1. Correlation

The following plots help to examine how well correlated two variables are.

Scatterplot

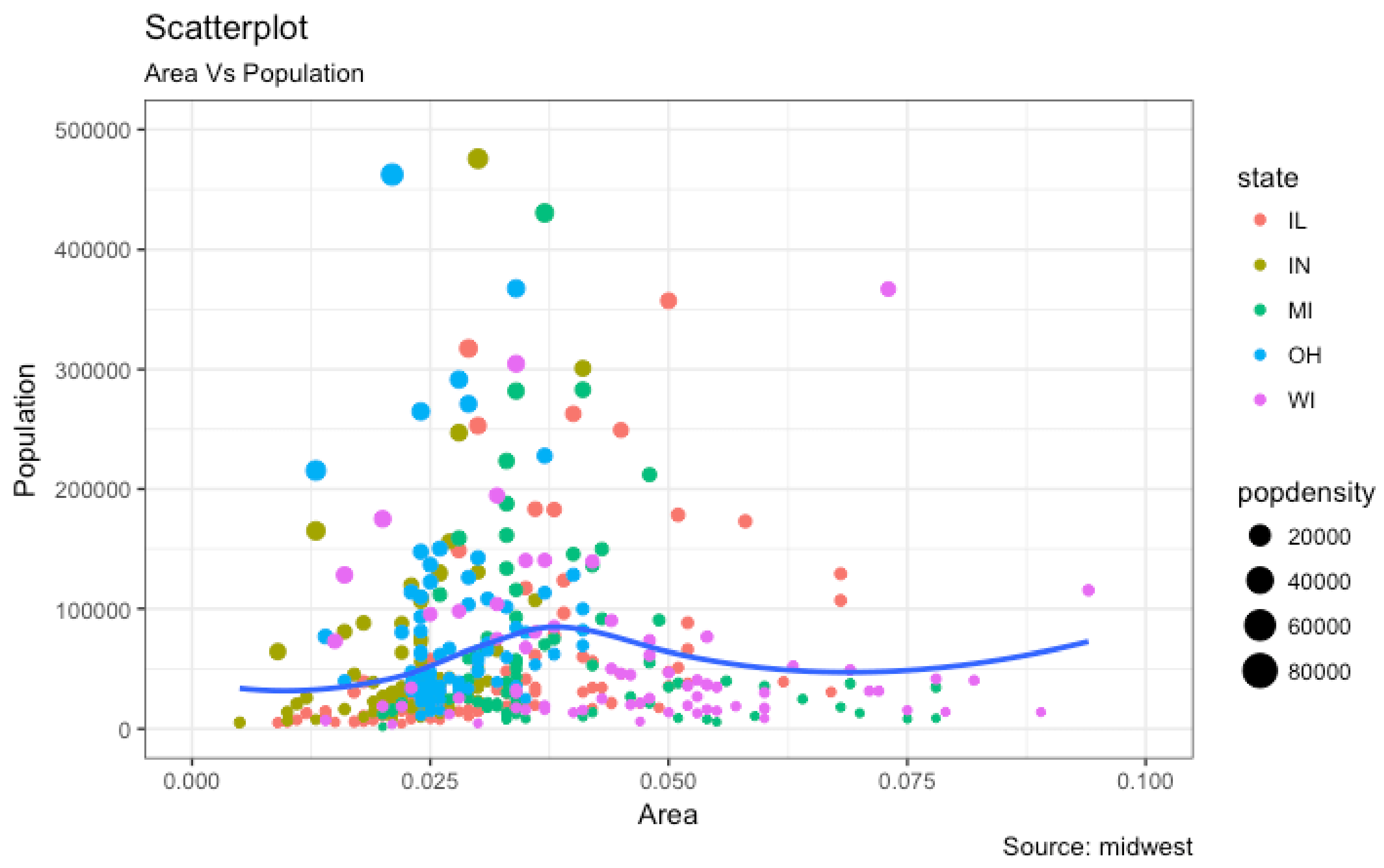
The most frequently used plot for data analysis is undoubtedly the scatterplot. Whenever you want to understand the nature of relationship between two variables, invariably the first choice is the scatterplot.

It can be drawn using `geom_point()`. Additionally, `geom_smooth` which draws a smoothing line (based on loess) by default, can be tweaked to draw the line of best fit by setting `method='lm'`.

```
# install.packages("ggplot2")
# load package and data
options(scipen=999)  # turn-off scientific notation like 1e+48
library(ggplot2)
theme_set(theme_bw())  # pre-set the bw theme.
data("midwest", package = "ggplot2")
# midwest <- read.csv("http://goo.gl/G1K41K")  # bkup data source

# Scatterplot
gg <- 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")

plot(gg)
```



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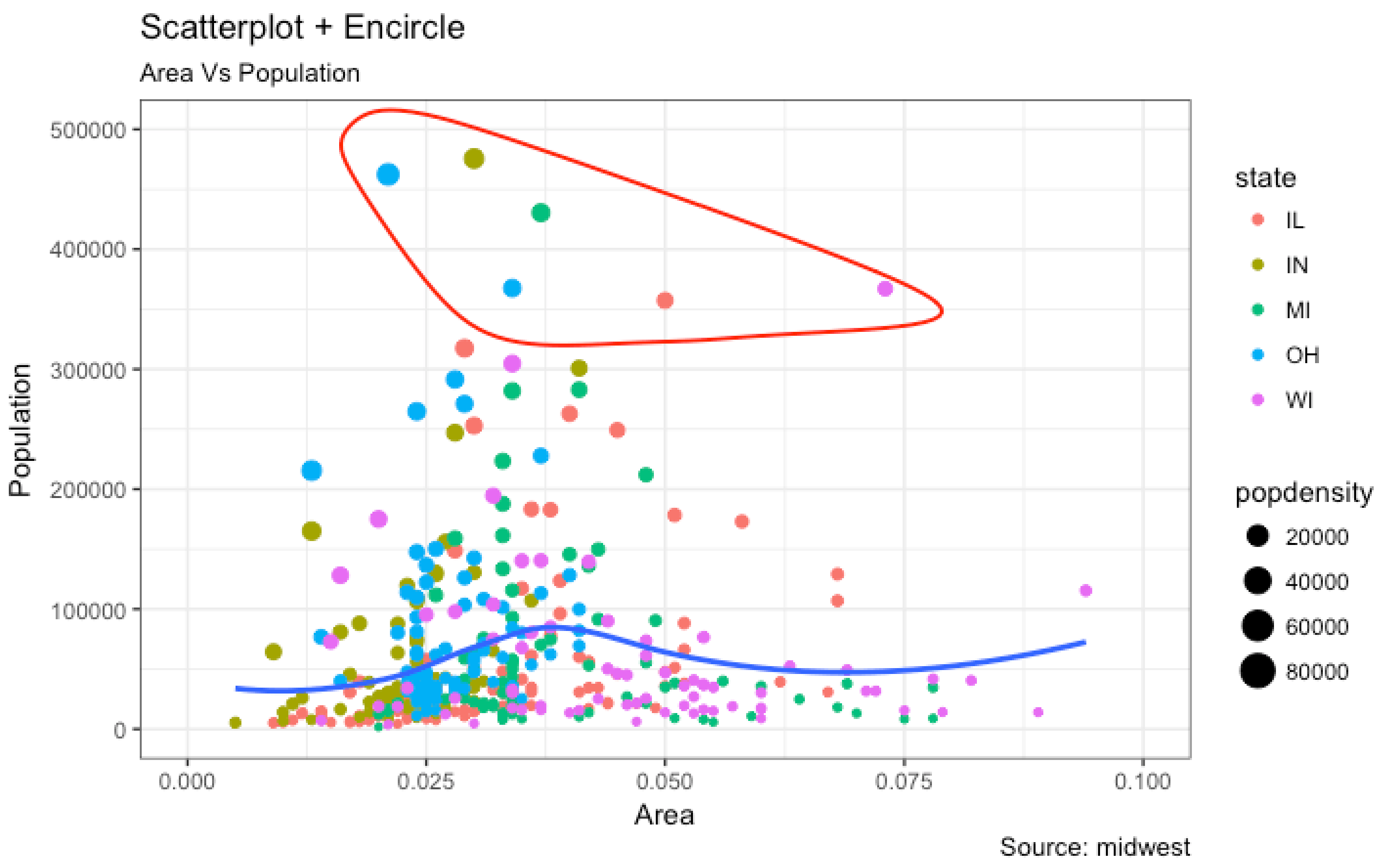
Scatterplot With Encircling

When presenting the results, sometimes I would encirlce certain special group of points or region in the chart so as to draw the attention to those peculiar cases. This can be conveniently done using the `geom_encircle()` in `ggalt` package.

Within `geom_encircle()`, set the `data` to a new dataframe that contains only the points (rows) or interest. Moreover, You can `expand` the curve so as to pass just outside the points. The `color` and `size` (thickness) of the curve can be modified as well. See below example.

```
# install 'ggalt' pkg
# devtools::install_github("hrbrmstr/ggalt")
options(scipen = 999)
library(ggplot2)
library(ggalt)
midwest_select <- midwest[midwest$poptotal > 350000 &
                            midwest$poptotal <= 500000 &
                            midwest$area > 0.01 &
                            midwest$area < 0.1, ]

# Plot
ggplot(midwest, aes(x=area, y=poptotal)) +
  geom_point(aes(col=state, size=popdensity)) +   # draw points
  geom_smooth(method="loess", se=F) +
  xlim(c(0, 0.1)) +
  ylim(c(0, 500000)) +   # draw smoothing line
  geom_encircle(aes(x=area, y=poptotal),
                data=midwest_select,
                color="red",
                size=2,
                expand=0.08) +   # encircle
  labs(subtitle="Area Vs Population",
       y="Population",
       x="Area",
       title="Scatterplot + Encircle",
       caption="Source: midwest")
```



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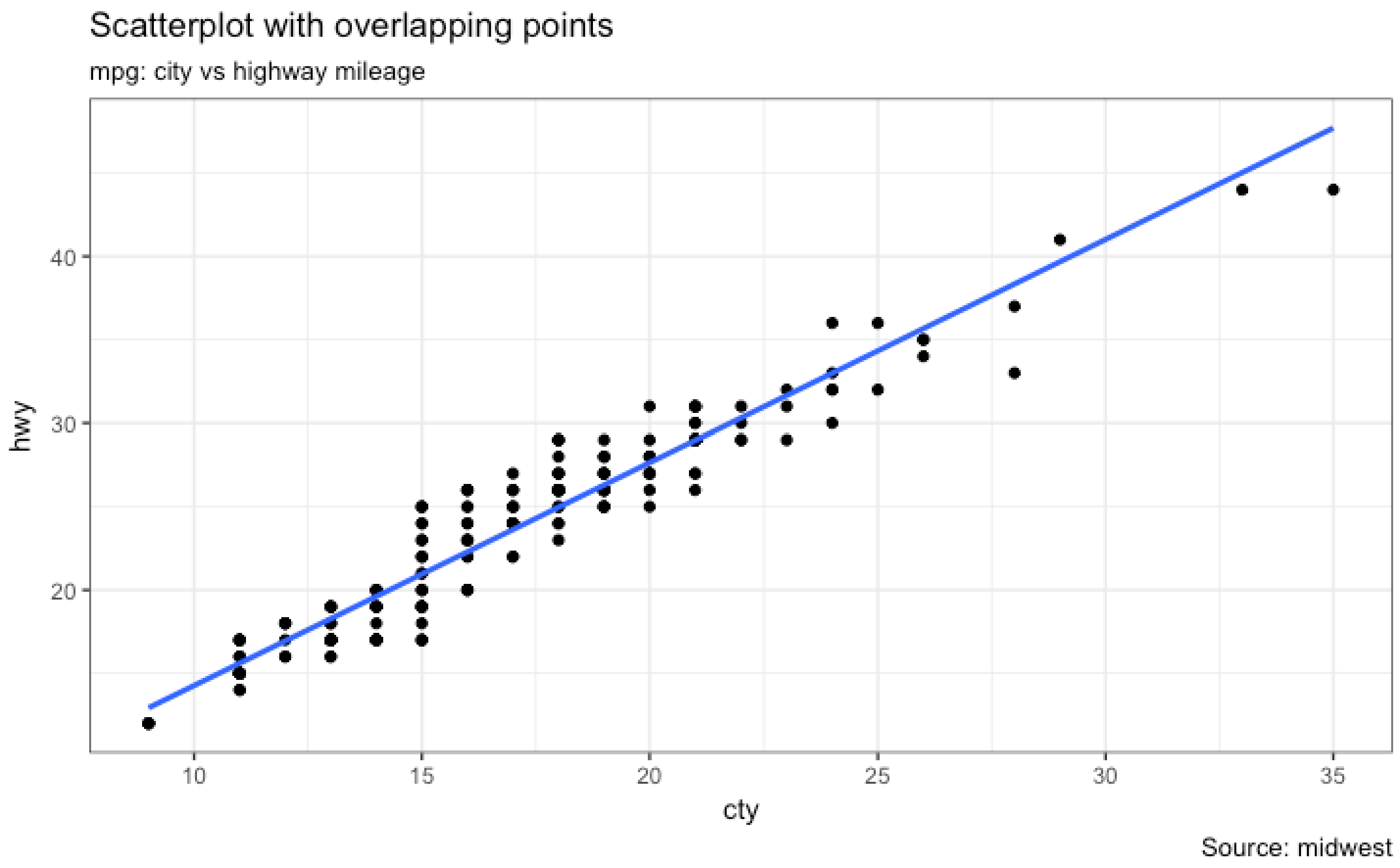
Jitter Plot

Let’s look at a new data to draw the scatterplot. This time, I will use the `mpg` dataset to plot city mileage (`cty`) vs highway mileage (`hwy`).

```
# load package and data
library(ggplot2)
data(mpg, package="ggplot2") # alternate source: "http://goo.gl/uEeRGu")
theme_set(theme_bw())  # pre-set the bw theme.

g <- ggplot(mpg, aes(cty, hwy))

# Scatterplot
g + geom_point() +
  geom_smooth(method="lm", se=F) +
  labs(subtitle="mpg: city vs highway mileage",
       y="hwy",
       x="cty",
       title="Scatterplot with overlapping points",
       caption="Source: midwest")
```



What we have here is a scatterplot of city and highway mileage in `mpg` dataset. We have seen a similar scatterplot and this looks neat and gives a clear idea of how the city mileage (`cty`) and highway mileage (`hwy`) are well correlated.

But, this innocent looking plot is *hiding* something. Can you find out?

```
dim(mpg)
```

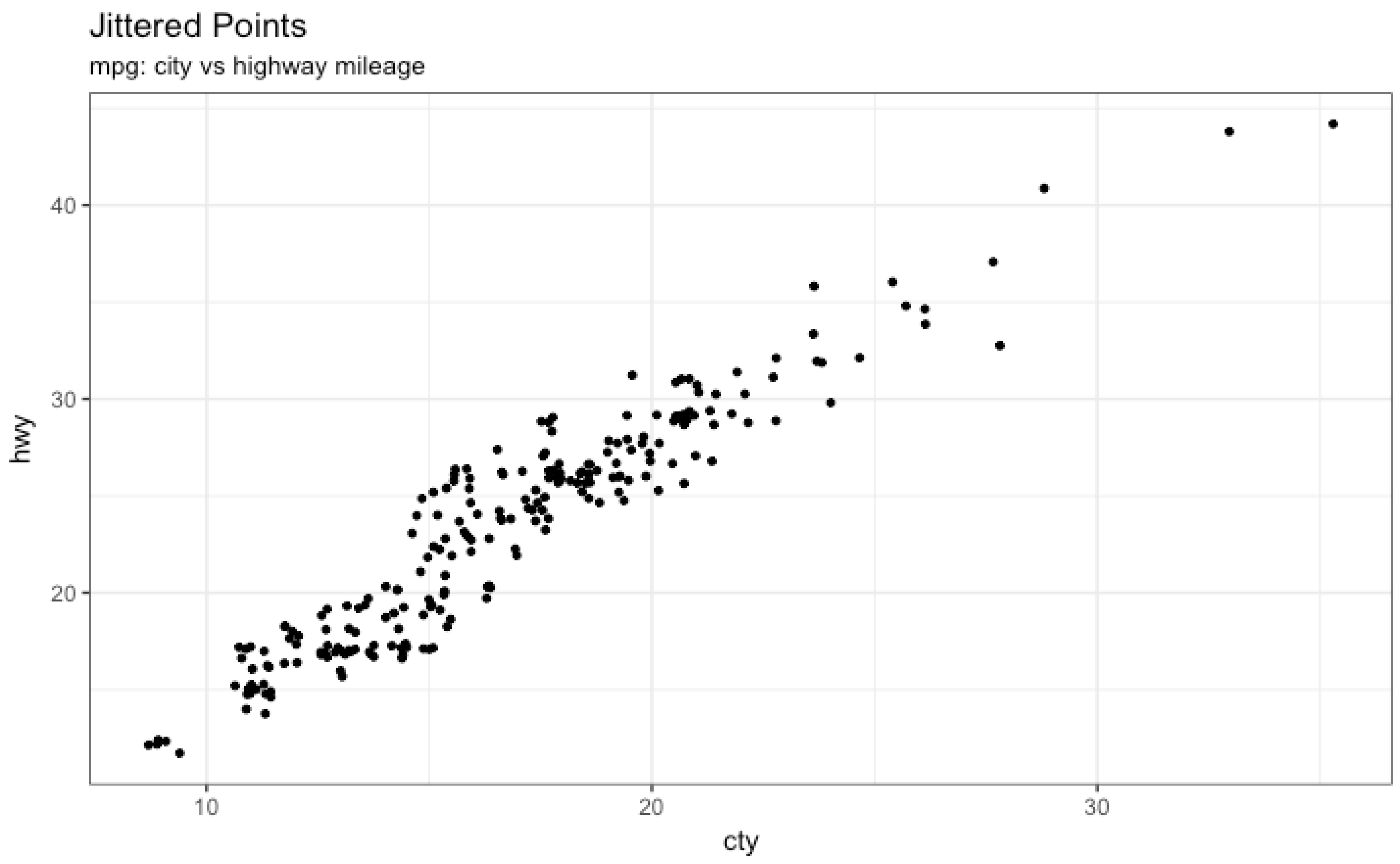
The original data has 234 data points but the chart seems to display fewer points. What has happened? This is because there are many overlapping points appearing as a single dot. The fact that both `cty` and `hwy` are integers in the source dataset made it all the more convenient to hide this detail. So just be extra careful the next time you make scatterplot with integers.

So how to handle this? There are few options. We can make a jitter plot with `jitter_geom()`. As the name suggests, the overlapping points are randomly jittered around its original position based on a threshold controlled by the `width` argument.

```
# load package and data
library(ggplot2)
data(mpg, package="ggplot2")
# mpg <- read.csv("http://goo.gl/uEeRGu")

# Scatterplot
```

```
theme_set(theme_bw())  # pre-set the bw theme.
g <- ggplot(mpg, aes(cty, hwy))
g + geom_jitter(width = .5, size=1) +
  labs(subtitle="mpg: city vs highway mileage",
       y="hwy",
       x="cty",
       title="Jittered Points")
```



More points are revealed now. More the `width`, more the points are moved jittered from their original position.

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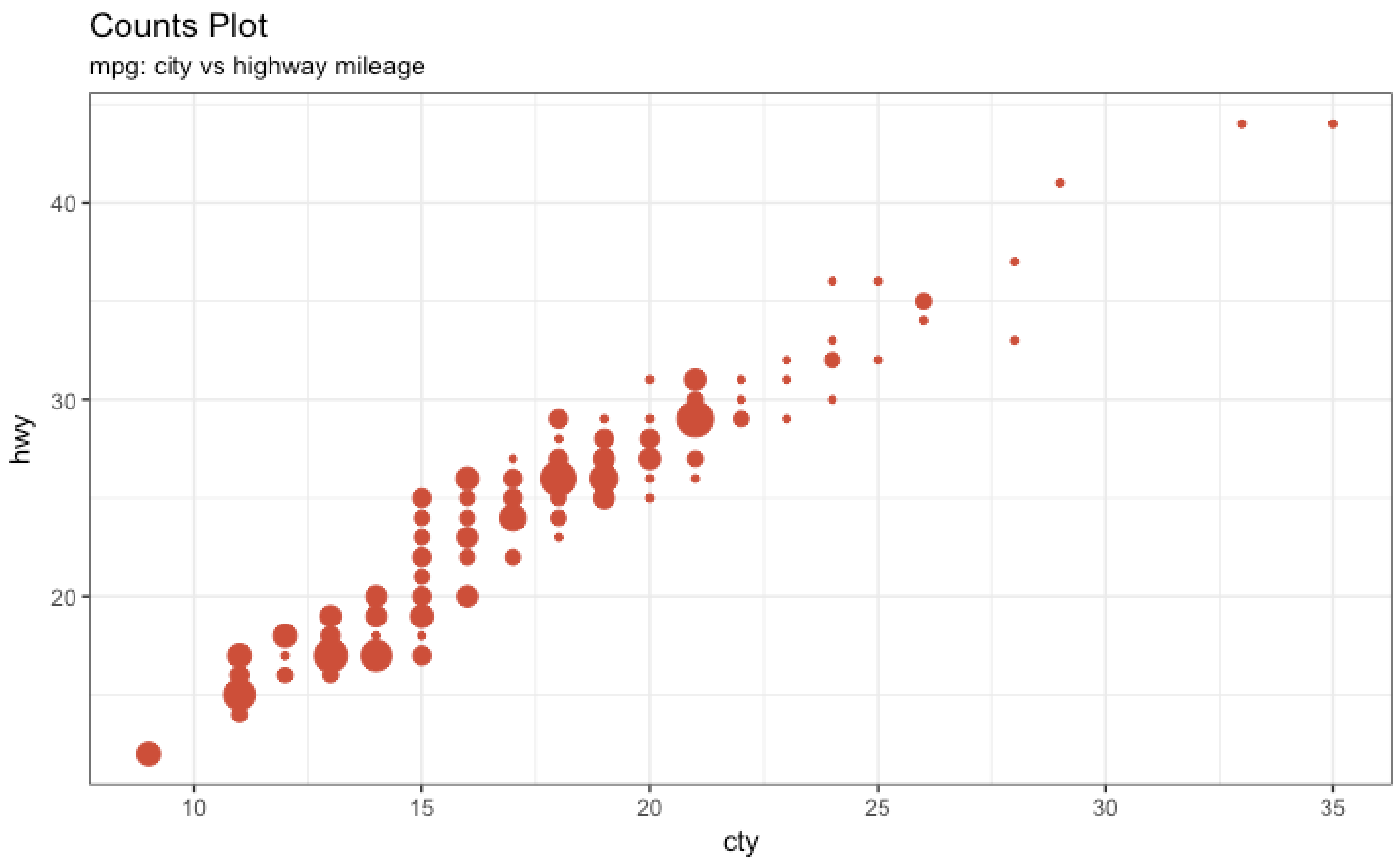
Counts Chart

The second option to overcome the problem of data points overlap is to use what is called a *counts chart*. Whereever there is more points overlap, the size of the circle gets bigger.

```
# load package and data
library(ggplot2)
data(mpg, package="ggplot2")
# mpg <- read.csv("http://goo.gl/uEeRGu")

# Scatterplot
theme_set(theme_bw())  # pre-set the bw theme.
g <- ggplot(mpg, aes(cty, hwy))
g + geom_count(col="tomato3", show.legend=F) +
  labs(subtitle="mpg: city vs highway mileage",
       y="hwy",
       x="cty",
       title="Counts Plot")
```



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Bubble plot

While scatterplot lets you compare the relationship between 2 continuous variables, bubble chart serves well if you want to understand relationship within the underlying groups based on:

1. A Categorical variable (by changing the color) and
2. Another continuous variable (by changing the size of points).

In simpler words, bubble charts are more suitable if you have 4-Dimensional data where two of them are numeric (X and Y) and one other categorical (color) and another numeric variable (size).

The bubble chart clearly distinguishes the range of `displ` between the manufacturers and how the slope of lines-of-best-fit varies, providing a better visual comparison between the groups.

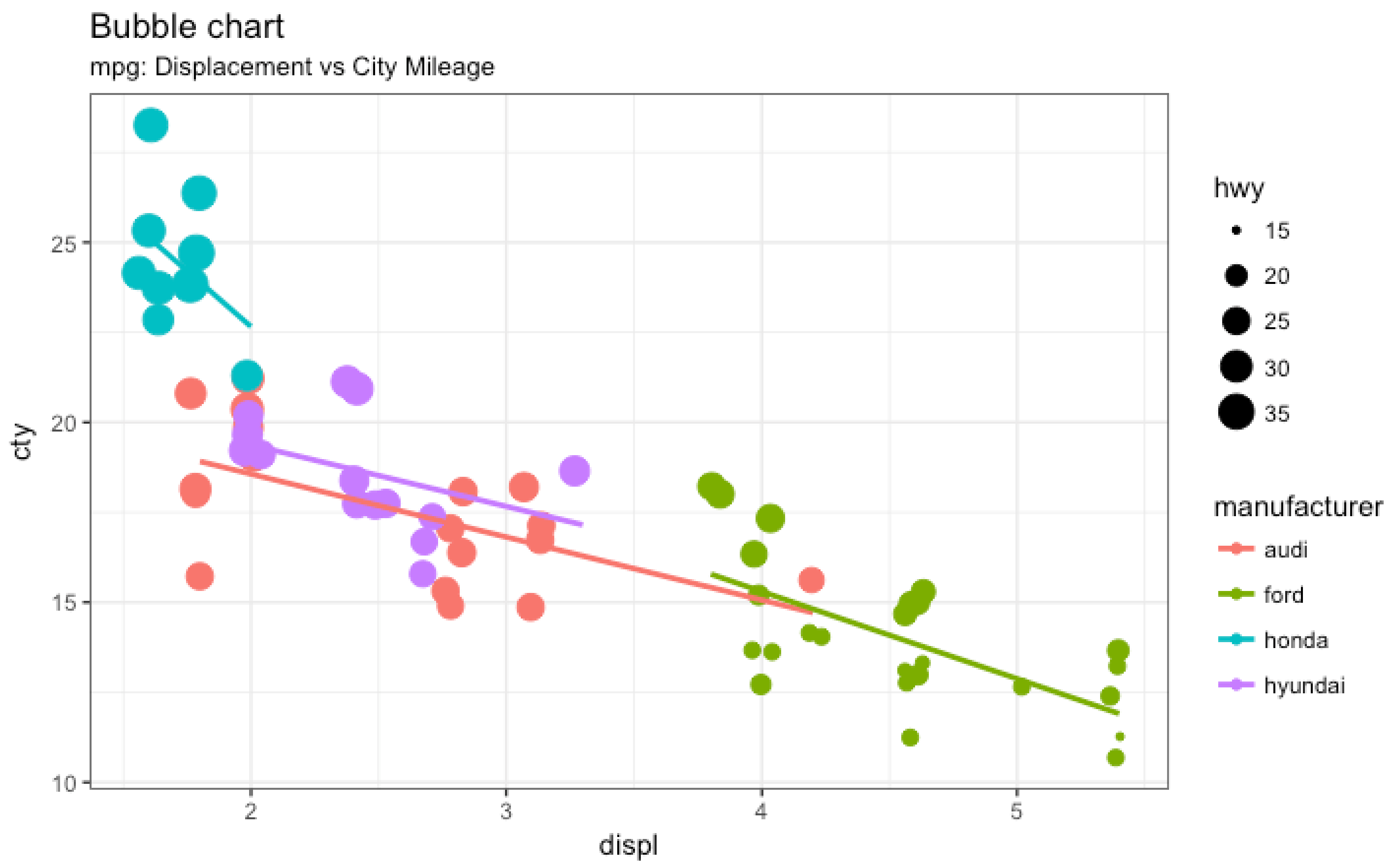
```
# load package and data
library(ggplot2)
data(mpg, package="ggplot2")
# mpg <- read.csv("http://goo.gl/uEeRGu")

mpg_select <- mpg[mpg$manufacturer %in% c("audi", "ford", "honda", "hyundai"), ]

# Scatterplot
theme_set(theme_bw())  # pre-set the bw theme.
```

```
g <- ggplot(mpg_select, aes(displ, cty)) +
  labs(subtitle="mpg: Displacement vs City Mileage",
       title="Bubble chart")

g + geom_jitter(aes(col=manufacturer, size=hwy)) +
  geom_smooth(aes(col=manufacturer), method="lm", se=F)
```



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Animated Bubble chart

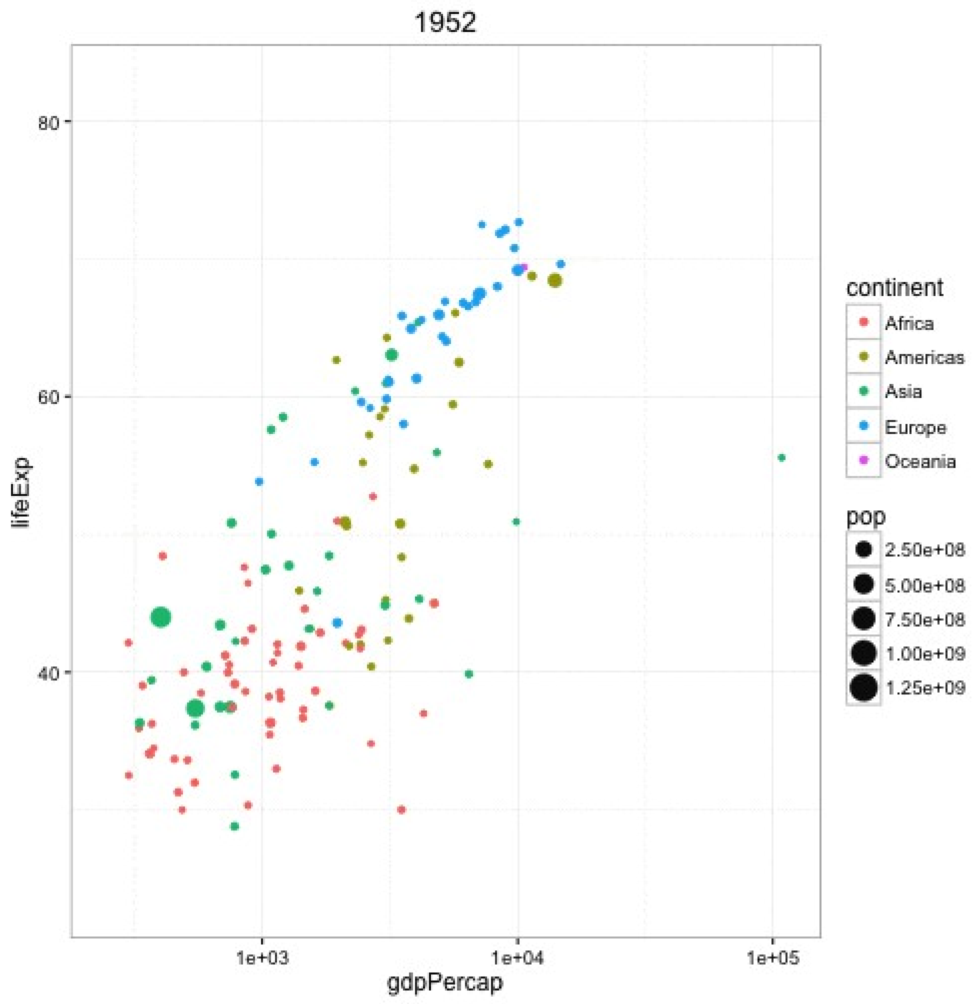
An animated bubble chart can be implemented using the `gganimate` package. It is same as the bubble chart, but, you have to show how the values change over a fifth dimension (typically time).

The key thing to do is to set the `aes(frame)` to the desired column on which you want to animate. Rest of the procedure related to plot construction is the same. Once the plot is constructed, you can animate it using `gganimate()` by setting a chosen `interval`.

```
# Source: https://github.com/dgrtwo/gganimate
# install.packages("cowplot")  # a gganimate dependency
# devtools::install_github("dgrtwo/gganimate")
library(ggplot2)
library(gganimate)
library(gapminder)
theme_set(theme_bw())  # pre-set the bw theme.

g <- ggplot(gapminder, aes(gdpPercap, lifeExp, size = pop, frame = year)) +
  geom_point() +
  geom_smooth(aes(group = year),
              method = "lm",
              show.legend = FALSE) +
  facet_wrap(~continent, scales = "free") +
  scale_x_log10()  # convert to log scale

gganimate(g, interval=0.2)
```



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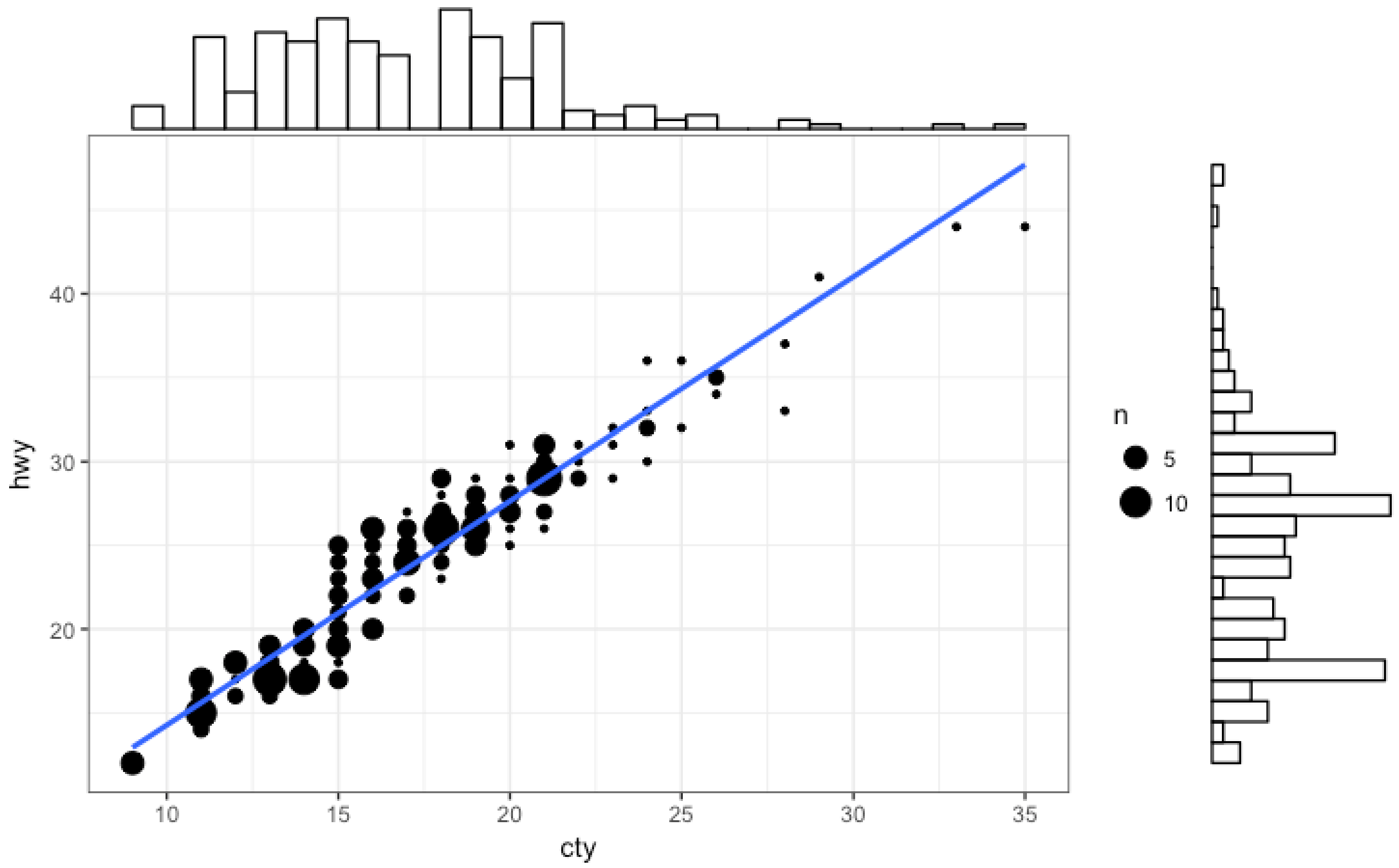
Marginal Histogram / Boxplot

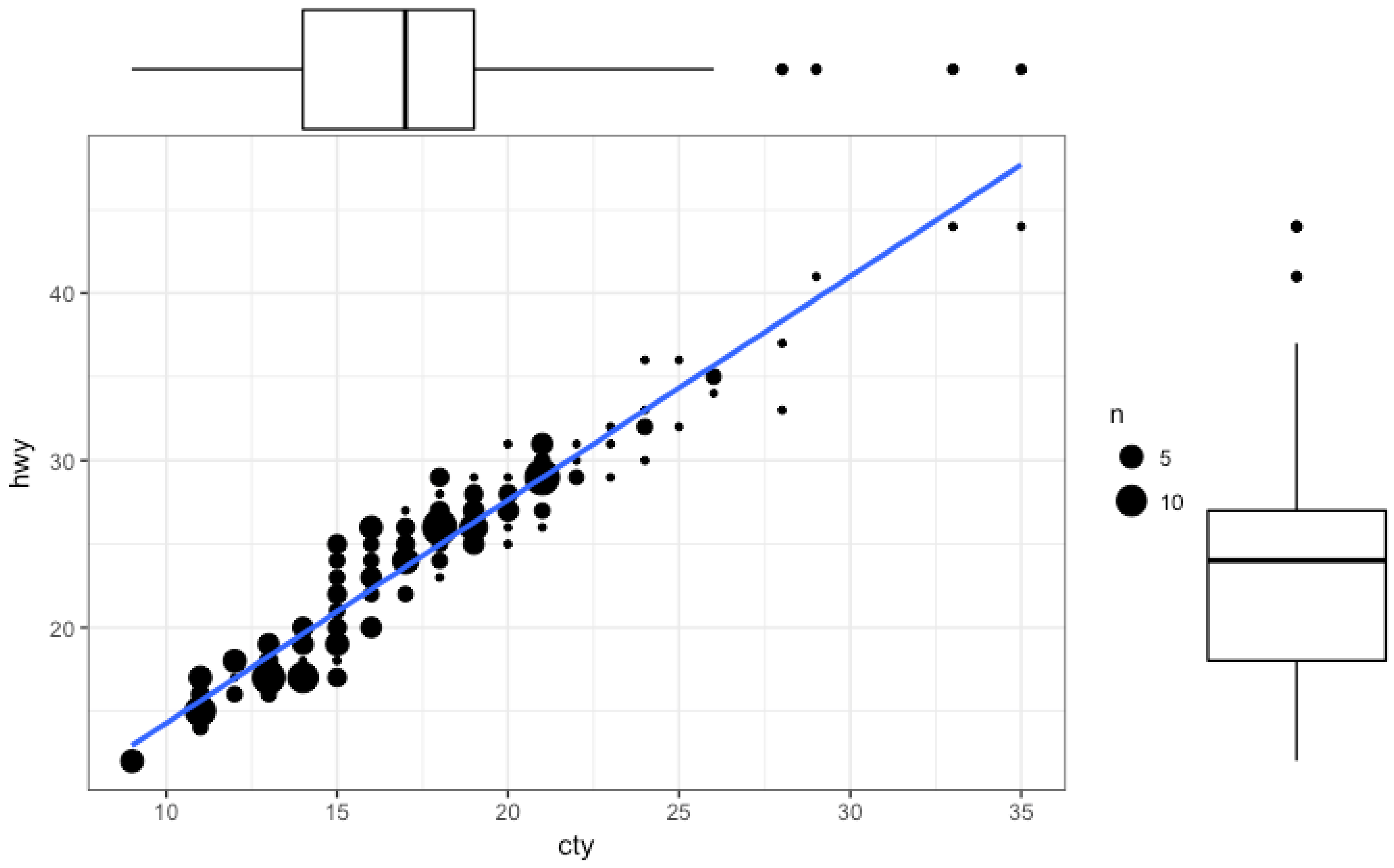
If you want to show the relationship as well as the distribution in the same chart, use the marginal histogram. It has a histogram of the X and Y variables at the margins of the scatterplot.

This can be implemented using the `ggMarginal()` function from the ‘`ggExtra`’ package. Apart from a `histogram`, you could choose to draw a marginal `boxplot` or `density` plot by setting the respective `type` option.

```
# load package and data
library(ggplot2)
library(ggExtra)
data(mpg, package="ggplot2")
# mpg <- read.csv("http://goo.gl/uEeRGu")
# Scatterplot
theme_set(theme_bw())  # pre-set the bw theme.
mpg_select <- mpg[mpg$hwy >= 35 & mpg$cty > 27, ]
g <- ggplot(mpg, aes(cty, hwy)) +
  geom_count() +
  geom_smooth(method="lm", se=F)

ggMarginal(g, type = "histogram", fill="transparent")
ggMarginal(g, type = "boxplot", fill="transparent")
# ggMarginal(g, type = "density", fill="transparent")
```





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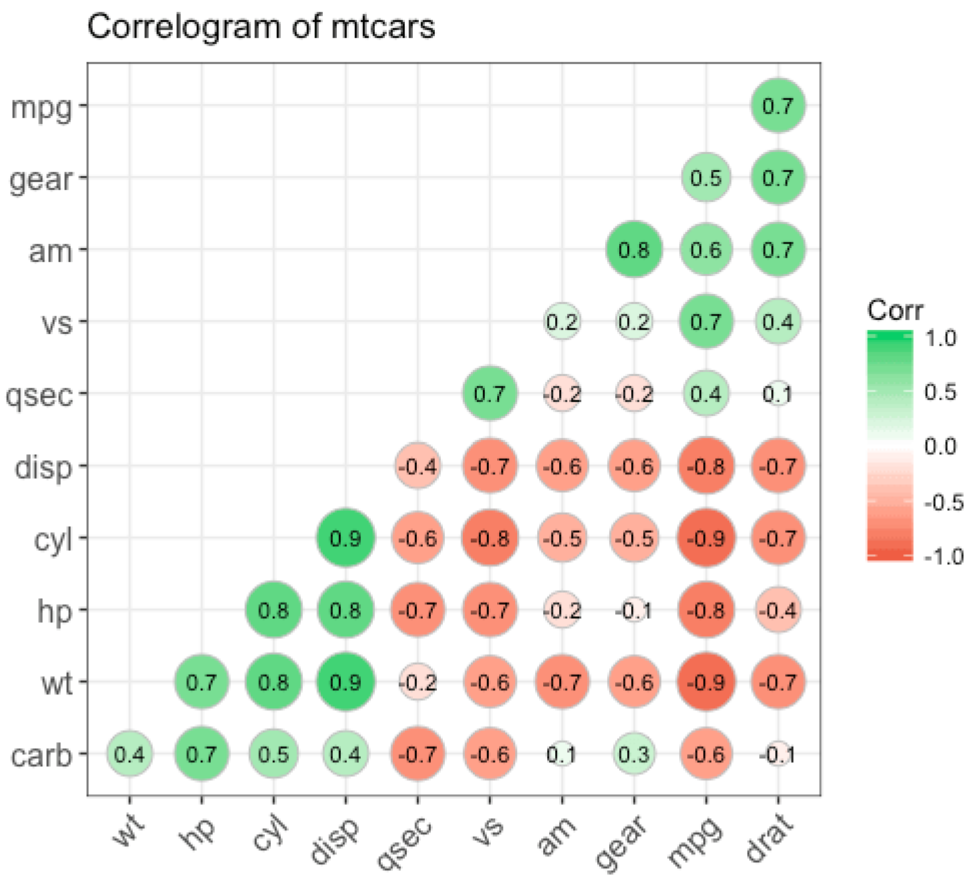
Correlogram

Correlogram let’s you examine the corellation of multiple continuous variables present in the same dataframe. This is conveniently implemented using the `ggcorrplot` package.

```
# devtools::install_github("kassambara/ggcorrplot")
library(ggplot2)
library(ggcorrplot)

# Correlation matrix
data(mtcars)
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)
```



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2. Deviation

Compare variation in *values* between small number of items (or categories) with respect to a fixed reference.

Diverging bars

Diverging Bars is a bar chart that can handle both negative and positive values. This can be implemented by a smart tweak with `geom_bar()`. But the usage of `geom_bar()` can be quite confusing. Thats because, it can be used to make a bar chart as well as a histogram. Let me explain.

By default, `geom_bar()` has the `stat` set to `count`. That means, when you provide just a continuous X variable (and no Y variable), it tries to make a histogram out of the data.

In order to make a bar chart create bars instead of histogram, you need to do two things.

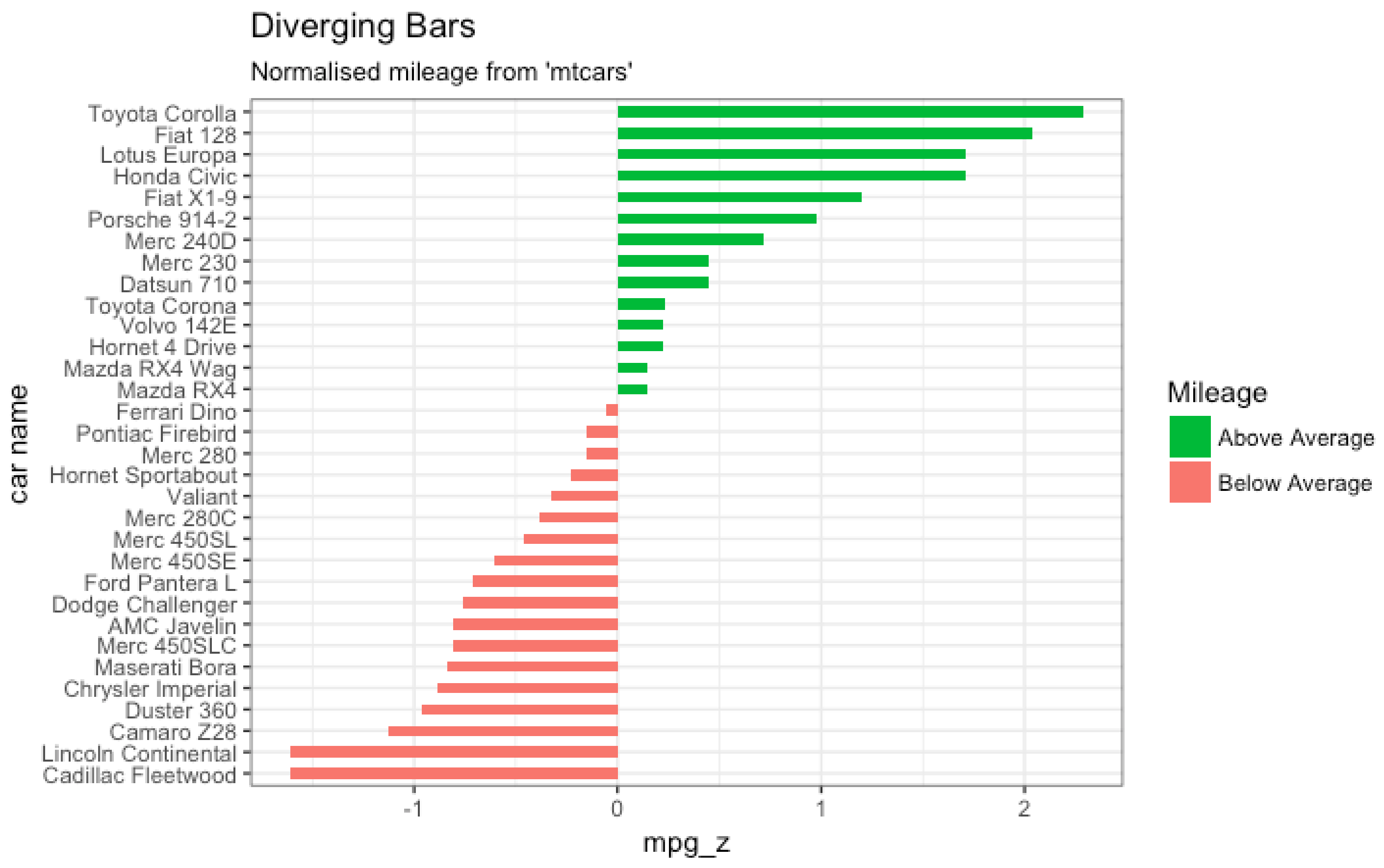
1. Set `stat=identity`
2. Provide both `x` and `y` inside `aes()` where, `x` is either `character` or `factor` and `y` is numeric.

In order to make sure you get diverging bars instead of just bars, make sure, your categorical variable has 2 categories that changes values at a certain threshold of the continuous variable. In below example, the `mpg` from mtcars dataset is normalised by computing the z score. Those vehicles with mpg above zero are marked green and those below are marked red.

```
library(ggplot2)
theme_set(theme_bw())

# Data Prep
data("mtcars")  # load data
mtcars$`car name` <- rownames(mtcars)  # create new column for car names
mtcars$mpg_z <- round((mtcars$mpg - mean(mtcars$mpg))/sd(mtcars$mpg), 2)  # compute
normalized mpg
mtcars$mpg_type <- ifelse(mtcars$mpg_z < 0, "below", "above")  # above / below avg
flag
mtcars <- mtcars[order(mtcars$mpg_z), ]  # sort
mtcars$`car name` <- factor(mtcars$`car name`, levels = mtcars$`car name`)  #
convert to factor to retain sorted order in plot.

# Diverging Barcharts
ggplot(mtcars, 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") +
  coord_flip()
```



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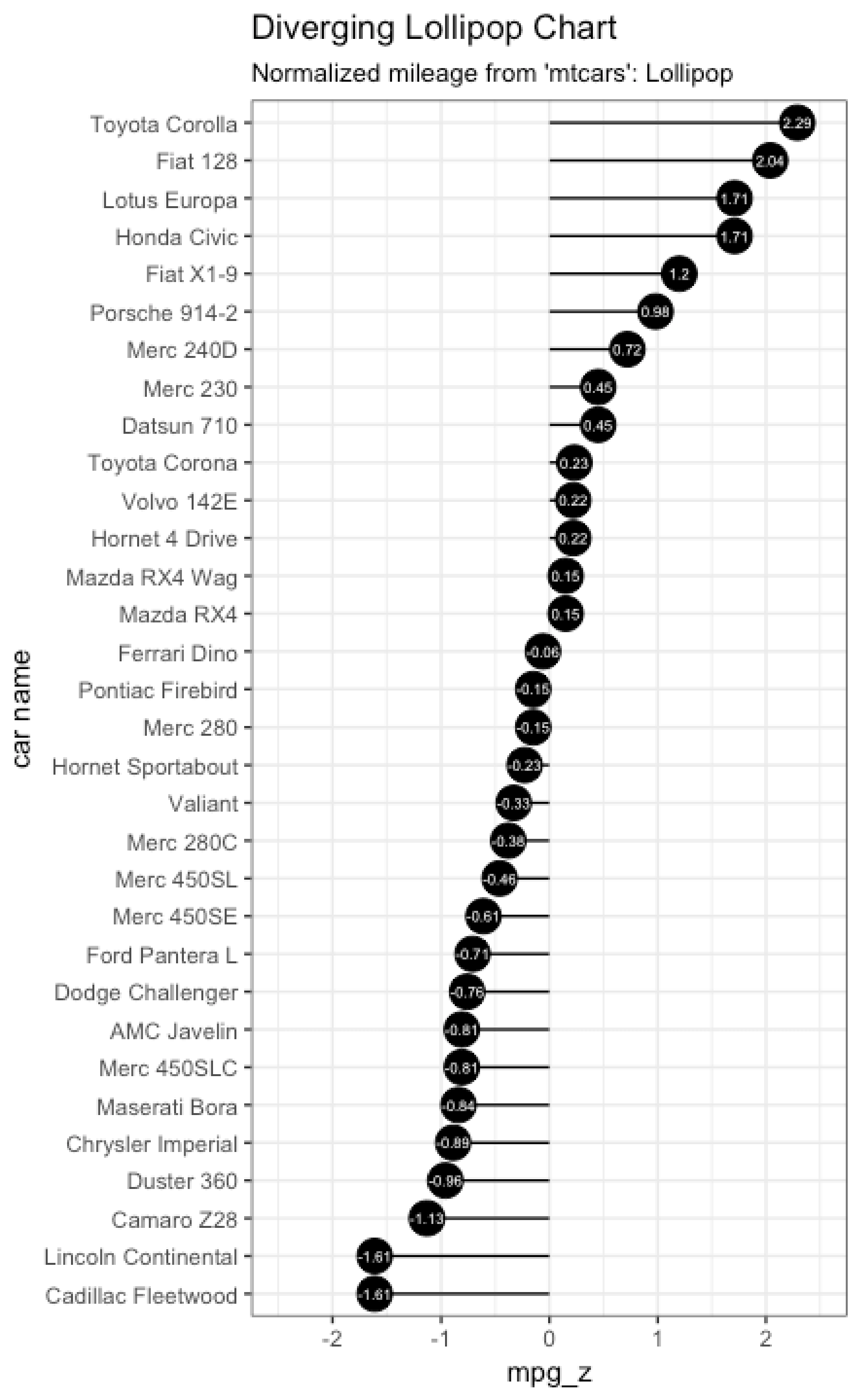
Diverging Lollipop Chart

Lollipop chart conveys the same information as bar chart and diverging bar. Except that it looks more modern. Instead of geom_bar, I use `geom_point` and `geom_segment` to get the lollipops right. Let’s draw a lollipop using the same data I prepared in the previous example of diverging bars.

```
library(ggplot2)
theme_set(theme_bw())

ggplot(mtcars, aes(x=`car name`, y=mpg_z, label=mpg_z)) +
  geom_point(stat='identity', fill="black", size=6)  +
  geom_segment(aes(y = 0,
                   x = `car name`,
                   yend = mpg_z,
                   xend = `car name`),
               color = "black") +
  geom_text(color="white", size=2) +
  labs(title="Diverging Lollipop Chart",
       subtitle="Normalized mileage from 'mtcars': Lollipop") +
  ylim(-2.5, 2.5) +
  coord_flip()
```



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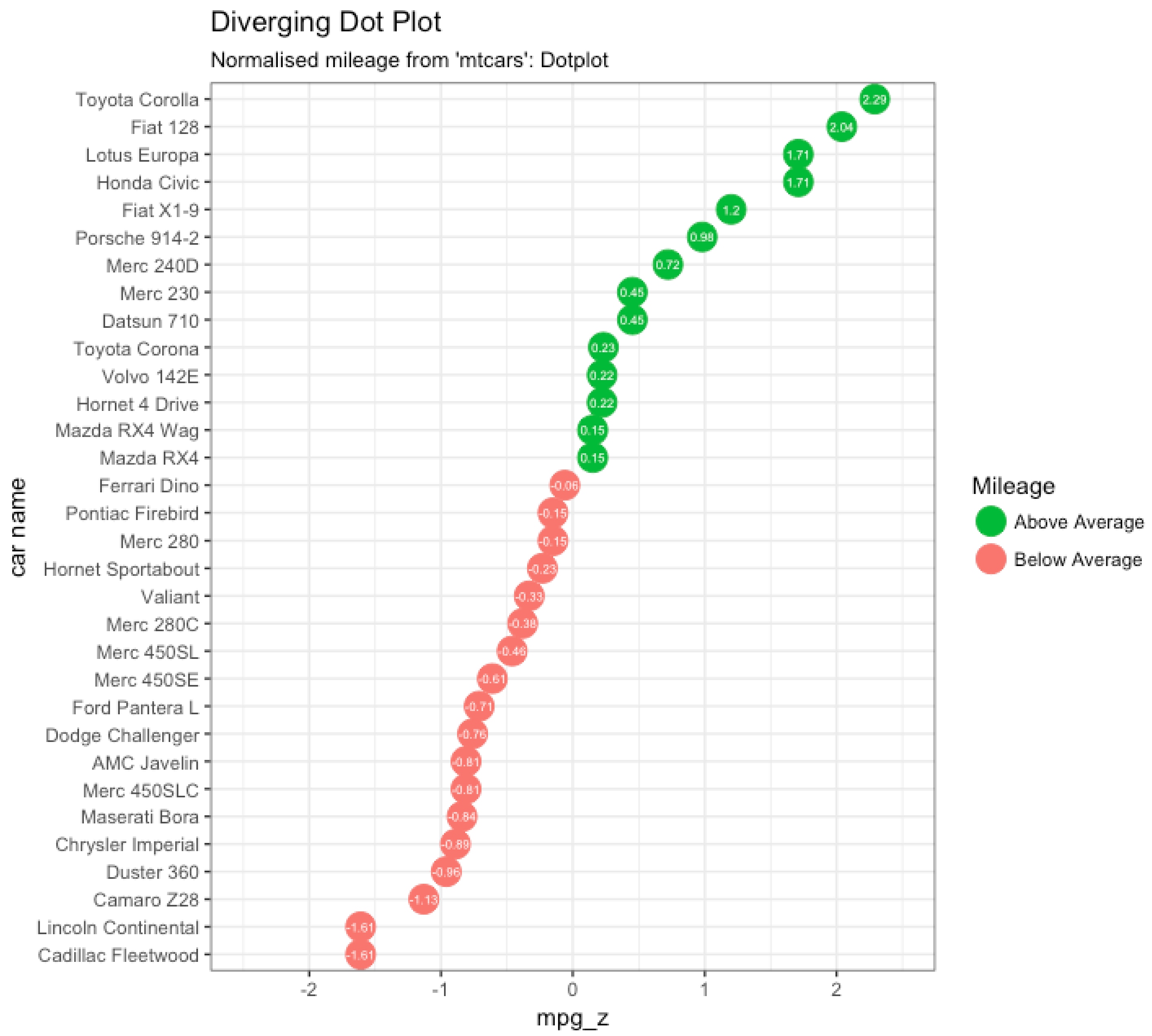
Diverging Dot Plot

Dot plot conveys similar information. The principles are same as what we saw in Diverging bars, except that only point are used. Below example uses the same data prepared in the diverging bars example.

```
library(ggplot2)
theme_set(theme_bw())
```

```
# Plot
ggplot(mtcars, aes(x=`car name`, y=mpg_z, label=mpg_z)) +
  geom_point(stat='identity', aes(col=mpg_type), size=6)  +
  scale_color_manual(name="Mileage",
                     labels = c("Above Average", "Below Average"),
                     values = c("above"="#00ba38", "below"="#f8766d")) +
  geom_text(color="white", size=2) +
  labs(title="Diverging Dot Plot",
       subtitle="Normalized mileage from 'mtcars': Dotplot") +
  ylim(-2.5, 2.5) +
  coord_flip()
```



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Area Chart

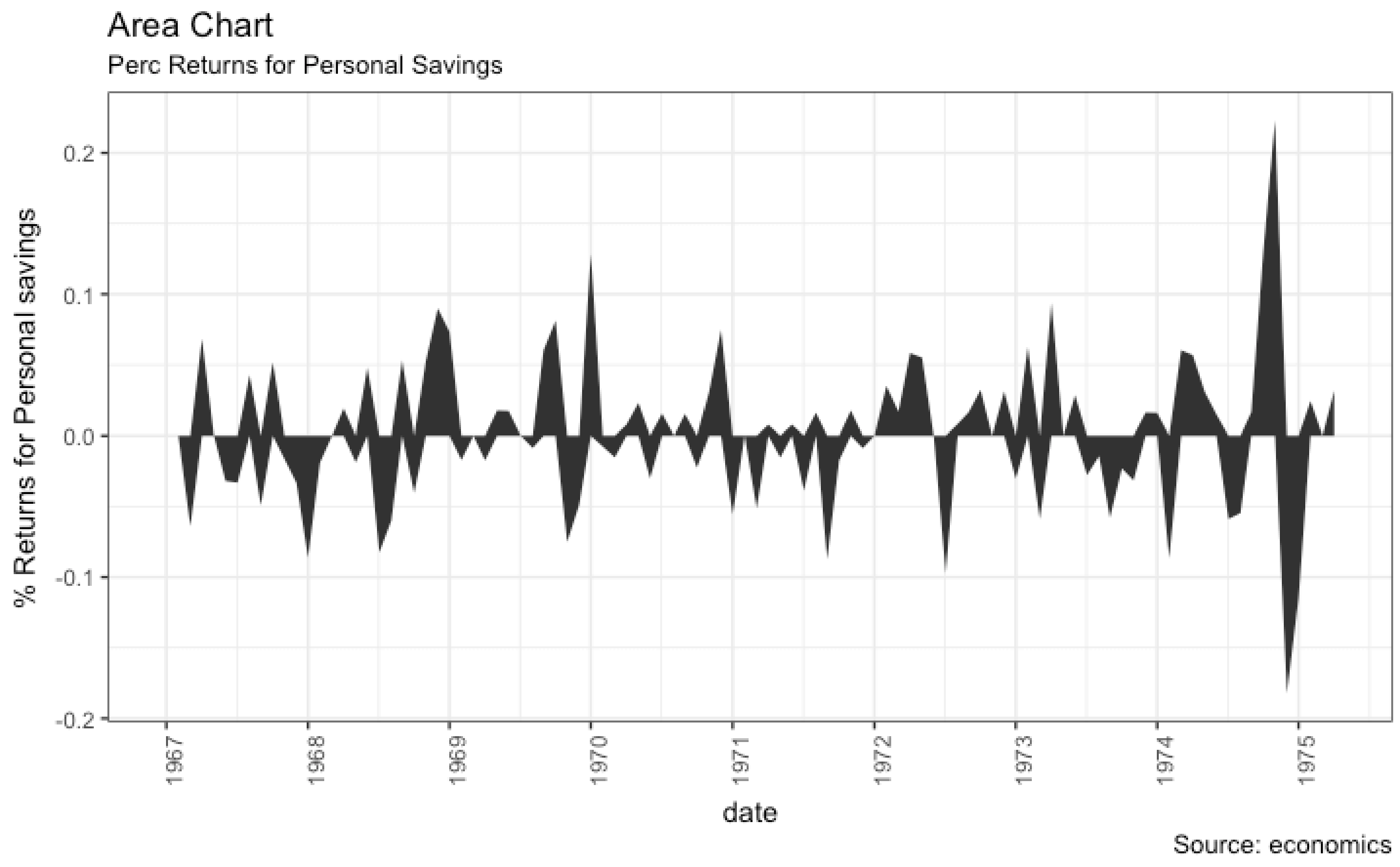
Area charts are typically used to visualize how a particular metric (such as % returns from a stock) performed compared to a certain baseline. Other types of %returns or %change data are also commonly used. The `geom_area()` implements this.

```
library(ggplot2)
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)]
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")
```



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3. Ranking

Used to compare the position or performance of multiple items with respect to each other. Actual values matters somewhat less than the ranking.

Ordered Bar Chart

Ordered Bar Chart is a Bar Chart that is ordered by the Y axis variable. Just sorting the dataframe by the variable of interest isn't enough to order the bar chart. In order for the bar chart to retain the order of the rows, the X axis variable (i.e. the categories) has to be converted into a factor.

Let's plot the mean city mileage for each manufacturer from `mpg` dataset. First, aggregate the data and sort it before you draw the plot. Finally, the X variable is converted to a factor.

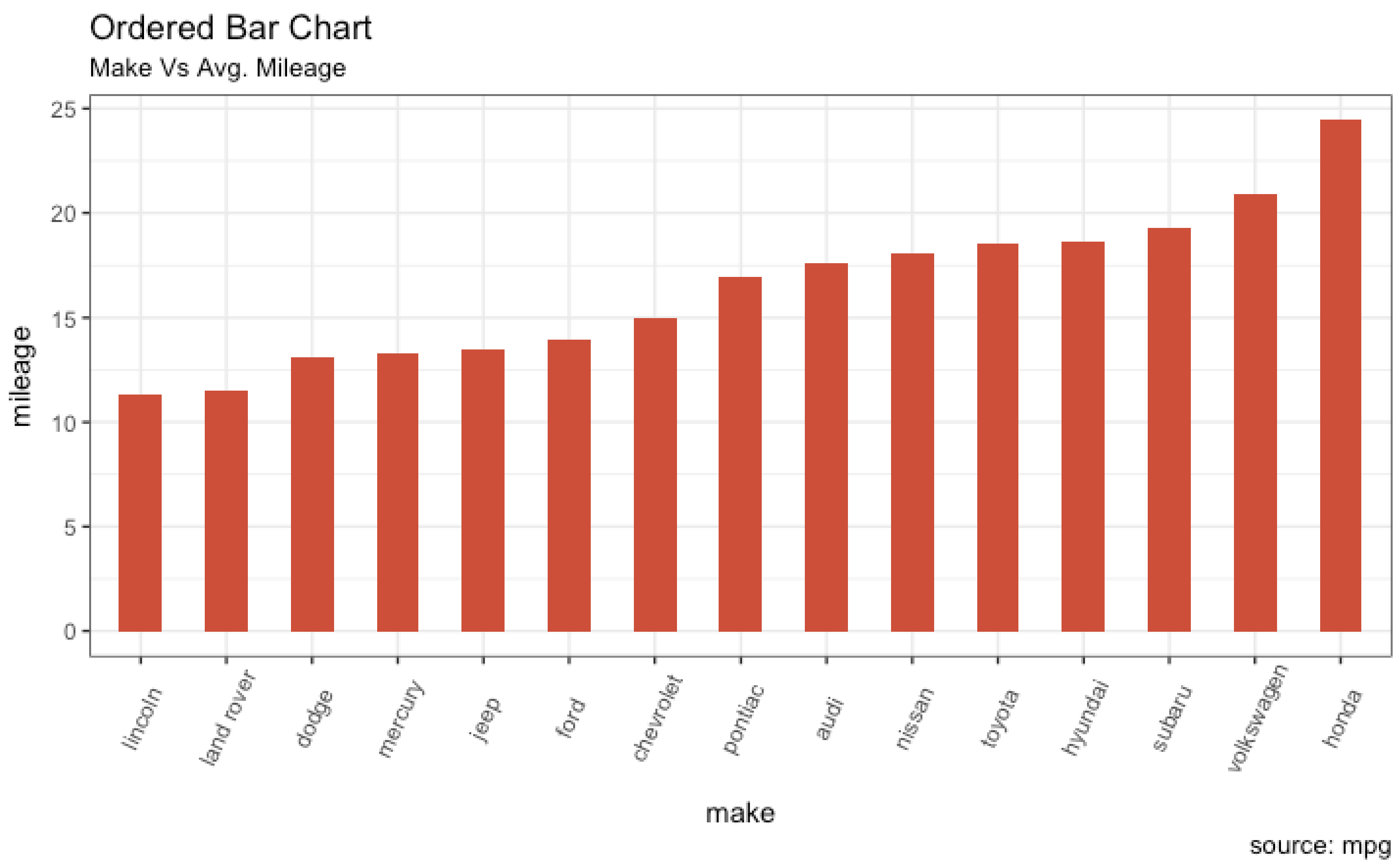
Let's see how that is done.

```
# Prepare data: group mean city mileage by manufacturer.
cty_mpg <- aggregate(mpg$cty, by=list(mpg$manufacturer), FUN=mean)  # aggregate
colnames(cty_mpg) <- c("make", "mileage")  # change column names
cty_mpg <- cty_mpg[order(cty_mpg$mileage), ]  # sort
cty_mpg$make <- factor(cty_mpg$make, levels = cty_mpg$make)  # to retain the order
in plot.
head(cty_mpg, 4)
#>          make  mileage
#> 9     lincoln 11.33333
#> 8  land rover 11.50000
#> 3       dodge 13.13514
#> 10    mercury 13.25000
```

The X variable is now a `factor`, let's plot.

```
library(ggplot2)
theme_set(theme_bw())

# 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))
```



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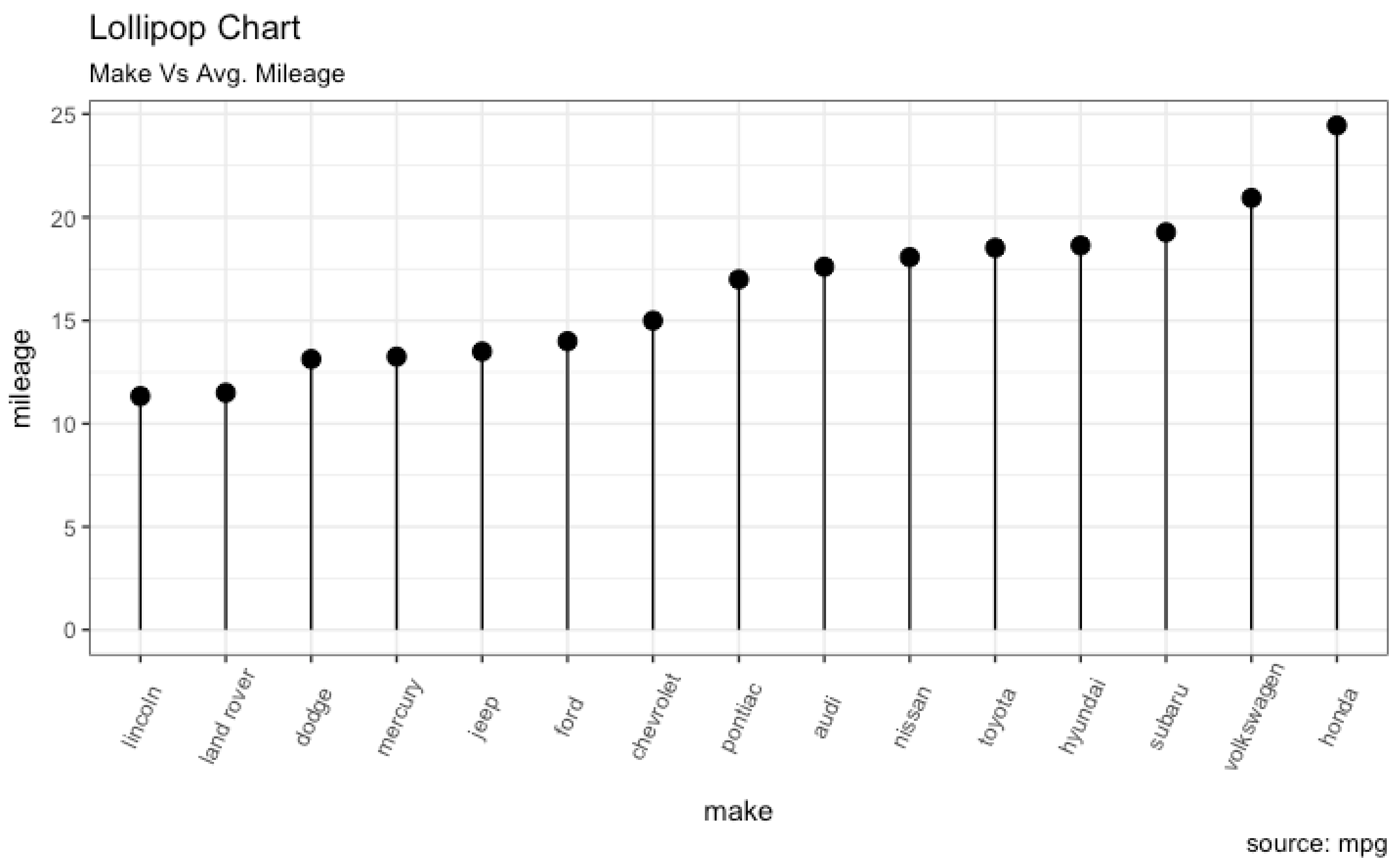
Lollipop Chart

Lollipop charts conveys the same information as in bar charts. By reducing the thick bars into thin lines, it reduces the clutter and lays more emphasis on the value. It looks nice and modern.

```
library(ggplot2)
theme_set(theme_bw())

# Plot
ggplot(cty_mpg, aes(x=make, y=mileage)) +
  geom_point(size=3) +
  geom_segment(aes(x=make,
                   xend=make,
                   y=0,
                   yend=mileage)) +
  labs(title="Lollipop Chart",
       subtitle="Make Vs Avg. Mileage",
       caption="source: mpg") +
  theme(axis.text.x = element_text(angle=65, vjust=0.6))
```



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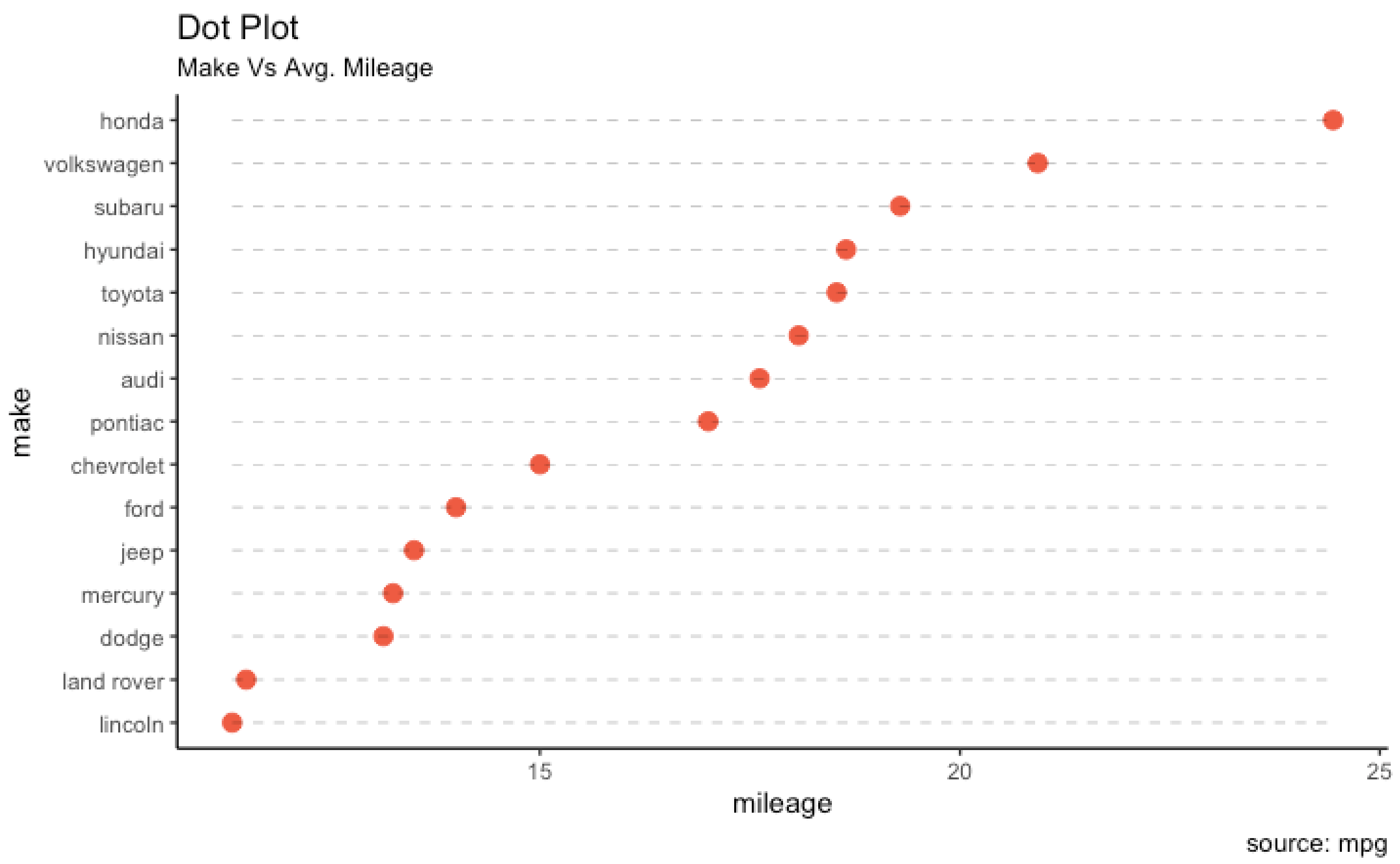
Dot Plot

Dot plots are very similar to lollipops, but without the line and is flipped to horizontal position. It emphasizes more on the rank ordering of items with respect to actual values and how far apart are the entities with respect to each other.

```
library(ggplot2)
library(scales)
theme_set(theme_classic())

# Plot
ggplot(cty_mpg, aes(x=make, y=mileage)) +
  geom_point(col="tomato2", size=3) +   # Draw points
  geom_segment(aes(x=make,
                   xend=make,
                   y=min(mileage),
                   yend=max(mileage)),
               linetype="dashed",
               size=0.1) +   # Draw dashed lines
  labs(title="Dot Plot",
       subtitle="Make Vs Avg. Mileage",
       caption="source: mpg") +
  coord_flip()
```



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Slope Chart

Slope charts are an excellent way of comparing the positional placements between 2 points on time. At the moment, there is no builtin function to construct this. Following code serves as a pointer about how you may approach this.

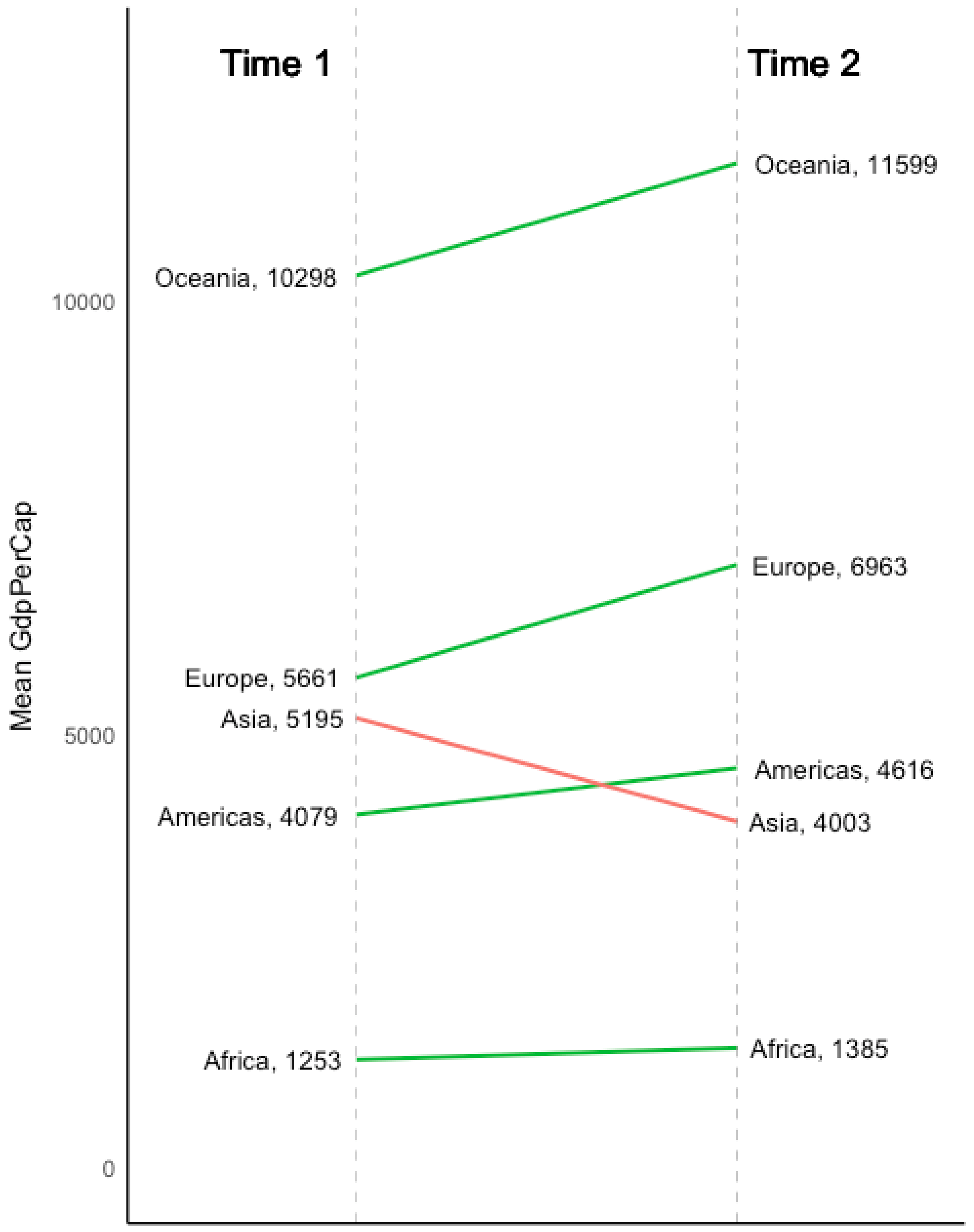
```
library(ggplot2)
library(scales)
theme_set(theme_classic())

# prep data
df <-
read.csv("https://raw.githubusercontent.com/selva86/datasets/master/gdppercap.csv")
colnames(df) <- c("continent", "1952", "1957")
left_label <- paste(df$continent, round(df$`1952`),sep=", ")
right_label <- paste(df$continent, round(df$`1957`),sep=", ")
df$class <- ifelse((df$`1957` - df$`1952`) < 0, "red", "green")

# Plot
p <- ggplot(df) + geom_segment(aes(x=1, xend=2, y=`1952`, yend=`1957`, col=class),
size=.75, show.legend=F) +
                  geom_vline(xintercept=1, linetype="dashed", size=.1) +
                  geom_vline(xintercept=2, linetype="dashed", size=.1) +
                  scale_color_manual(labels = c("Up", "Down"),
                                     values = c("green"="#00ba38",
"red"="#f8766d")) +  # color of lines
                  labs(x="", y="Mean GdpPerCap") +  # Axis labels
                  xlim(.5, 2.5) + ylim(0,(1.1*(max(df$`1952`, df$`1957`))))  # X
and Y axis limits

# Add texts
p <- p + geom_text(label=left_label, y=df$`1952`, x=rep(1, NROW(df)), hjust=1.1,
size=3.5)
p <- p + geom_text(label=right_label, y=df$`1957`, x=rep(2, NROW(df)), hjust=-0.1,
size=3.5)
p <- p + geom_text(label="Time 1", x=1, y=1.1*(max(df$`1952`, df$`1957`)),
hjust=1.2, size=5)  # title
p <- p + geom_text(label="Time 2", x=2, y=1.1*(max(df$`1952`, df$`1957`)), hjust=-
0.1, size=5)  # title

# Minify theme
p + theme(panel.background = element_blank(),
           panel.grid = element_blank(),
           axis.ticks = element_blank(),
           axis.text.x = element_blank(),
           panel.border = element_blank(),
           plot.margin = unit(c(1,2,1,2), "cm"))
```



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Dumbbell Plot

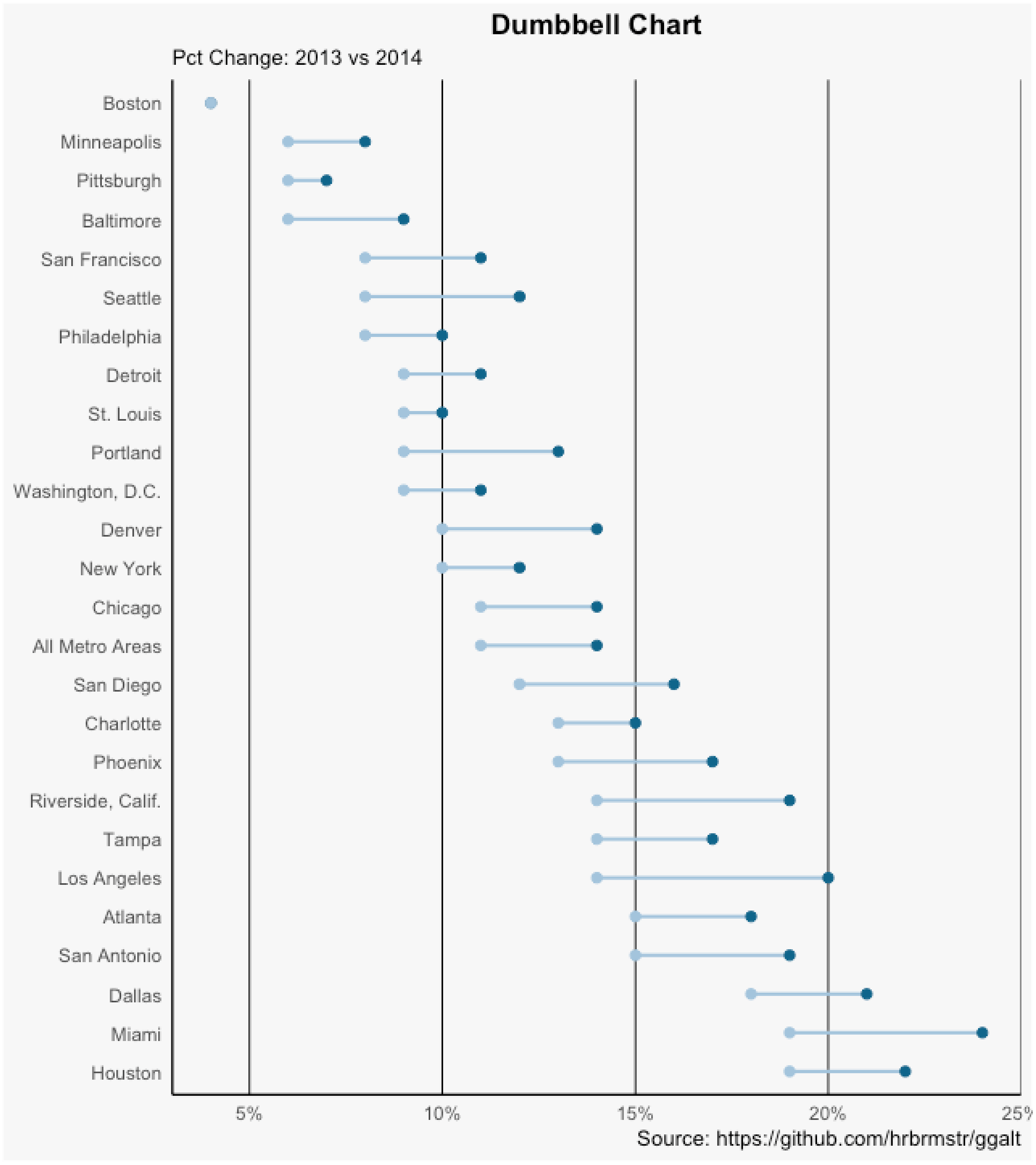
Dumbbell charts are a great tool if you wish to: 1. Visualize relative positions (like growth and decline) between two points in time. 2. Compare distance between two categories.

In order to get the correct ordering of the dumbbells, the Y variable should be a factor and the levels of the factor variable should be in the same order as it should appear in the plot.

```
# devtools::install_github("hrbrmstr/ggalt")
library(ggplot2)
library(ggalt)
theme_set(theme_classic())

health <-
read.csv("https://raw.githubusercontent.com/selva86/datasets/master/health.csv")
health$Area <- factor(health$Area, levels=as.character(health$Area))  # for right
ordering of the dumbells

# 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=percent) +
        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)
```



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4. Distribution

When you have lots and lots of data points and want to study where and how the data points are distributed.

Histogram

By default, if only one variable is supplied, the `geom_bar()` tries to calculate the count. In order for it to behave like a bar chart, the `stat=identity` option has to be set and `x` and `y` values must be provided.

Histogram on a continuous variable

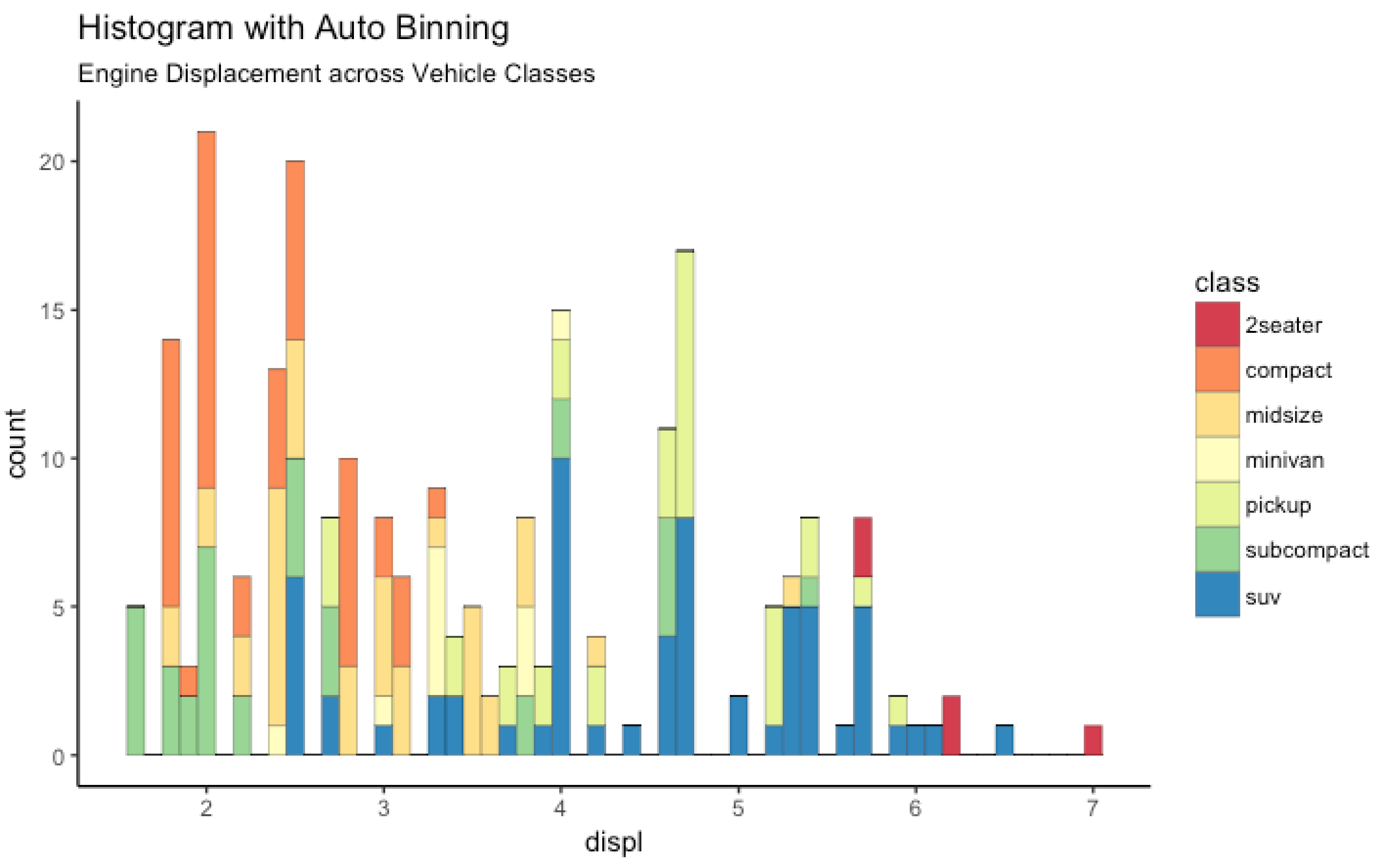
Histogram on a continuous variable can be accomplished using either `geom_bar()` or `geom_histogram()`. When using `geom_histogram()`, you can control the number of bars using the `bins` option. Else, you can set the range covered by each bin using `binwidth`. The value of `binwidth` is on the same scale as the continuous variable on which histogram is built. Since, `geom_histogram` gives facility to control both number of `bins` as well as `binwidth`, it is the preferred option to create histogram on continuous variables.

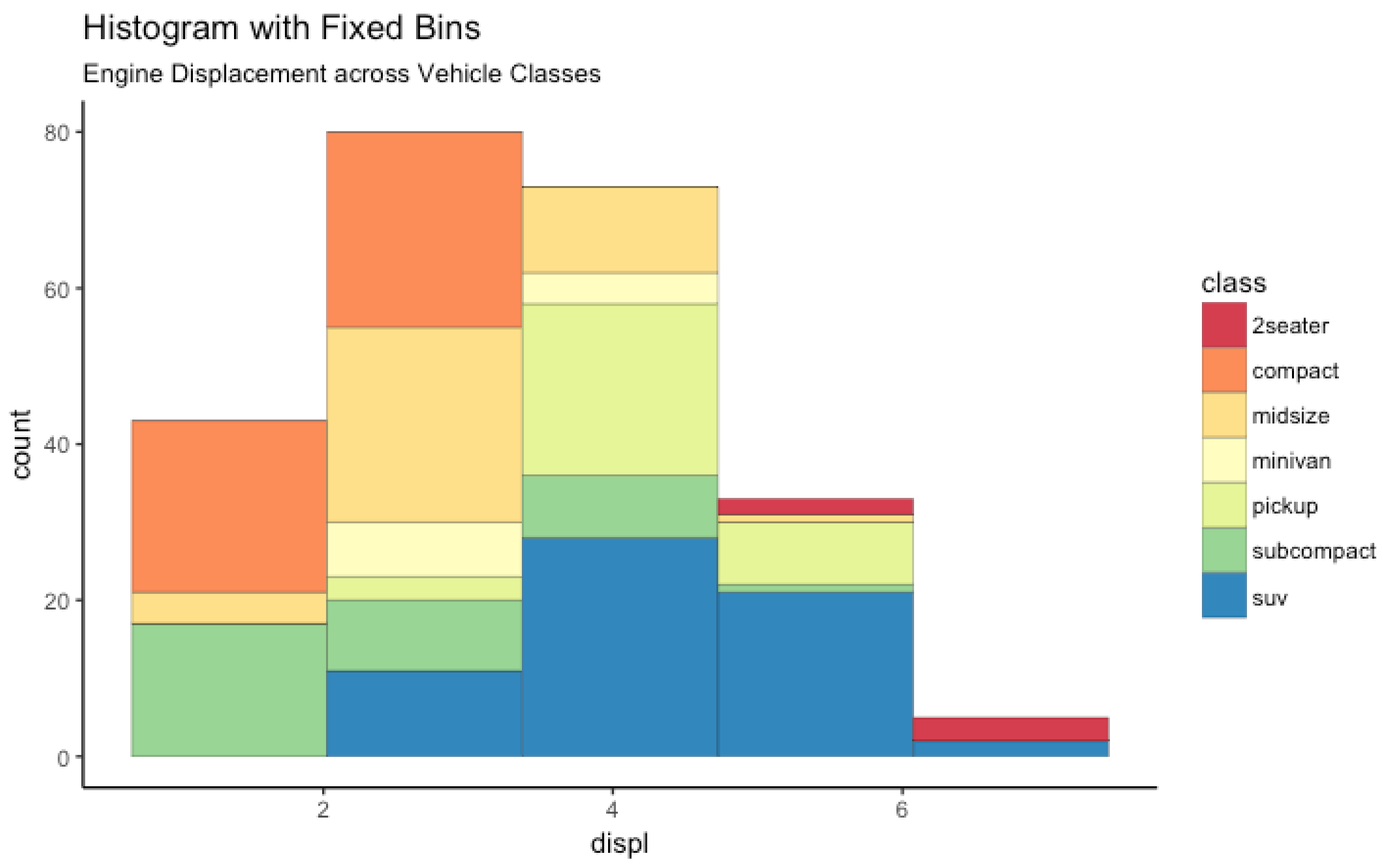
```
library(ggplot2)
theme_set(theme_classic())

# Histogram on a Continuous (Numeric) Variable
g <- ggplot(mpg, aes(displ)) + scale_fill_brewer(palette = "Spectral")

g + geom_histogram(aes(fill=class),
                   binwidth = .1,
                   col="black",
                   size=.1) +  # change binwidth
  labs(title="Histogram with Auto Binning",
       subtitle="Engine Displacement across Vehicle Classes")

g + geom_histogram(aes(fill=class),
                   bins=5,
                   col="black",
                   size=.1) +   # change number of bins
  labs(title="Histogram with Fixed Bins",
       subtitle="Engine Displacement across Vehicle Classes")
```


Histogram with Auto Binning
Engine Displacement across Vehicle Classes
count
displ
0
5
10
15
20
2
3
4
5
6
7
class
2seater
compact
midsize
minivan
pickup
subcompact
suv



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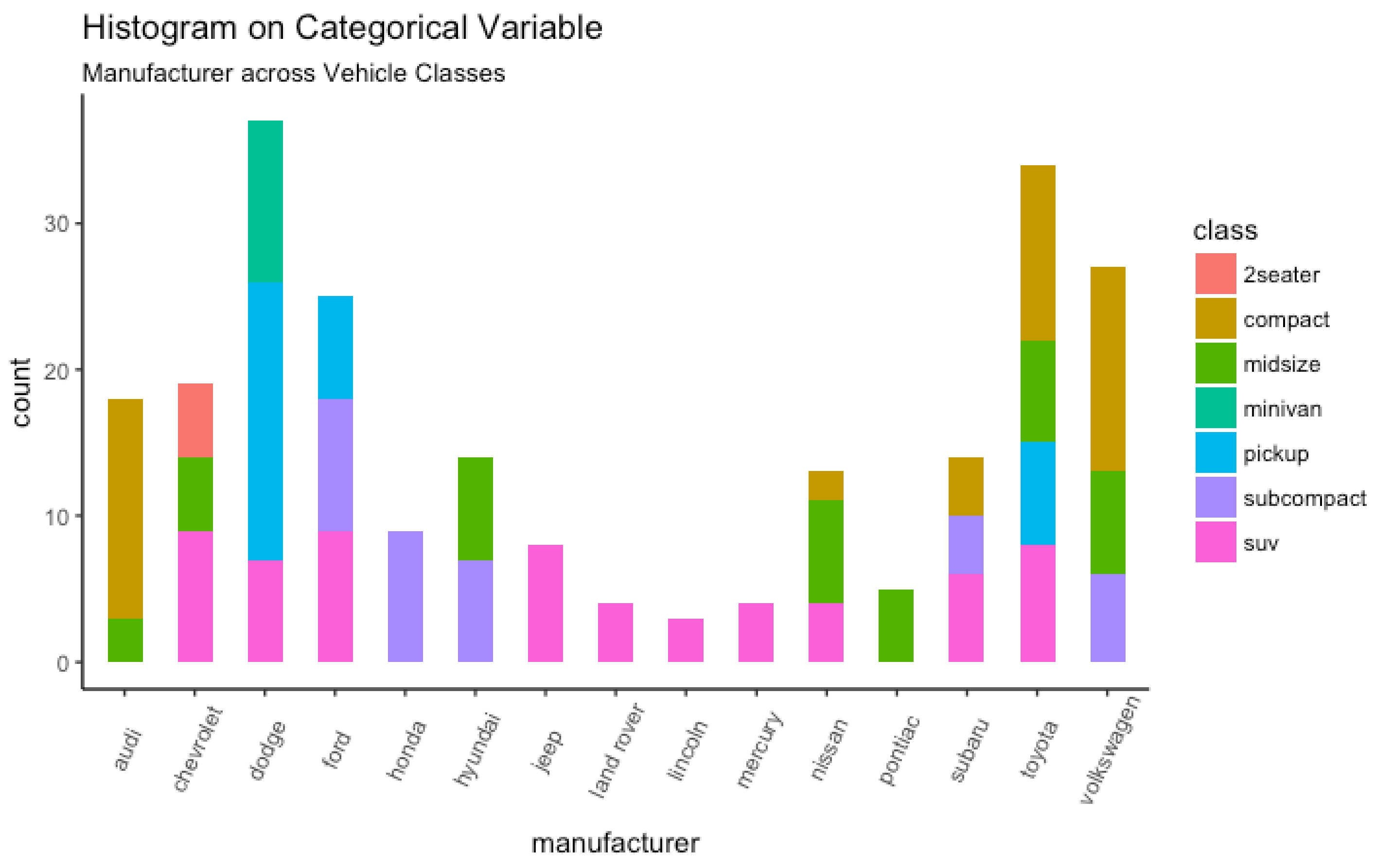
Histogram on a categorical variable

Histogram on a categorical variable would result in a frequency chart showing bars for each category. By adjusting `width`, you can adjust the thickness of the bars.

```
library(ggplot2)
theme_set(theme_classic())

# Histogram on a Categorical variable
g <- ggplot(mpg, aes(manufacturer))
g + geom_bar(aes(fill=class), width = 0.5) +
  theme(axis.text.x = element_text(angle=65, vjust=0.6)) +
  labs(title="Histogram on Categorical Variable",
       subtitle="Manufacturer across Vehicle Classes")
```



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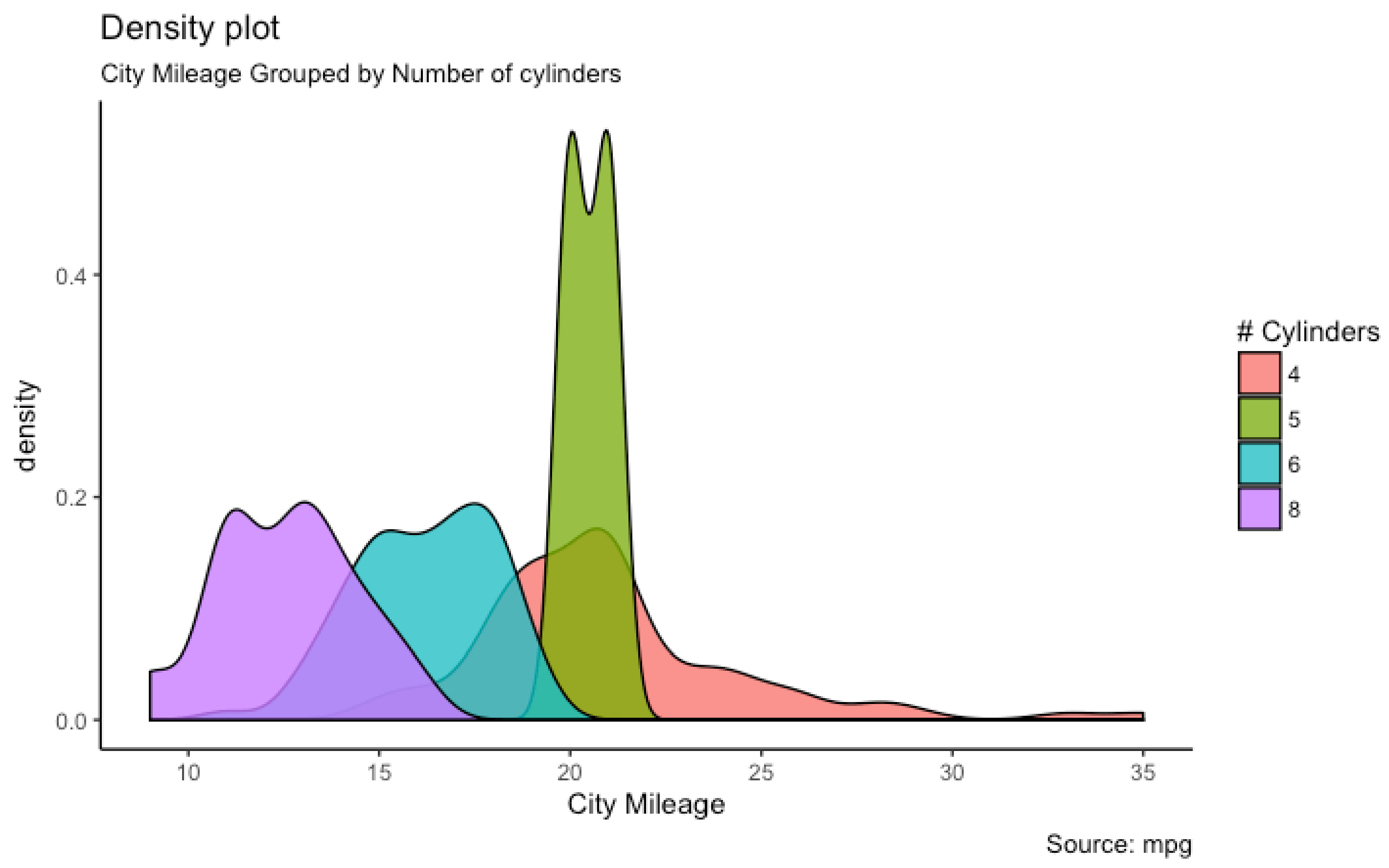
Density plot

```
library(ggplot2)
theme_set(theme_classic())

# Plot
g <- ggplot(mpg, aes(cty))
g + 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")
```



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Box Plot

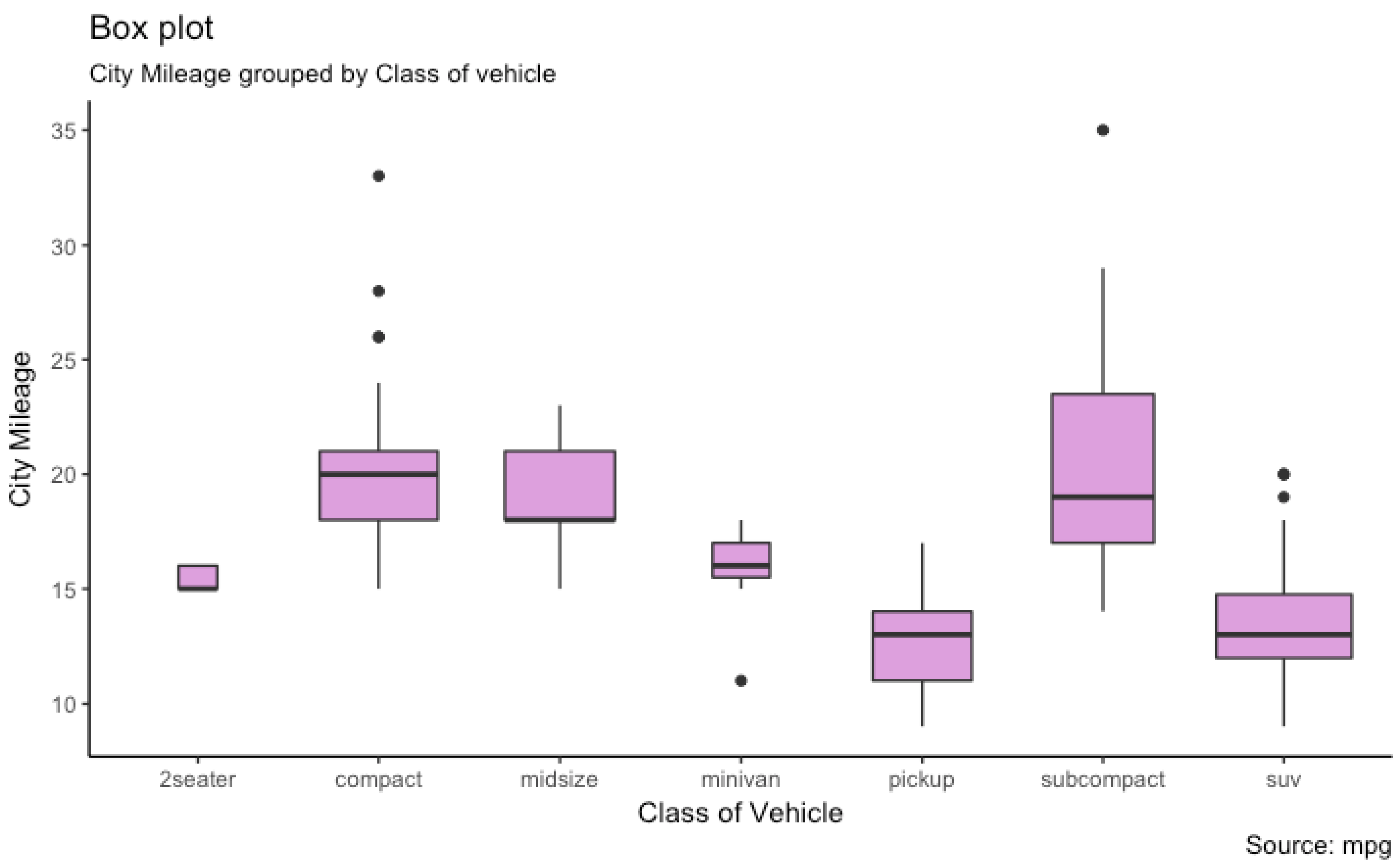
Box plot is an excellent tool to study the distribution. It can also show the distributions within multiple groups, along with the median, range and outliers if any.

The dark line inside the box represents the median. The top of box is 75%ile and bottom of box is 25%ile. The end points of the lines (aka whiskers) is at a distance of 1.5*IQR, where IQR or Inter Quartile Range is the distance between 25th and 75th percentiles. The points outside the whiskers are marked as dots and are normally considered as extreme points.

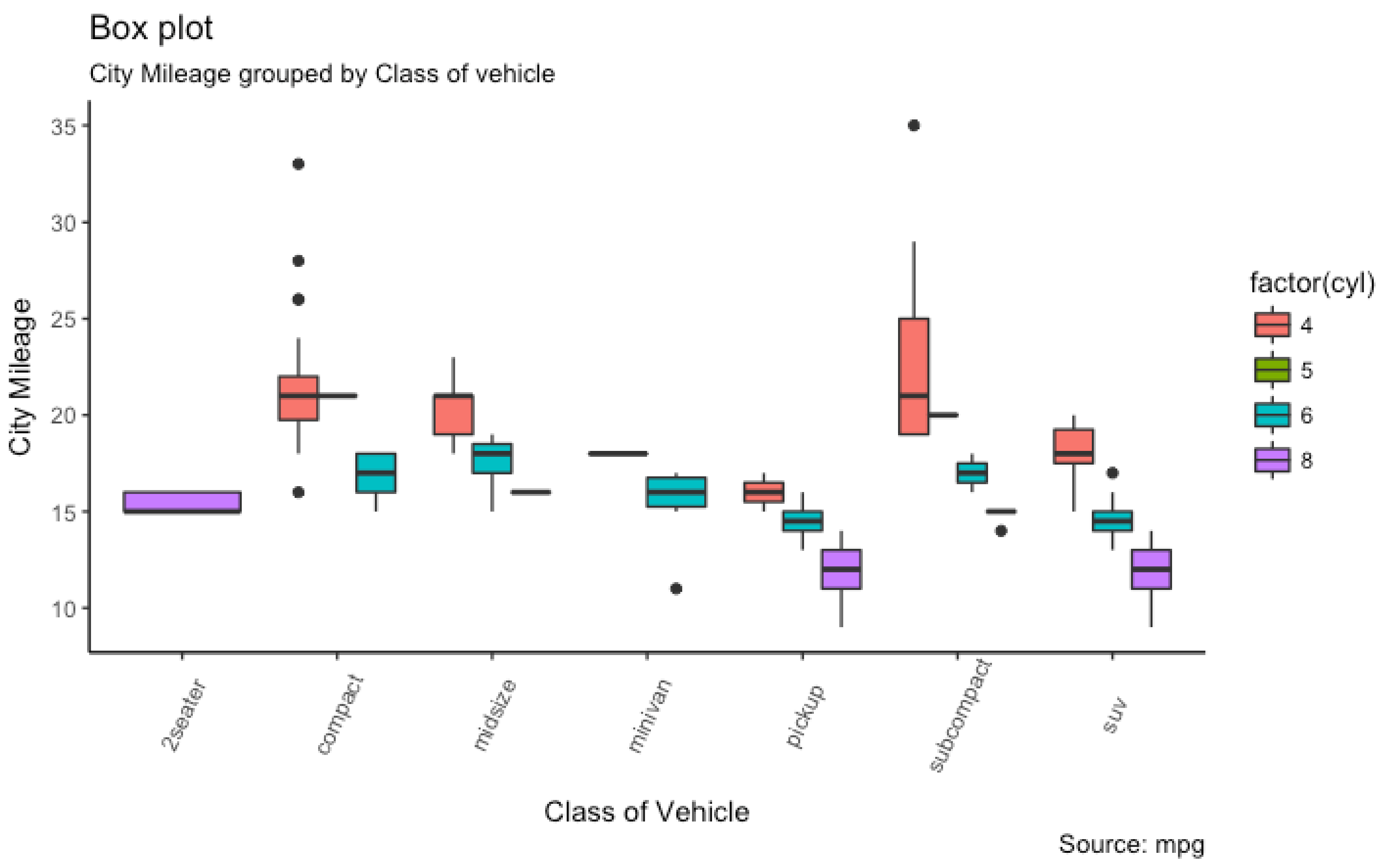
Setting `varwidth=T` adjusts the width of the boxes to be proportional to the number of observation it contains.

```
library(ggplot2)
theme_set(theme_classic())

# Plot
g <- ggplot(mpg, aes(class, cty))
g + geom_boxplot(varwidth=T, fill="plum") +
    labs(title="Box plot",
         subtitle="City Mileage grouped by Class of vehicle",
         caption="Source: mpg",
         x="Class of Vehicle",
         y="City Mileage")
```



```
library(ggthemes)
g <- ggplot(mpg, aes(class, cty))
g + geom_boxplot(aes(fill=factor(cyl))) +
  theme(axis.text.x = element_text(angle=65, vjust=0.6)) +
  labs(title="Box plot",
       subtitle="City Mileage grouped by Class of vehicle",
       caption="Source: mpg",
       x="Class of Vehicle",
       y="City Mileage")
```



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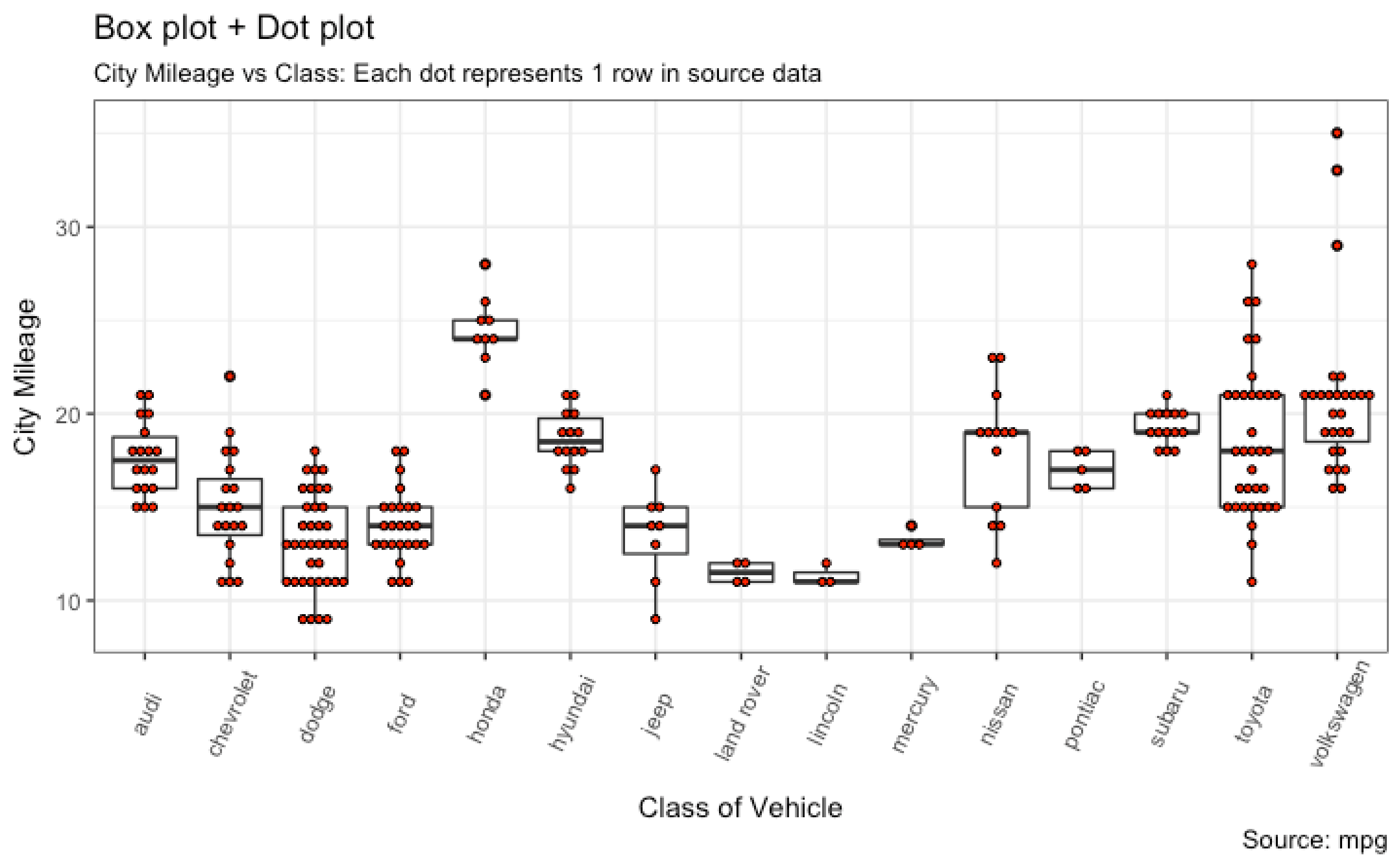
Dot + Box Plot

On top of the information provided by a box plot, the dot plot can provide more clear information in the form of summary statistics by each group. The dots are staggered such that each dot represents one observation. So, in below chart, the number of dots for a given manufacturer will match the number of rows of that manufacturer in source data.

```
library(ggplot2)
theme_set(theme_bw())

# plot
g <- ggplot(mpg, aes(manufacturer, cty))
g + 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="Box plot + Dot plot",
       subtitle="City Mileage vs Class: Each dot represents 1 row in source data",
       caption="Source: mpg",
       x="Class of Vehicle",
       y="City Mileage")
```



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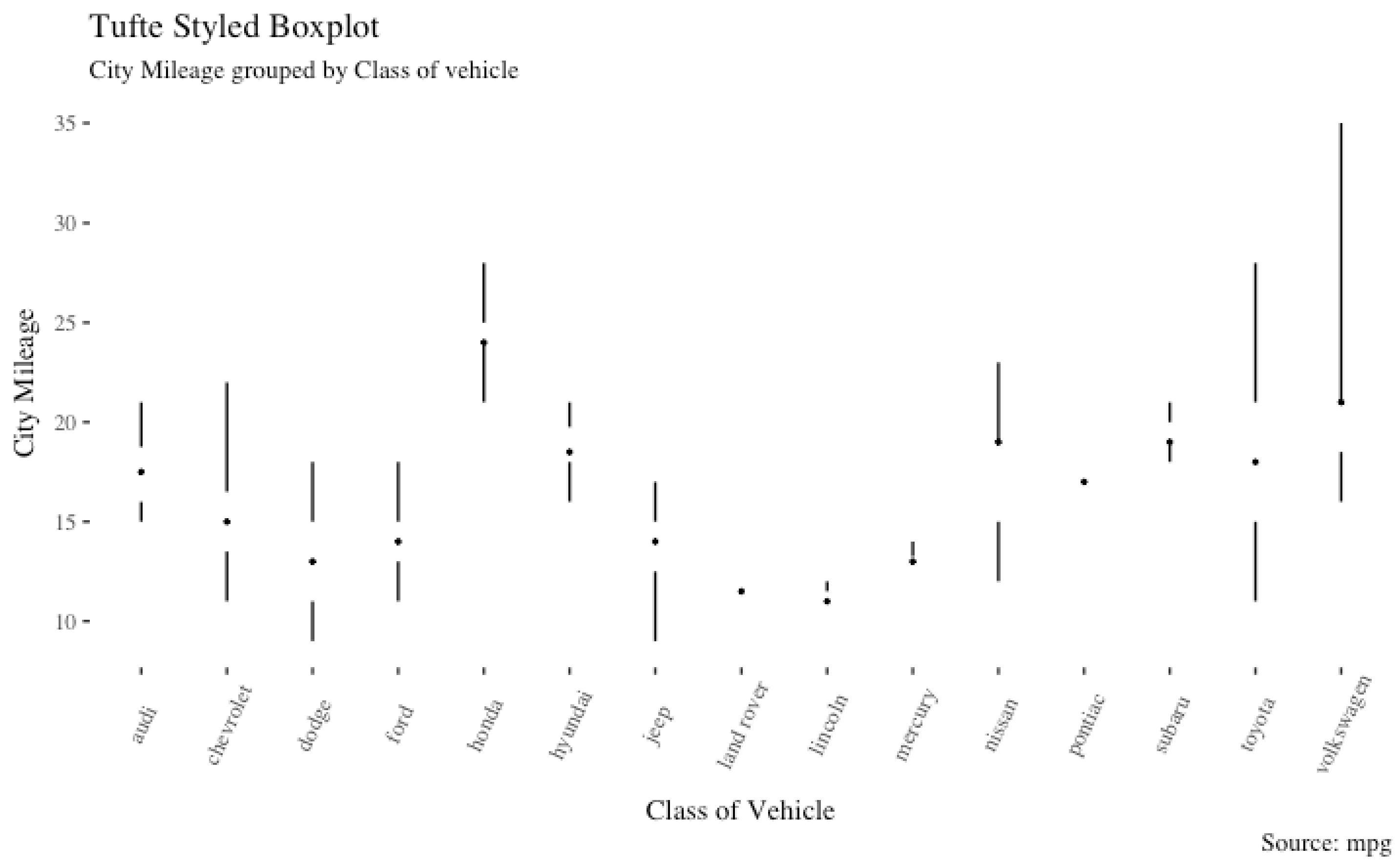
Tufte Boxplot

Tufte box plot, provided by `ggthemes` package is inspired by the works of Edward Tufte. Tufte's Box plot is just a box plot made minimal and visually appealing.

```
library(ggthemes)
library(ggplot2)
theme_set(theme_tufte())  # from ggthemes

# plot
g <- ggplot(mpg, aes(manufacturer, cty))
g + geom_tufteboxplot() +
      theme(axis.text.x = element_text(angle=65, vjust=0.6)) +
      labs(title="Tufte Styled Boxplot",
           subtitle="City Mileage grouped by Class of vehicle",
           caption="Source: mpg",
           x="Class of Vehicle",
           y="City Mileage")
```



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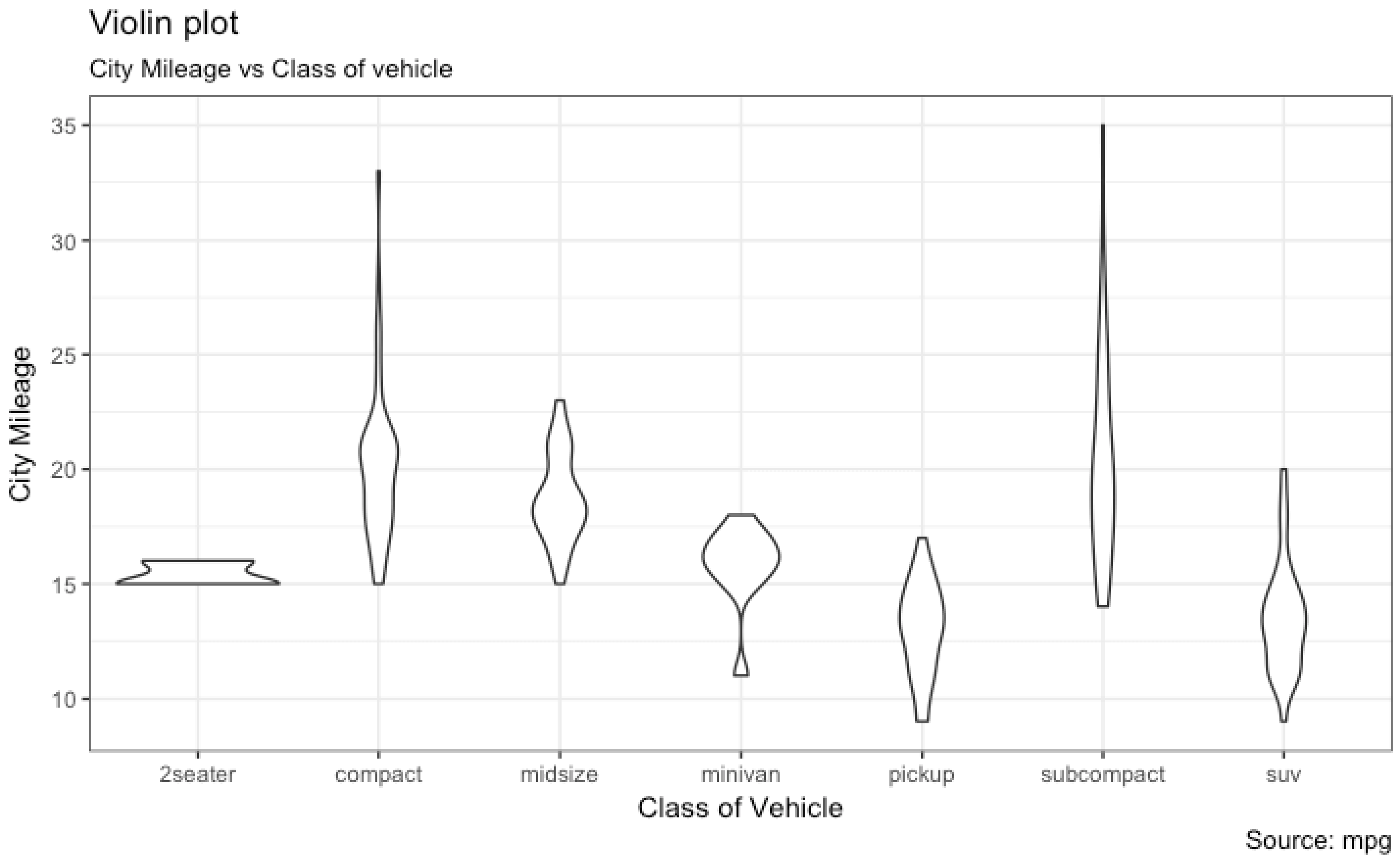
Violin Plot

A violin plot is similar to box plot but shows the density within groups. Not much info provided as in boxplots. It can be drawn using `geom_violin()`.

```
library(ggplot2)
theme_set(theme_bw())

# plot
g <- ggplot(mpg, aes(class, cty))
g + geom_violin() +
  labs(title="Violin plot",
       subtitle="City Mileage vs Class of vehicle",
       caption="Source: mpg",
       x="Class of Vehicle",
       y="City Mileage")
```



Population Pyramid

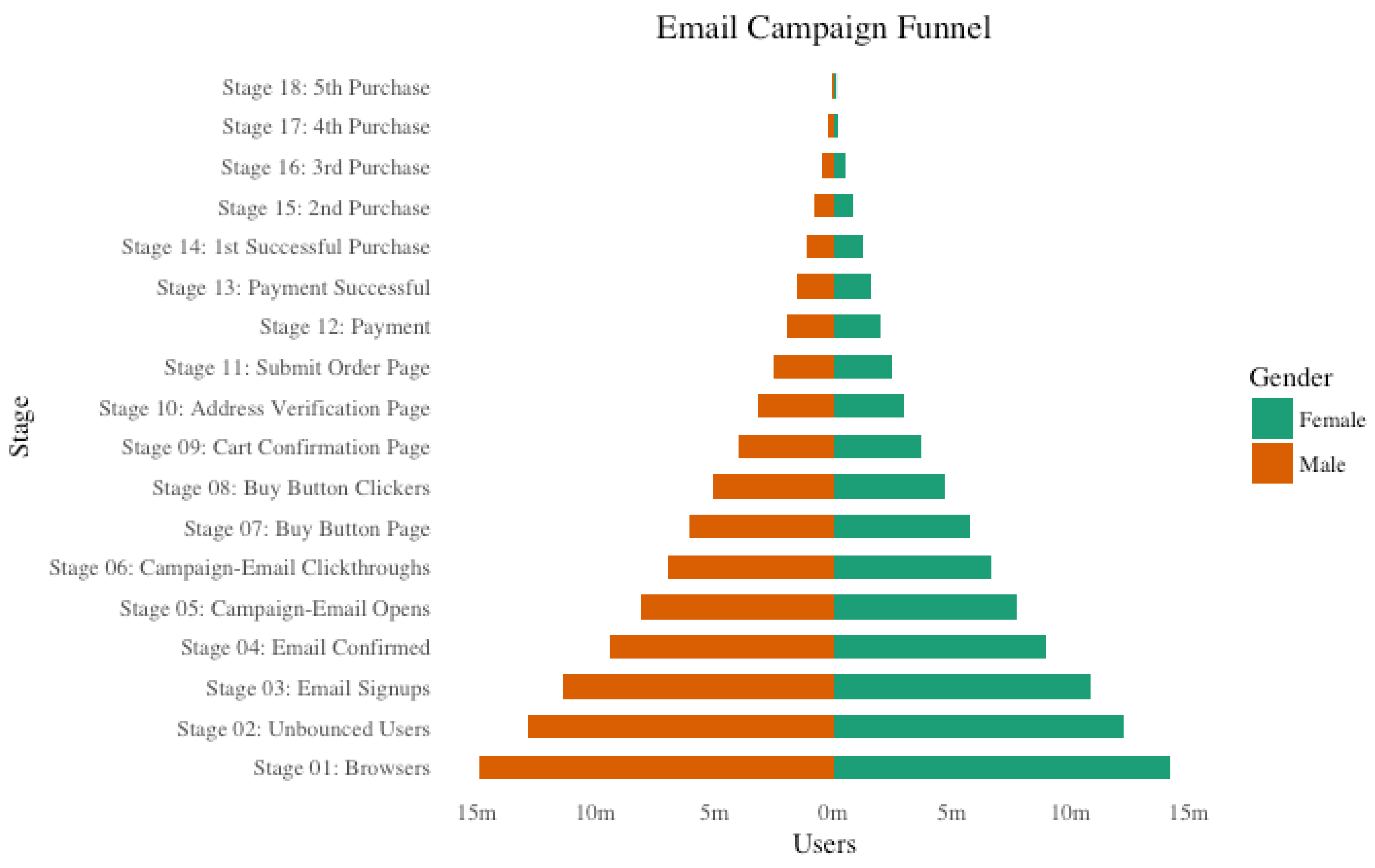
Population pyramids offer a unique way of visualizing how much population or what percentage of population fall under a certain category. The below pyramid is an excellent example of how many users are retained at each stage of a email marketing campaign funnel.

```
library(ggplot2)
library(ggthemes)
options(scipen = 999)  # turns of scientific notations like 1e+40

# 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)) +   # Fill 
column
                              geom_bar(stat = "identity", width = .6) +   # draw 
the bars
                              scale_y_continuous(breaks = brks,   # Breaks
                                                 labels = lbls) + # Labels
                              coord_flip() +  # Flip axes
                              labs(title="Email Campaign Funnel") +
                              theme_tufte() +  # Tufte theme from ggfortify
                              theme(plot.title = element_text(hjust = .5),
                                    axis.ticks = element_blank()) +   # Centre plot
title
                              scale_fill_brewer(palette = "Dark2")  # Color palette
```



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5. Composition

Waffle Chart

Waffle charts is a nice way of showing the categorical composition of the total population. Though there is no direct function, it can be articulated by smartly maneuvering the ggplot2 using `geom_tile()` function. The below template should help you create your own waffle.

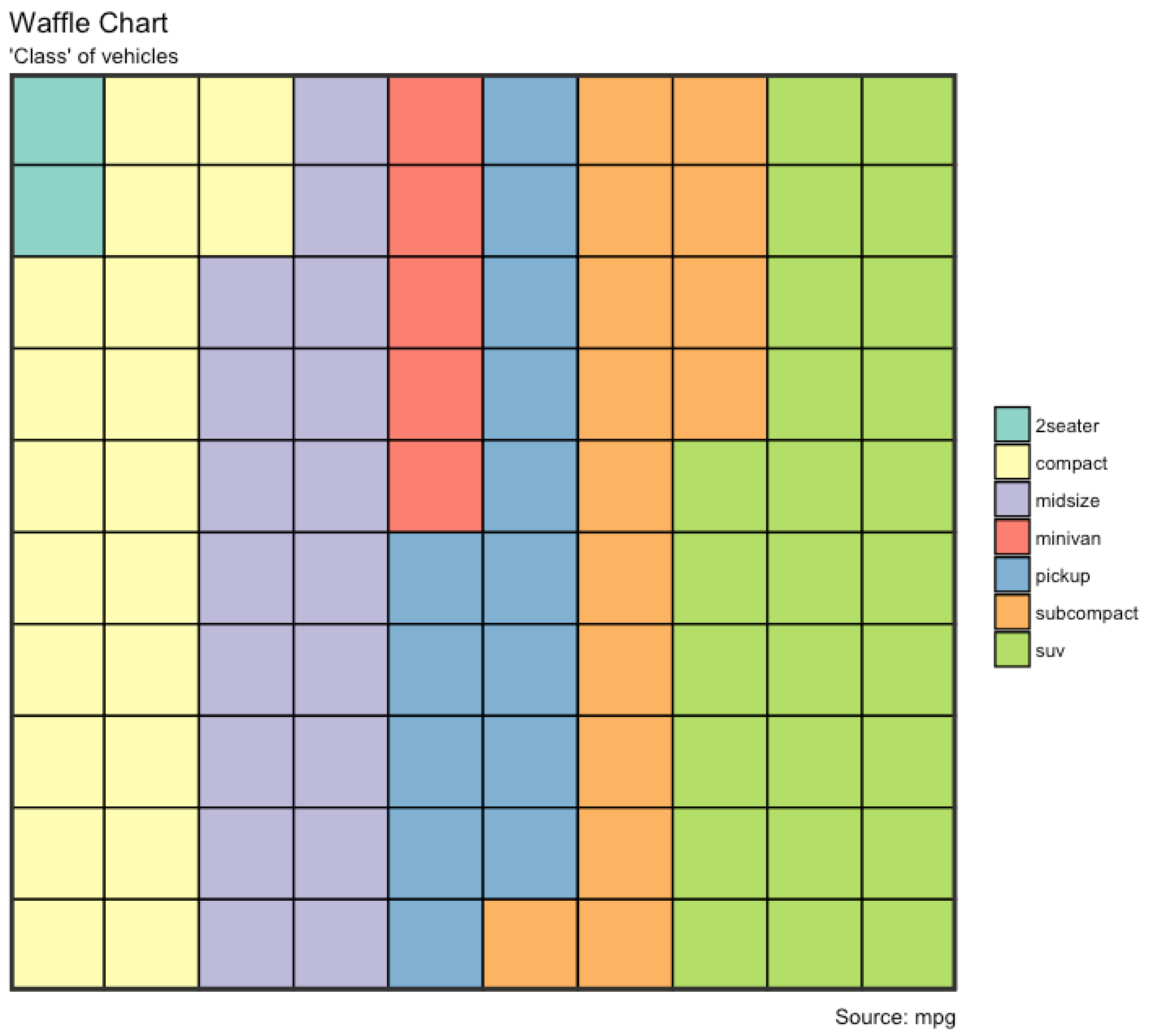
```
var <- mpg$class  # the categorical data

## Prep data (nothing to change here)
nrows <- 10
df <- expand.grid(y = 1:nrows, x = 1:nrows)
categ_table <- round(table(var) * ((nrows*nrows)/(length(var))))
categ_table
#>    2seater    compact    midsize    minivan     pickup subcompact        suv
#>          2         20         18          5         14         15         26

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

```
# NOTE: if sum(categ_table) is not 100 (i.e. nrows^2), it will need adjustment to
make the sum to 100.

## Plot
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") +
        theme(panel.border = element_rect(size = 2),
              plot.title = element_text(size = rel(1.2)),
              axis.text = element_blank(),
              axis.title = element_blank(),
              axis.ticks = element_blank(),
              legend.title = element_blank(),
              legend.position = "right")
```



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Pie Chart

Pie chart, a classic way of showing the compositions is equivalent to the waffle chart in terms of the information conveyed. But is a slightly tricky to implement in ggplot2 using the `coord_polar()`.

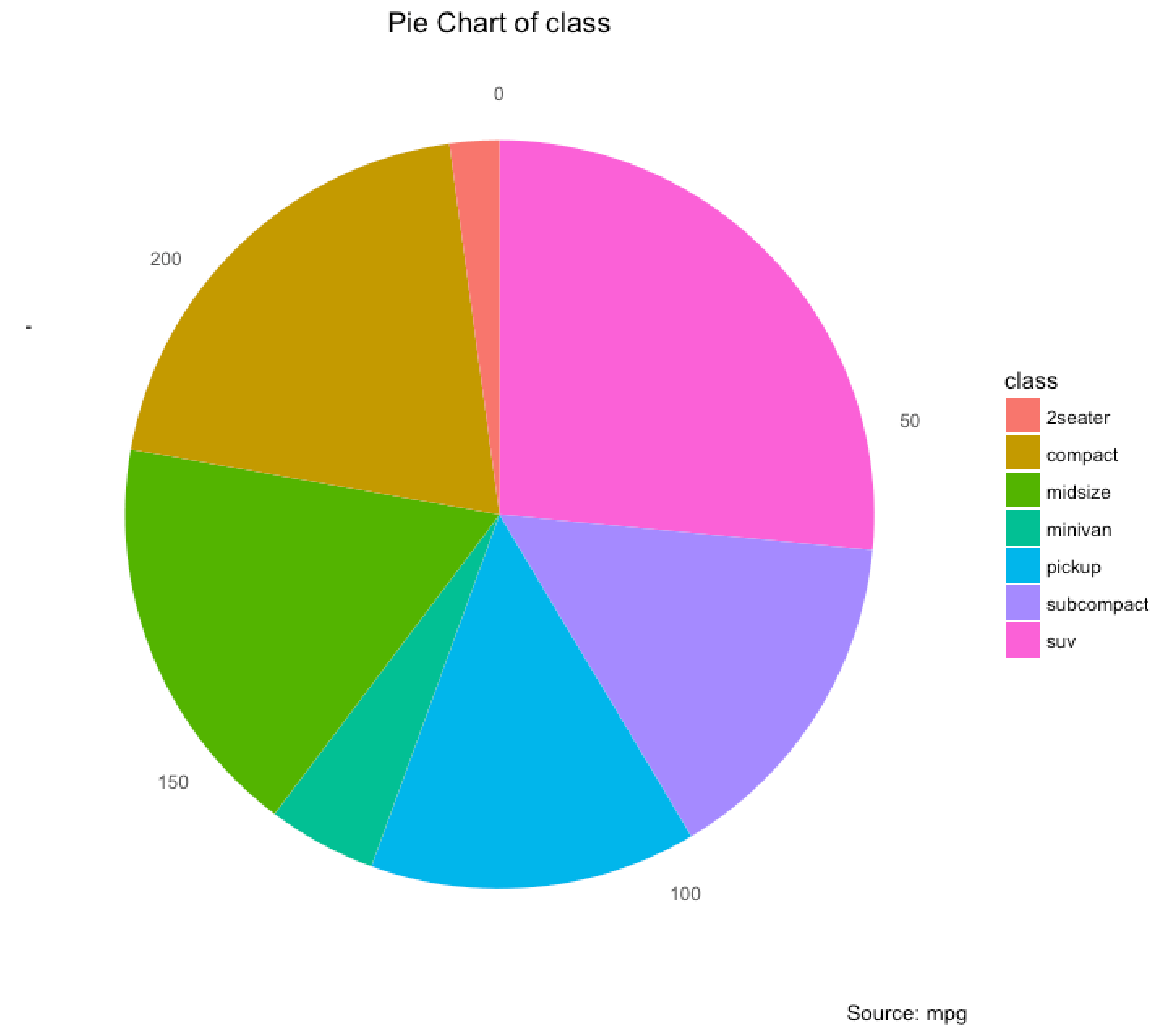
```
library(ggplot2)
theme_set(theme_classic())

# Source: Frequency table
df <- as.data.frame(table(mpg$class))
colnames(df) <- c("class", "freq")
pie <- ggplot(df, aes(x = "", y=freq, fill = factor(class))) +
  geom_bar(width = 1, stat = "identity") +
  theme(axis.line = element_blank(),
        plot.title = element_text(hjust=0.5)) +
  labs(fill="class",
       x=NULL,
       y=NULL,
       title="Pie Chart of class",
       caption="Source: mpg")

pie + coord_polar(theta = "y", start=0)

# Source: Categorical variable.
# mpg$class
pie <- ggplot(mpg, aes(x = "", fill = factor(class))) +
  geom_bar(width = 1) +
  theme(axis.line = element_blank(),
        plot.title = element_text(hjust=0.5)) +
  labs(fill="class",
       x=NULL,
       y=NULL,
       title="Pie Chart of class",
       caption="Source: mpg")

pie + coord_polar(theta = "y", start=0)
```



```
# http://www.r-graph-gallery.com/128-ring-or-donut-plot/
```

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Treemap

Treemap is a nice way of displaying hierarchical data by using nested rectangles. The `treemapify` package provides the necessary functions to convert the data in desired format (`treemapify`) as well as draw the actual plot (`ggplotify`).

In order to create a treemap, the data must be converted to desired format using `treemapify()`. The important requirement is, your data must have one variable each that describes the `area` of the tiles, variable for `fill` color, variable that has the tile's `label` and finally the parent `group`.

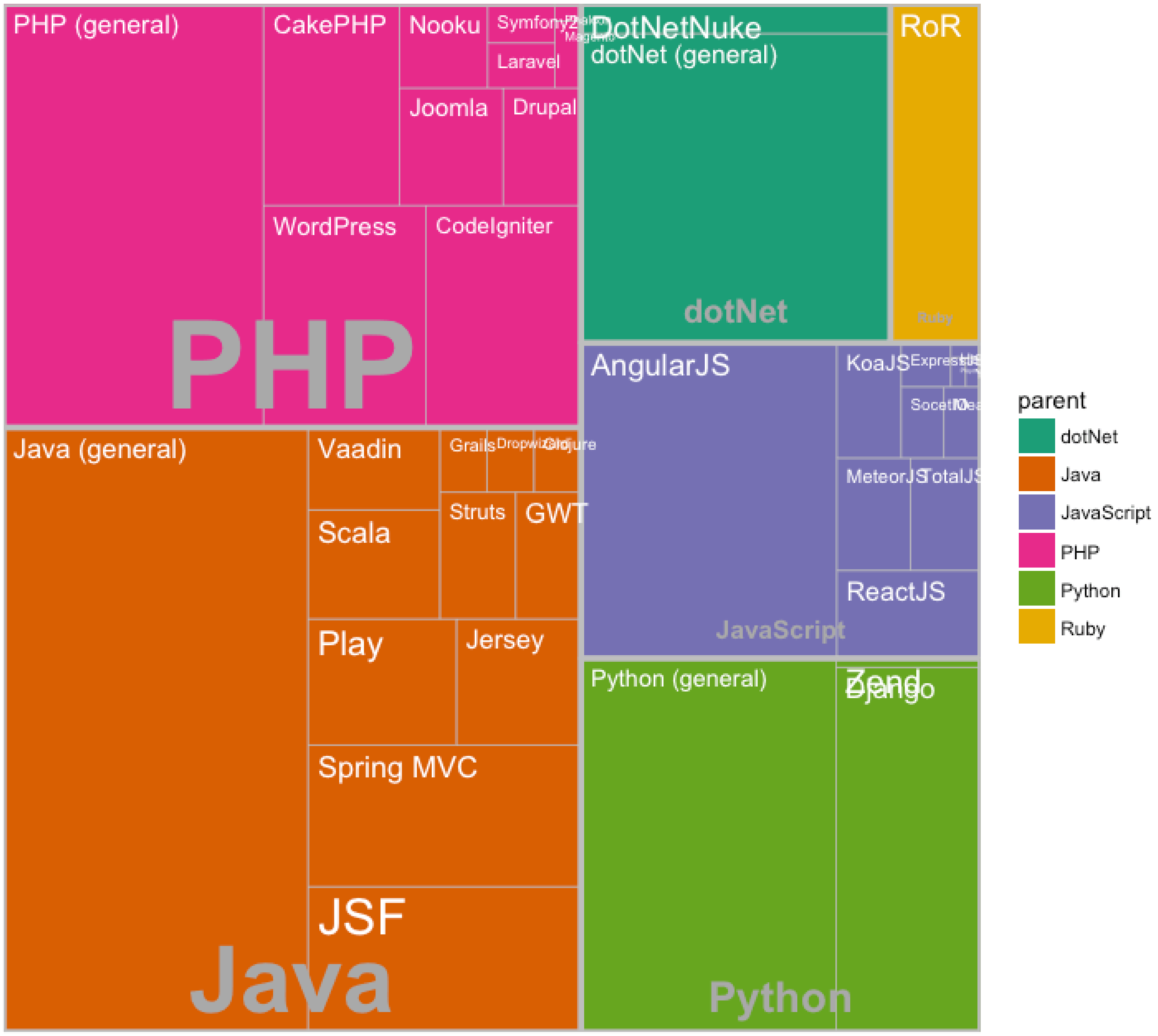
Once the data formatting is done, just call `ggplotify()` on the treemapified data.

```
library(ggplot2)
library(treemapify)
proglangs <-
read.csv("https://raw.githubusercontent.com/selva86/datasets/master/proglanguages.c
sv")

# plot
treeMapCoordinates <- treemapify(proglangs,
                                 area = "value",
                                 fill = "parent",
                                 label = "id",
                                 group = "parent")

treeMapPlot <- ggplotify(treeMapCoordinates) +
                  scale_x_continuous(expand = c(0, 0)) +
                  scale_y_continuous(expand = c(0, 0)) +
                  scale_fill_brewer(palette = "Dark2")

print(treeMapPlot)
```



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Bar Chart

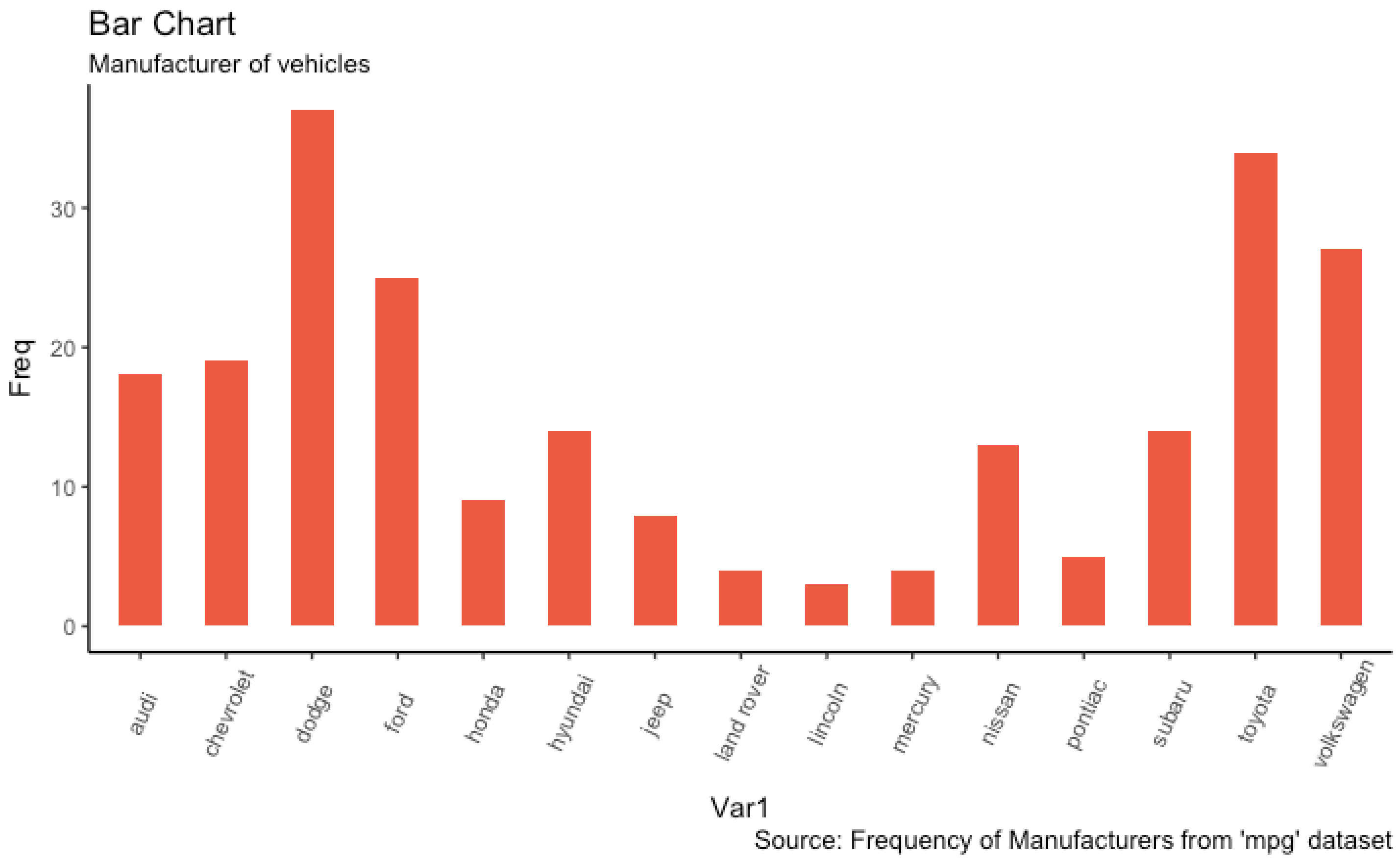
By default, `geom_bar()` has the `stat` set to `count`. That means, when you provide just a continuous X variable (and no Y variable), it tries to make a histogram out of the data.

In order to make a bar chart create bars instead of histogram, you need to do two things.

1. Set `stat=identity`
2. Provide both `x` and `y` inside `aes()` where, `x` is either `character` or `factor` and `y` is numeric.

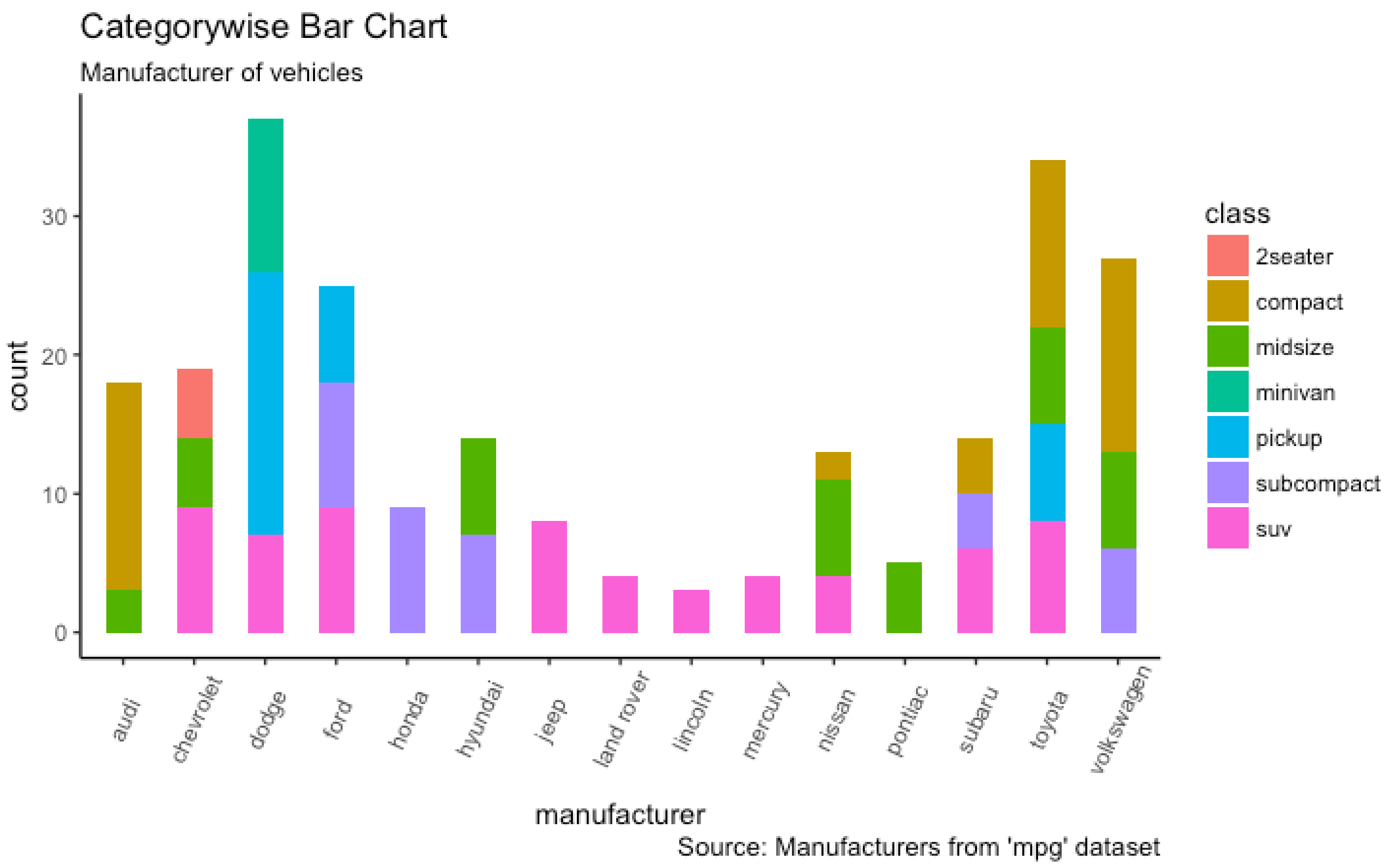
A bar chart can be drawn from a categorical column variable or from a separate frequency table. By adjusting `width`, you can adjust the thickness of the bars. If your data source is a frequency table, that is, if you don't want ggplot to compute the counts, you need to set the `stat=identity` inside the `geom_bar()`.

```
# prep frequency table
freqtable <- table(mpg$manufacturer)
df <- as.data.frame.table(freqtable)
head(df)
#>         Var1 Freq
#> 1       audi   18
#> 2  chevrolet   19
#> 3      dodge   37
#> 4       ford   25
#> 5      honda    9
#> 6    hyundai   14

# plot
library(ggplot2)
theme_set(theme_classic())

# Plot
g <- ggplot(df, aes(Var1, Freq))
g + geom_bar(stat="identity", width = 0.5, fill="tomato2") +
      labs(title="Bar Chart",
           subtitle="Manufacturer of vehicles",
           caption="Source: Frequency of Manufacturers from 'mpg' dataset") +
      theme(axis.text.x = element_text(angle=65, vjust=0.6))
```



It can be computed directly from a column variable as well. In this case, only X is provided and `stat=identity` is *not* set.

```
# From on a categorical column variable
g <- ggplot(mpg, aes(manufacturer))
g + geom_bar(aes(fill=class), width = 0.5) +
  theme(axis.text.x = element_text(angle=65, vjust=0.6)) +
  labs(title="Categorywise Bar Chart",
       subtitle="Manufacturer of vehicles",
       caption="Source: Manufacturers from 'mpg' dataset")
```



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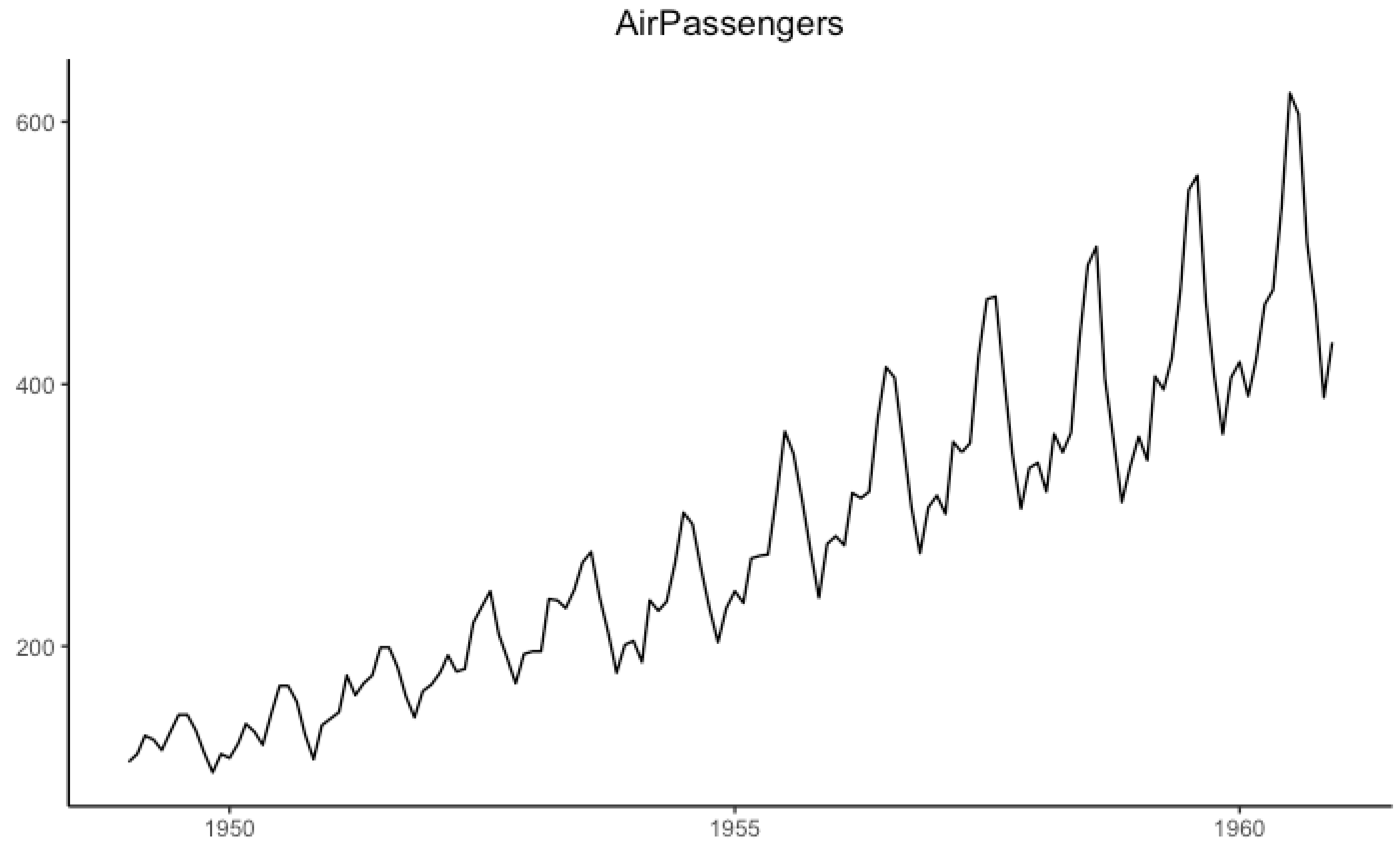
6. Change

Time Series Plot From a Time Series Object (`ts`)

The `ggfortify` package allows autoplot to automatically plot directly from a time series object (`ts`).

```
## From Timeseries object (ts)
library(ggplot2)
library(ggfortify)
theme_set(theme_classic())

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



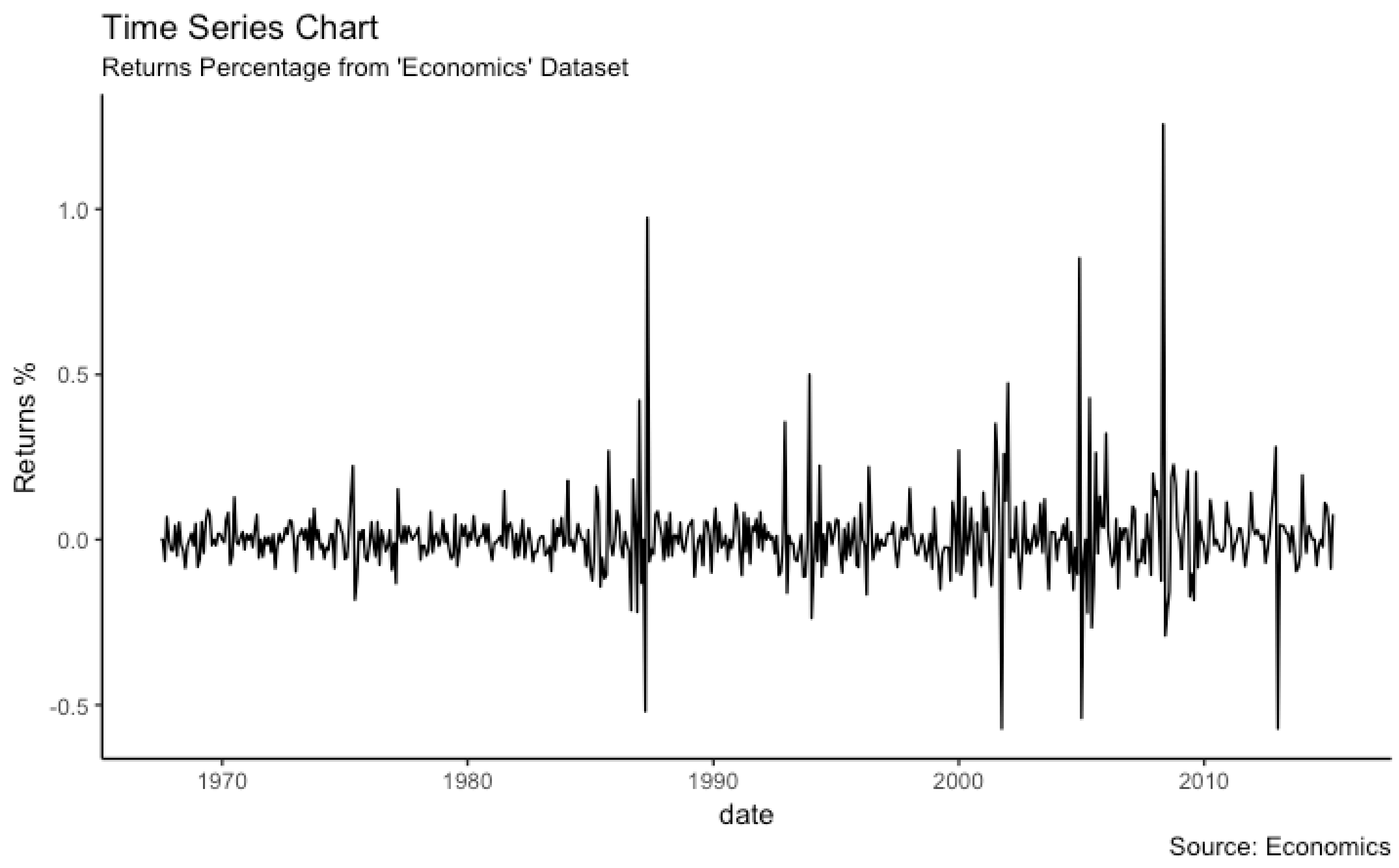
Time Series Plot From a Data Frame

Using `geom_line()`, a time series (or line chart) can be drawn from a `data.frame` as well. The X axis breaks are generated by default. In below example, the breaks are formed once every 10 years.

Default X Axis Labels

```
library(ggplot2)
theme_set(theme_classic())

# Allow Default X Axis Labels
ggplot(economics, aes(x=date)) +
  geom_line(aes(y=returns_perc)) +
  labs(title="Time Series Chart",
       subtitle="Returns Percentage from 'Economics' Dataset",
       caption="Source: Economics",
       y="Returns %")
```



Time Series Plot For a *Monthly* Time Series

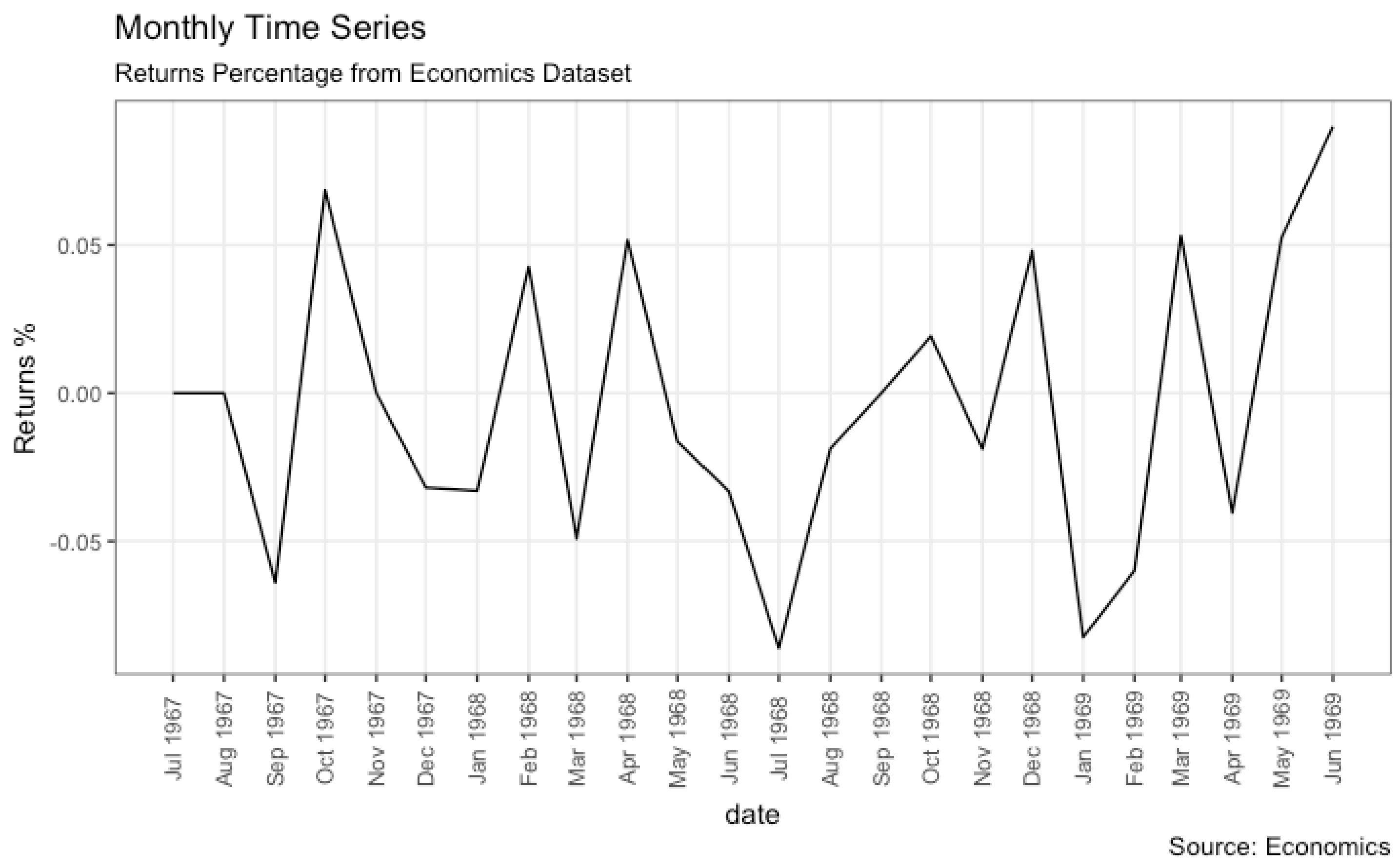
If you want to set your own time intervals (breaks) in X axis, you need to set the breaks and labels using `scale_x_date()`.

```
library(ggplot2)
library(lubridate)
theme_set(theme_bw())

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=returns_perc)) +
  labs(title="Monthly Time Series",
       subtitle="Returns Percentage from Economics Dataset",
       caption="Source: Economics",
       y="Returns %") +  # title and caption
  scale_x_date(labels = lbls,
               breaks = brks) +  # change to monthly ticks and labels
  theme(axis.text.x = element_text(angle = 90, vjust=0.5),  # rotate x axis text
        panel.grid.minor = element_blank())  # turn off minor grid
```



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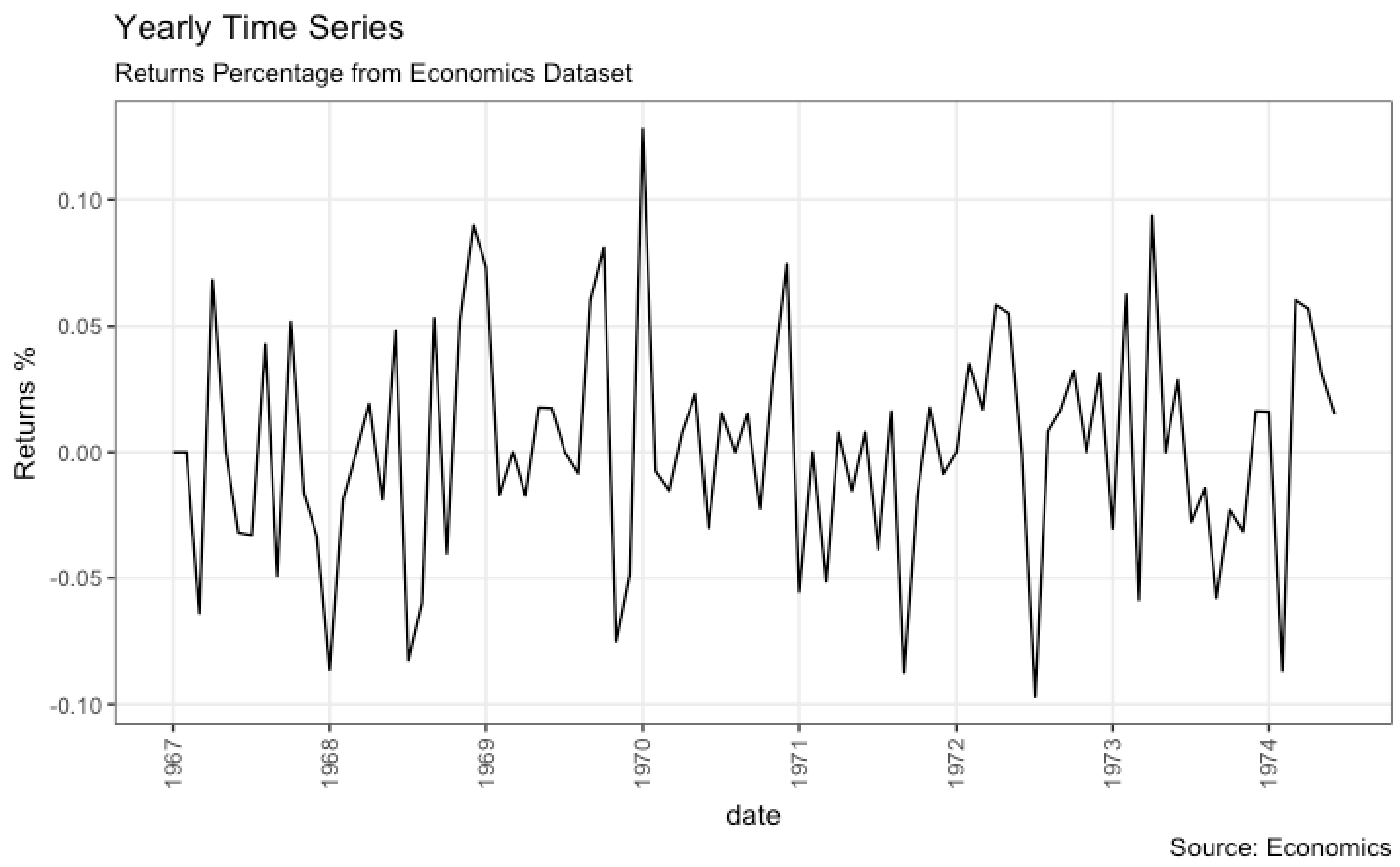
Time Series Plot For a *Yearly* Time Series

```
library(ggplot2)
library(lubridate)
theme_set(theme_bw())

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=returns_perc)) +
  labs(title="Yearly Time Series",
       subtitle="Returns Percentage from Economics Dataset",
       caption="Source: Economics",
       y="Returns %") +  # title and caption
  scale_x_date(labels = lbls,
               breaks = brks) +  # change to monthly ticks and labels
  theme(axis.text.x = element_text(angle = 90, vjust=0.5),  # rotate x axis text
        panel.grid.minor = element_blank())  # turn off minor grid
```



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Time Series Plot From Long Data Format: Multiple Time Series in Same Dataframe Column

In this example, I construct the ggplot from a long data format. That means, the column names and respective values of all the columns are stacked in just 2 variables (`variable` and `value` respectively). If you were to convert this data to wide format, it would look like the `economics` dataset.

In below example, the `geom_line` is drawn for `value` column and the `aes(col)` is set to `variable`. This way, with just one call to `geom_line`, multiple colored lines are drawn, one each for each unique value in `variable` column. The `scale_x_date()` changes the X axis breaks and labels, and `scale_color_manual` changes the color of the lines.

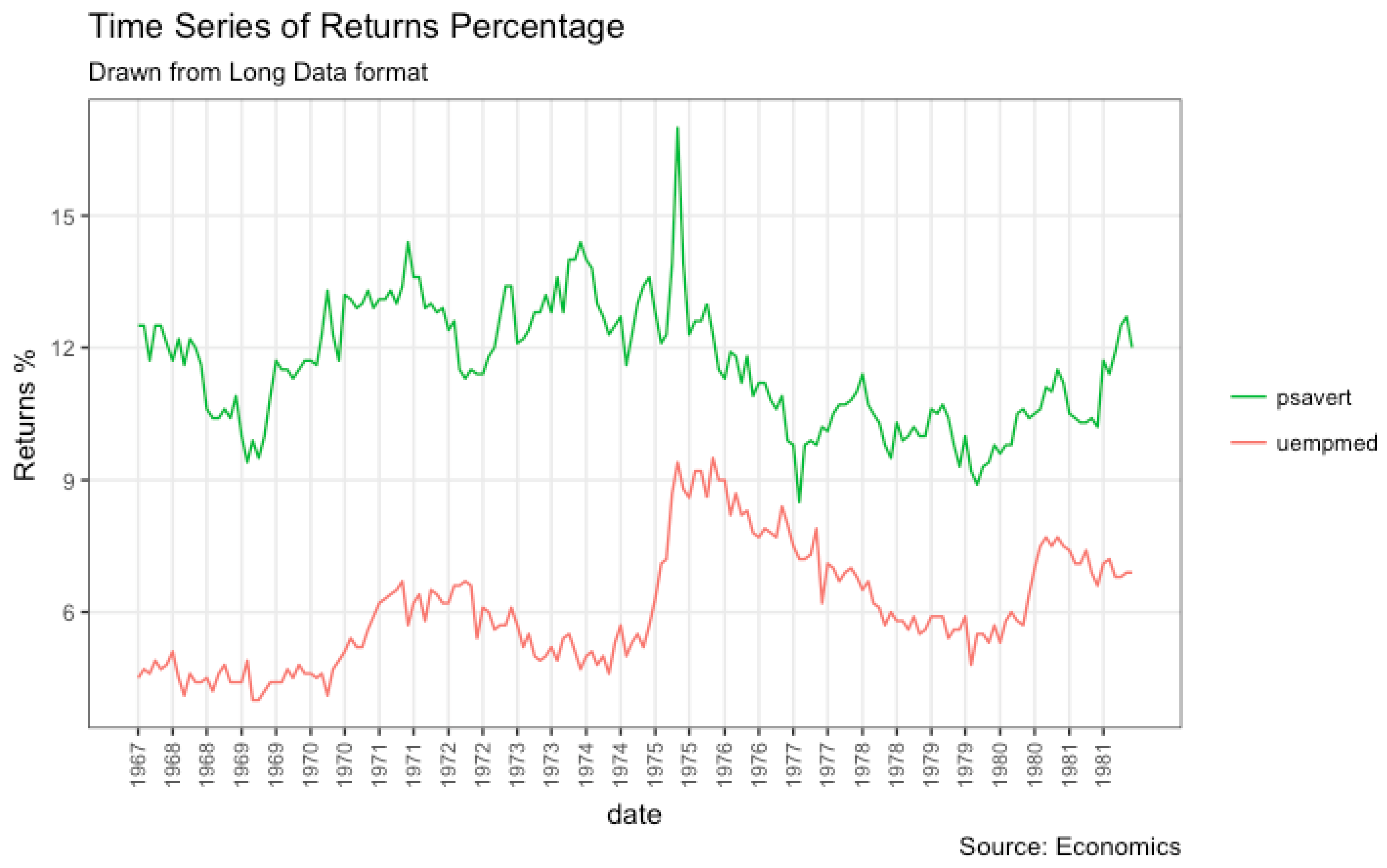
```
data(economics_long, package = "ggplot2")
head(economics_long)
#>         date variable value      value01
#>       <date>   <fctr> <dbl>        <dbl>
#> 1 1967-07-01      pce 507.4 0.0000000000
#> 2 1967-08-01      pce 510.5 0.0002660008
#> 3 1967-09-01      pce 516.3 0.0007636797
#> 4 1967-10-01      pce 512.9 0.0004719369
#> 5 1967-11-01      pce 518.1 0.0009181318
#> 6 1967-12-01      pce 525.8 0.0015788435
```

```
library(ggplot2)
library(lubridate)
theme_set(theme_bw())

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) +  # title and caption
  scale_x_date(labels = lbls, breaks = brks) +  # change to monthly ticks and
labels
  scale_color_manual(labels = c("psavert", "uempmed"),
                     values = c("psavert"="#00ba38", "uempmed"="#f8766d")) +  #
line color
  theme(axis.text.x = element_text(angle = 90, vjust=0.5, size = 8),  # rotate x
axis text
        panel.grid.minor = element_blank())  # turn off minor grid
```



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Time Series Plot From Wide Data Format: Data in Multiple Columns of Dataframe

As noted in the part 2 of this tutorial, whenever your plot's geom (like points, lines, bars, etc) changes the `fill`, `size`, `col`, `shape` or `stroke` based on another column, a legend is automatically drawn.

But if you are creating a time series (or even other types of plots) from a wide data format, you have to draw each line manually by calling `geom_line()` once for every line. So, a legend will not be drawn by default.

However, having a legend would still be nice. This can be done using the `scale_aesthetic_manual()` format of functions (like, `scale_color_manual()` if only the color of your lines change). Using this function, you can give a legend title with the `name` argument, tell what color the legend should take with the `values` argument and also set the legend labels.

Even though the below plot looks exactly like the previous one, the approach to construct this is different.

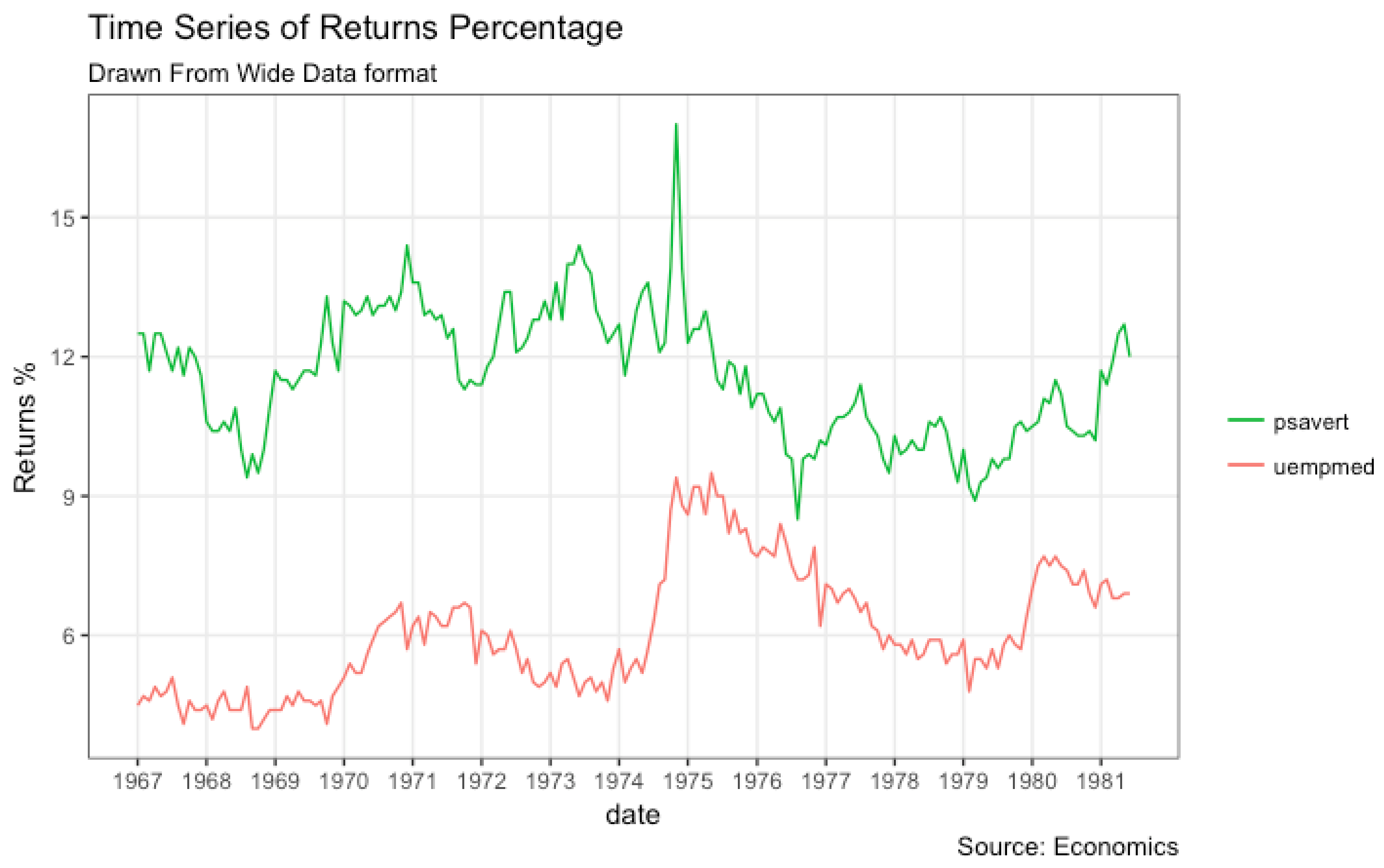
You might wonder why I used this function in previous example for long data format as well. Note that, in previous example, it was used to change the color of the line only. Without `scale_color_manual()`, you would still have got a legend, but the lines would be of a different (default) color. But in current example, without `scale_color_manual()`, you wouldn't even have a legend. Try it out!

```
library(ggplot2)
library(lubridate)
theme_set(theme_bw())

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_line(aes(y=psavert, col="psavert")) +
  geom_line(aes(y=uempmed, col="uempmed")) +
  labs(title="Time Series of Returns Percentage",
       subtitle="Drawn From Wide Data format",
       caption="Source: Economics", y="Returns %") +  # title and caption
  scale_x_date(labels = lbls, breaks = brks) +  # change to monthly ticks and
labels
  scale_color_manual(name="",
                     values = c("psavert"="#00ba38", "uempmed"="#f8766d")) +  #
line color
  theme(panel.grid.minor = element_blank())  # turn off minor grid
```



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Stacked Area Chart

Stacked area chart is just like a line chart, except that the region below the plot is all colored. This is typically used when:

1. You want to describe how a quantity or volume (rather than something like price) changed over time
2. You have many data points. For very few data points, consider plotting a bar chart.
3. You want to show the contribution from individual components.

This can be plotted using `geom_area` which works very much like `geom_line`. But there is an important point to note. By default, each `geom_area()` starts from the bottom of Y axis (which is typically 0), but, if you want to show the contribution from individual components, you want the `geom_area` to be stacked over the top of previous component, rather than the floor of the plot itself. So, you have to add all the bottom layers while setting the `y` of `geom_area`.

In below example, I have set it as `y=psavert+uempmed` for the topmost `geom_area()`.

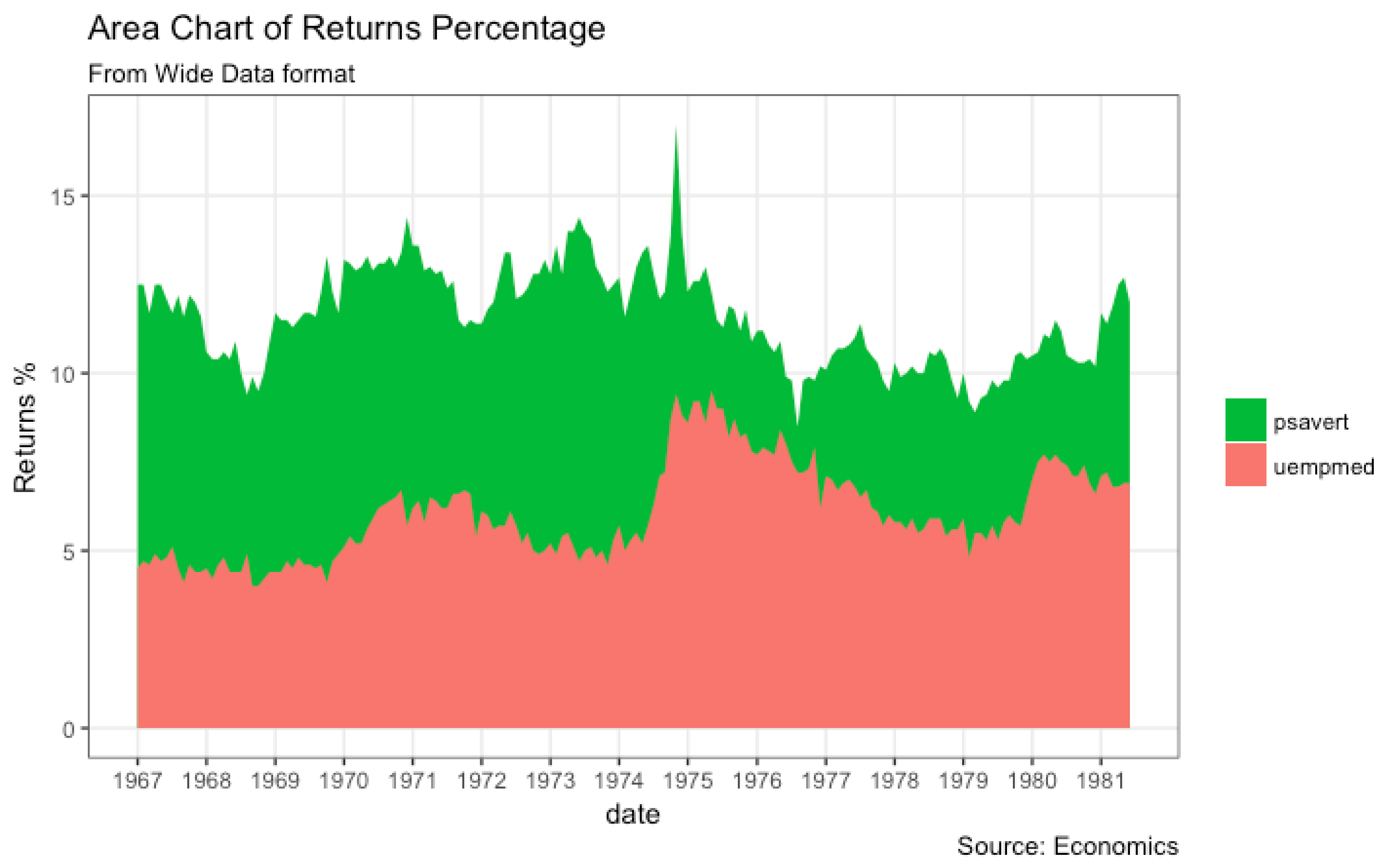
However nice the plot looks, the caveat is that, it can easily become complicated and uninterprettable if there are too many components.

```
library(ggplot2)
library(lubridate)
theme_set(theme_bw())
```

```
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 %") +  # title and caption
  scale_x_date(labels = lbls, breaks = brks) +  # change to monthly ticks and
labels
  scale_fill_manual(name="",
                    values = c("psavert"="#00ba38", "uempmed"="#f8766d")) +  # line
color
  theme(panel.grid.minor = element_blank())  # turn off minor grid
```



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Calendar Heatmap

When you want to see the variation, especially the highs and lows, of a metric like stock price, on an actual calendar itself, the calendar heat map is a great tool. It emphasizes the variation visually over time rather than the actual value itself.

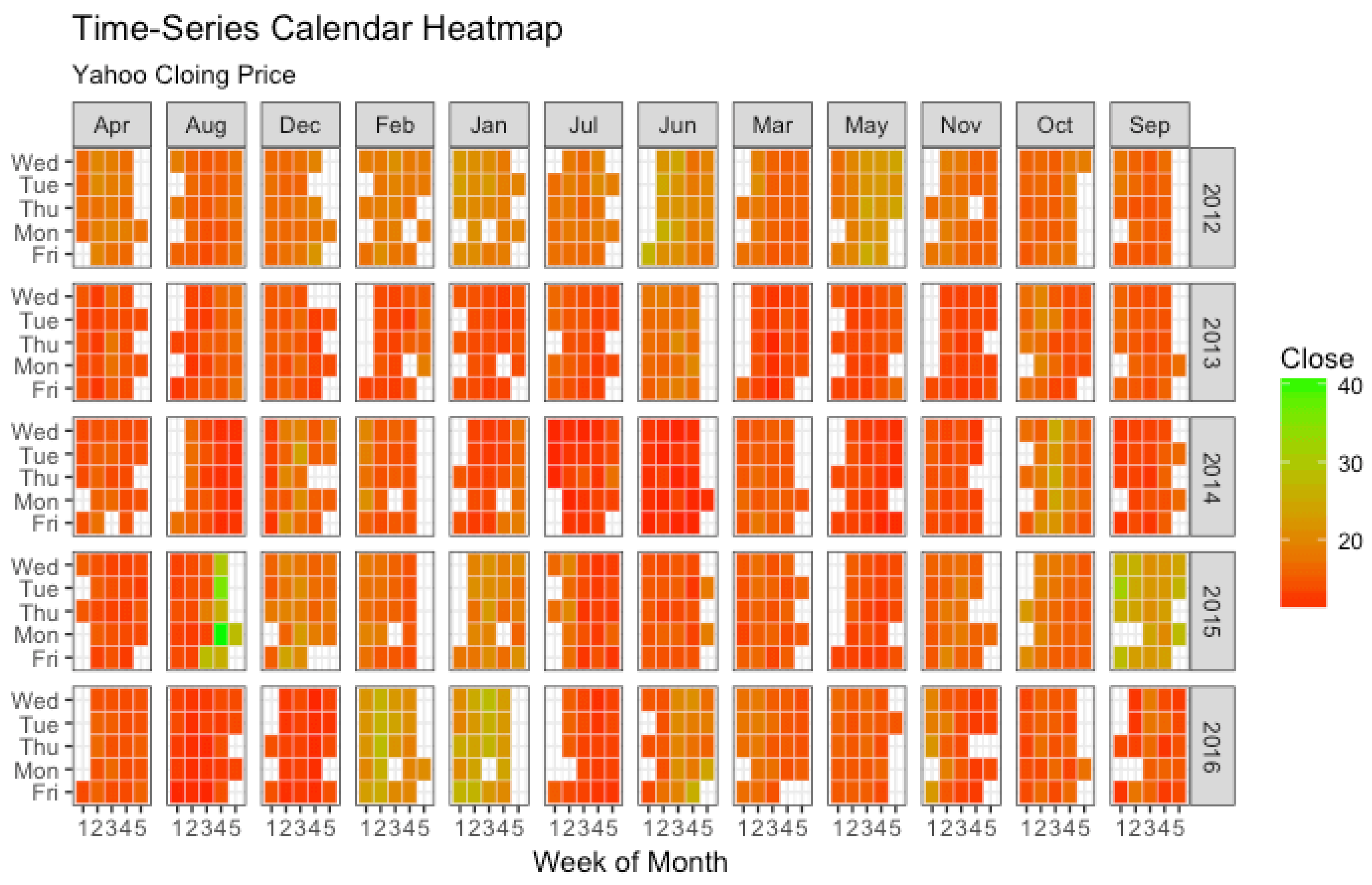
This can be implemented using the `geom_tile`. But getting it in the right format has more to do with the data preparation rather than the plotting itself.

```
# http://margintale.blogspot.in/2012/04/ggplot2-time-series-heatmaps.html
library(ggplot2)
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")
```



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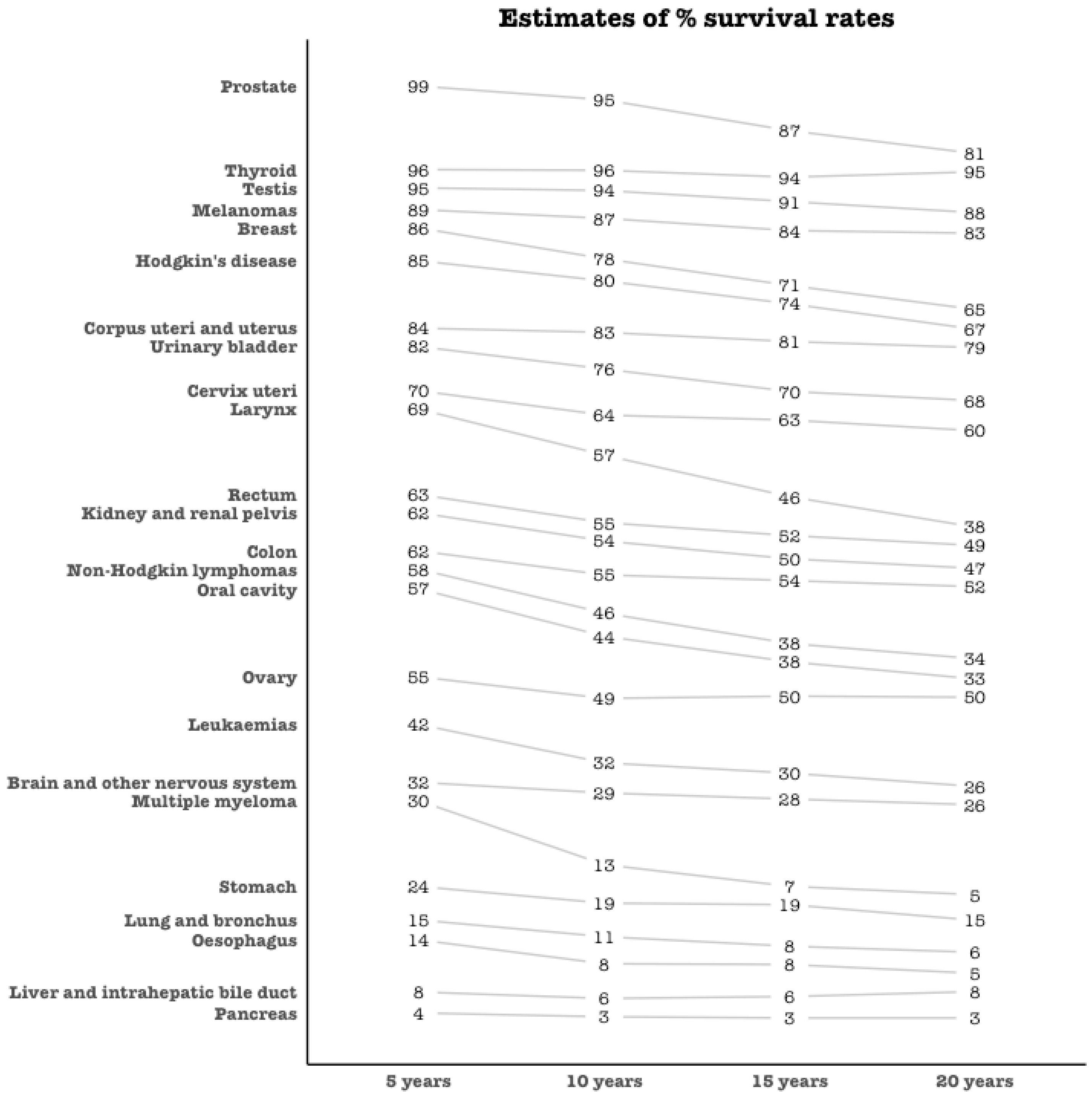
Slope Chart

Slope chart is a great tool of you want to visualize change in value and ranking between categories. This is more suitable over a time series when there are very few time points.

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

# Define functions. Source: https://github.com/jkeirstead/r-slopegraph
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 to ensure every combination has a defined 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))
    ## Start at "bottom" row
    ## Repeat for rest of the rows until you hit the top
    for (i in 2:nrow(tmp)) {
        ## Shift subsequent row up by equal space so gap between
        ## two entries is >= minimum
        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")
    ## Store these gaps in a separate variable so that they can be scaled ypos =
a*yshift + 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, family="American Typewriter") +
        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"))
```



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Seasonal Plot

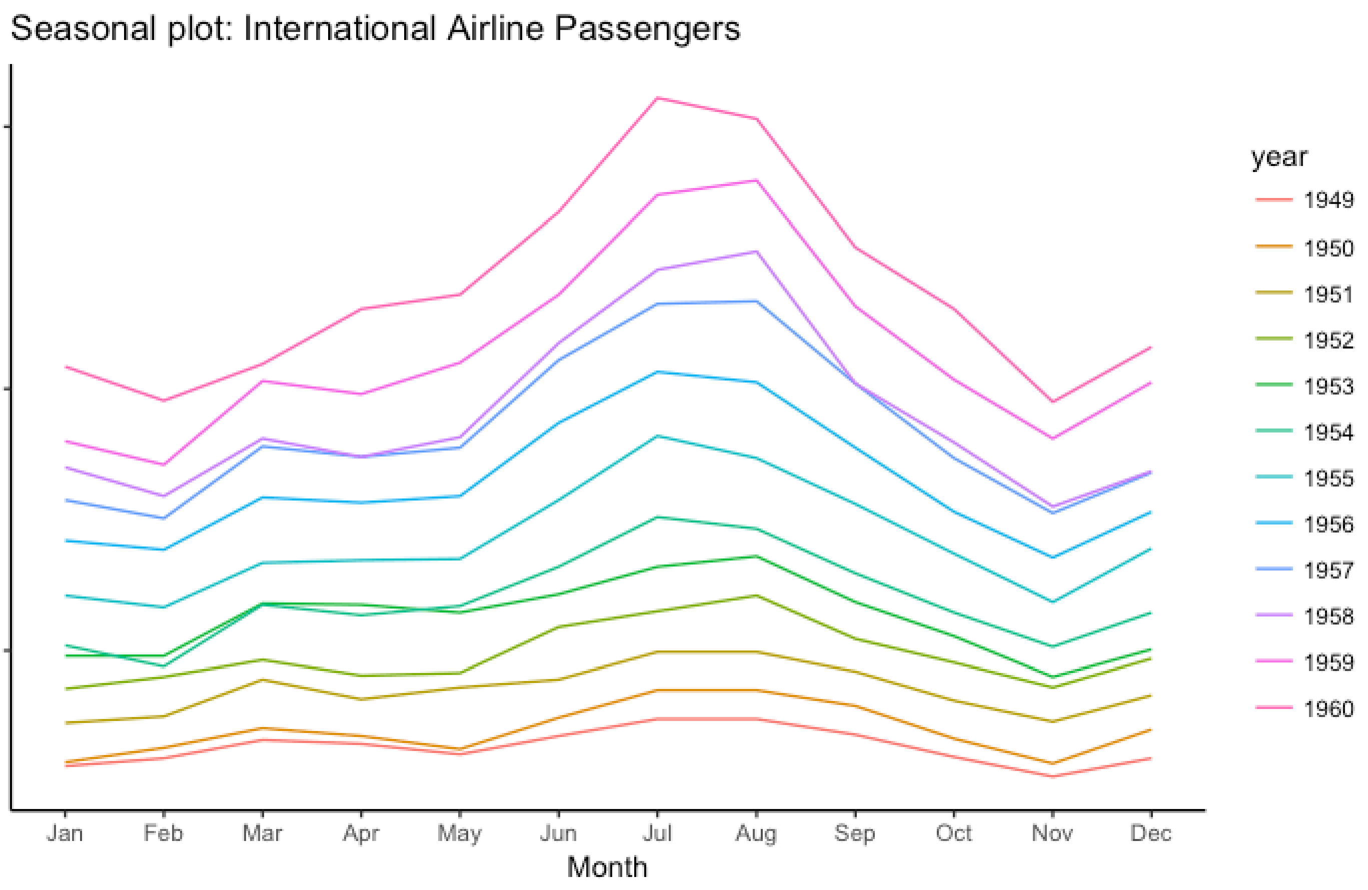
If you are working with a time series object of class `ts` or `xts`, you can view the seasonal fluctuations through a seasonal plot drawn using `forecast::ggseasonplot`. Below is an example using the native `AirPassengers` and `nottem` time series.

You can see the traffic increase in air passengers over the years along with the repetitive seasonal patterns in traffic. Whereas Nottingham does not show an increase in overal temperatures over the years, but they definitely follow a seasonal pattern.

```
library(ggplot2)
library(forecast)
theme_set(theme_classic())

# Subset data
nottem_small <- window(nottem, start=c(1920, 1), end=c(1925, 12))  # subset a
smaller timewindow

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


Seasonal plot: International Airline Passengers
600
400
200
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Month
year
1949
1950
1951
1952
1953
1954
1955
1956
1957
1958
1959
1960

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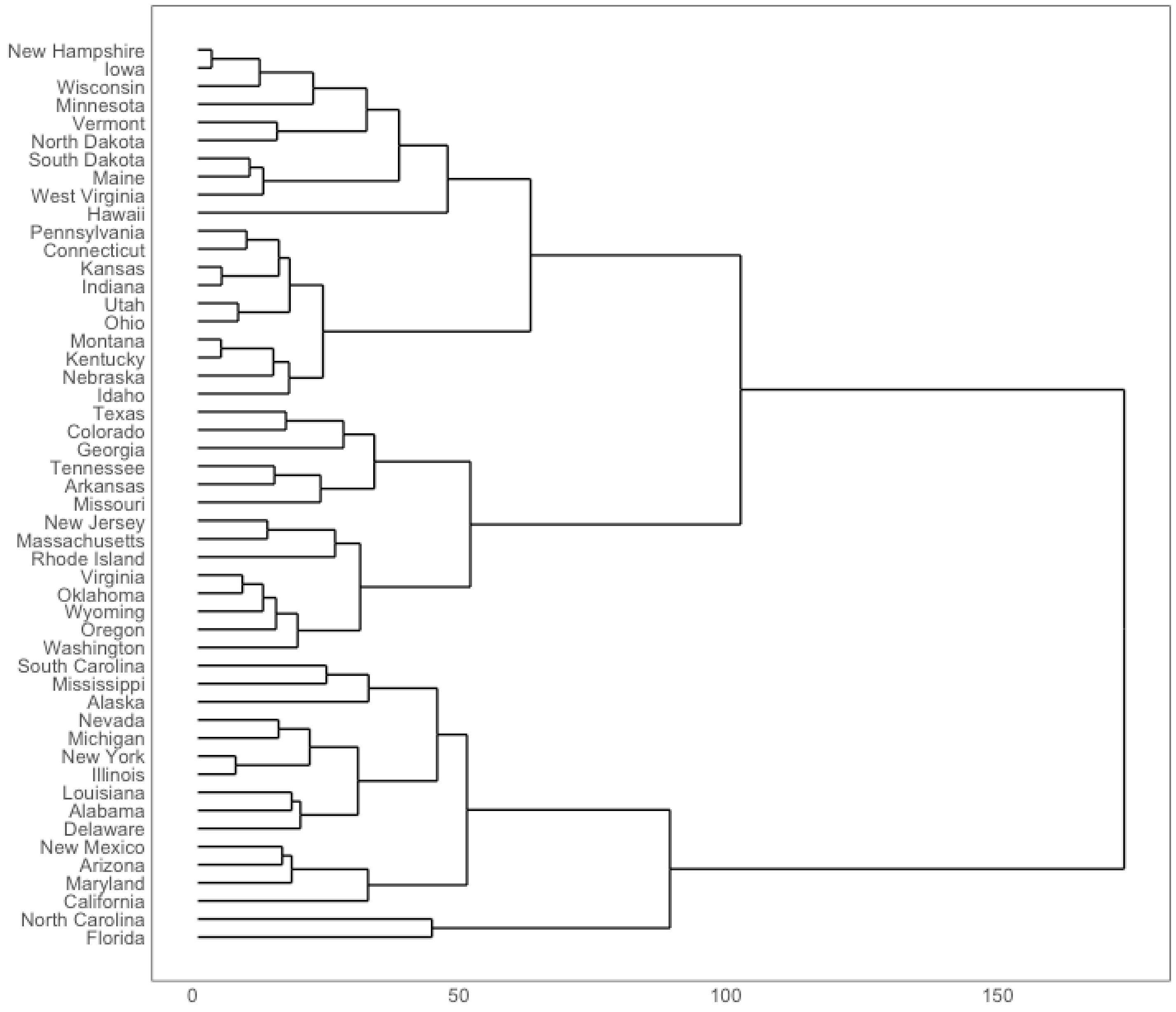
7. Groups

Hierarchical Dendrogram

```
# install.packages("ggdendro")
library(ggplot2)
library(ggdendro)
theme_set(theme_bw())

hc <- hclust(dist(USArrests), "ave")  # hierarchical clustering

# plot
ggdendrogram(hc, rotate = TRUE, size = 2)
```



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Clusters

It is possible to show the distinct clusters or groups using `geom_encircle()`. If the dataset has multiple weak features, you can compute the principal components and draw a scatterplot using PC1 and PC2 as X and Y axis.

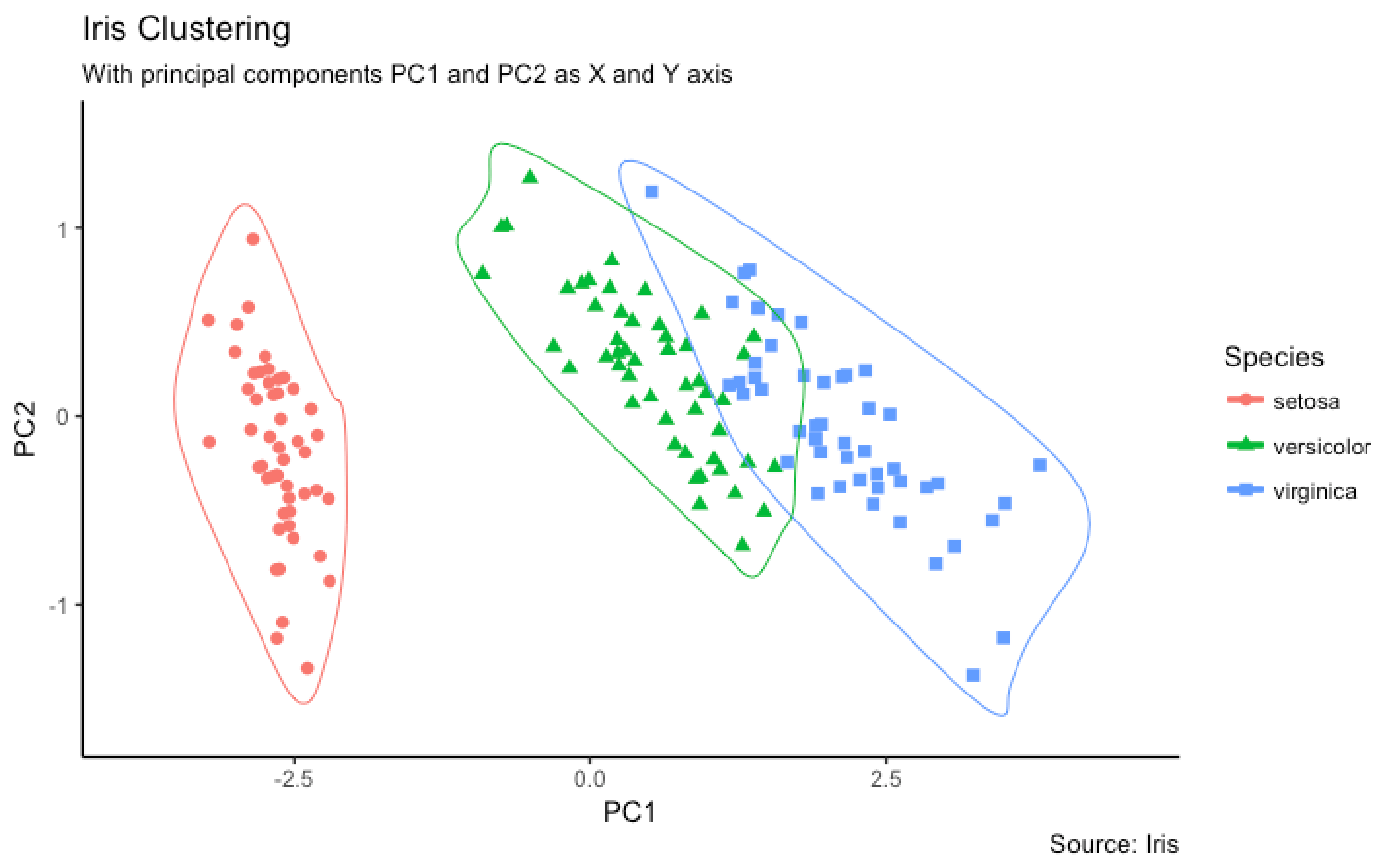
The `geom_encircle()` can be used to encircle the desired groups. The only thing to note is the `data` argument to `geom_circle()`. You need to provide a subsetted dataframe that contains only the observations (rows) that belong to the group as the `data` argument.

```
# devtools::install_github("hrbrmstr/ggalt")
library(ggplot2)
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)  # dataframe of principal
components
df_pc_vir <- df_pc[df_pc$Species == "virginica", ]  # df for 'virginica'
df_pc_set <- df_pc[df_pc$Species == "setosa", ]  # df for 'setosa'
df_pc_ver <- df_pc[df_pc$Species == "versicolor", ]  # df for 'versicolor'

# Plot ----------------------------------------------------
ggplot(df_pc, aes(PC1, PC2, col=Species)) +
  geom_point(aes(shape=Species), size=2) +   # draw points
  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))) +   # change axis
limits
  geom_encircle(data = df_pc_vir, aes(x=PC1, y=PC2)) +   # draw circles
  geom_encircle(data = df_pc_set, aes(x=PC1, y=PC2)) +
  geom_encircle(data = df_pc_ver, aes(x=PC1, y=PC2))
```



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8. Spatial

The `ggmap` package provides facilities to interact with the google maps api and get the coordinates (latitude and longitude) of places you want to plot. The below example shows satellite, road and hybrid maps of the city of Chennai, encircling some of the places. I used the `geocode()` function to get the coordinates of these places and `qmap()` to get the maps. The type of map to fetch is determined by the value you set to the `maptype`.

You can also zoom into the map by setting the `zoom` argument. The default is 10 (suitable for large cities). Reduce this number (up to 3) if you want to zoom out. It can be zoomed in till 21, suitable for buildings.

```
# Better install the dev versions ----------
# devtools::install_github("dkahle/ggmap")
# devtools::install_github("hrbrmstr/ggalt")

# load packages
library(ggplot2)
library(ggmap)
library(ggalt)

# Get Chennai's Coordinates --------------------------------
chennai <-  geocode("Chennai")  # get longitude and latitude

# Get the Map ----------------------------------------------
# Google Satellite Map
chennai_ggl_sat_map <- qmap("chennai", zoom=12, source = "google",
maptype="satellite")

# Google Road Map
chennai_ggl_road_map <- qmap("chennai", zoom=12, source = "google",
maptype="roadmap")

# Google Hybrid Map
chennai_ggl_hybrid_map <- qmap("chennai", zoom=12, source = "google",
maptype="hybrid")

# Open Street Map
chennai_osm_map <- qmap("chennai", zoom=12, source = "osm")

# Get Coordinates for Chennai's Places ---------------------
chennai_places <- c("Kolathur",
                    "Washermanpet",
                    "Royapettah",
                    "Adyar",
                    "Guindy")

places_loc <- geocode(chennai_places)  # get longitudes and latitudes


# Plot Open Street Map -------------------------------------
chennai_osm_map + geom_point(aes(x=lon, y=lat),
                             data = places_loc,
                             alpha = 0.7,
                             size = 7,
                             color = "tomato") +
                  geom_encircle(aes(x=lon, y=lat),
                                data = places_loc, size = 2, color = "blue")

# Plot Google Road Map -------------------------------------
```

```
chennai_ggl_road_map + geom_point(aes(x=lon, y=lat),
                                  data = places_loc,
                                  alpha = 0.7,
                                  size = 7,
                                  color = "tomato") +
                       geom_encircle(aes(x=lon, y=lat),
                                     data = places_loc, size = 2, color = "blue")

# Google Hybrid Map ----------------------------------------
chennai_ggl_hybrid_map + geom_point(aes(x=lon, y=lat),
                                    data = places_loc,
                                    alpha = 0.7,
                                    size = 7,
                                    color = "tomato") +
                         geom_encircle(aes(x=lon, y=lat),
                                       data = places_loc, size = 2, color =
"blue")
```

Open Street Map

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Google Road Map

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Google Hybrid Map