graphs for each group

A Simple Example

```
data(iris)
library(ggplot2)
library(ggthemes)
ggplot(data = iris) +
    geom_point(mapping = aes(x=Petal.Length,y=Sepal.Length, colour=Species, shape=Species)) +
    scale_colour_colorblind()
```




```
ggplot(data = <DATA_SOURCE>) +
    <GEOM_OBJECT>(mapping = aes(<MAPPINGS>)) +
    <EVENTUALLY_OTHER_LAYERS>
```

Both the `data` and `mapping` components can be defined locally (within some geom) or globally (at the ggplot call)

Visualizing Amounts

Visualizing Amounts

- Comparing the magnitude of a set of numbers
- May include comparisons across different groups

Bar plots

- Displays the set of values as heights of different bars

Example data set: wins and losses of NBA teams of Atlantic Division

Team	Wins	Losses	Season
Toronto Raptors	58	24	2018_19
Philadelphia 76ers	51	31	2018_19
Boston Celtics	49	33	2018_19
Brooklyn Nets	42	40	2018_19

Bar plots

Two frequent settings

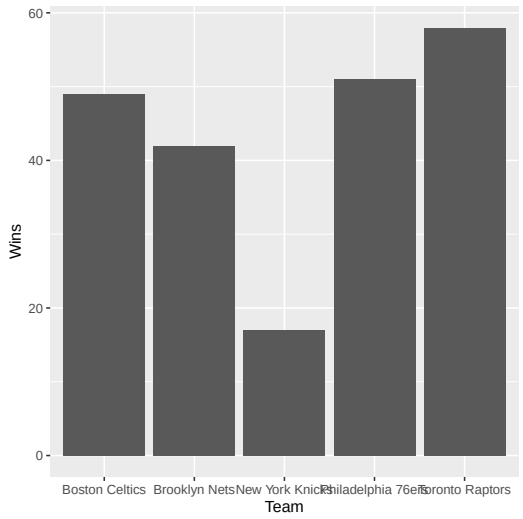
1. The values to show are already in the data set
2. The values to show need to be computed from the data

Bar plots

Values in the data set

- Showing the number of wins on 2018/19

```
library(ggplot2)
ggplot(data = filter(nba,Season=="2018_19"), mapping = aes(x=Team,y=Wins)) + geom_col()
```

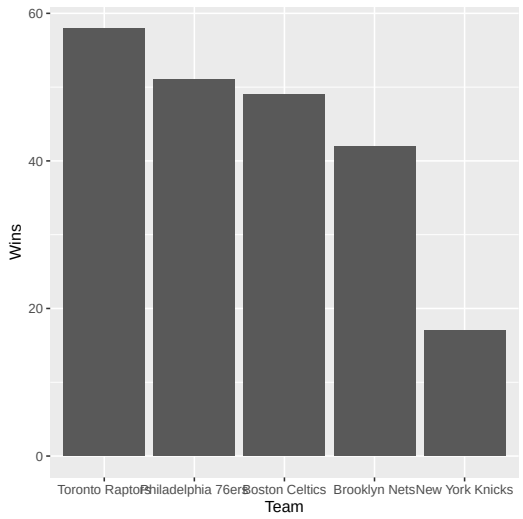


Bar plots

Ordering the bars

- If the order of the values (team names) has no meaning then the bars should be order by decreasing value for better readability

```
ggplot(data = filter(nba,Season=="2018_19"), mapping = aes(x=reorder(Team,-Wins), y=Wins)) +
    geom_col() + xlab("Team")
```

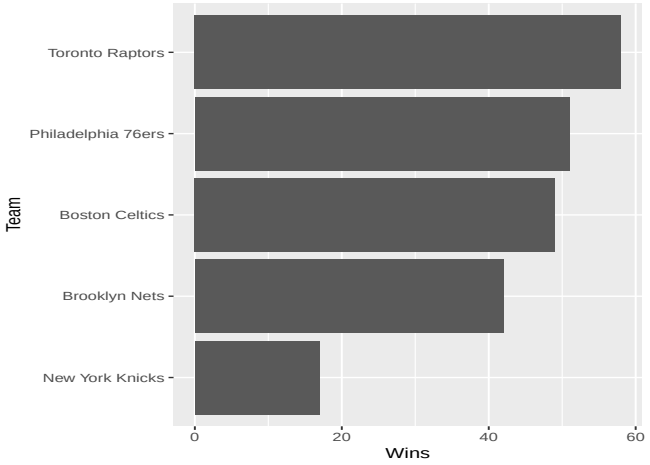


Bar plots

Horizontal bars

- When the X labels are long or are far too many, horizontal bars may be more readable

```
ggplot(data = filter(nba,Season=="2018_19"), mapping = aes(x=reorder(Team, Wins), y=Wins)) +
    coord_flip() + geom_col() + xlab("Team")
```

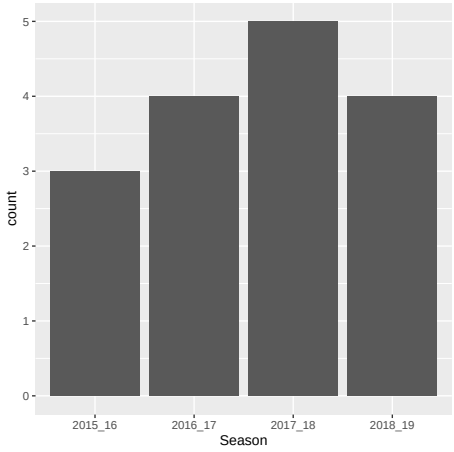


Bar plots

Values need to be calculated

- Showing how many teams had a percentage of wins larger than 30% per season

```
ggplot(data = filter(nba,Wins/(Wins+Losses) > .3), mapping = aes(x=Season)) + geom_bar()
```



NOTE: ordering the bars here would be wrong as the labels have an implicit ordering (time)

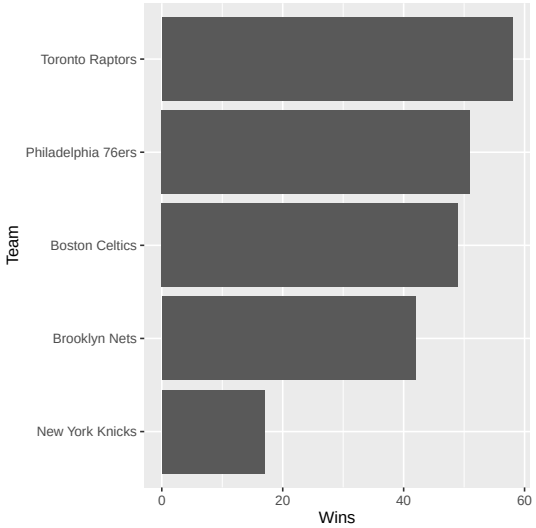
Bar plots

Problems

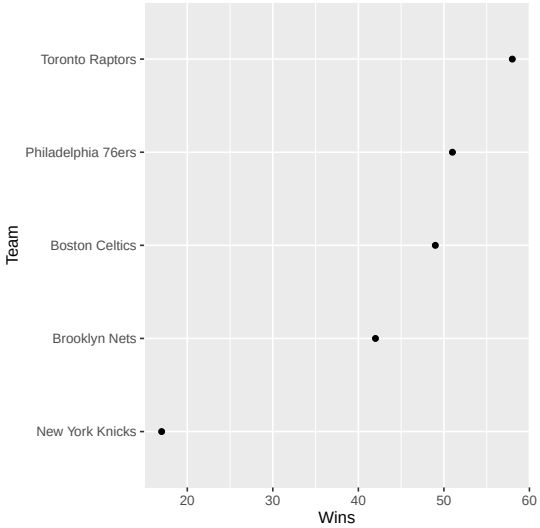
- Bars always must start from zero
- This may create a problem known as *zero baseline*
- When the bars have similar height, due to the start on zero, the differences are hard to perceive
- Barplots should not be used in these situations - dot plots are better representations

Dot plots

```
ggplot(filter(nba,Season=="2018_19"),
       aes(x=reorder(Team,Wins), y=Wins)) +
    geom_col() + coord_flip() + xlab("Team")
```



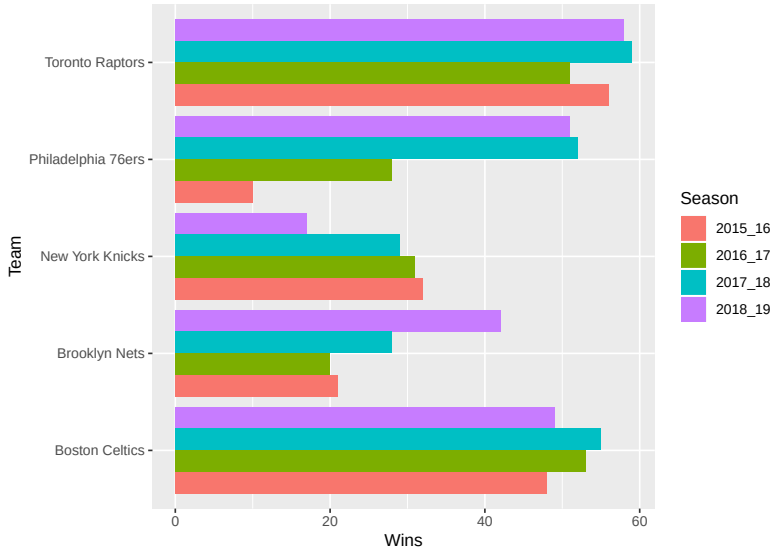

```
ggplot(filter(nba,Season=="2018_19"),
       aes(x=reorder(Team,Wins), y=Wins)) +
    geom_point() + coord_flip() + xlab("Team")
```



Grouped bar plots

- Sometimes we want to contrast amounts for different groups
- Number of wins of the Teams along the Seasons

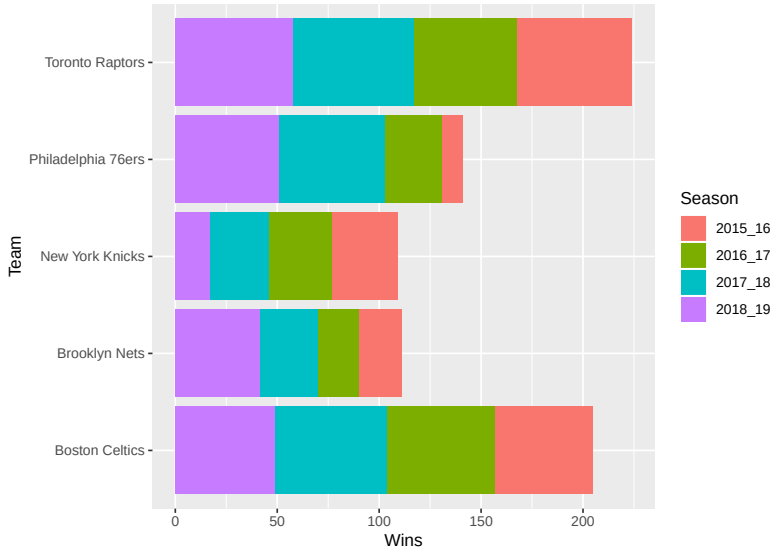
```
ggplot(nba,aes(x=Team,y=Wins,fill=Season)) + geom_col(position="dodge") + coord_flip()
```



Stacked bar plots

- Sometimes we want to contrast amounts for different groups
- Number of wins of the Teams along the Seasons

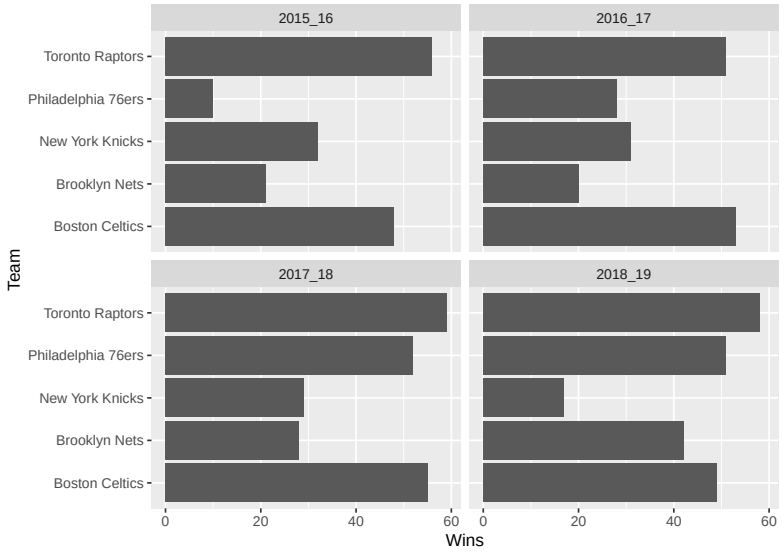
```
ggplot(nba,aes(x=Team,y=Wins,fill=Season)) + geom_col() + coord_flip()
```



Facets

- Yet another alternative of contrasting different groups

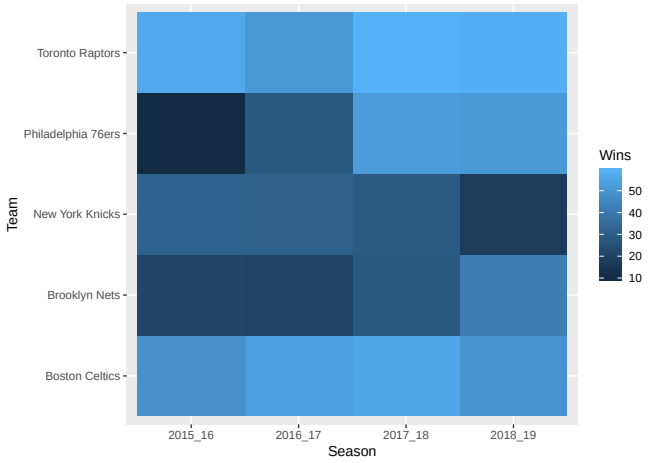
```
ggplot(nba,aes(x=Team,y=Wins)) + geom_col() + facet_wrap(~Season) + coord_flip()
```



Heatmaps

- Heatmaps can also be used to contrast different groups

```
ggplot(nba,aes(x=Season,y=Team,fill=Wins)) + geom_tile()
```



Visualizing Distributions of Variables

Visualizing Distributions

- The goal of these graphs is to understand how the values of a certain variable are distributed in our data set
- We will distinguish two common setups
  - Visualize a single distribution
  - Visualize multiple distributions

Histograms

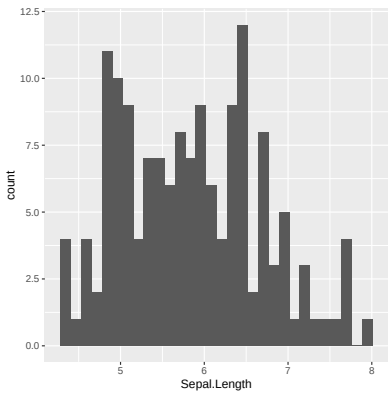
- Histograms visually look like barplots but they are rather different
- The number of bars in an histogram is determined by a **binning process** that divides the range of a numeric variable into a set of bins
- For each bin the number of values fitting inside of the bin is **counted** and that determines the height of the respective bar

Histograms

An example with the Iris dataset

- What is the distribution of the values of `Sepal.Lenght` in the **Iris** data set?

```
library(ggplot2)
data(iris)
ggplot(data = iris, mapping = aes(x=Sepal.Length)) + geom_histogram()

## `stat_bin()` using `bins = 30`.  Pick
## better value with `binwidth`.
```

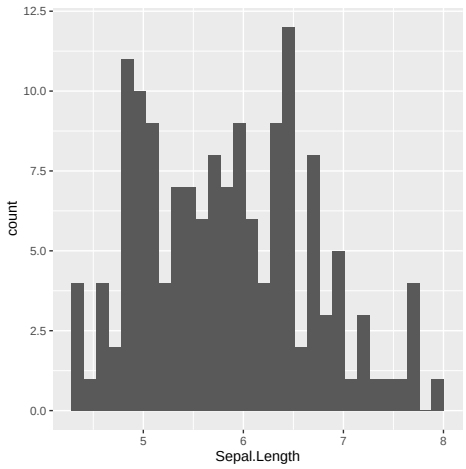


Histograms

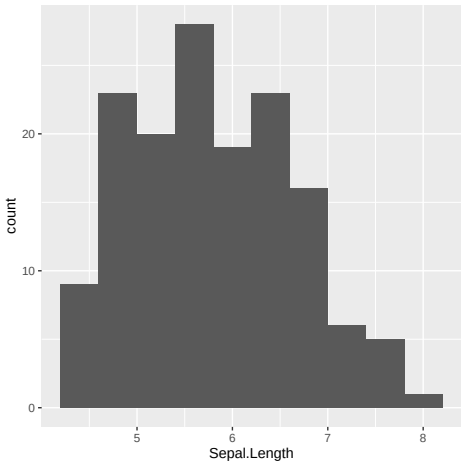
Effects of changing the number of bins

By default the range is divided into 30 bins

```
ggplot(iris,aes(x=Sepal.Length)) +
    geom_histogram()

## `stat_bin()` using `bins = 30`.  Pick
better value with `binwidth`.
```




```
ggplot(iris,aes(x=Sepal.Length)) +
    geom_histogram(bins=10)
```



Note: it is a good idea to try several values

Density plots

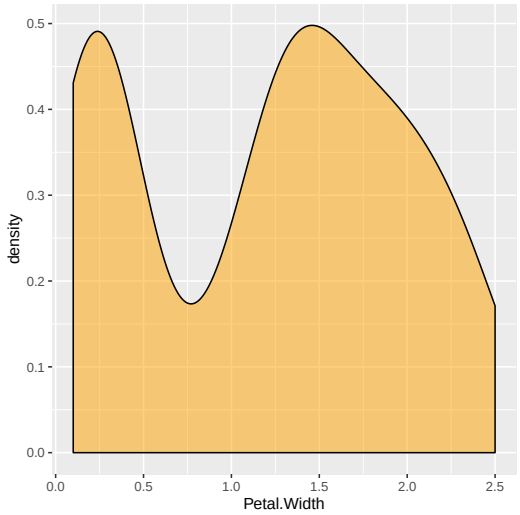
- An alternative to histograms is to use density plots
- They obtain an approaximation of the probability density function of the variable
- They are usually obtained using kernel density estimators (frequently the Gaussian kernel)
- These estimators typically depend on a parameter known as **bandwidth** that controls how sensitive are the estimates at each point
  - Changing its value has a similar effect as changing the number of bins in histograms

Density plots

An example with the Iris dataset

- What is the distribution of the values of `Petal.Width` in the **Iris** data set?

```
ggplot(iris,aes(x=Petal.Width)) +
    geom_density(fill="orange",alpha=0.5)
```



Note: by default this uses a bandwidth determined by a rule whose theoretical justification can be seen at the reference provided in the help page of function `bw.nrd0()`

Boxplots

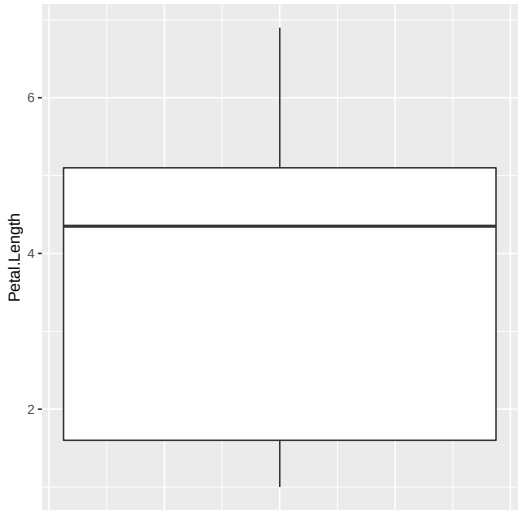
- Boxplots provide a synthetic representation of a distribution by showing a few summary statistics
- This obviously implies some loss of information on the full distribution
- Still, they provide interesting features like for instance identifying outliers
- They are better suited for comparing multiple distributions but they can also be used for a single distribution

Boxplots

An example with the Iris dataset

- What is the distribution of the values of `Petal.Lenght` in the **Iris** data set?

```
ggplot(iris,aes(y=Petal.Length)) + geom_boxplot() +
    theme(axis.ticks.x = element_blank(), axis.text.x = element_blank())
```



Empirical cumulative distribution functions (ECDF's)

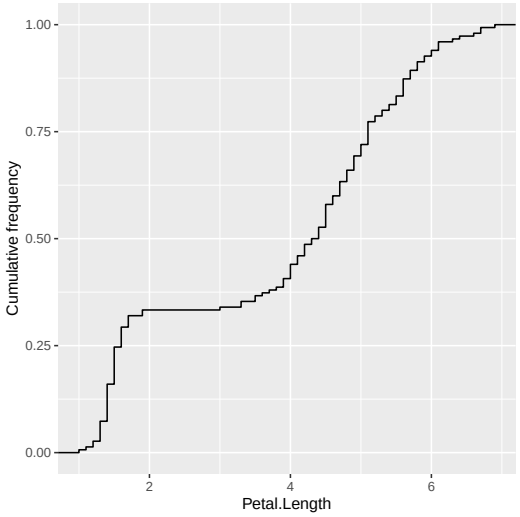
- ECDF's are interesting tools to visualize the distribution of a continuous variable
- They are obtained by ordering the sample values and then ploting them against the cumulative frequency proportion (a value between 0 and 1)

ECDFs

An example with the Iris dataset

- Plot the empirical cumulative distribution function of `Petal.Lenght` in the **Iris** data set?

```
ggplot(iris,aes(x=Petal.Length)) + stat_ecdf() + ylab("Cumulative frequency")
```



Quantile-quantile Plots (Q-Q plots)

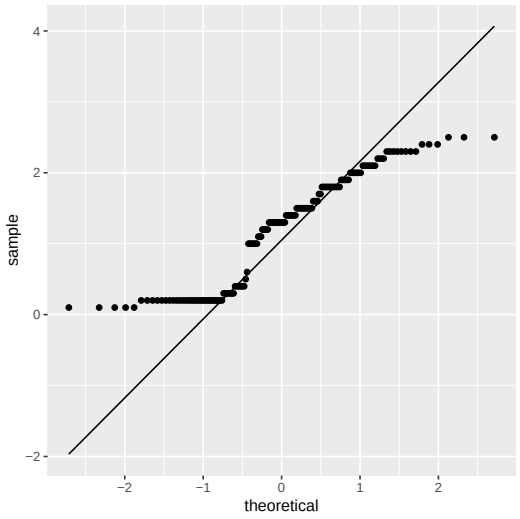
- These plots compare the sample quantiles of a continuous variable with the theoretical quantiles of a known distribution
- They are useful to check if some variable follows a certain distribution
- Frequently we compare the sample against the Normal distribution

Q-Q plots

An example with the Iris dataset

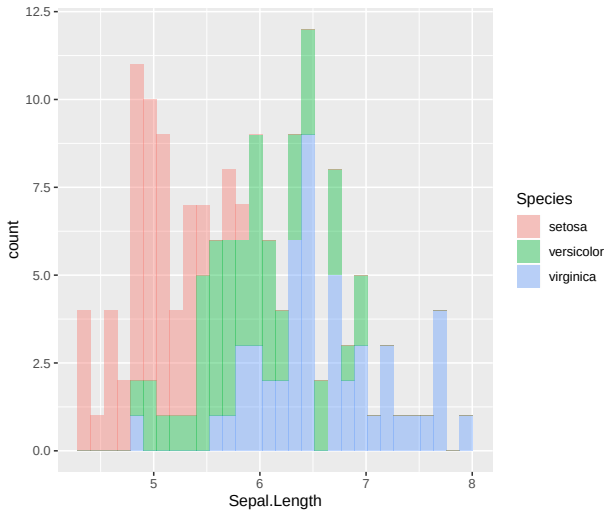
- Is it reasonable to think the variable `Petal.width` of the **Iris** data set follows a Normal distribution?

```
ggplot(iris, aes(sample = Petal.Width)) + stat_qq() + stat_qq_line()
```



Multiple Distributions using Histograms

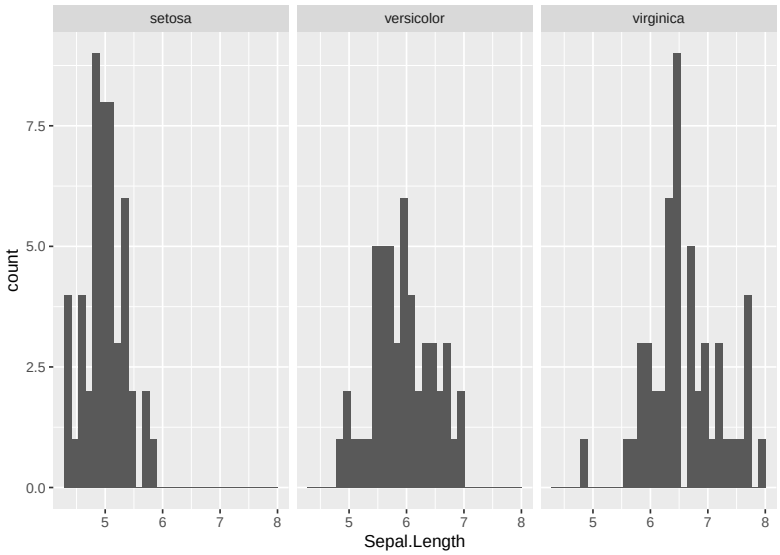
```
ggplot(iris,aes(x=Sepal.Length,  fill=Species)) +
    geom_histogram(alpha=0.4)

## `stat_bin()` using `bins = 30`.  Pick better value with `binwidth`.
```



- **This is bad - avoid!**
- Overplotting causes visualization problems

Multiple Distributions using Histograms - 2

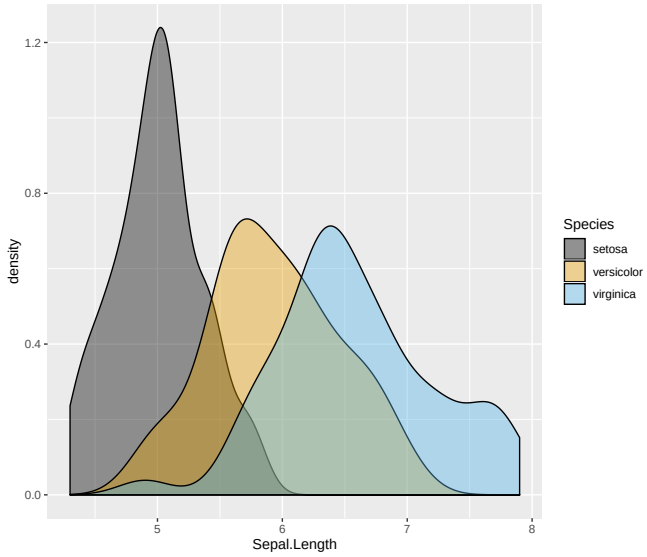
```
ggplot(iris,aes(x=Sepal.Length)) + geom_histogram() + facet_wrap(~ Species)

## `stat_bin()` using `bins = 30`.  Pick better value with `binwidth`.
```



- This is better

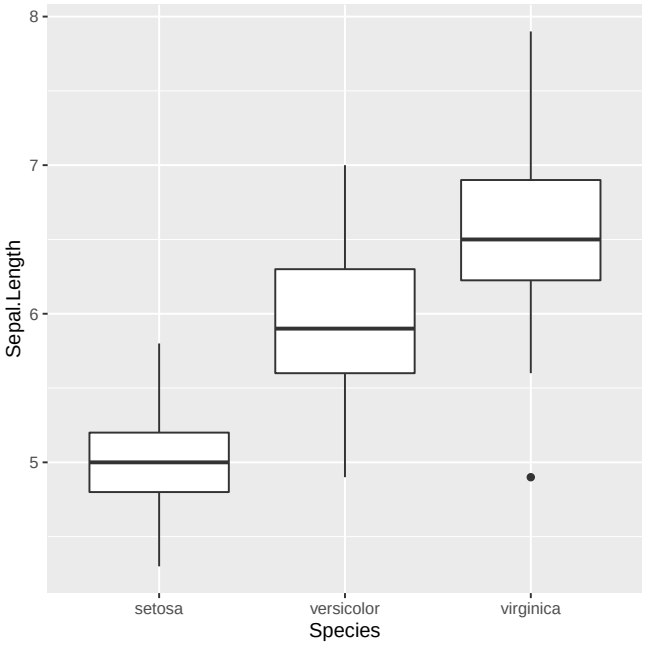
Multiple Distributions using Density Plots

```
library(ggthemes)
ggplot(iris,aes(x=Sepal.Length, fill=Species)) +
    geom_density(alpha=0.4) + scale_fill_colorblind()
```



Multiple Distributions with Box Plots

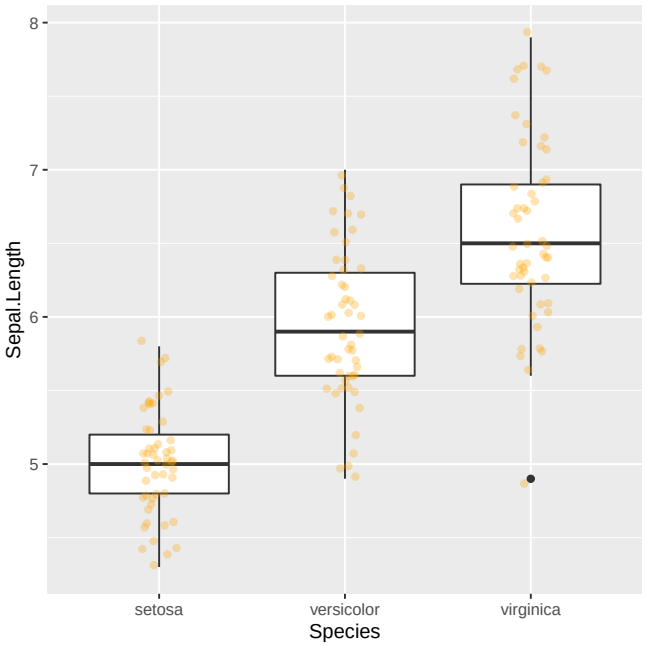
```
ggplot(iris,aes(x=Species,y=Sepal.Length)) +
    geom_boxplot()
```



Multiple Distributions with Box Plots

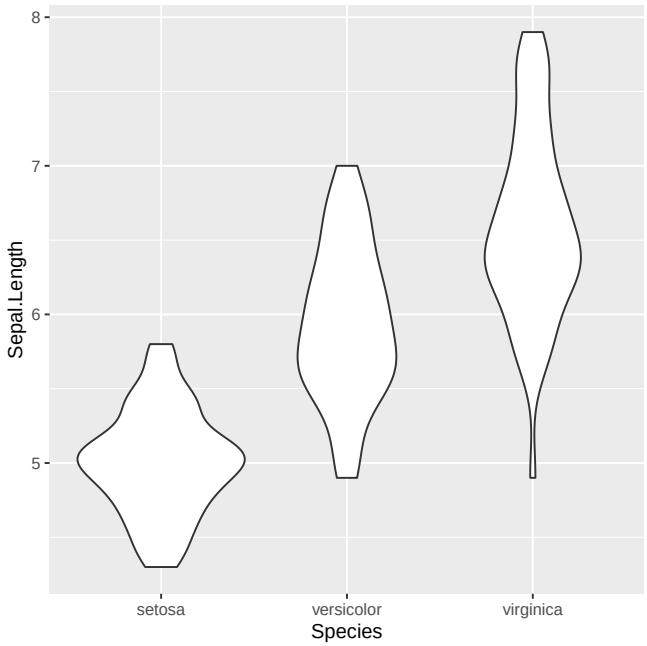
Adding information on the amount of values

```
ggplot(iris,aes(x=Species,y=Sepal.Length)) +
    geom_boxplot() + geom_jitter(color="orange",alpha=0.3,width=0.1)
```



Multiple Distributions with Violin Plots

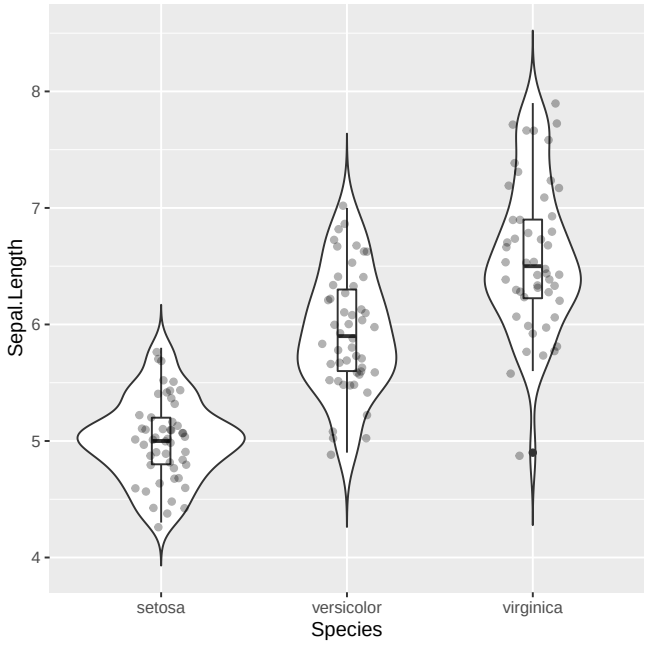
```
ggplot(iris,aes(x=Species,y=Sepal.Length)) +  geom_violin()
```



Note: similar to density plots...

Variations on Violin Plots

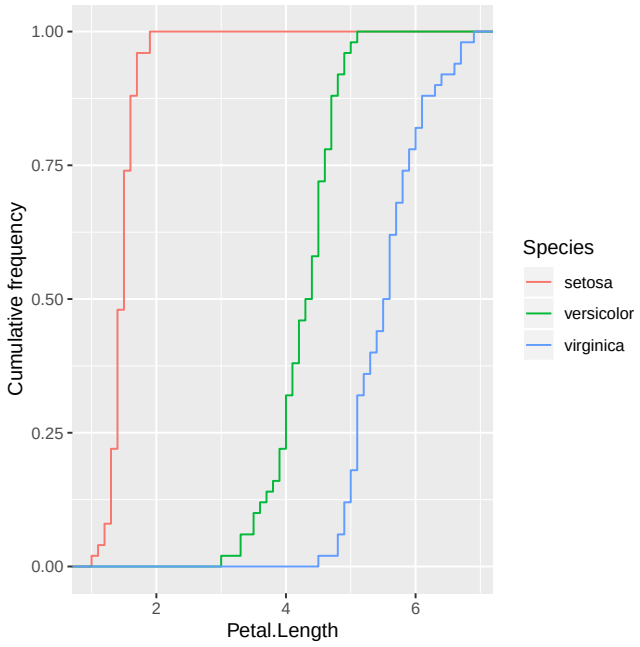
```
ggplot(iris,aes(x=Species,y=Sepal.Length)) +  geom_violin(trim=FALSE) +
    geom_boxplot(width=0.1) + geom_jitter(position=position_jitter(0.15),alpha=0.3)

## Warning in sample.int(.Machine$integer.max, 1L): '.Random.seed[1]' is not a valid integer,
so ignored
```



Note: similar to density plots...

Multiple Distributions with ECDFs

```
ggplot(iris,aes(x=Petal.Length,color=Species)) + stat_ecdf()+ ylab("Cumulative frequency")
```



Hands on Data Visualization - the Algae data set

Using the Algae data set from package `DMwR2` (extra package you need to install) answer to the following questions:

1. Create a graph that you find adequate to show the distribution of the values of algae `a6`
2. Show the distribution of the values of `size`
3. Check visually if it is plausible to consider that `oPO4` follows a normal distribution

Visualizing Proportions

Visualizing Proportions

- Goal: show how a certain information breaks down into proportions
  - e.g. how the clients of some company are distributed across different genders
- We will study three main tools for handling proporties, each with pros and cons
  - Pie charts
  - Stacked barcharts
  - Bar plots

Piecharts

- These plots associate the proportion values with slices of a pie
- Reading the values thus involves comparing areas of slices
- Piecharts are frequently criticized by being harder on the human eye, on the basis that it is easier to compare height of bars than areas of slices
- Technical note: pie charts are much easier to obtain with R base graphs than with ggplot2

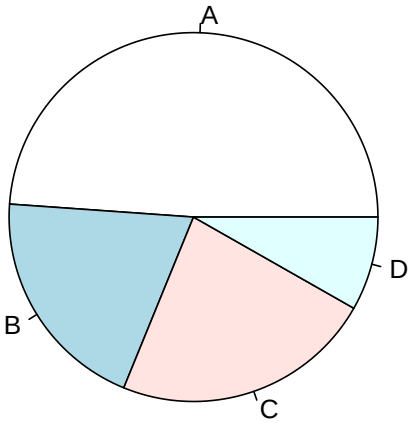
Example data set: the number of seats of four political parties in an election

Party	Seats
A	196
B	80
C	92
D	33

Pie Charts

- Comparing the parliement seats of the parties

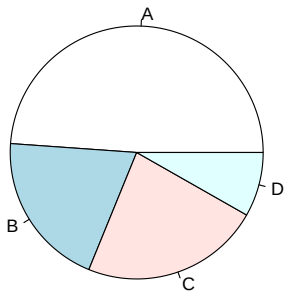
```
pie(dat$Seats, labels=dat$Party)
```



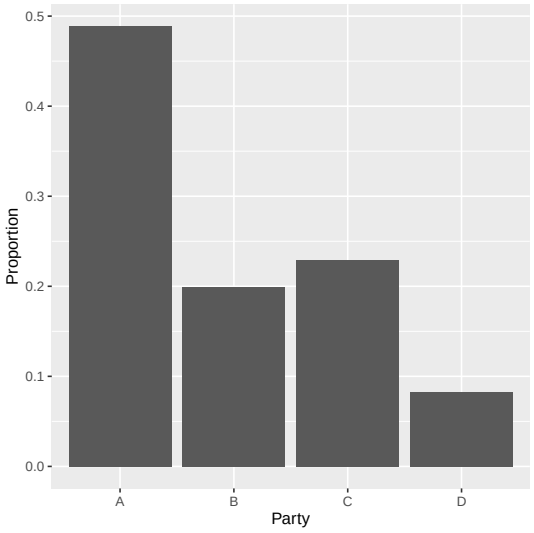
Pie Charts

Comparing with a barplot

```
pie(dat$Seats, labels=dat$Party)
```

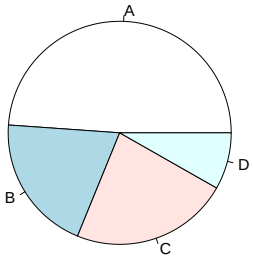


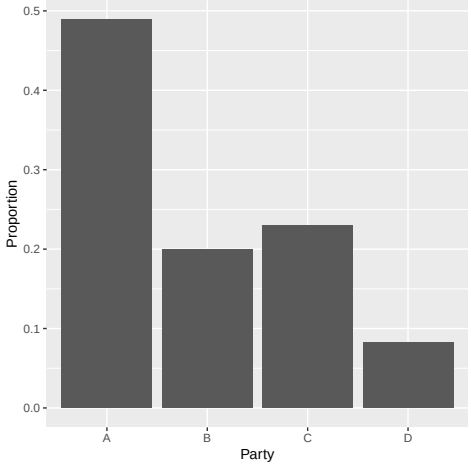

```
ggplot(mutate(dat,Prop=Seats/sum(dat$Seats)),
       aes(x=Party,y=Prop)) + geom_col() +
    ylab("Proportion")
```



Pie Charts

Discussion



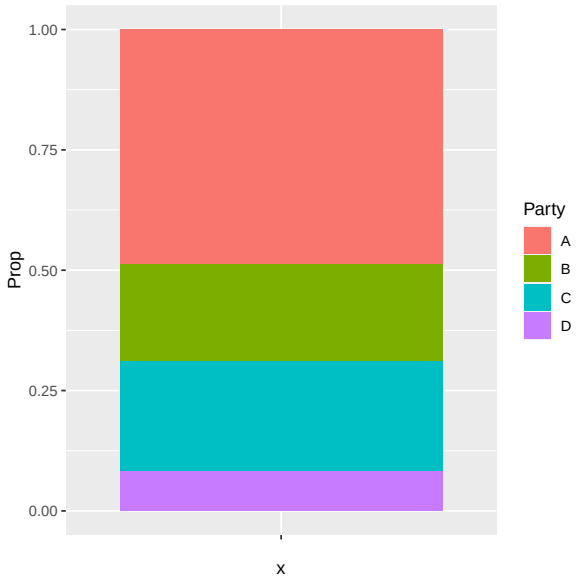


- On the pie it is not so easy to see that C has more seats than B
- On the bar plot it is not easy to see that A and D together have the majority of the seats and thus could form a government

Stacked barcharts

- Comparing the parliement seats of the parties

```
ggplot(mutate(dat,Prop=Seats/sum(dat$Seats)),
       aes(x="",y=Prop,fill=Party)) + geom_col()
```



X-Y Associations

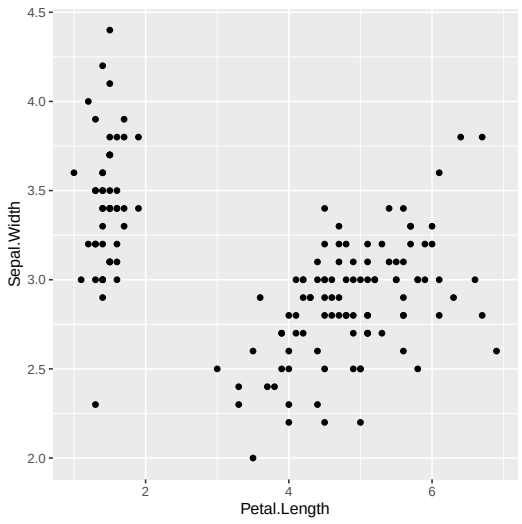
X-Y Associations

- Goal: understand how two continuous variables related with each other
  - e.g. is the growth of Petal.Length associated with a growth in Sepal.Width?

Scatter Plots

- The simplest way of checking this type of relationships is through a scatter plot
- Each of the numeric variables is associated with one of the plot axis

```
ggplot(iris, aes(x=Petal.Length, y= Sepal.Width)) + geom_point()
```

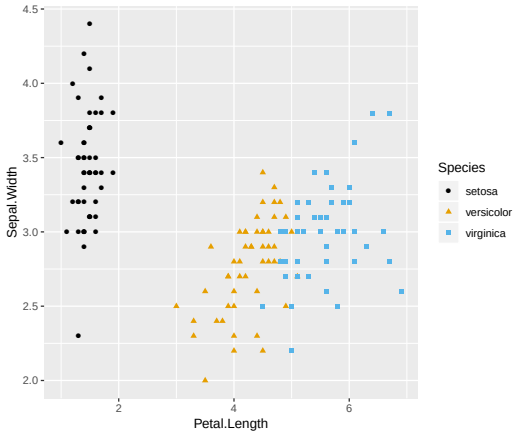


Scatter Plots

Grouped associations

- Sometimes the association may be different for different sub-groups of data

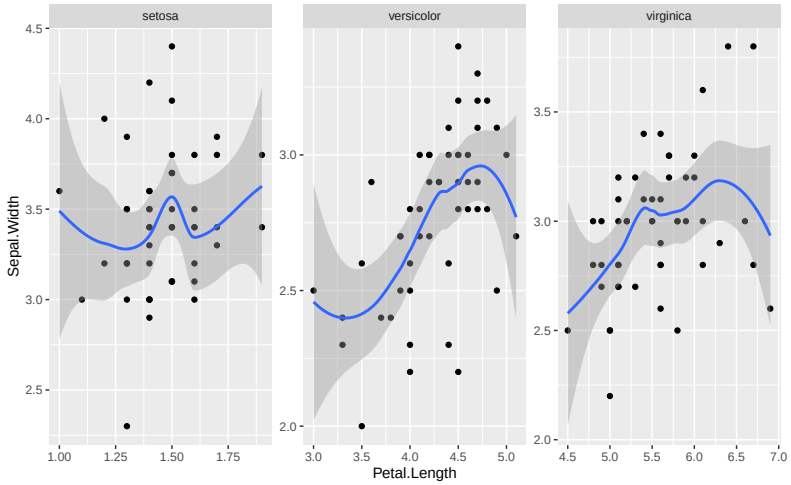
```
library(ggthemes)
ggplot(iris, aes(x=Petal.Length, y= Sepal.Width, color=Species, shape=Species)) +
    geom_point() + scale_color_colorblind()
```



Scatter Plots

Trying to “model” the associations

```
ggplot(iris, aes(x=Petal.Length, y= Sepal.Width)) +
    geom_point() + geom_smooth(method="loess", se=TRUE,level=0.95) +
    facet_wrap(~ Species,scales = "free")
```



Multiple Associations

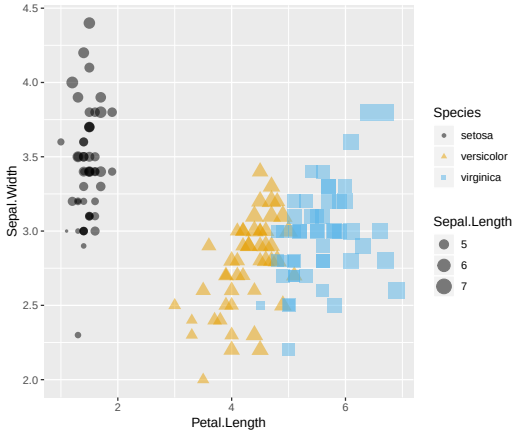
Multiple Associations

- Goal: understand how multiple variables related with each other

Scatter plots for more than two variables

- Using other aesthetic properties to code other variables
- Use with caution, t may get too confusing!

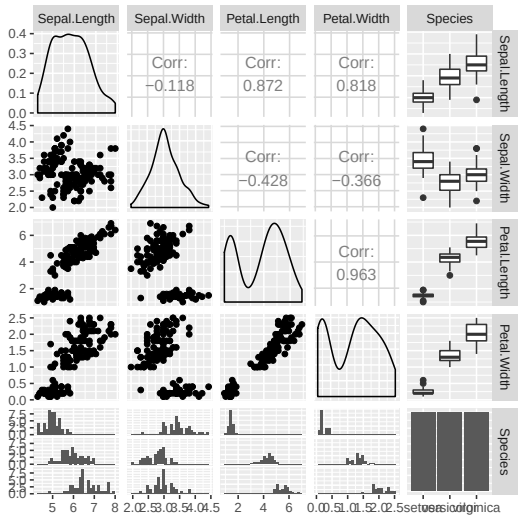
```
ggplot(iris,
       aes(x=Petal.Length, y= Sepal.Width, size=Sepal.Length, color= Species, shape=Species)) +
    geom_point(alpha=0.5) + scale_color_colorblind()
```



Scatterplot matrices through package `GGally`

- These graphs try to present all pairwise scatterplots in a data set.
- They are unfeasible for data sets with many variables.

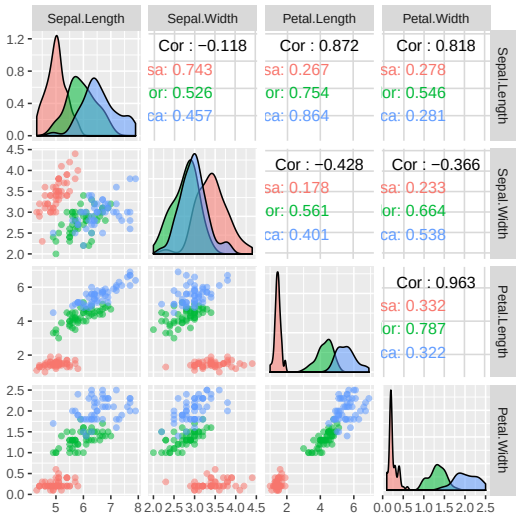
```
library(GGally)
ggpairs(iris)
```



Scatterplot matrices - a more interesting variant

- Differentiating with a nominal variable

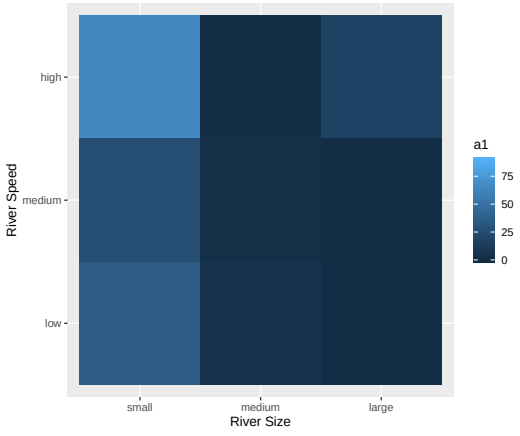
```
ggpairs(iris,columns = 1:4,ggplot2::aes(color=Species,alpha=0.5))
```



Heat Maps for more than two variables

- Axes are two nominal variables

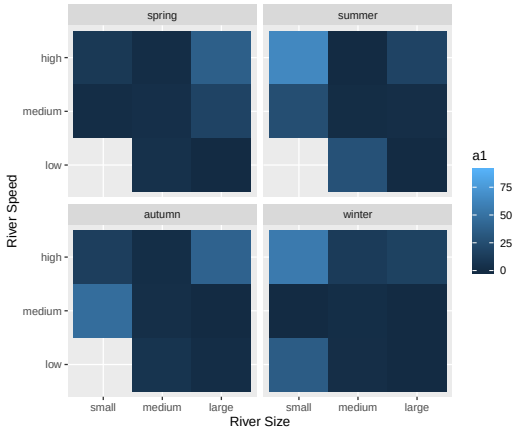
```
data(algae,package="DMwR2")
library(dplyr)
library(forcats)
mutate(algae,
       size = fct_relevel(size,c("small","medium","large")),
       speed = fct_relevel(speed,c("low","medium","high"))) %>%
ggplot(aes(x = size, y = speed, fill = a1)) +
    geom_tile() +xlab("River Size") + ylab("River Speed")
```



Heat Maps for more than two variables - 2

- Axes are two nominal variables, and a third as a facet

```
mutate(algae,
       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"))) %>%
ggplot(aes(x = size, y = speed, fill = a1)) +
    geom_tile() + facet_wrap(~ season) + xlab("River Size") + ylab("River Speed")
```

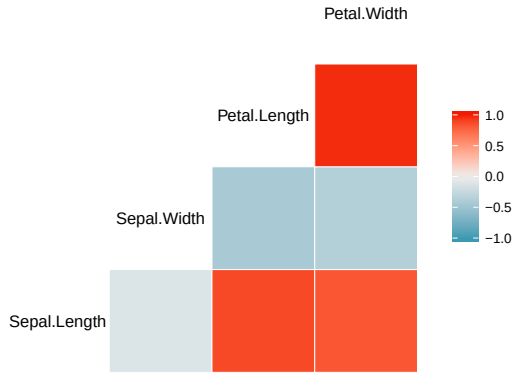


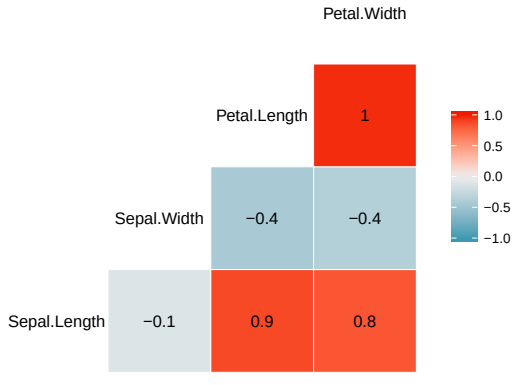
Correlograms

- For numeric variables we can calulate an represent the correlation value

```
library(GGally)
ggcorr(iris[,-5])
```

```
library(GGally)
ggcorr(iris[,-5],label = TRUE)
```





Parallel Plots

- Parallel plots are also interesting for visualizing a full data set

```
library(GGally)
ggparcoord(iris,columns = 1:4,groupColumn = "Species", alphaLines = 0.5)
```