ggplot - 50개의 예제

Learning Spoons

2018-05-20

An effective chart is one that:

1. Conveys the right information without distorting facts.
2. Is simple but elegant. It should not force you to think much in order to get it.
3. Aesthetics supports information rather that overshadow it.
4. Is not overloaded with information.

The list below sorts the visualizations based on its primary purpose. Primarily, there are 8 types of objectives you may construct plots. So, before you actually make the plot, try and figure what findings and relationships you would like to convey or examine through the visualization. Chances are it will fall under one (or sometimes more) of these 8 categories.

1. Correlation

- Scatterplot
- Scatterplot With Encircling
- Jitter Plot
- Counts Chart
- Bubble Plot
- Animated Bubble Plot
- Marginal Histogram / Boxplot
- Correlogram

2. Deviation

- Diverging Bars
- Diverging Lollipop Chart
- Diverging Dot Plot
- Area Chart

3. Ranking

- Ordered Bar Chart
- Lollipop Chart
- Dot Plot
- Slope Chart
- Dumbbell Plot

4. Distribution

- Histogram
- Density Plot
- Box Plot
- Dot + Box Plot
- Tufte Boxplot
- Violin Plot
- Population Pyramid

5. Composition

- Waffle Chart
- Pie Chart
- Treemap
- Bar Chart

6. Change

- Time Series Plots

1. Correlation

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

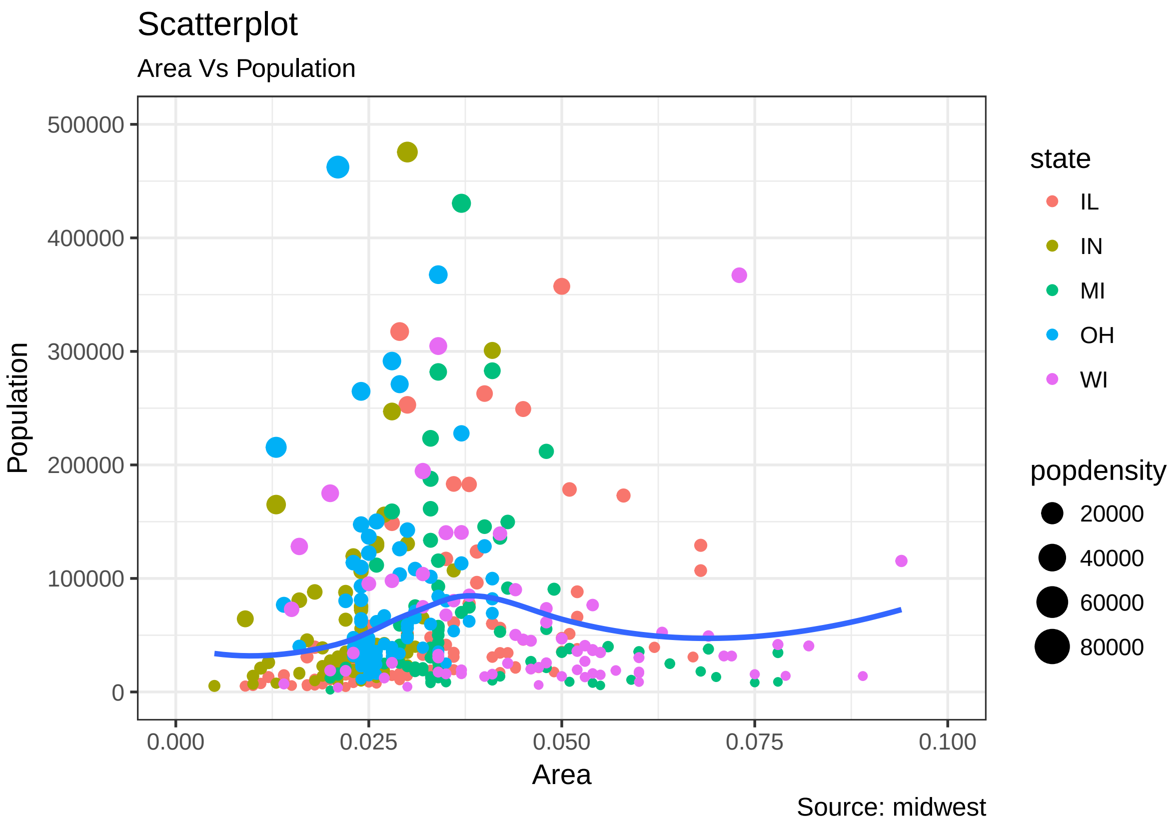
Scatterplot The most frequently used plot for data analysis is undoubtedly the scatterplot. Whenever you want to understand the nature of relationship between two variables, invariably the first choice is the scatterplot.

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'`.

```r
# 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)
```

```
## Warning: Removed 15 rows containing non-finite values (stat_smooth).
```

```
## Warning: Removed 15 rows containing missing values (geom_point).
```


Scatterplot
Area Vs Population
Population
500000
400000
300000
200000
100000
0
0.000
0.025
0.050
0.075
0.100
Area
Source: midwest
state
IL
IN
MI
OH
WI
popdensity
20000
40000
60000
80000

Scatterplot With Encircling

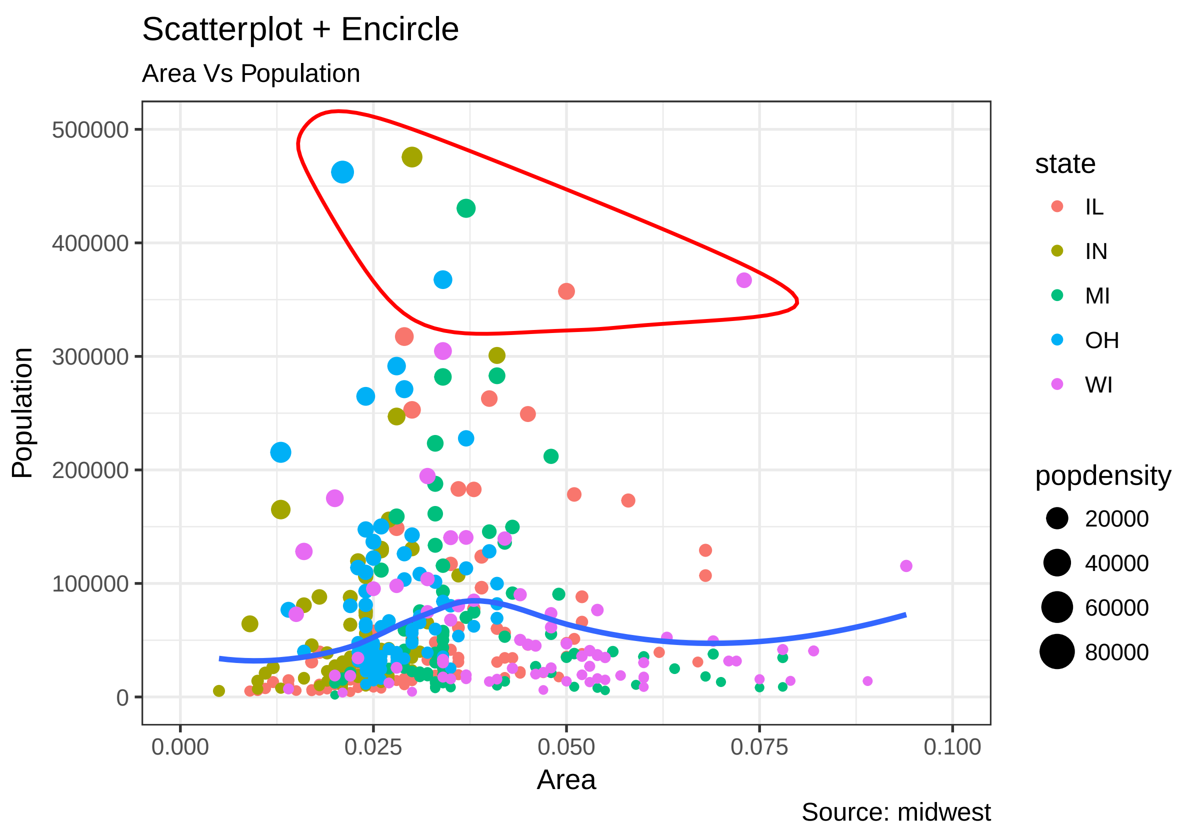
When presenting the results, sometimes I would encirlce certain special group of points or region in the chart so as to draw the attention to those peculiar cases. This can be conveniently done using the `geom_encircle()` in ggalt package.

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")
```

```
## Warning: Removed 15 rows containing non-finite values (stat_smooth).
```

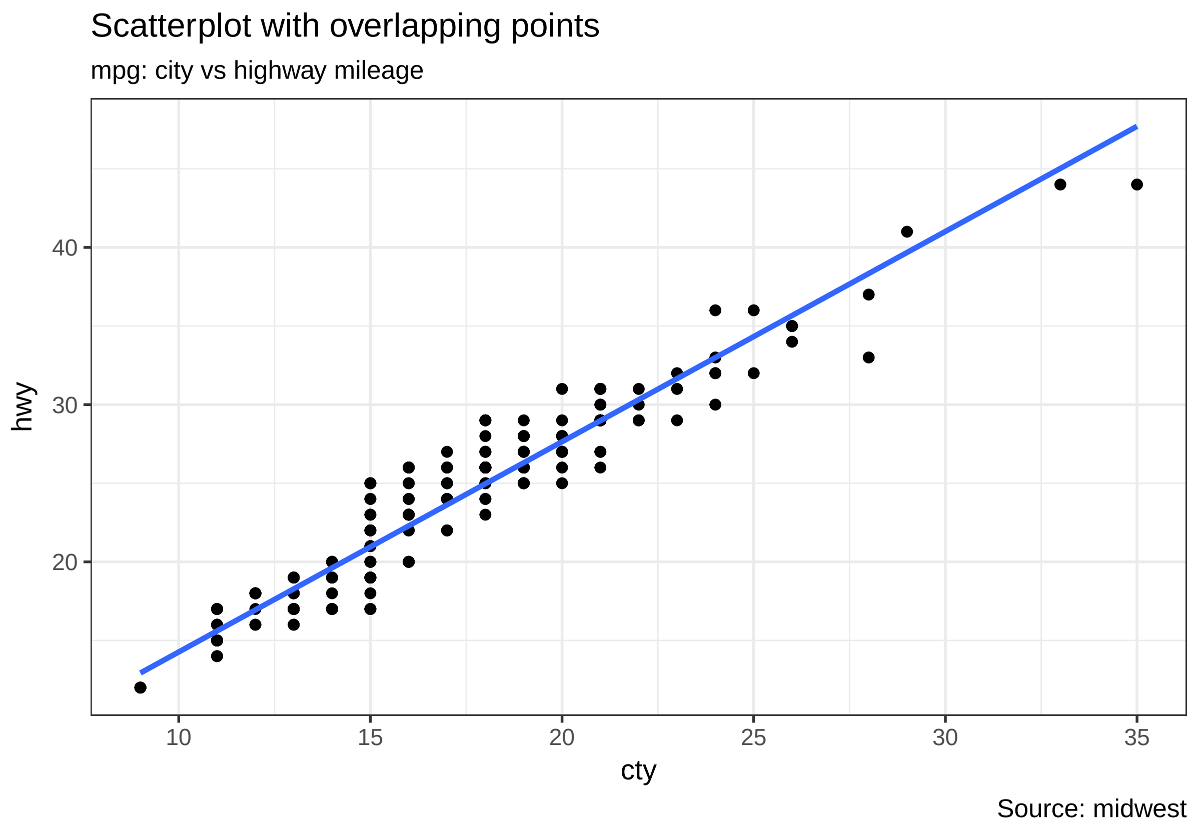
```
## Warning: Removed 15 rows containing missing values (geom_point).
```


Scatterplot + Encircle
Area Vs Population
Population
500000
400000
300000
200000
100000
0
0.000
0.025
0.050
0.075
0.100
Area
state
IL
IN
MI
OH
WI
popdensity
20000
40000
60000
80000
Source: midwest

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?

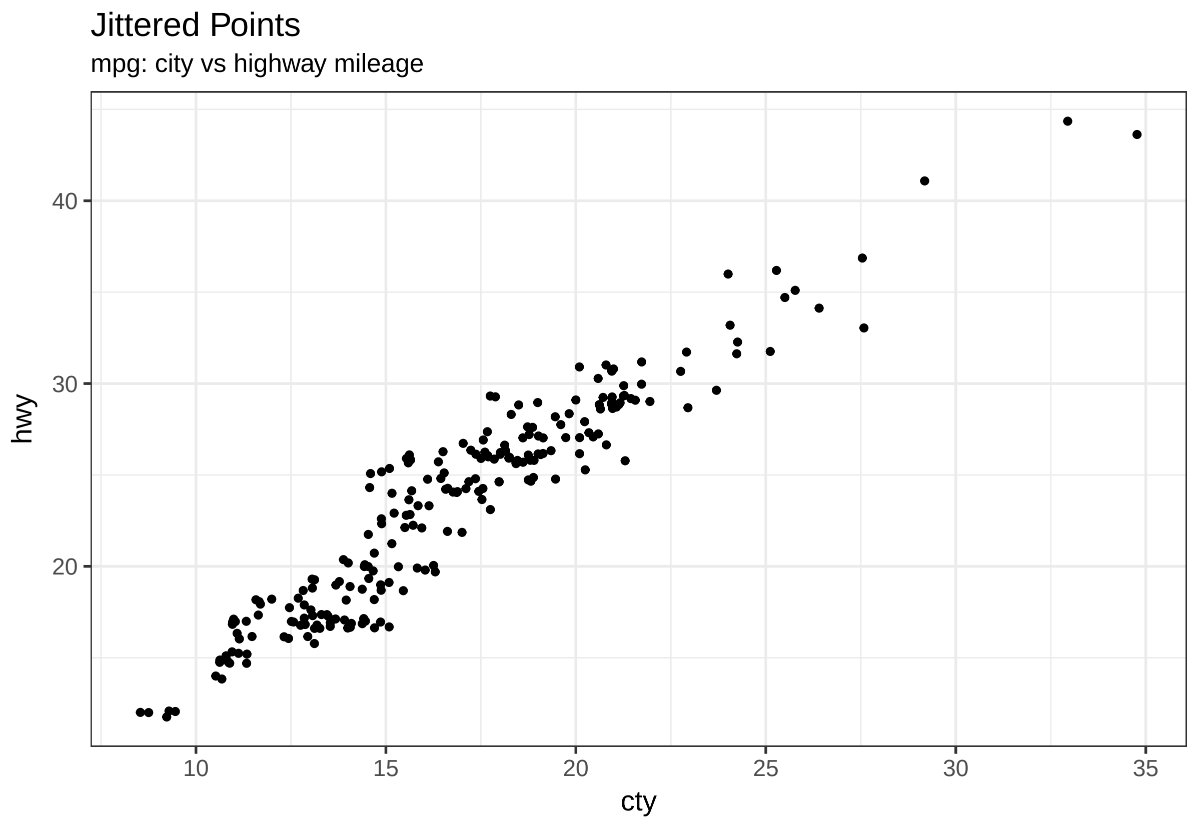
```
dim(mpg)
```

```
## [1] 234  11
```

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")
```

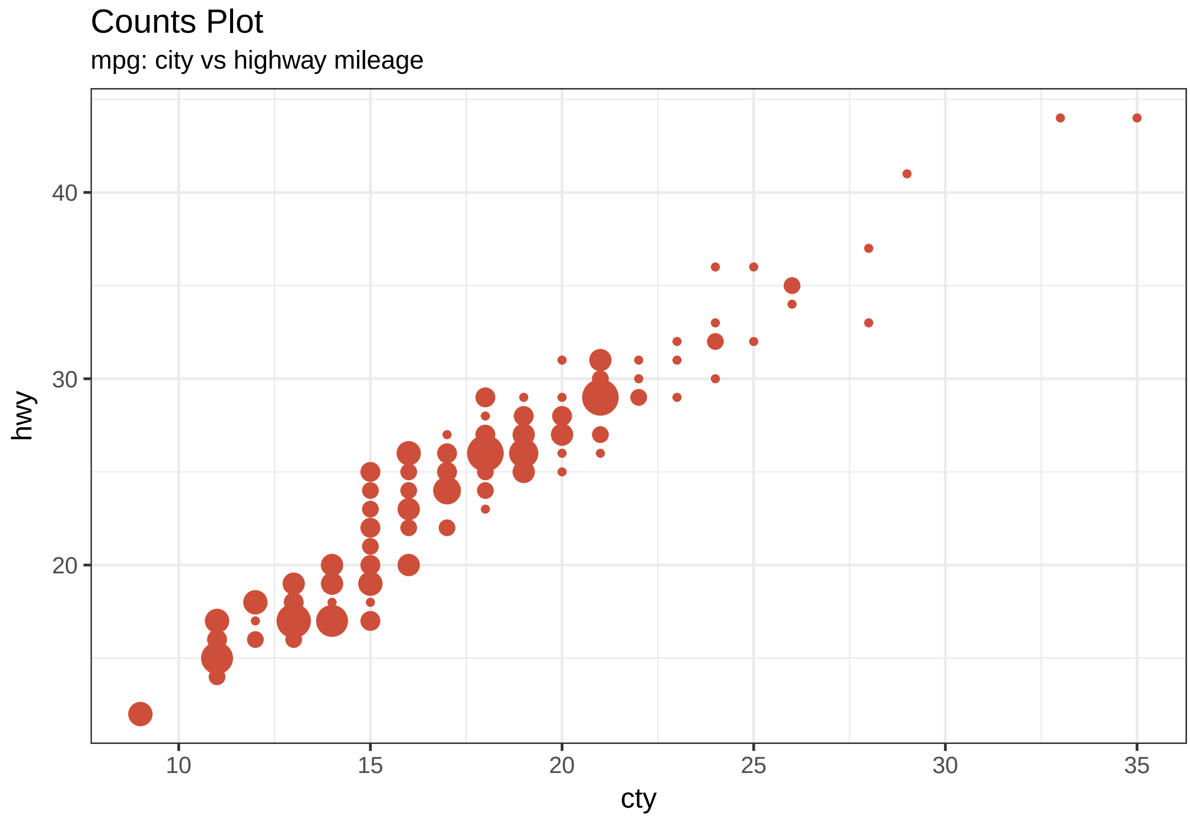


More points are revealed now. More the width, more the points are moved jittered from their original position.

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")
```



Bubble plot

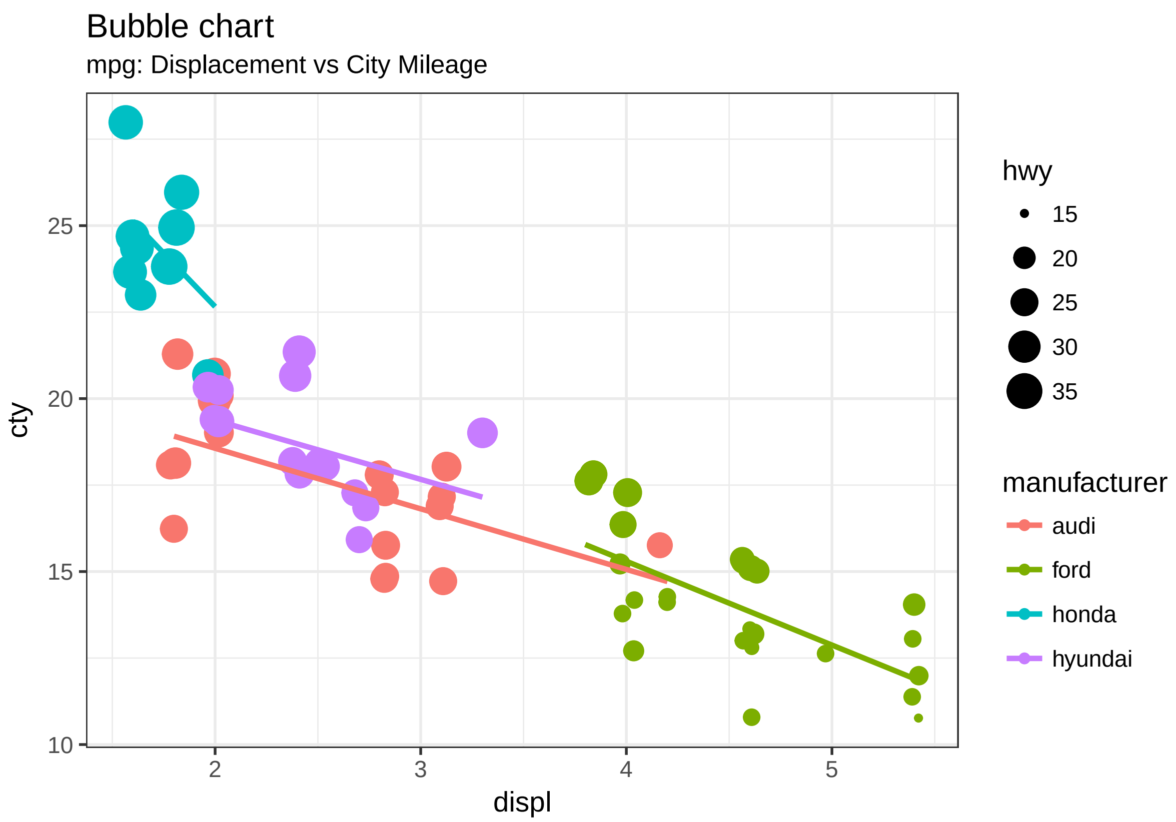
While scatterplot lets you compare the relationship between 2 continuous variables, bubble chart serves well if you want to understand relationship within the underlying groups based on:

> A Categorical variable (by changing the color) and 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)
```

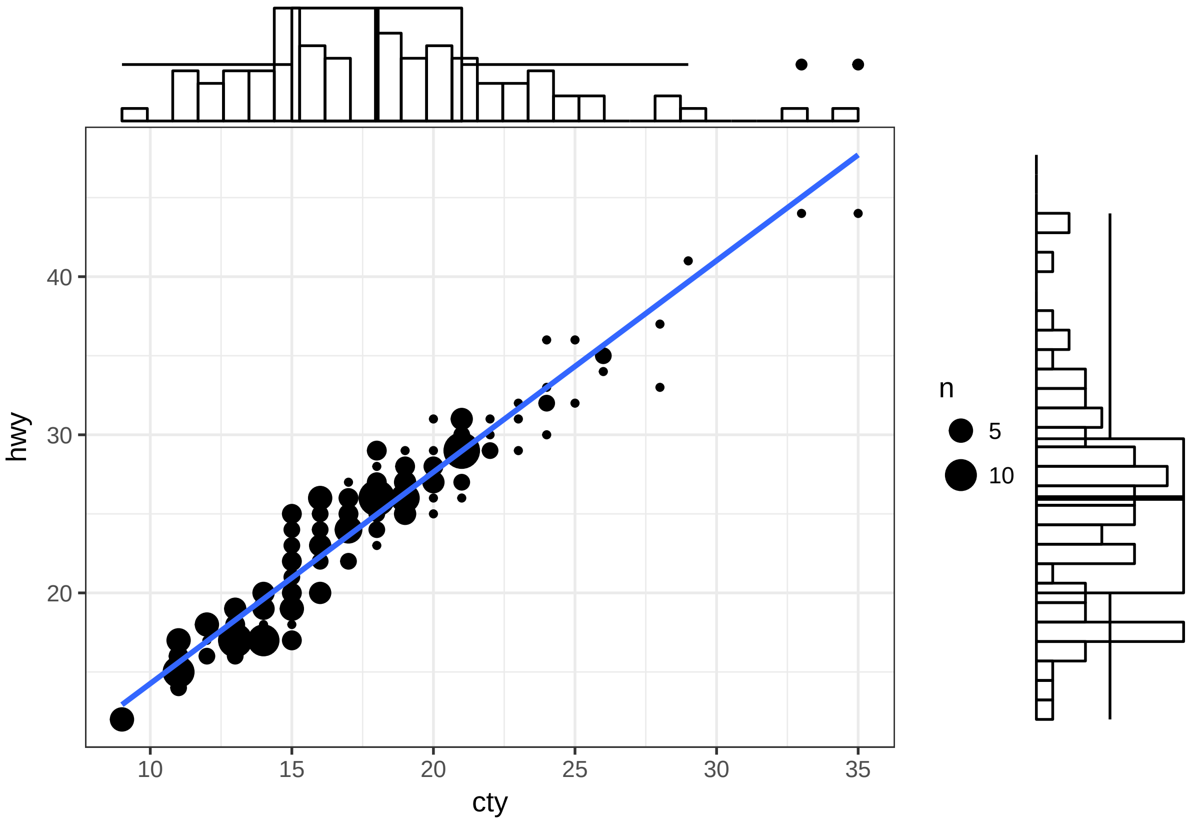


Marginal Histogram / Boxplot

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")
```

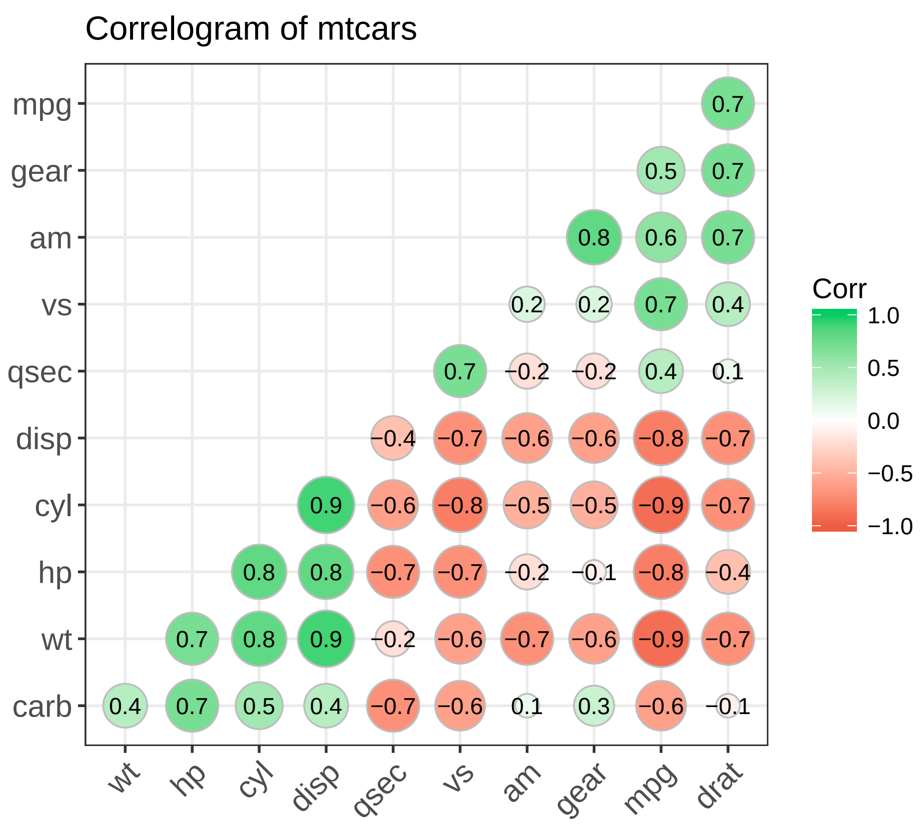



```
# ggMarginal(g, type = "density", fill="transparent")
```

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.

```r
# 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)
```



2. Deviation

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

Diverging bars

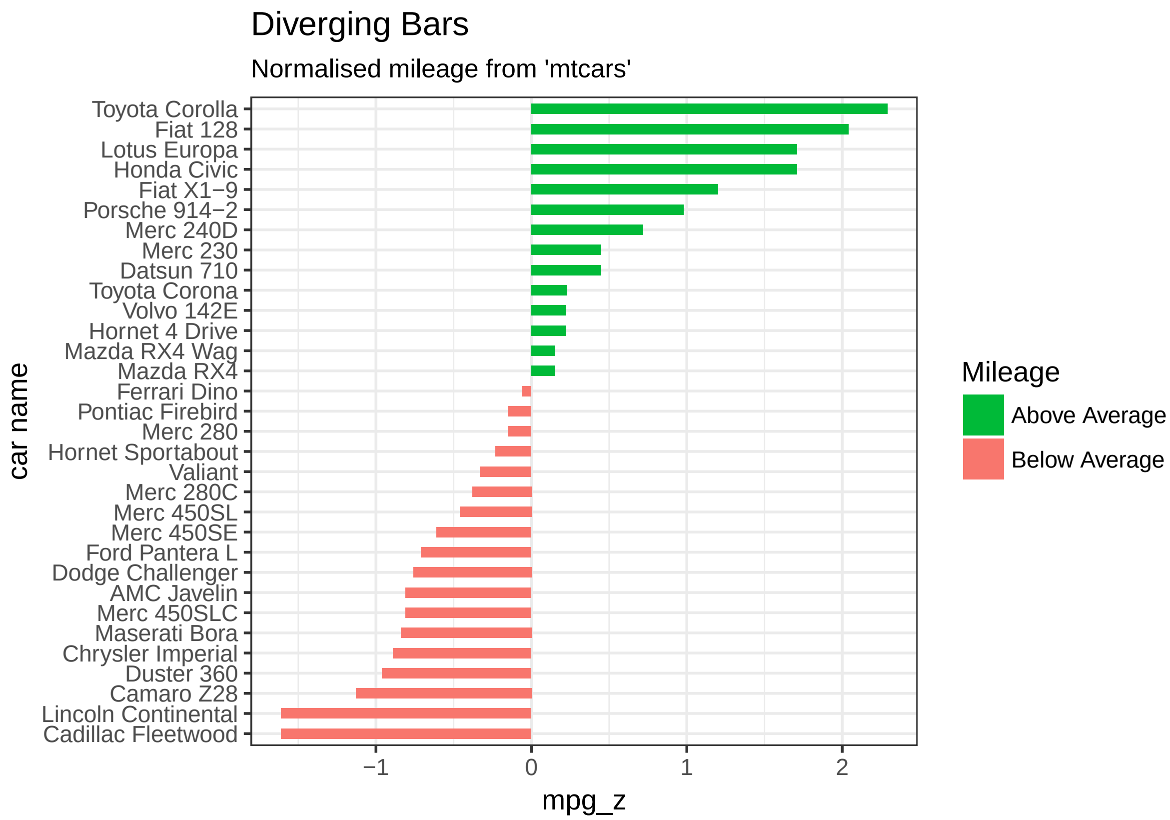
Diverging Bars is a bar chart that can handle both negative and positive values. This can be implemented by a smart tweak with `geom_bar()`. But the usage of `geom_bar()` can be quite confusing. Thats because, it can be used to make a bar chart as well as a histogram. Let me explain.

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.

> Set `stat=identity` 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()
```

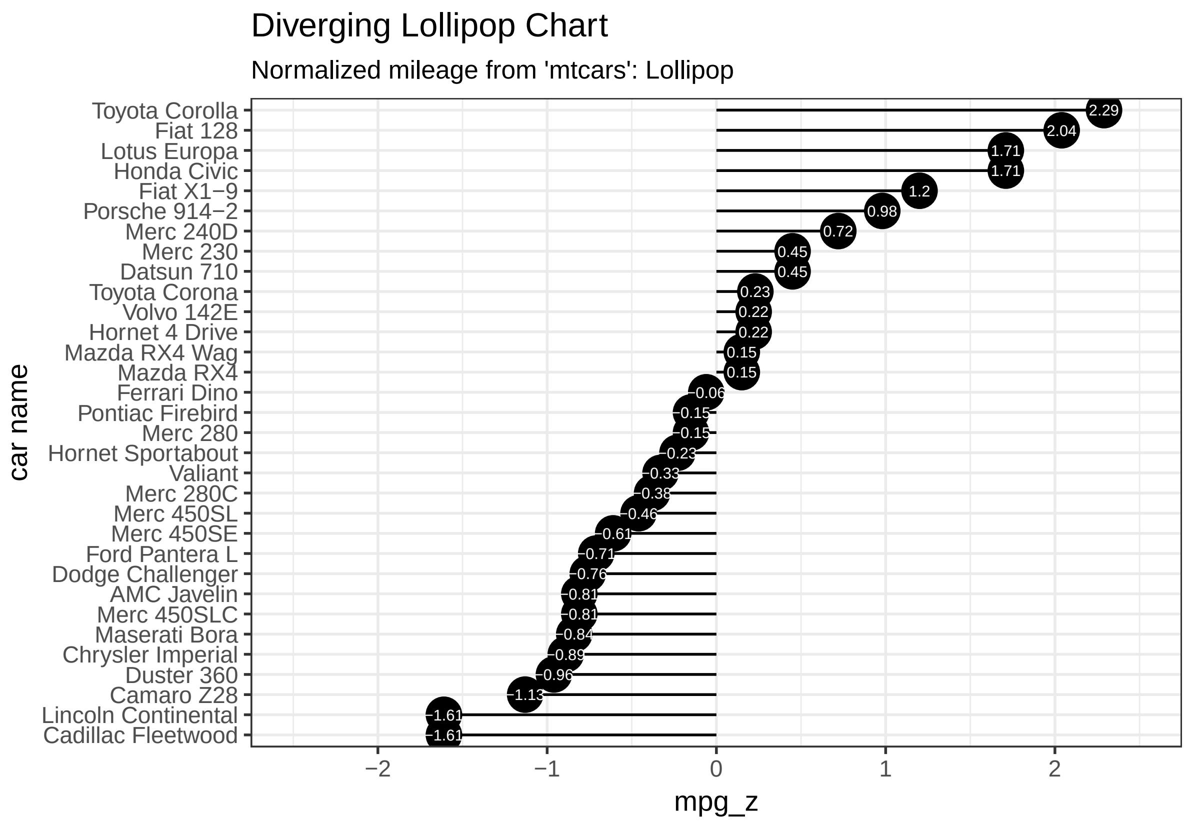


Diverging Bars
Normalised mileage from 'mtcars'
Toyota Corolla
Fiat 128
Lotus Europa
Honda Civic
Fiat X1−9
Porsche 914−2
Merc 240D
Merc 230
Datsun 710
Toyota Corona
Volvo 142E
Hornet 4 Drive
Mazda RX4 Wag
Mazda RX4
Ferrari Dino
Pontiac Firebird
Merc 280
Hornet Sportabout
Valiant
Merc 280C
Merc 450SL
Merc 450SE
Ford Pantera L
Dodge Challenger
AMC Javelin
Merc 450SLC
Maserati Bora
Chrysler Imperial
Duster 360
Camaro Z28
Lincoln Continental
Cadillac Fleetwood
car name
−1
0
1
2
mpg_z
Mileage
Above Average
Below Average

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.

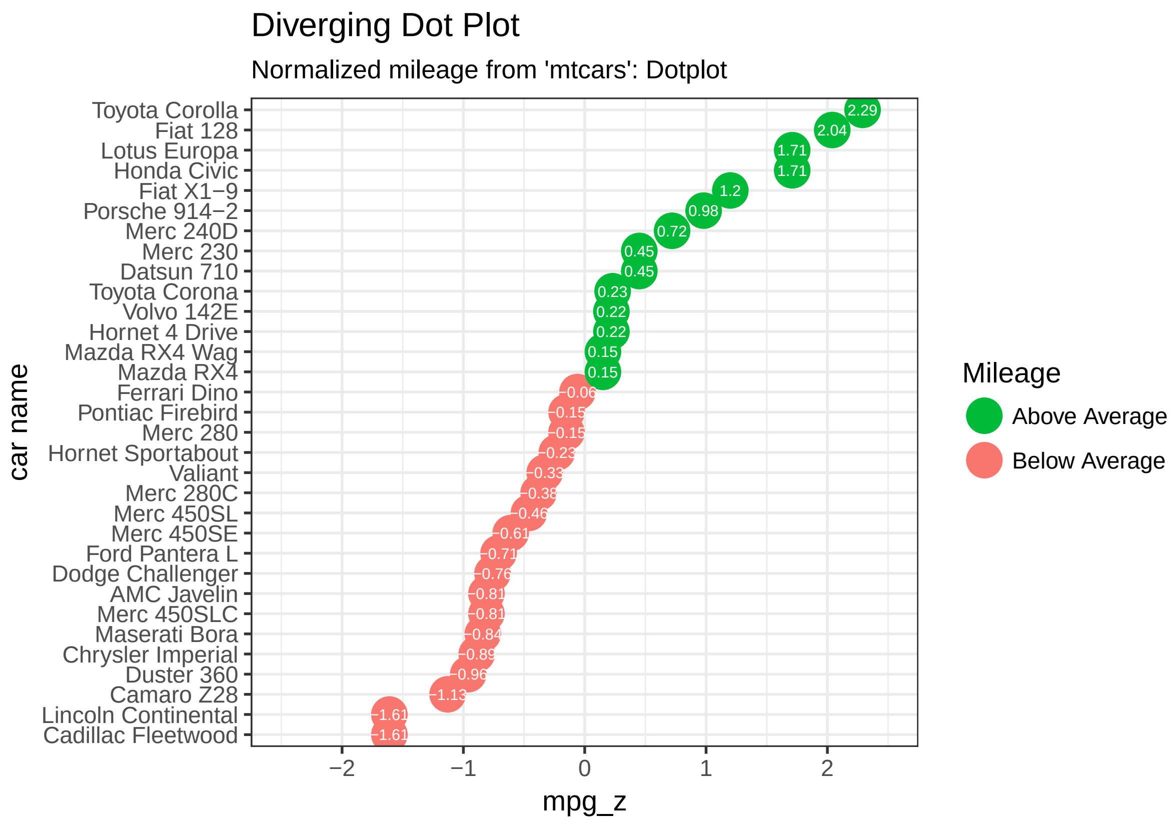
```
library(ggplot2)
theme_set(theme_bw())

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()
```



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()
```



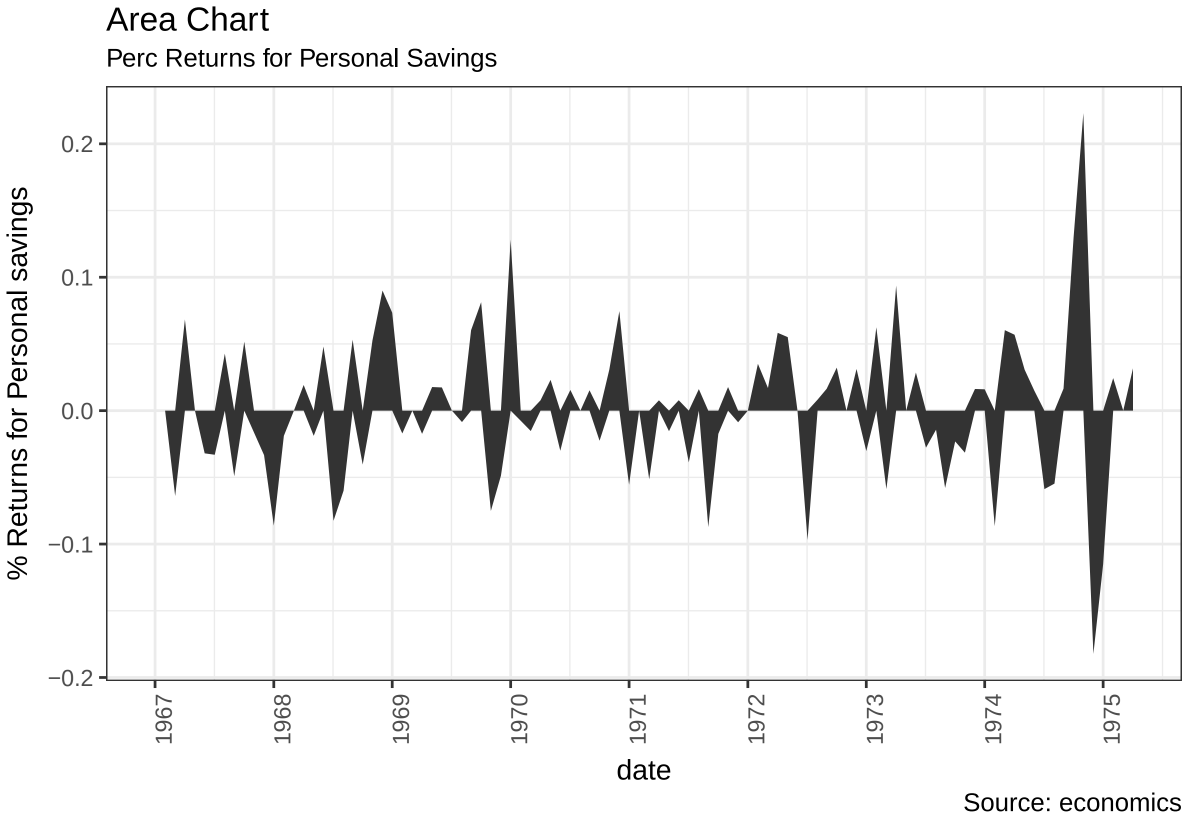
Area Chart

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)
```

```
## Loading required package: xts

## Loading required package: zoo

##
## Attaching package: 'zoo'

## The following objects are masked from 'package:base':
##
##     as.Date, as.Date.numeric

## Loading required package: TTR

## Version 0.4-0 included new data defaults. See ?getSymbols.
```

```
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")
```


Area Chart
Perc Returns for Personal Savings
0.2
0.1
0.0
−0.1
−0.2
% Returns for Personal savings
1967
1968
1969
1970
1971
1972
1973
1974
1975
date
Source: economics

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.

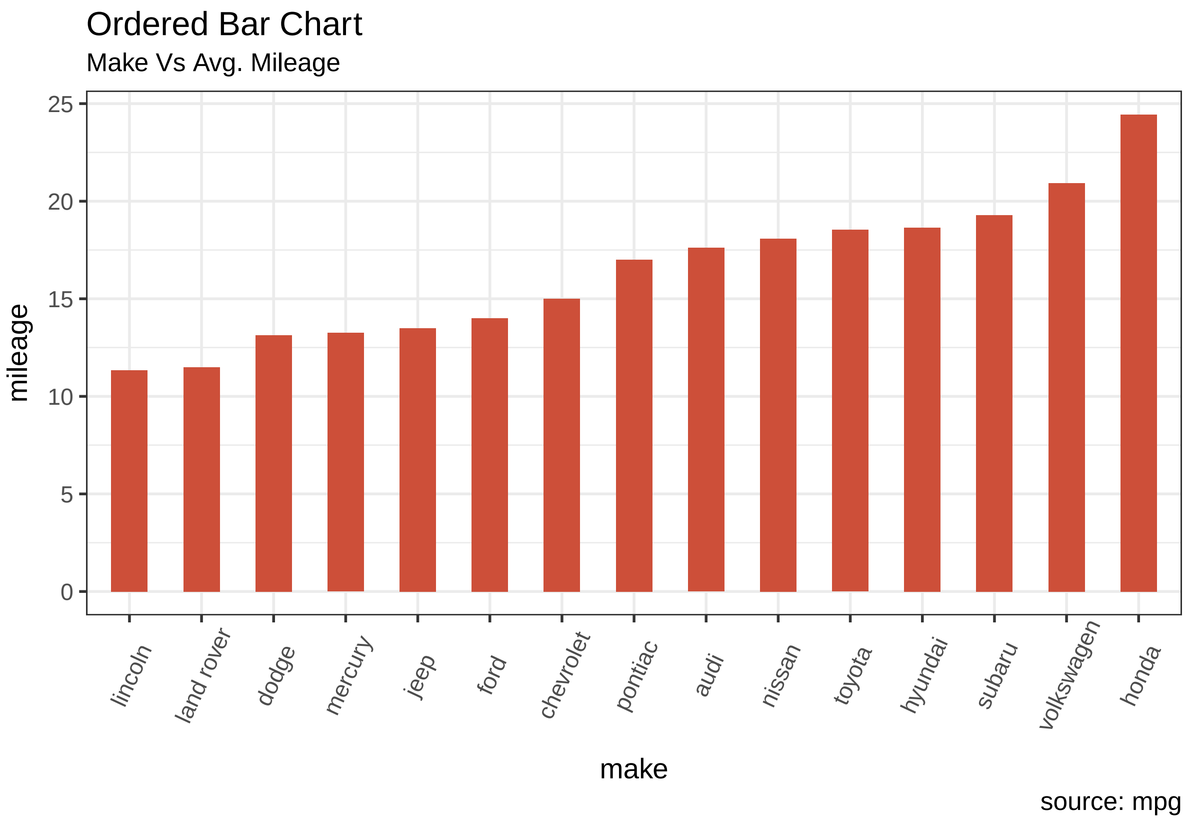
Let's see how that is done.

```
# 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.

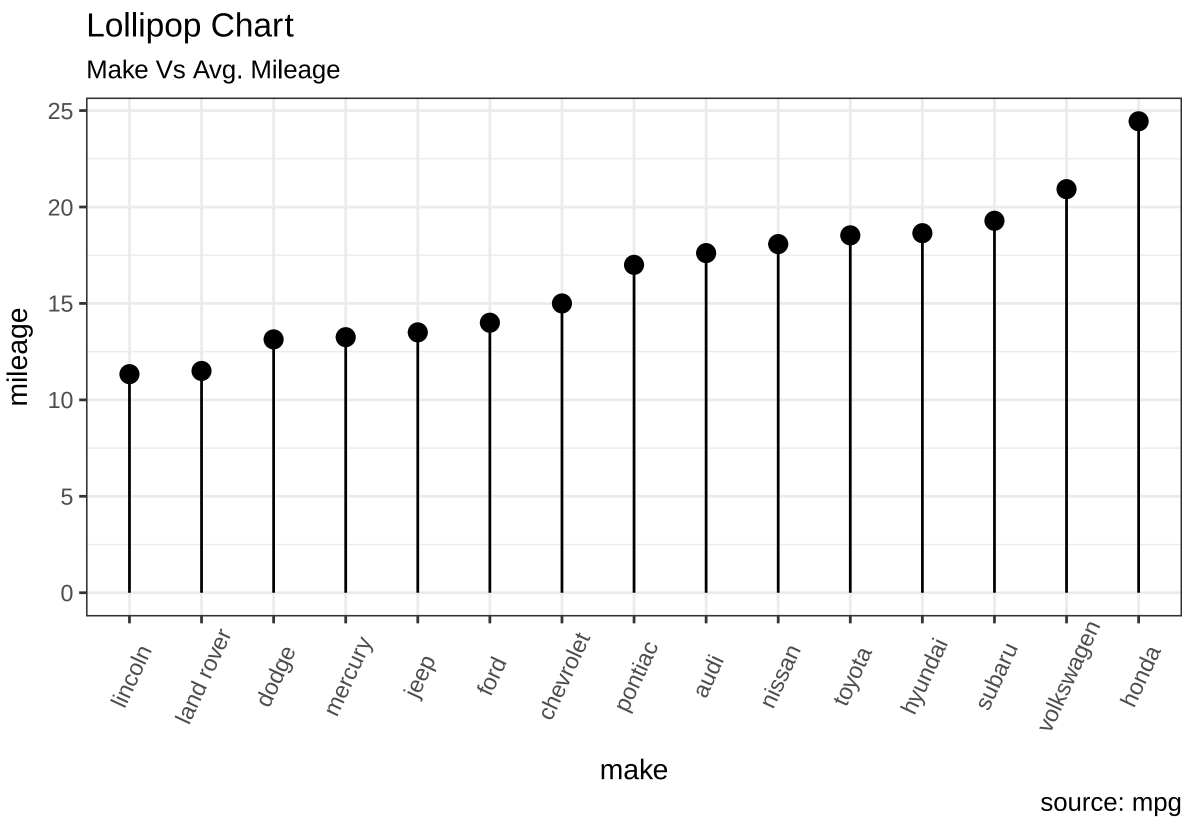
```
library(ggplot2)
theme_set(theme_bw())

# 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))
```


Ordered Bar Chart
Make Vs Avg. Mileage
mileage
0
5
10
15
20
25
lincoln
land rover
dodge
mercury
jeep
ford
chevrolet
pontiac
audi
nissan
toyota
hyundai
subaru
volkswagen
honda
make
source: mpg

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.

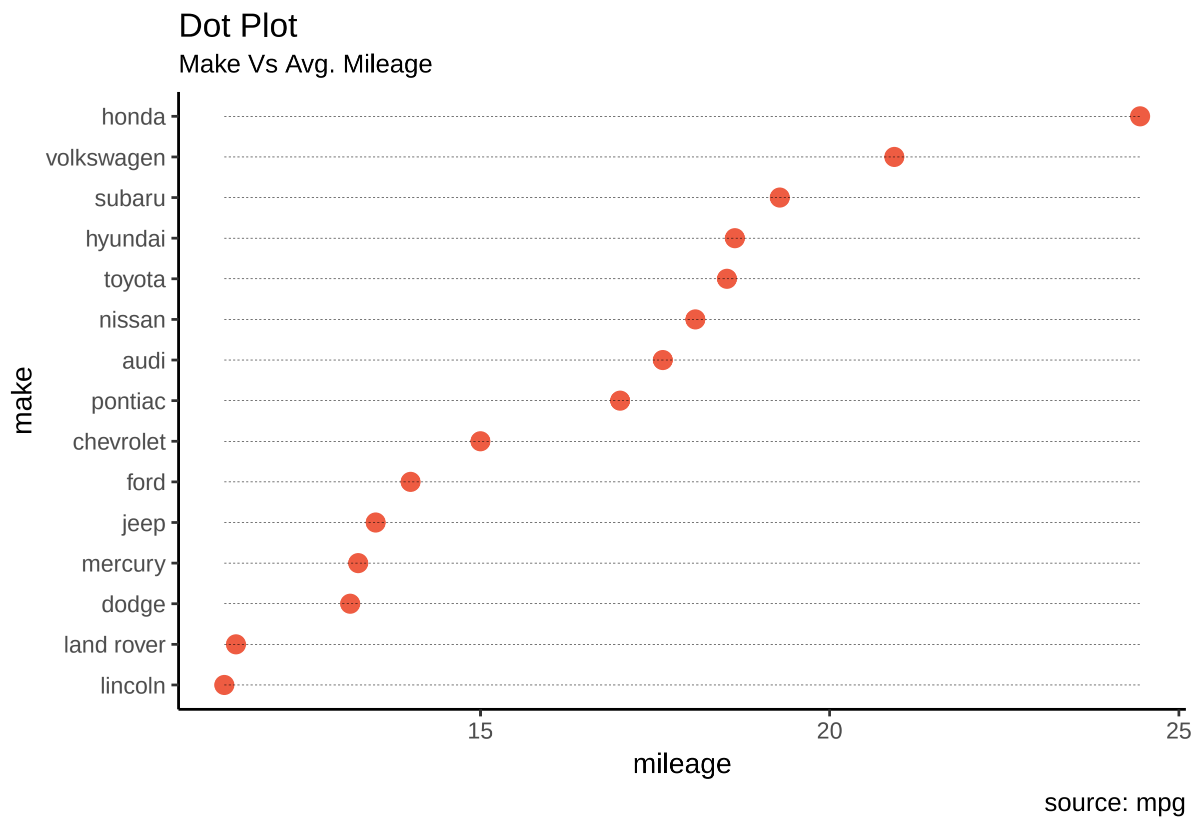
```r
library(ggplot2)
theme_set(theme_bw())

# 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))
```



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.

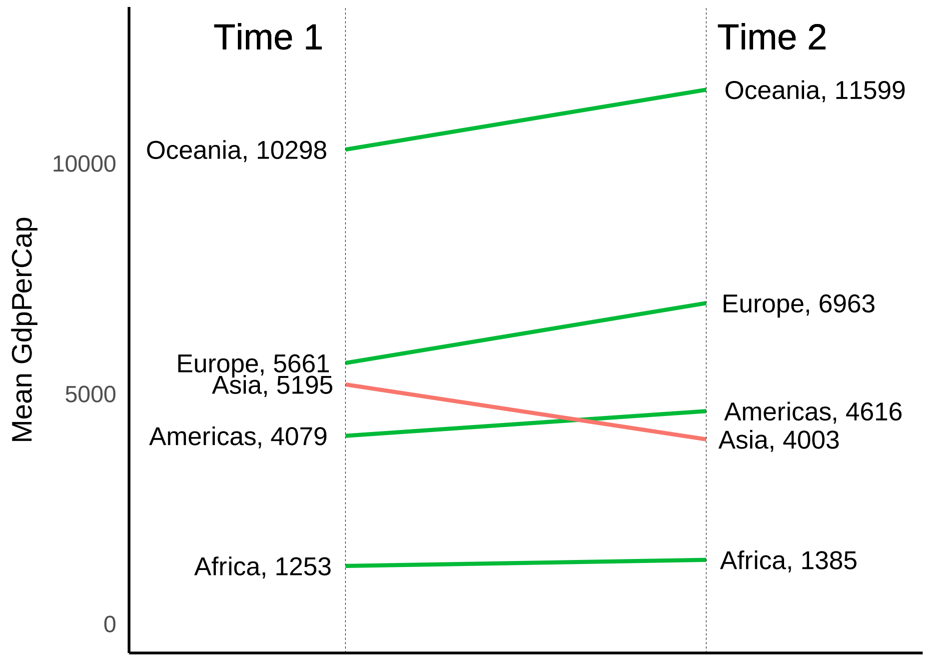
```
library(ggplot2)
library(scales)
theme_set(theme_classic())

# 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()
```



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.

```r
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"))
```



Time 1
Time 2
Mean GdpPerCap
10000
5000
0
Oceania, 10298
Europe, 5661
Asia, 5195
Americas, 4079
Africa, 1253
Oceania, 11599
Europe, 6963
Americas, 4616
Asia, 4003
Africa, 1385

Dumbbell Plot

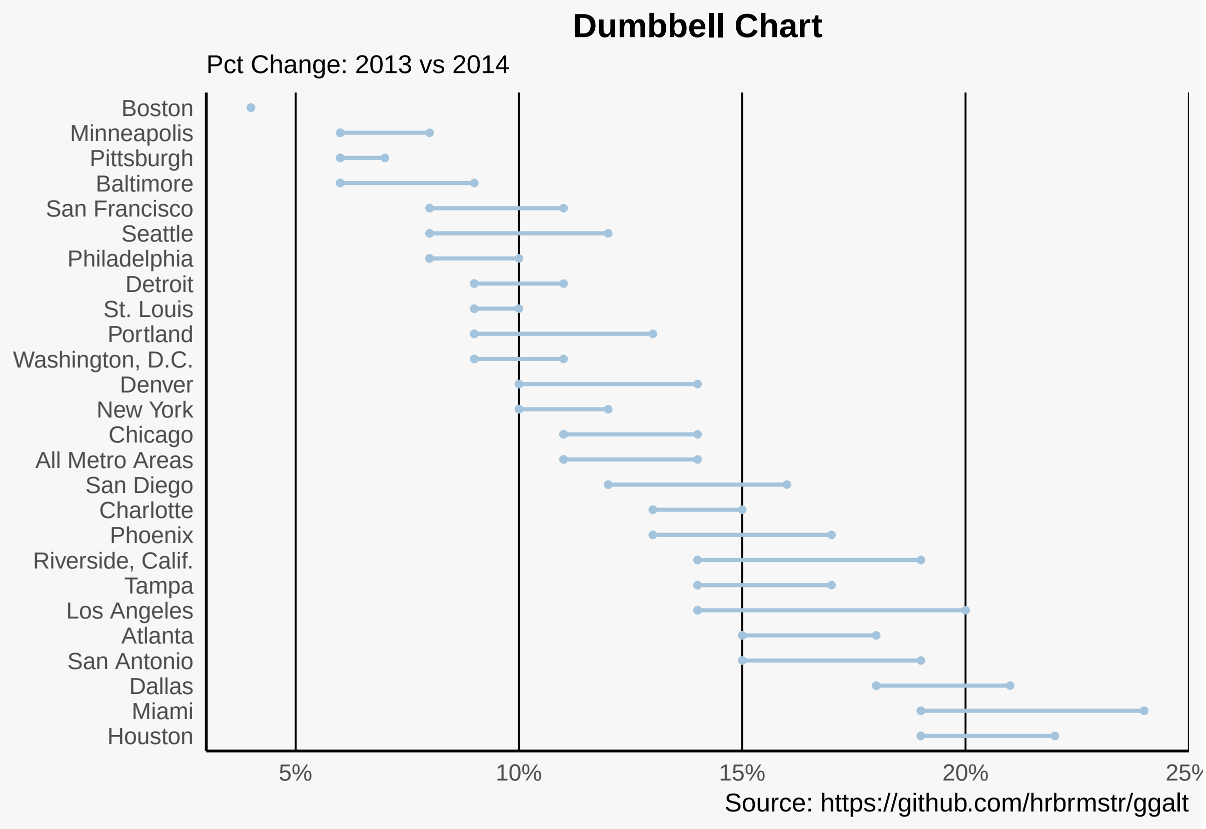
Dumbbell charts are a great tool if you wish to: 1. Visualize relative positions (like growth and decline) between two points in time. 2. Compare distance between two categories.

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())
```

```
## Warning: Ignoring unknown parameters: point.colour.l
```

```
plot(gg)
```


Dumbbell Chart
Pct Change: 2013 vs 2014
Boston
Minneapolis
Pittsburgh
Baltimore
San Francisco
Seattle
Philadelphia
Detroit
St. Louis
Portland
Washington, D.C.
Denver
New York
Chicago
All Metro Areas
San Diego
Charlotte
Phoenix
Riverside, Calif.
Tampa
Los Angeles
Atlanta
San Antonio
Dallas
Miami
Houston
5%
10%
15%
20%
25%
Source: https://github.com/hrbrmstr/ggalt

4. Distribution

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

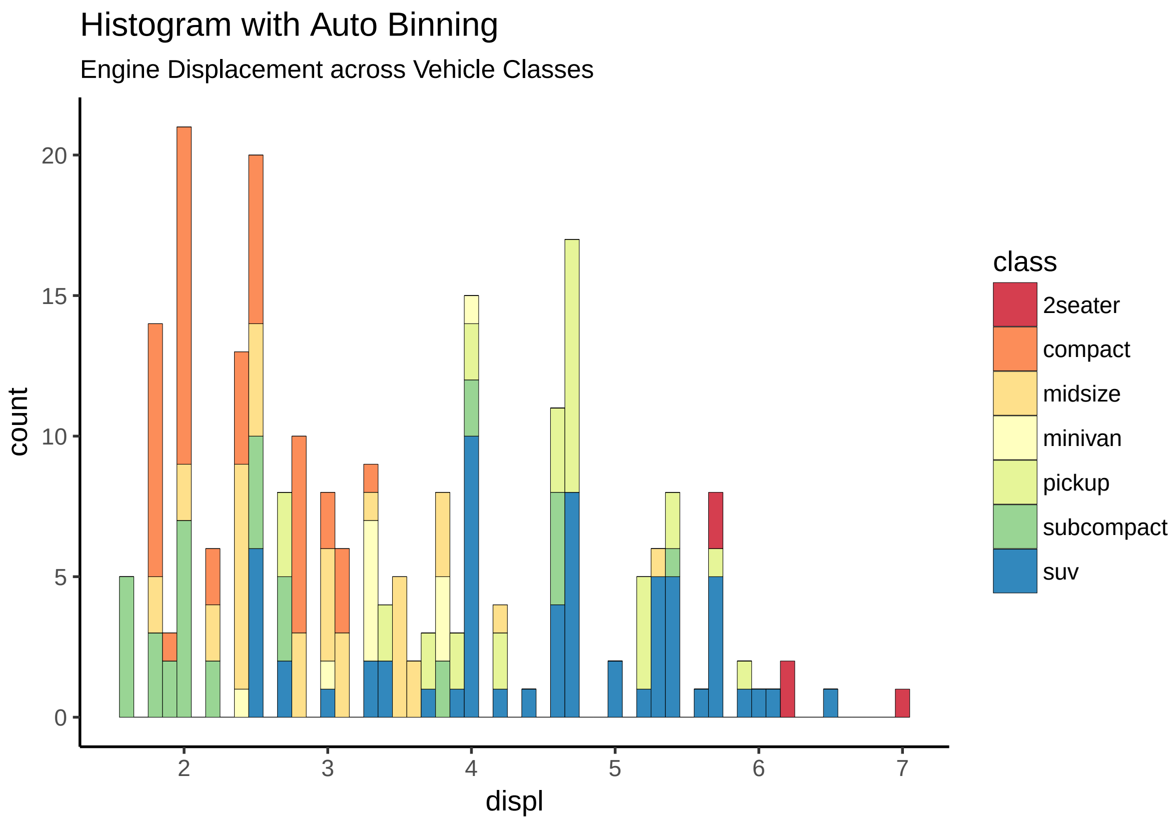
Histogram

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

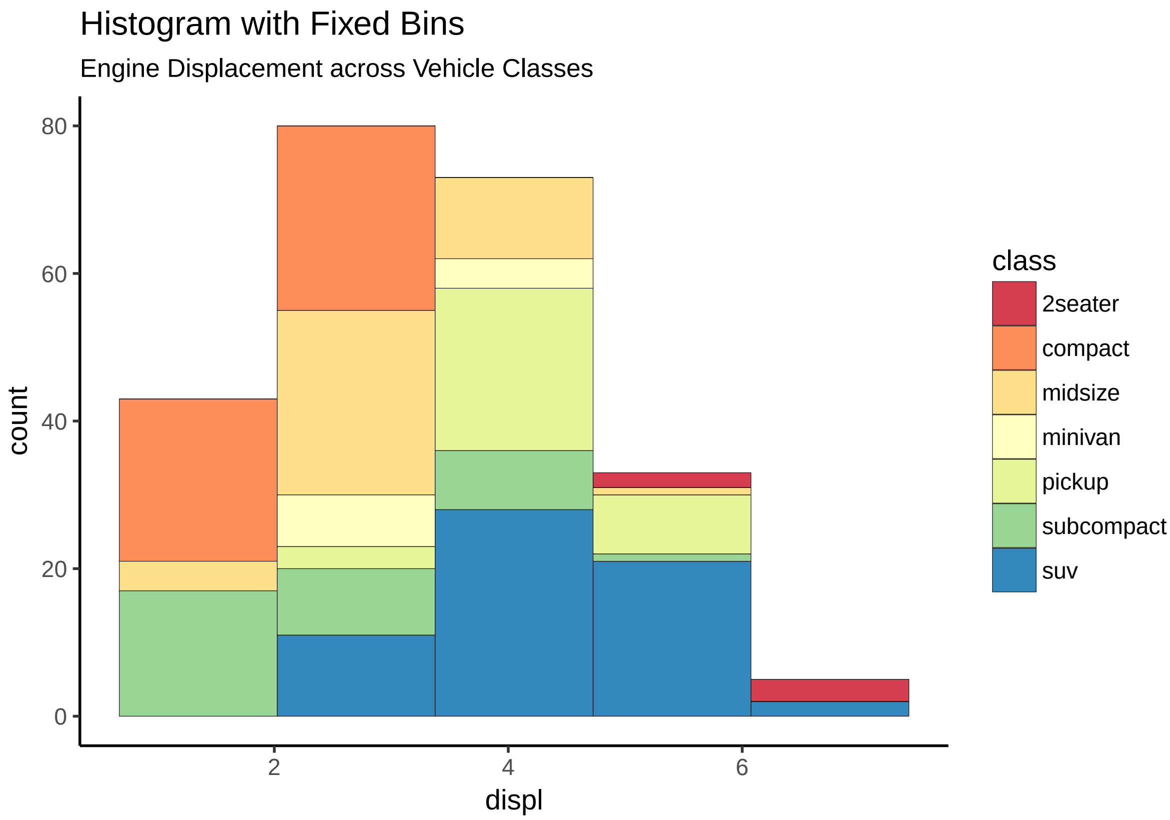
Histogram on a continuous variable can be accomplished using either `geom_bar()` or `geom_histogram()`. When using `geom_histogram()`, you can control the number of bars using the bins option. Else, you can set the range covered by each bin using binwidth. The value of binwidth is on the same scale as 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
```

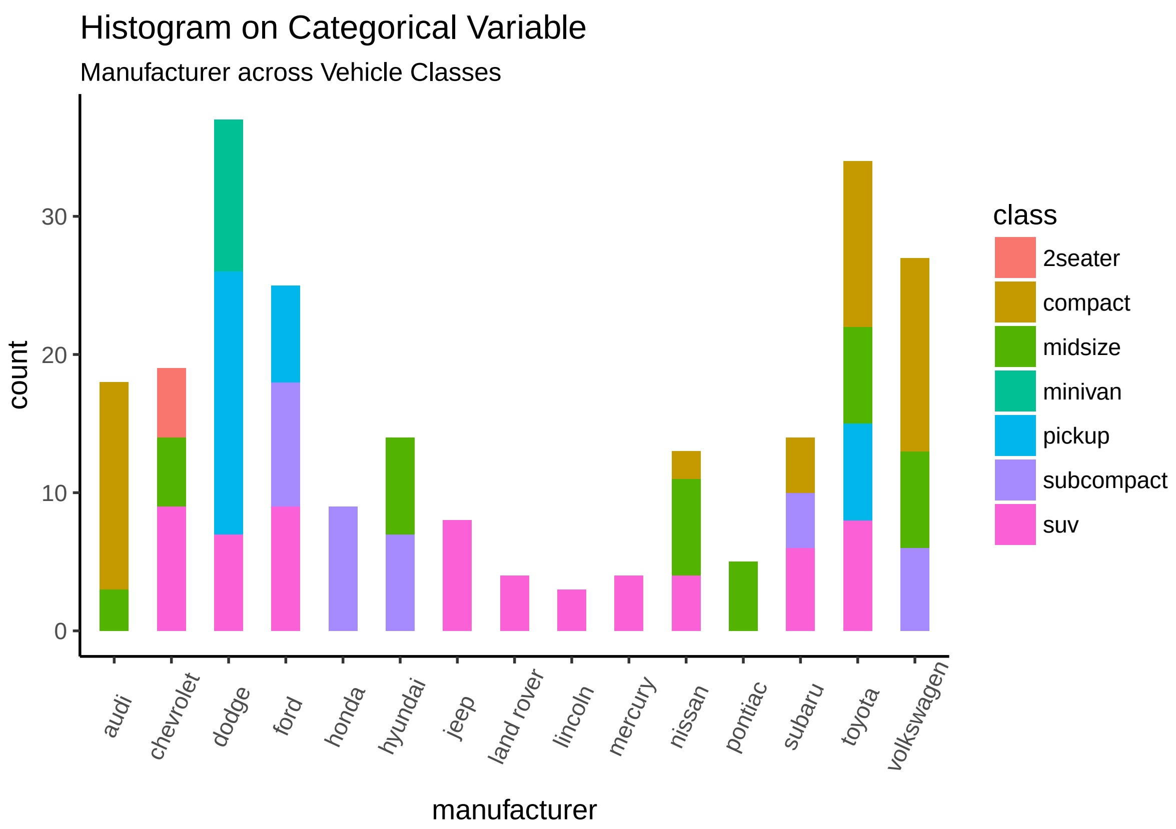
```r
  labs(title="Histogram with Fixed Bins",
       subtitle="Engine Displacement across Vehicle Classes")
```



Histogram on a categorical variable

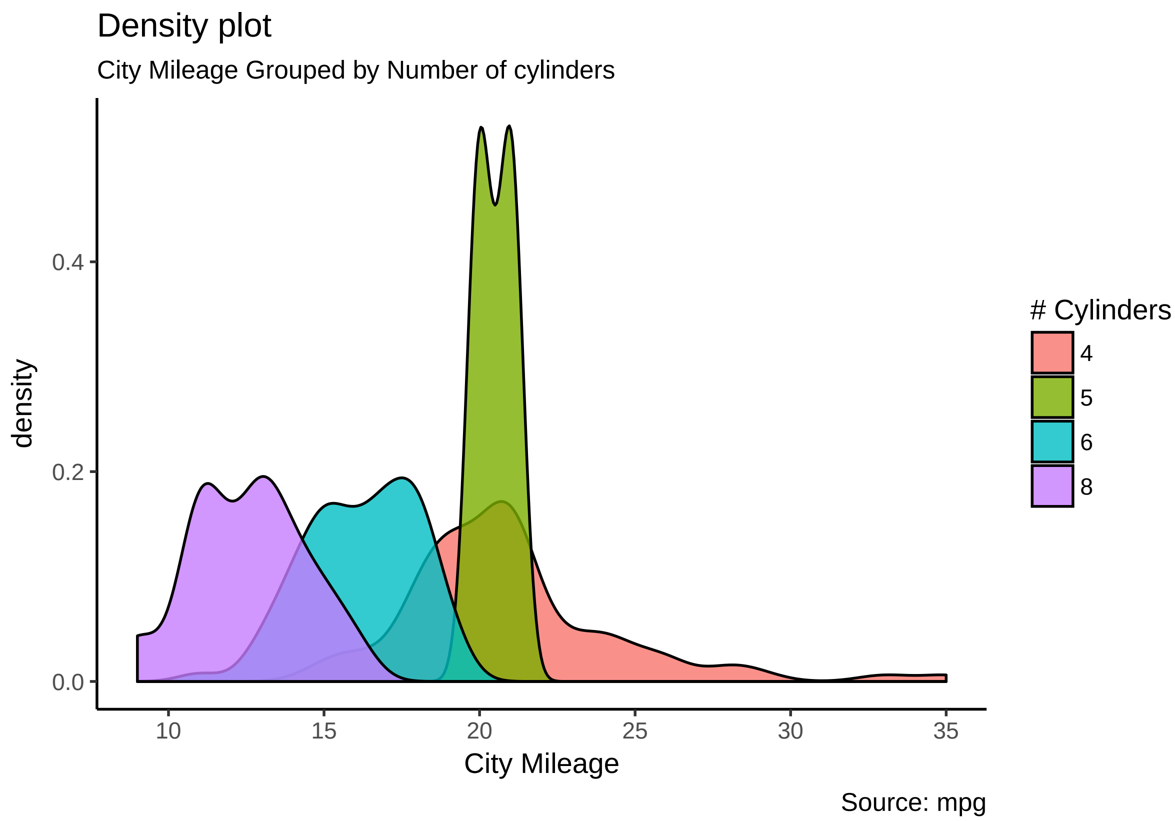
Histogram on a categorical variable would result in a frequency chart showing bars for each category. By adjusting width, you can adjust the thickness of the bars.

```
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")
```



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")
```



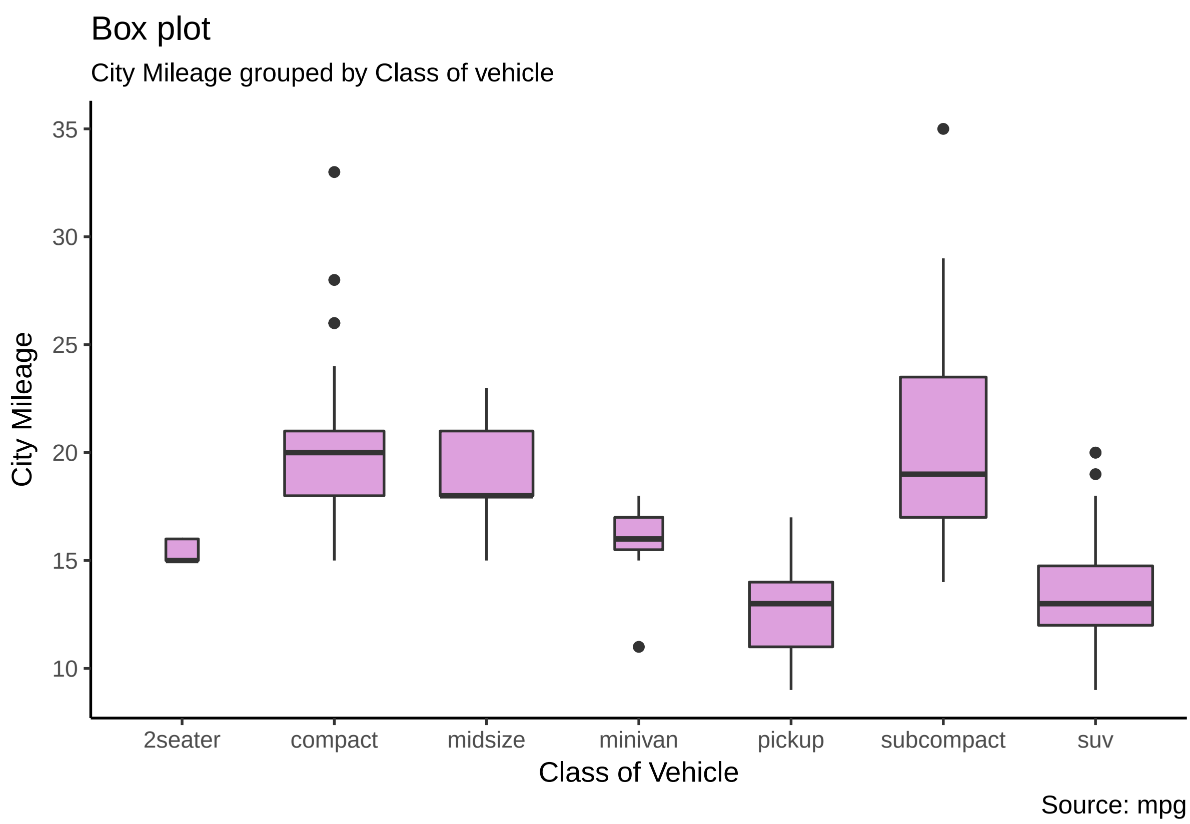
Box Plot

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.

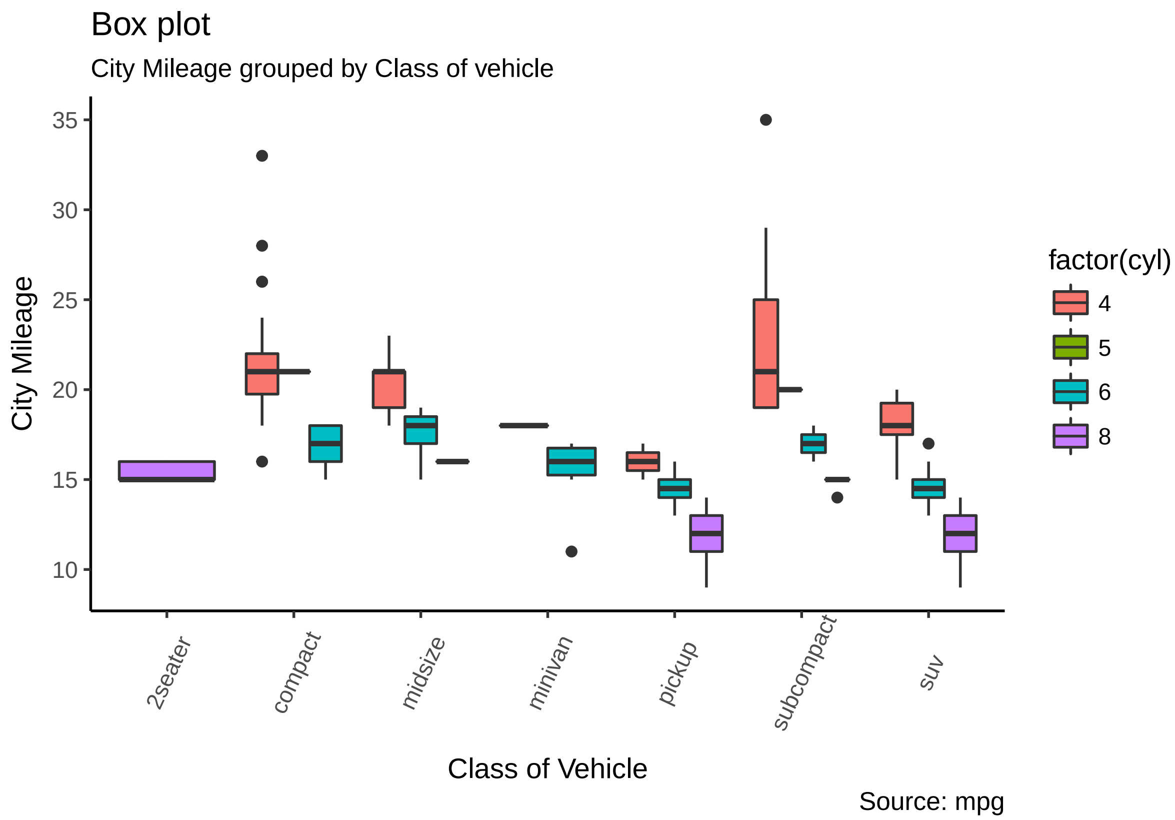
The dark line inside the box represents the median. The top of box is 75%ile and bottom of box is 25%ile. The end points of the lines (aka whiskers) is at a distance of 1.5*IQR, where IQR or Inter Quartile Range is the distance between 25th and 75th percentiles. The points outside the whiskers are marked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

```r
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")
```




```r
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")
```

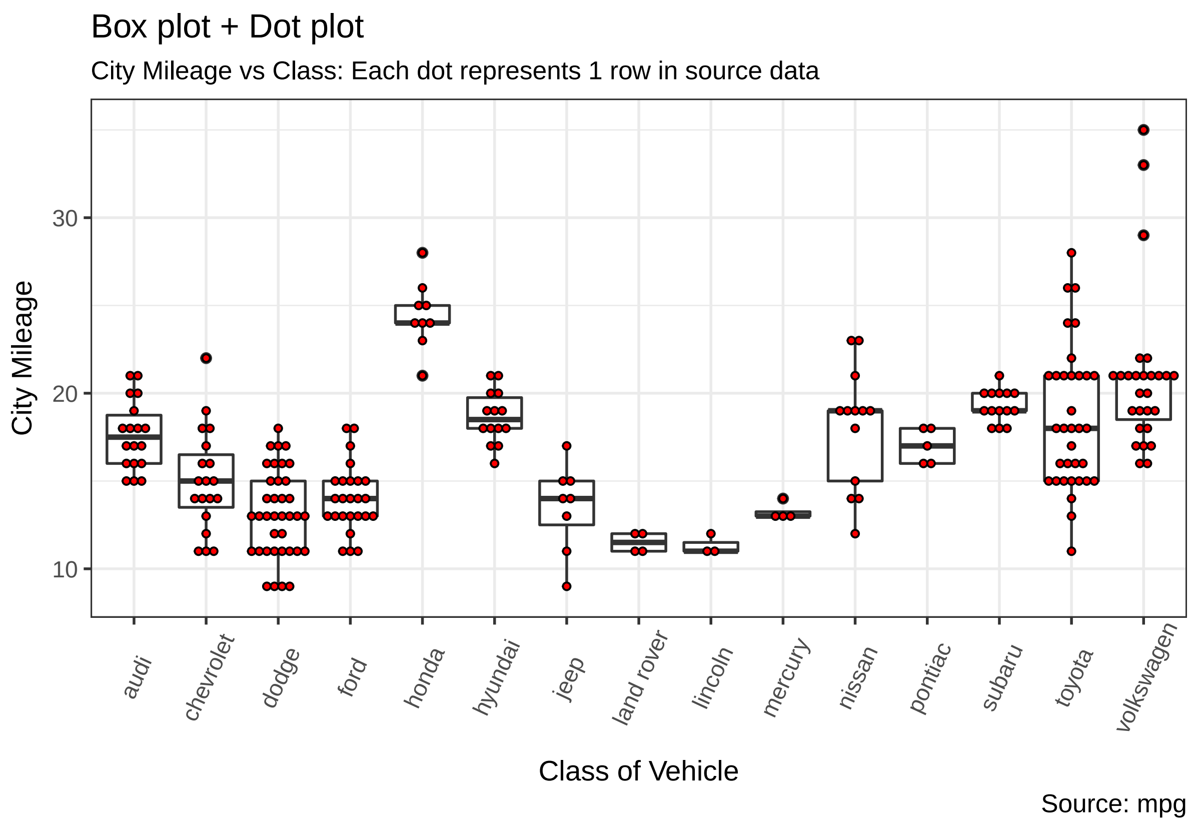

Box plot
City Mileage grouped by Class of vehicle
35
30
25
20
15
10
City Mileage
factor(cyl)
4
5
6
8
2seater
compact
midsize
minivan
pickup
subcompact
suv
Class of Vehicle
Source: mpg

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")
```

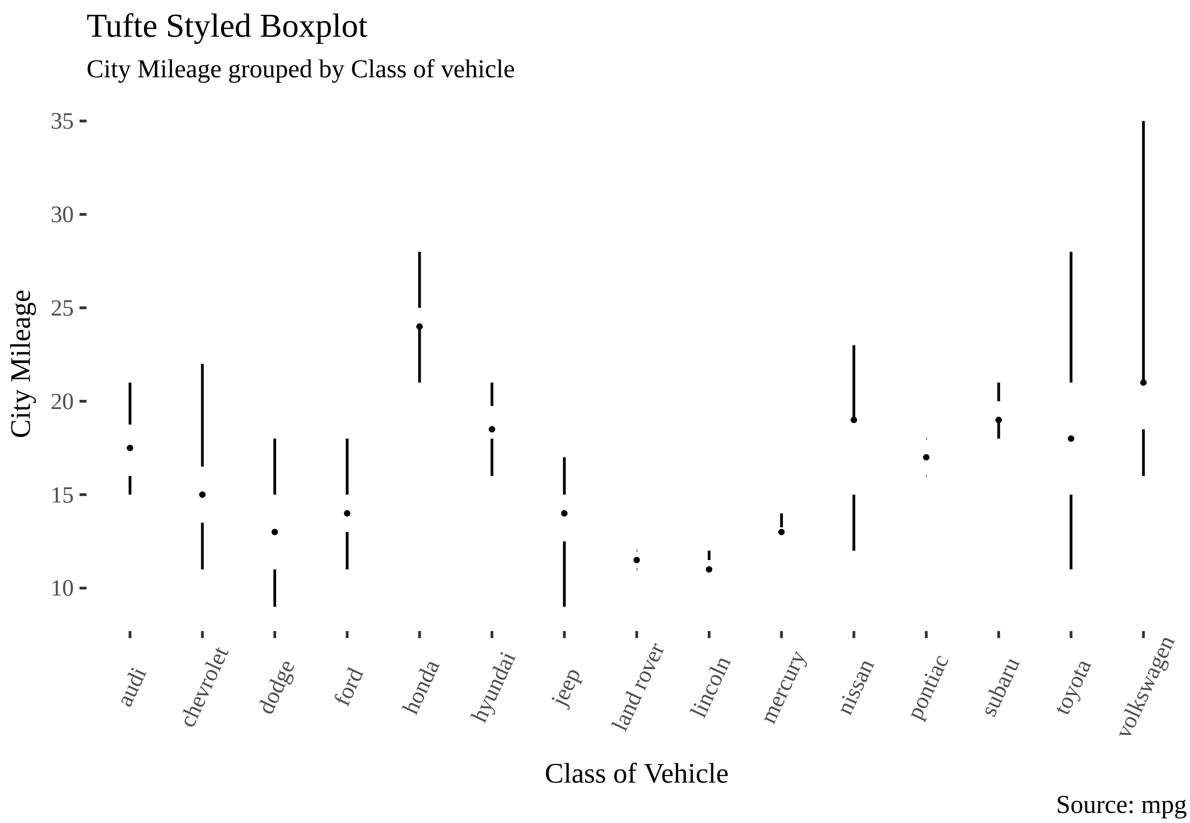
```
## `stat_bindot()` using `bins = 30`. Pick better value with `binwidth`.
```



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.

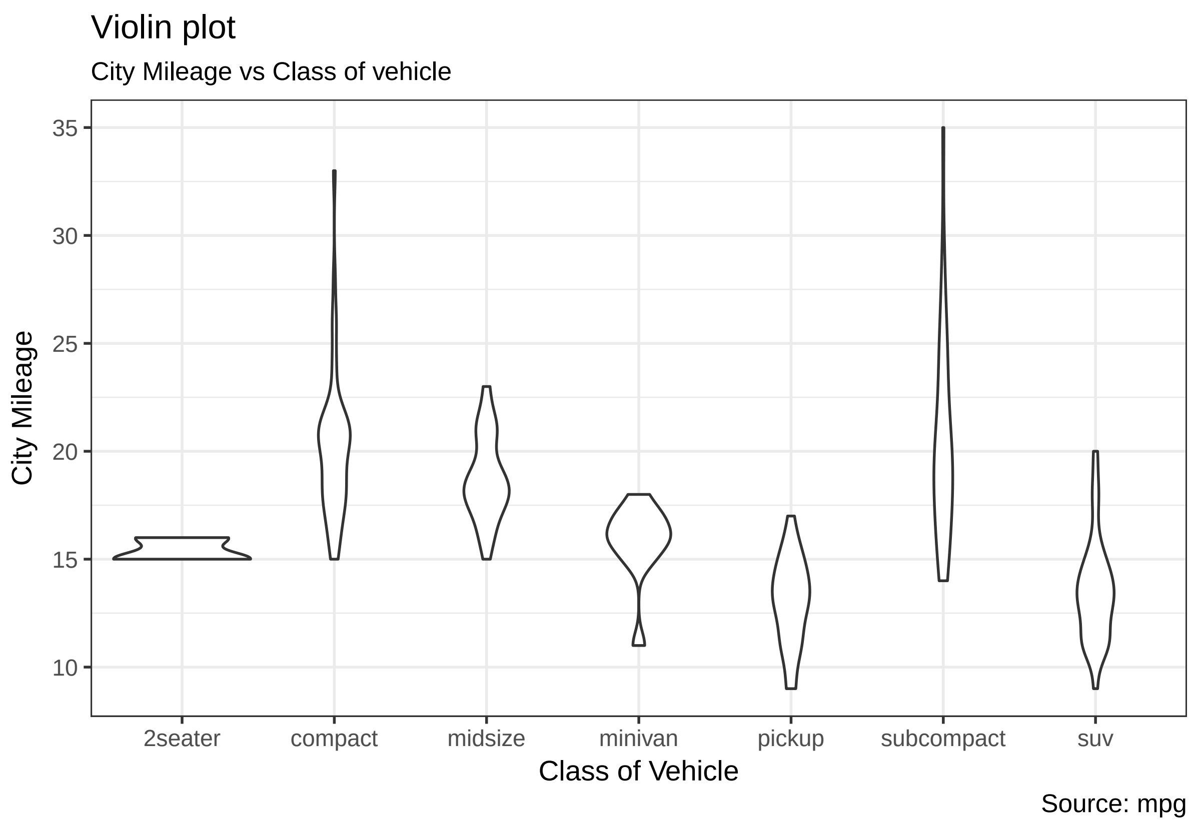
```
library(ggthemes)
library(ggplot2)
theme_set(theme_tufte())  # from ggthemes

# 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")
```



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().

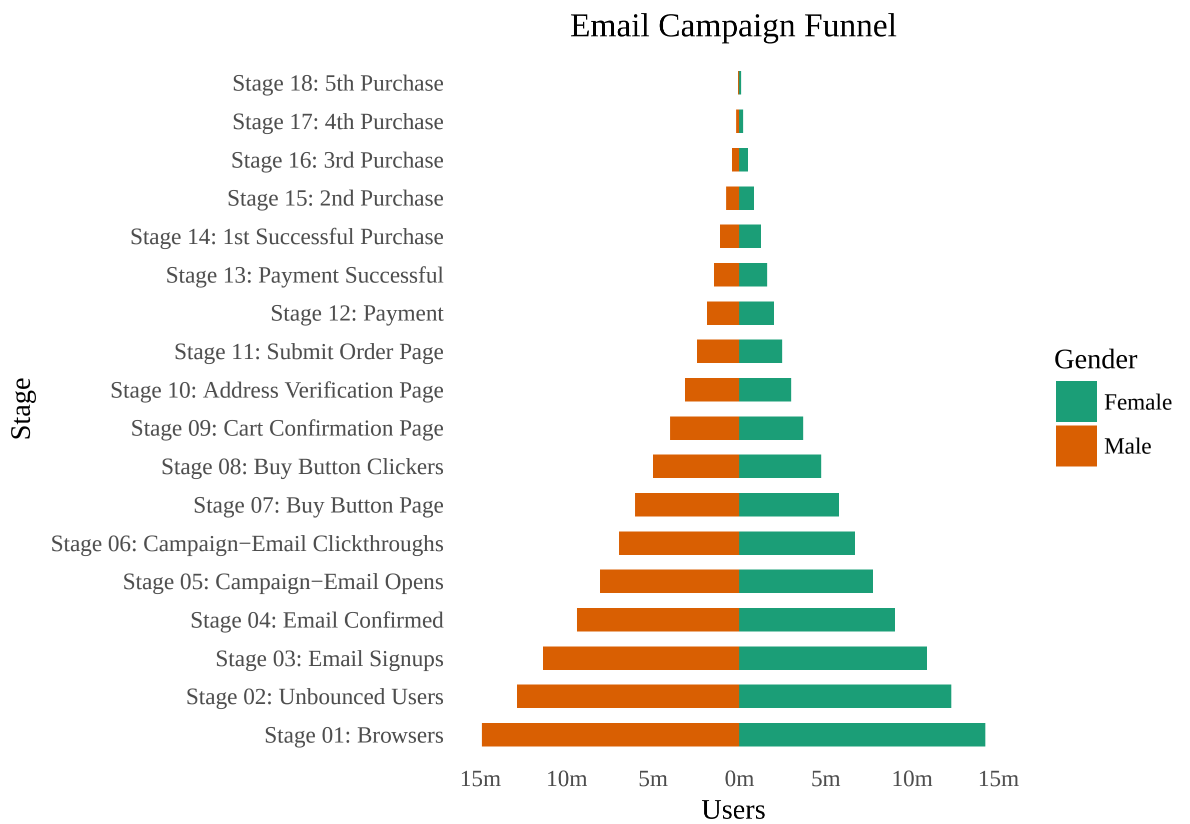
```
library(ggplot2)
theme_set(theme_bw())

# 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.

```r
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
```



5. Composition

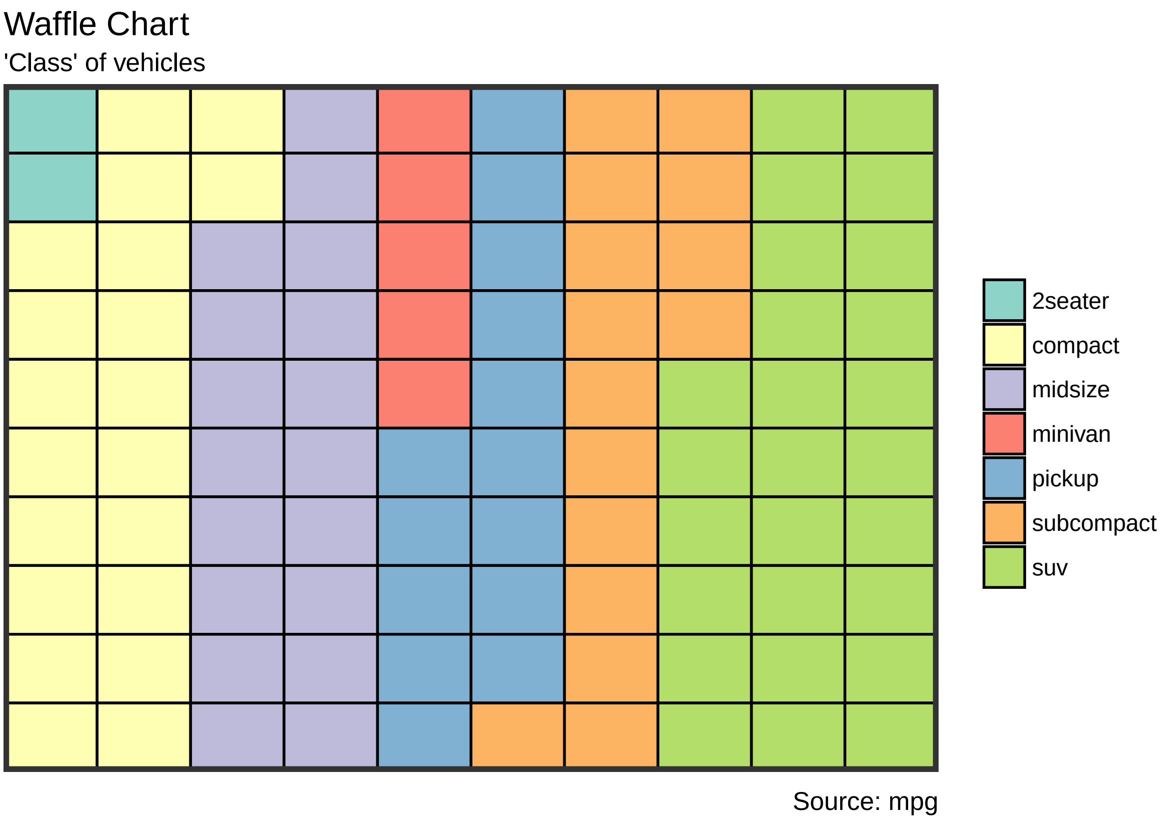
Waffle Chart

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
```

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

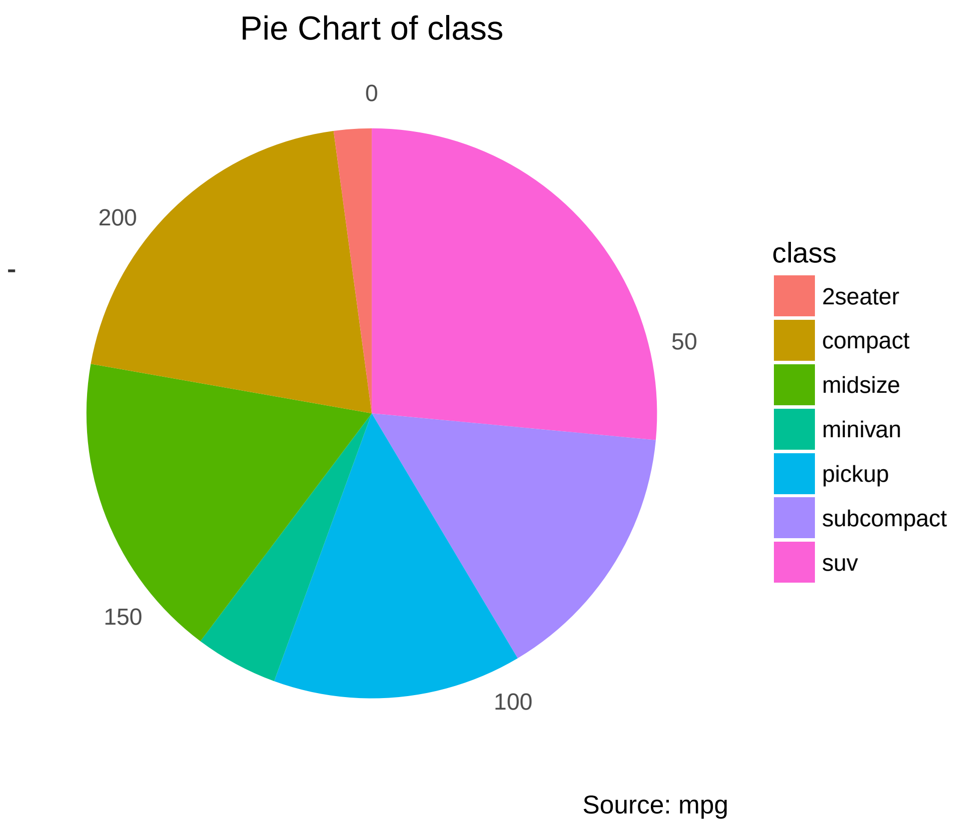
```
#>   2seater    compact    midsize    minivan     pickup subcompact        suv
#>         2         20         18          5         14         15         26

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")
```


Waffle Chart
'Class' of vehicles
2seater
compact
midsize
minivan
pickup
subcompact
suv
Source: mpg

Pie Chart

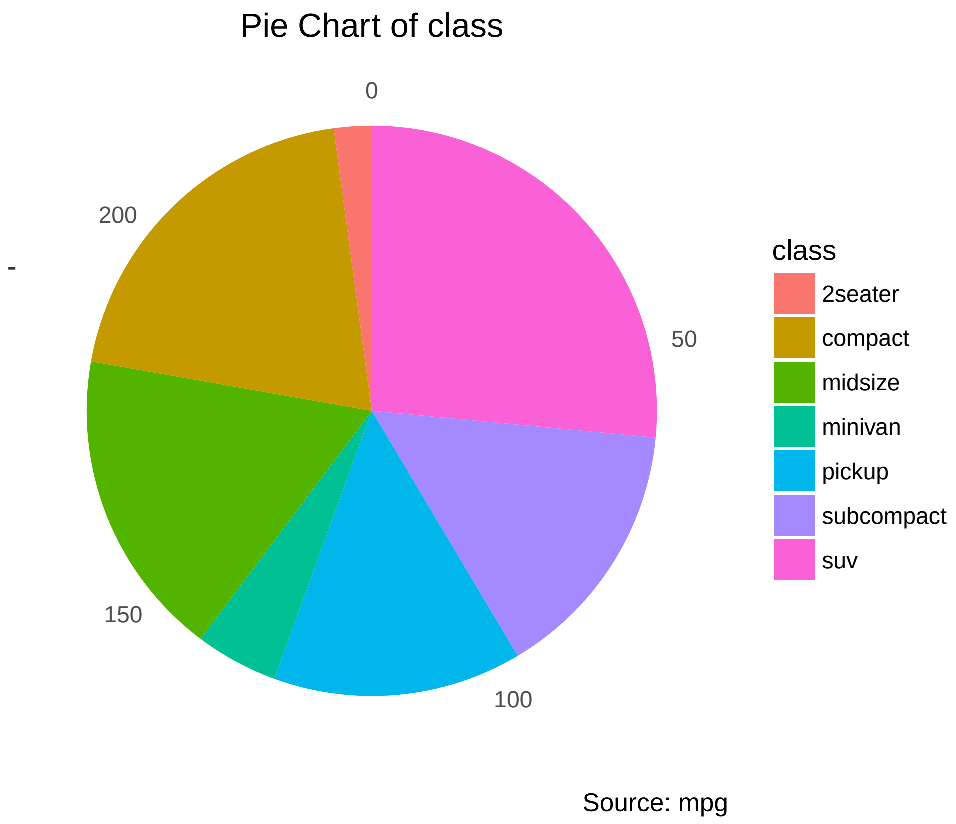
Pie chart, a classic way of showing the compositions is equivalent to the waffle chart in terms of the information conveyed. But is a slightly tricky to implement in ggplot2 using the coord_polar().

```
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",
```

```r
       caption="Source: mpg")

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




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

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.

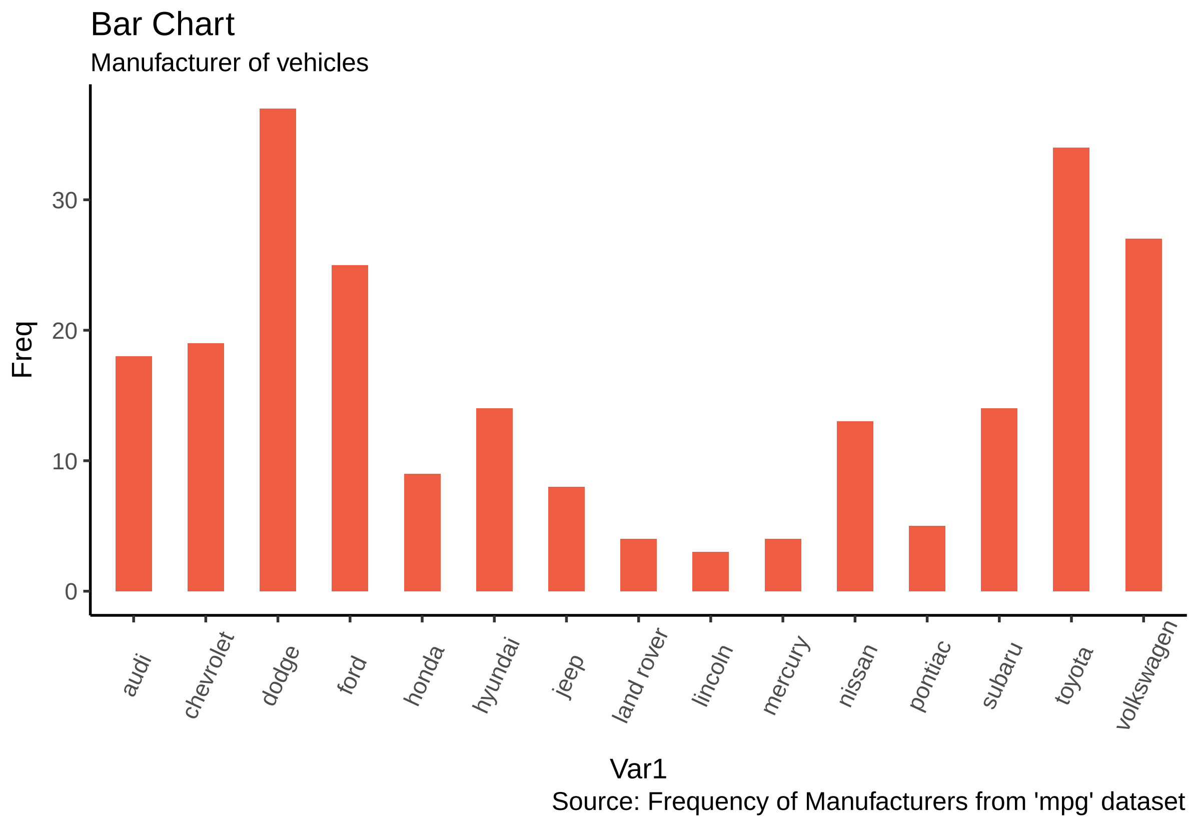
> Set stat=identity Provide both x and y inside `aes()` where, x is either character or factor and y is numeric.

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()`.

```r
# prep frequency table
freqtable <- table(mpg$manufacturer)
df <- as.data.frame.table(freqtable)
head(df)
```

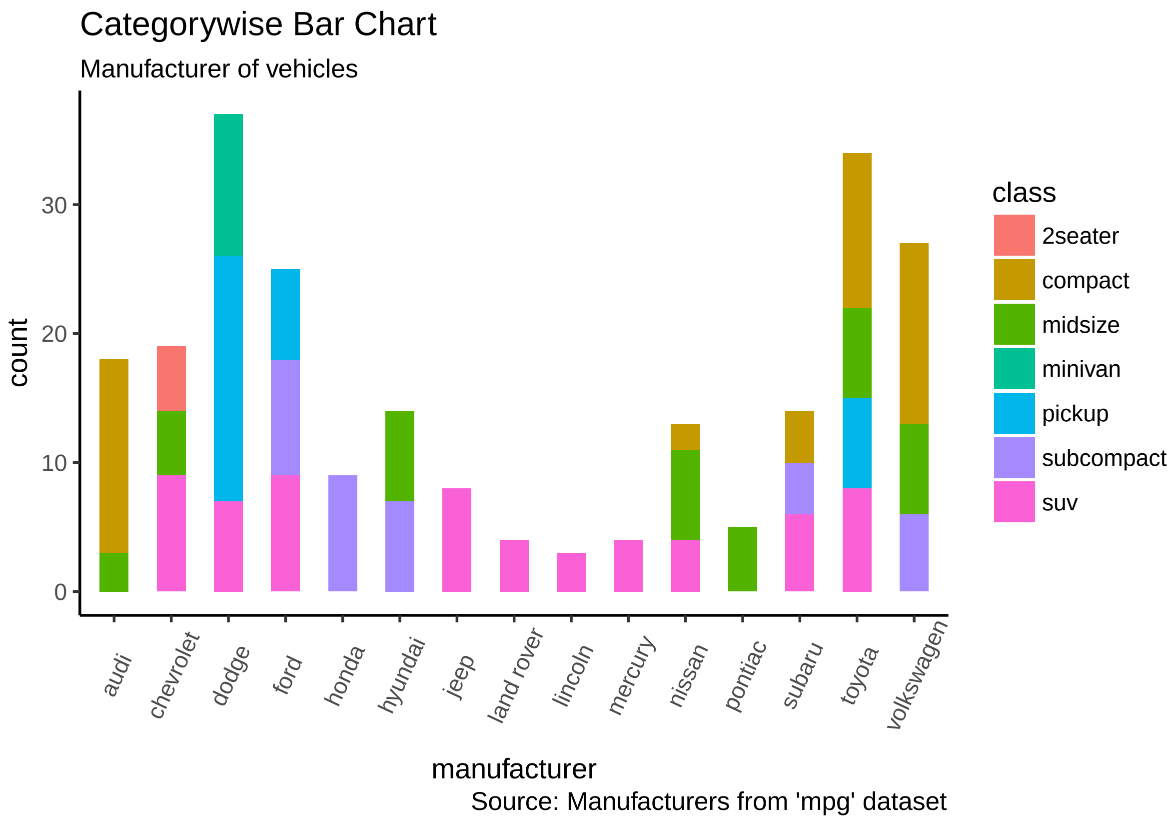
```
##         Var1 Freq
## 1       audi   18
## 2  chevrolet   19
## 3      dodge   37
## 4       ford   25
## 5      honda    9
## 6    hyundai   14
```

```r
# 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")
```


Categorywise Bar Chart
Manufacturer of vehicles
count
30
20
10
0
audi
chevrolet
dodge
ford
honda
hyundai
jeep
land rover
lincoln
mercury
nissan
pontiac
subaru
toyota
volkswagen
manufacturer
class
2seater
compact
midsize
minivan
pickup
subcompact
suv
Source: Manufacturers from 'mpg' dataset

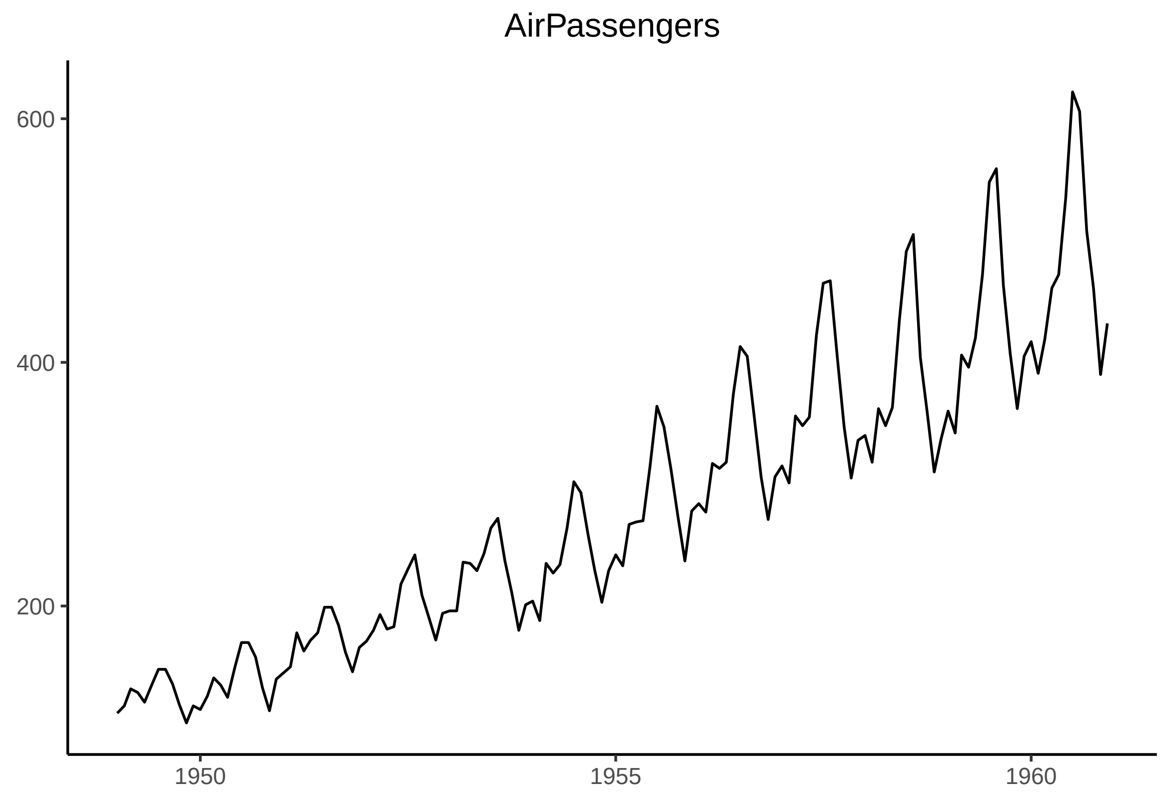
blank

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))
```

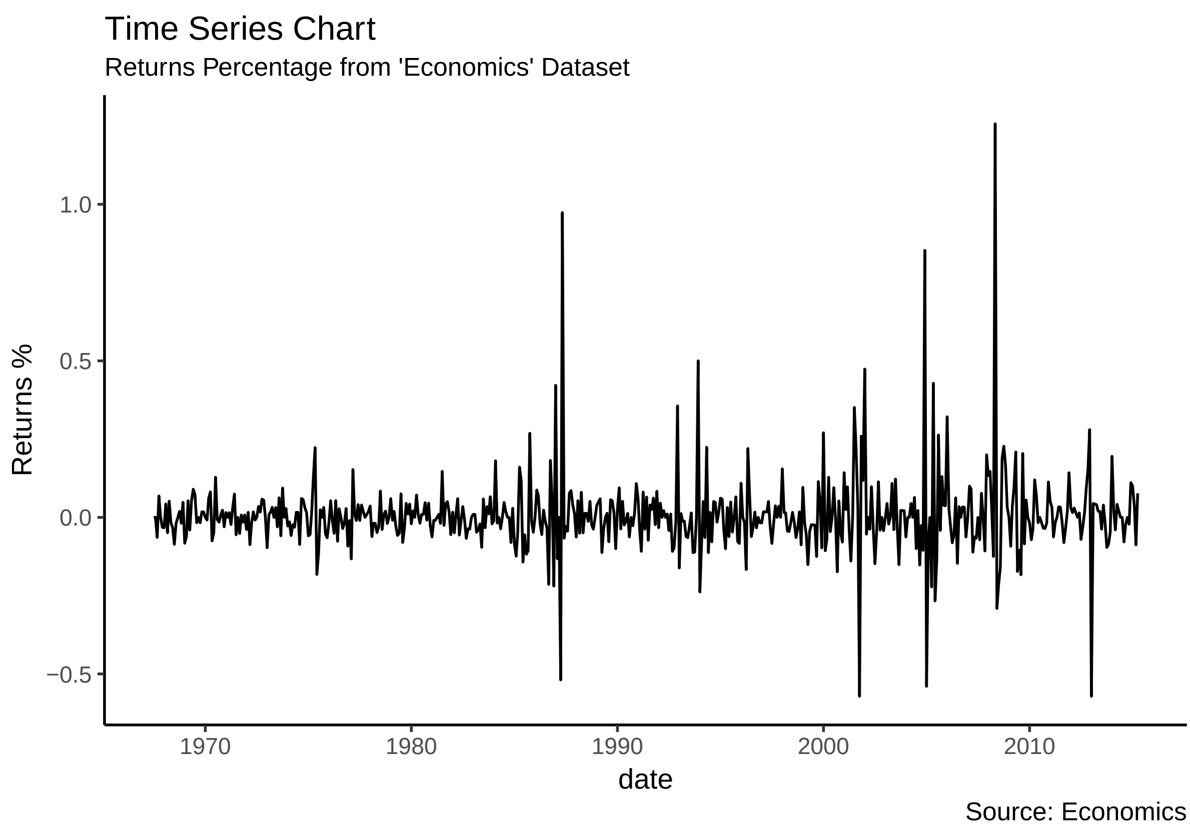


Time Series Plot From a Data Frame

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 %")
```



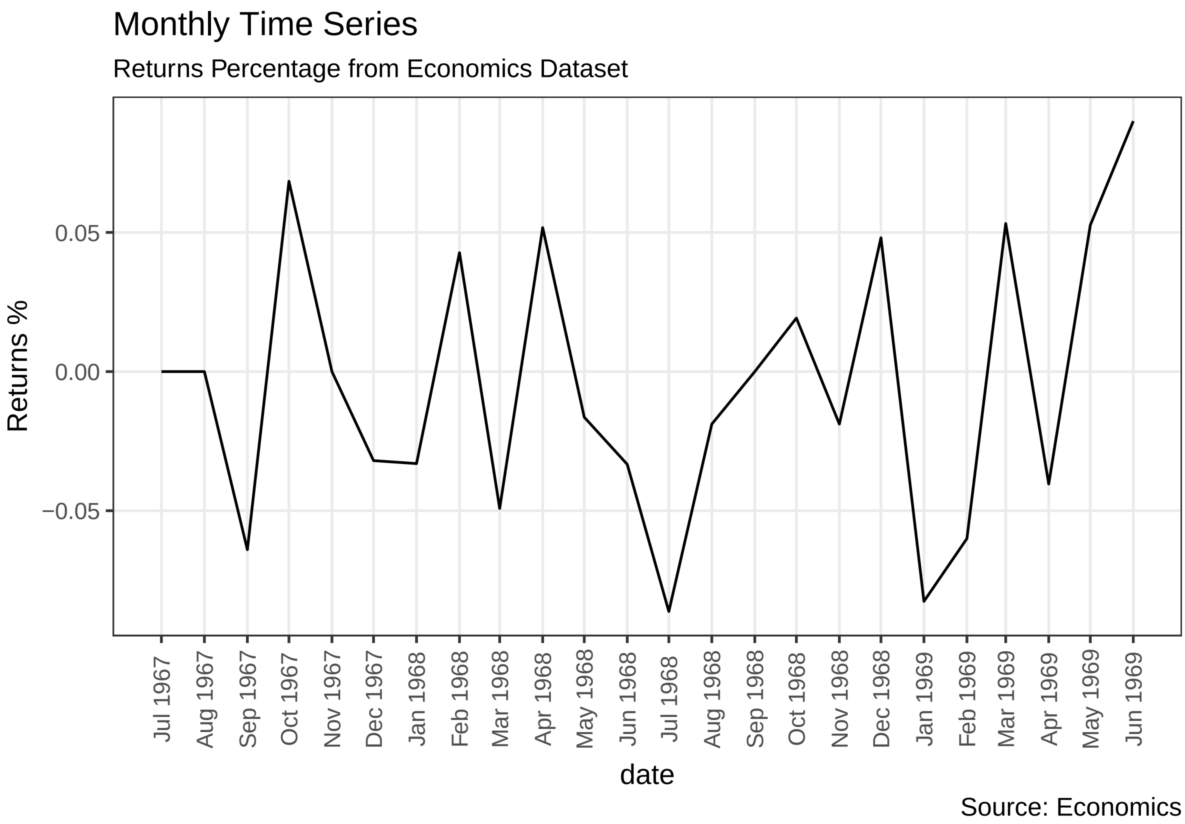
Time Series Plot For a Monthly Time Series

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)
```

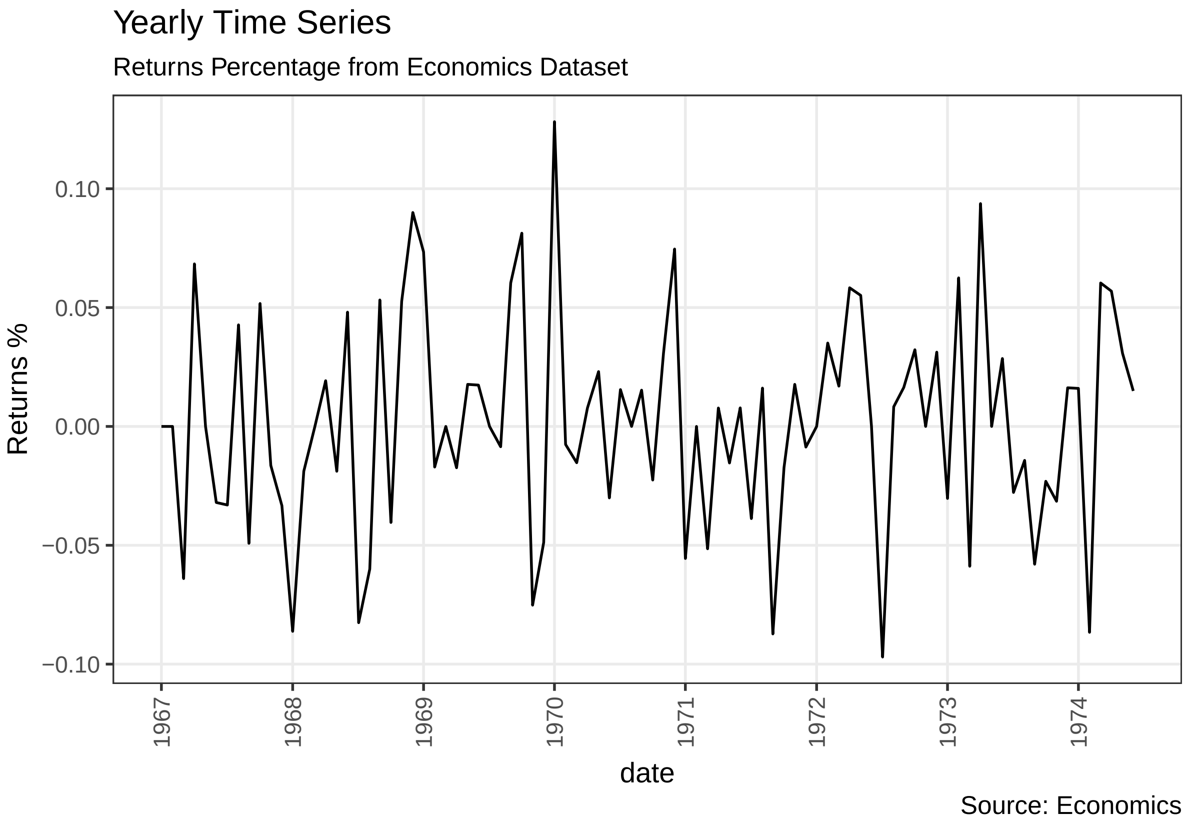
```
##
## Attaching package: 'lubridate'

## The following object is masked from 'package:base':
##
##     date
```

```
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
```


Monthly Time Series
Returns Percentage from Economics Dataset
Returns %
0.05
0.00
−0.05
Jul 1967
Aug 1967
Sep 1967
Oct 1967
Nov 1967
Dec 1967
Jan 1968
Feb 1968
Mar 1968
Apr 1968
May 1968
Jun 1968
Jul 1968
Aug 1968
Sep 1968
Oct 1968
Nov 1968
Dec 1968
Jan 1969
Feb 1969
Mar 1969
Apr 1969
May 1969
Jun 1969
date
Source: Economics

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
```



blank

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

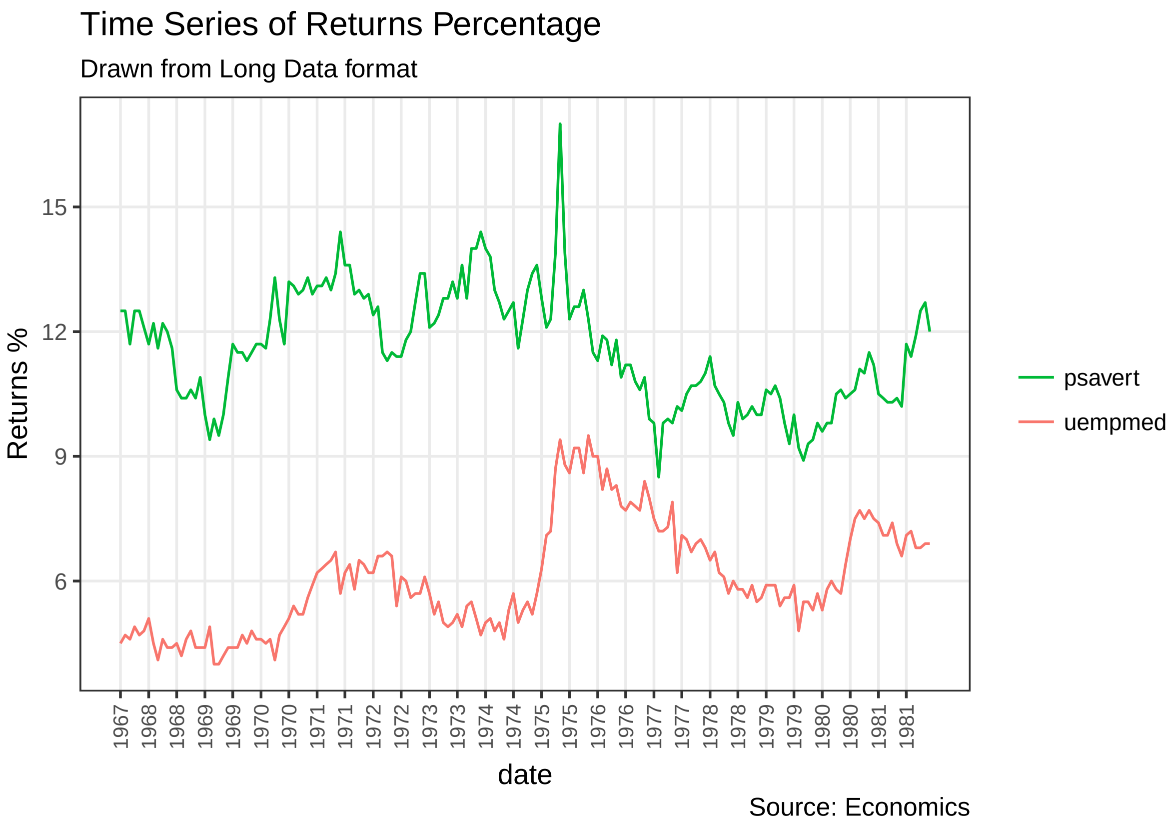
In this example, I construct the ggplot from a long data format. That means, the column names and respective values of all the columns are stacked in just 2 variables (variable and value respectively). If you were to convert this data to wide format, it would look like the economics dataset.

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)
```

```
## # A tibble: 6 x 4
## # Groups:   variable [1]
##   date       variable value  value01
##   <date>     <fct>    <dbl>    <dbl>
## 1 1967-07-01 pce       507. 0
## 2 1967-08-01 pce       510. 0.000266
## 3 1967-09-01 pce       516. 0.000764
## 4 1967-10-01 pce       513. 0.000472
## 5 1967-11-01 pce       518. 0.000918
## 6 1967-12-01 pce       526. 0.00158
```

```
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
```



Time Series of Returns Percentage
Drawn from Long Data format
Returns %
15
12
9
6
1967
1968
1968
1969
1969
1970
1970
1971
1971
1972
1972
1973
1973
1974
1974
1975
1975
1976
1976
1977
1977
1978
1978
1979
1979
1980
1980
1981
1981
date
Source: Economics
psavert
uempmed

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.

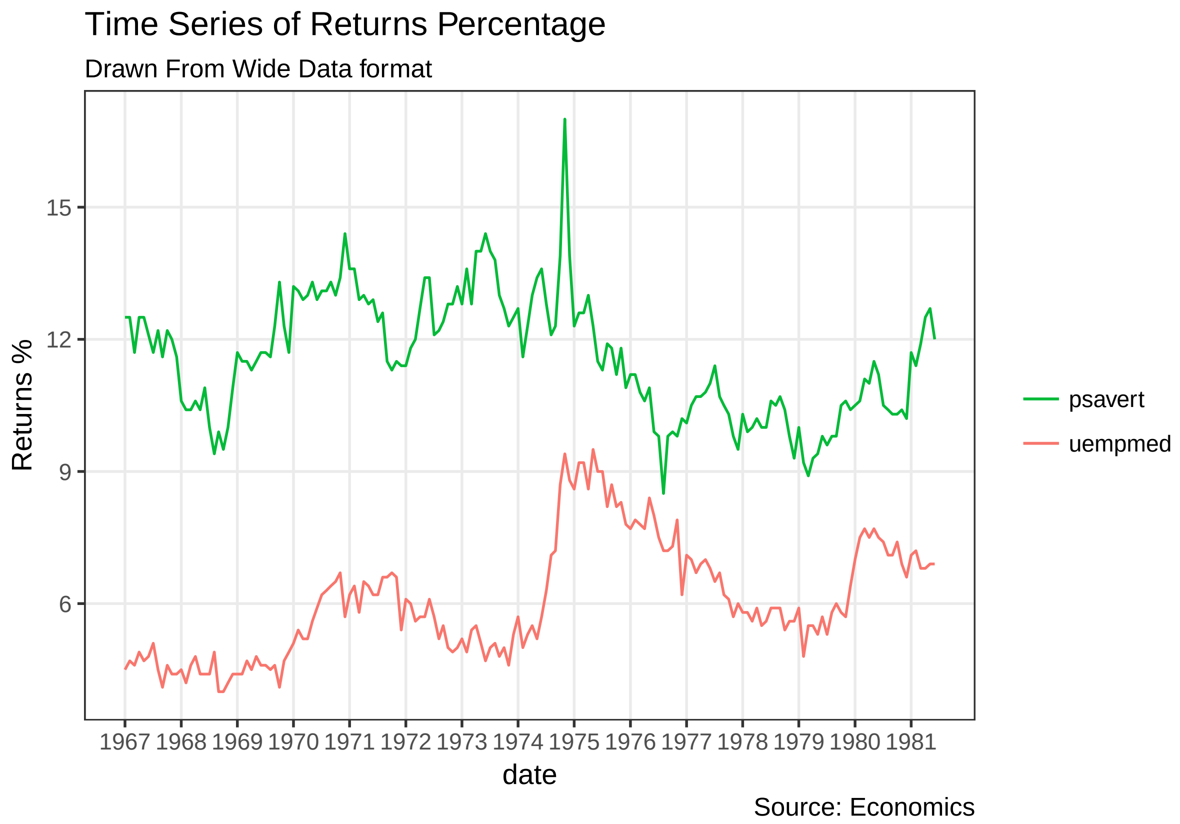
But if you are creating a time series (or even other types of plots) from a wide data format, you have to draw each line manually by calling `geom_line()` once for every line. So, a legend will not be drawn by default.

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
```


Time Series of Returns Percentage
Drawn From Wide Data format
Returns %
15
12
9
6
1967 1968 1969 1970 1971 1972 1973 1974 1975 1976 1977 1978 1979 1980 1981
date
psavert
uempmed
Source: Economics

Stacked Area Chart

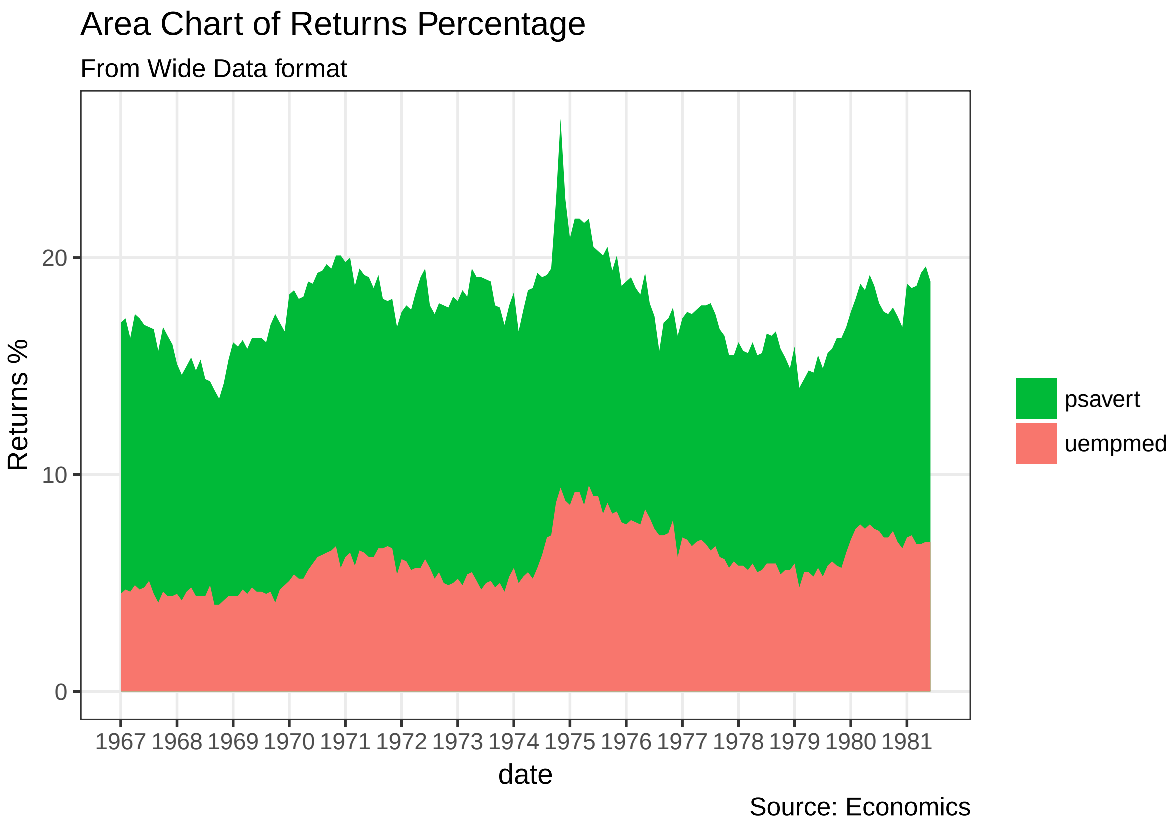
Stacked area chart is just like a line chart, except that the region below the plot is all colored. This is typically used when:

> You want to describe how a quantity or volume (rather than something like price) changed over time You have many data points. For very few data points, consider plotting a bar chart. 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.

```r
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
```


Area Chart of Returns Percentage
From Wide Data format
Returns %
20
10
0
1967 1968 1969 1970 1971 1972 1973 1974 1975 1976 1977 1978 1979 1980 1981
date
Source: Economics
psavert
uempmed

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.

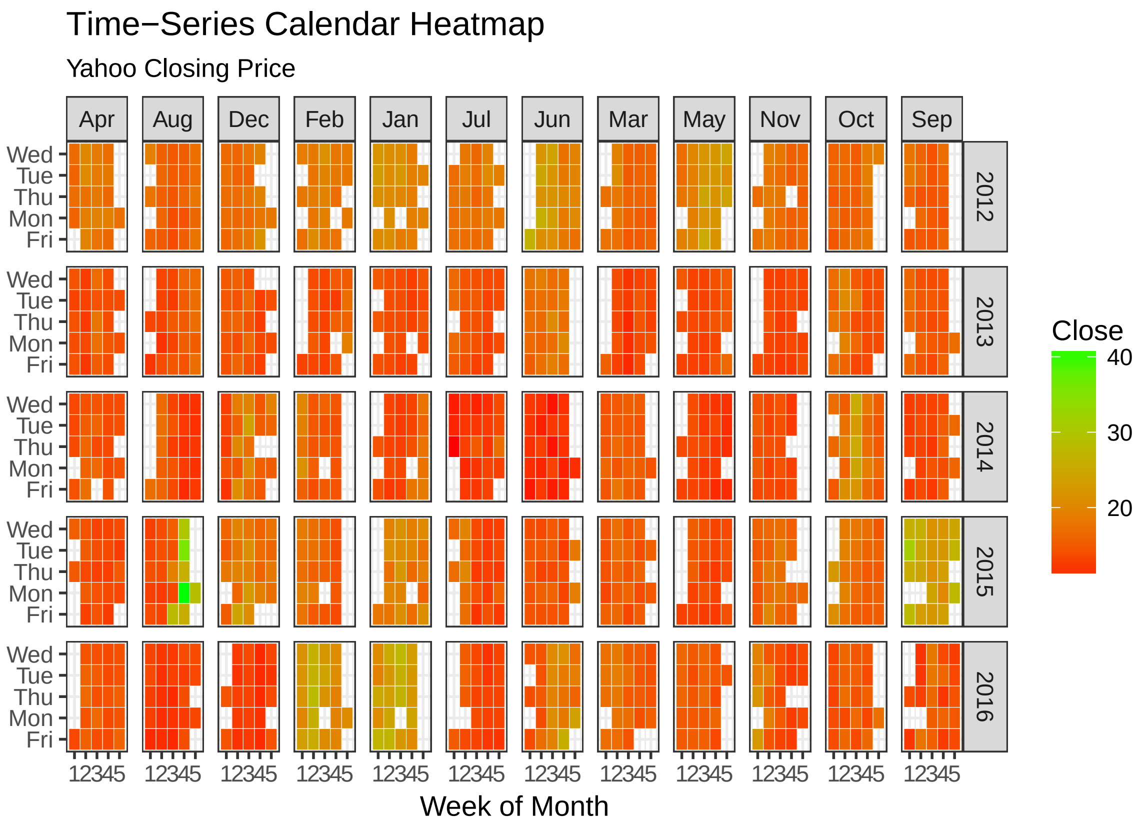
```
# http://margintale.blogspot.in/2012/04/ggplot2-time-series-heatmaps.html
library(ggplot2)
library(plyr)
```

```
##
## Attaching package: 'plyr'

## The following object is masked from 'package:lubridate':
##
##     here
```

```
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   1 2012    Jan    1         1      Tue     22.97
## 2 2012   1 2012    Jan    1         1      Wed     22.22
## 3 2012   1 2012    Jan    1         1      Thu     21.48
## 4 2012   1 2012    Jan    1         1      Fri     20.63
## 5 2012   1 2012    Jan    2         2      Mon     21.07
## 6 2012   1 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")
```

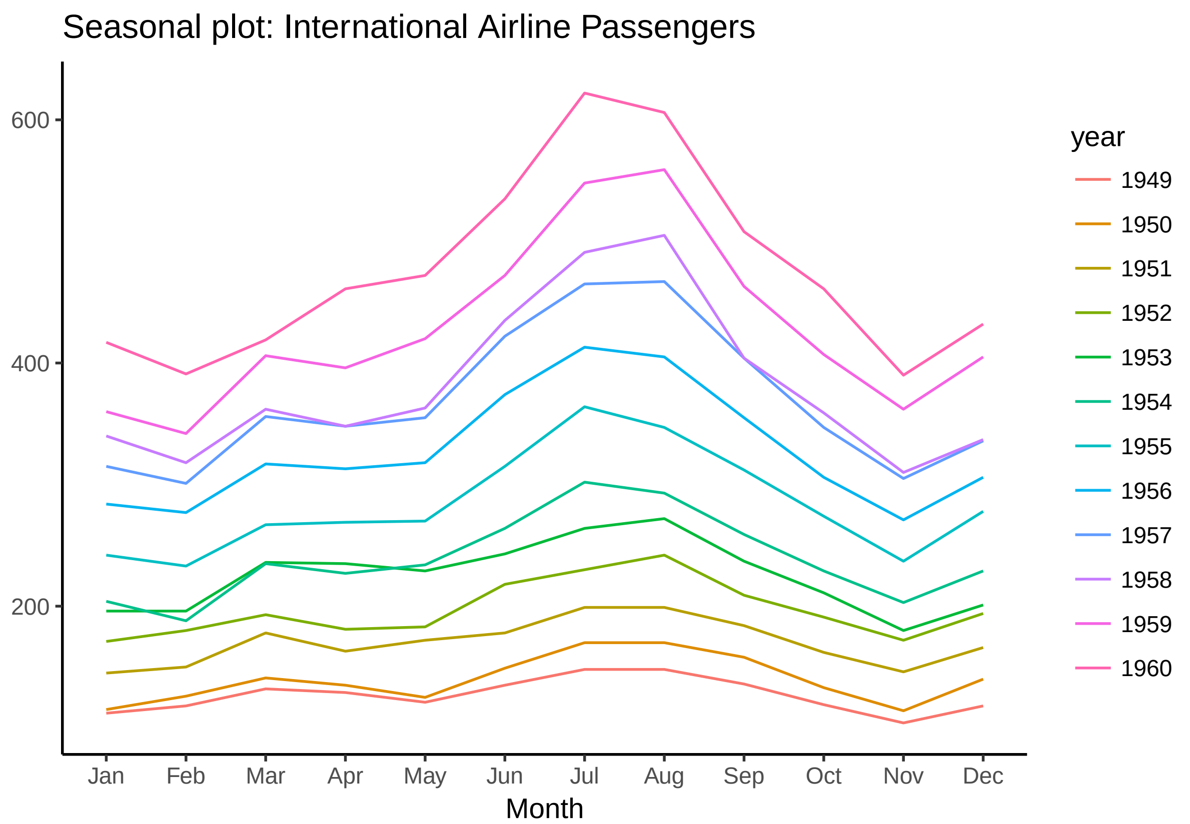

Time−Series Calendar Heatmap
Yahoo Closing Price
Apr
Aug
Dec
Feb
Jan
Jul
Jun
Mar
May
Nov
Oct
Sep
2012
2013
2014
2015
2016
Wed
Tue
Thu
Mon
Fri
12345
Week of Month
Close
40
30
20

Seasonal Plot

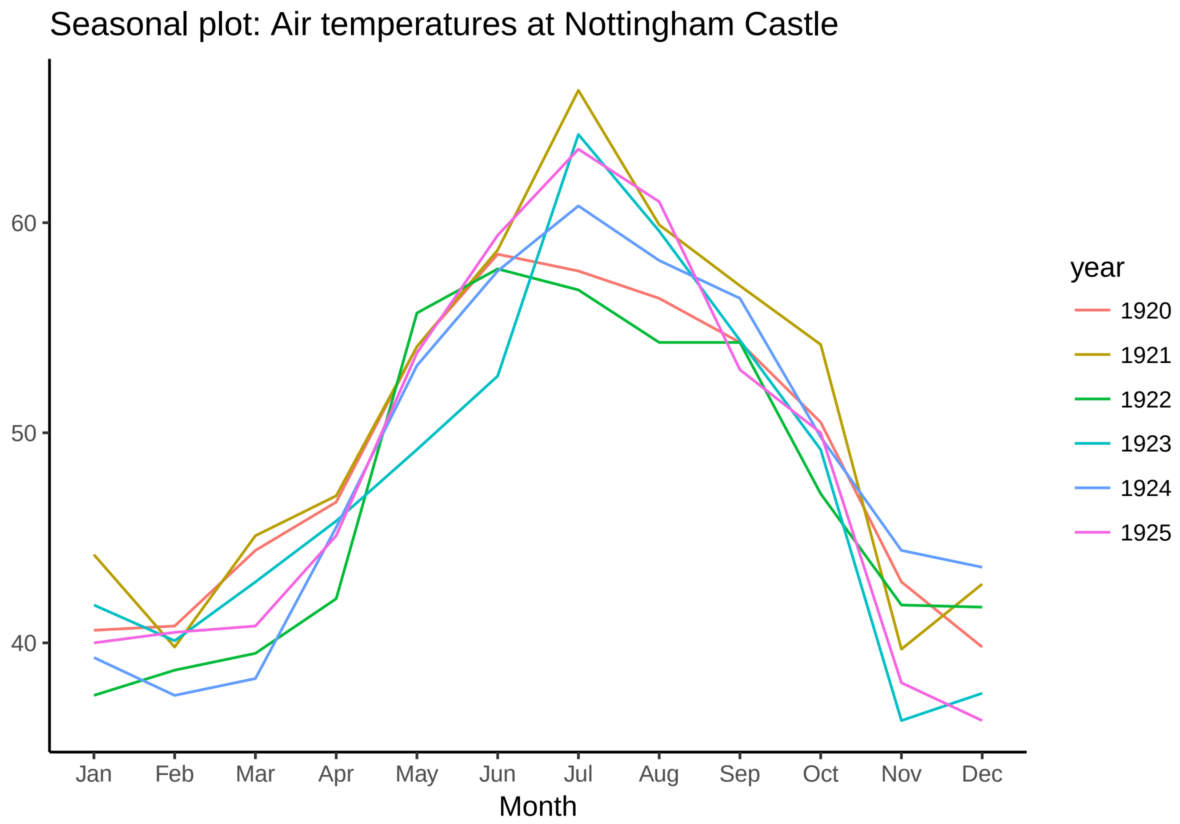
If you are working with a time series object of class ts or xts, you can view the seasonal fluctuations through a seasonal plot drawn using `forecast::ggseasonplot`. Below is an example using the native AirPassengers and nottem time series.

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")
```

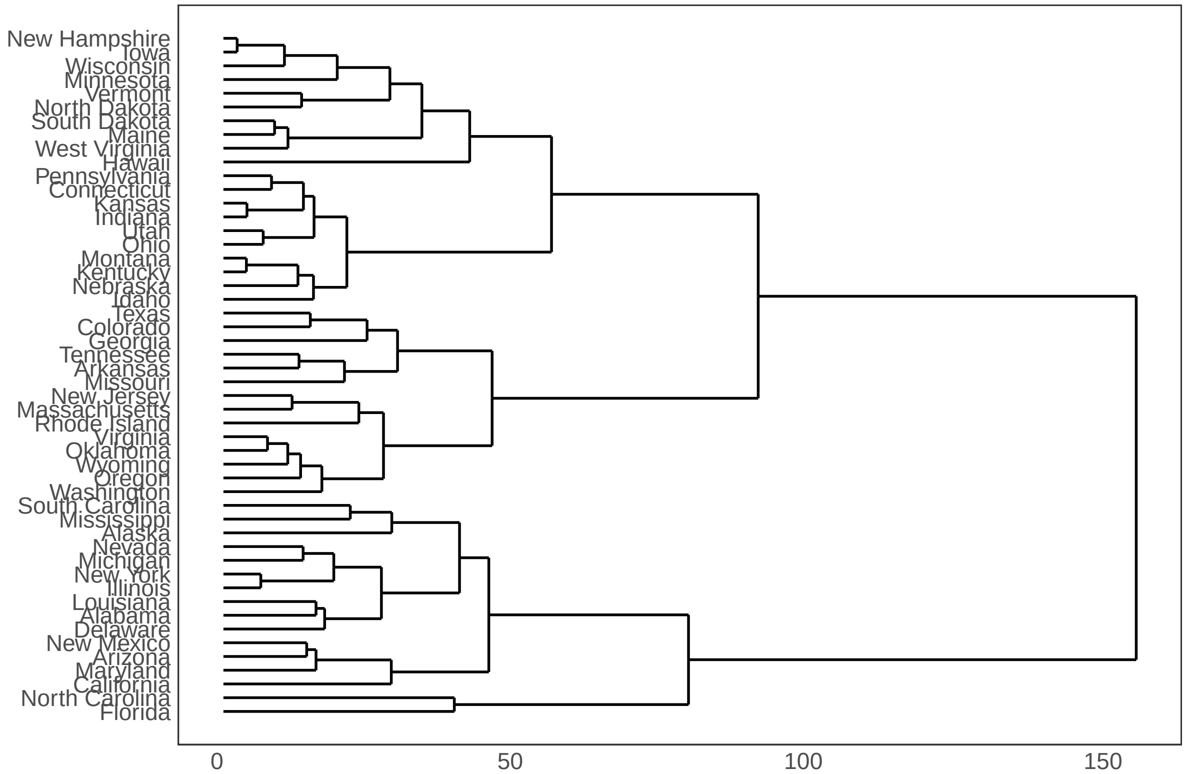


Seasonal plot: Air temperatures at Nottingham Castle
60
50
40
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Month
year
1920
1921
1922
1923
1924
1925

7. Groups

Hierarchical Dendrogram

```r
# 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)
```



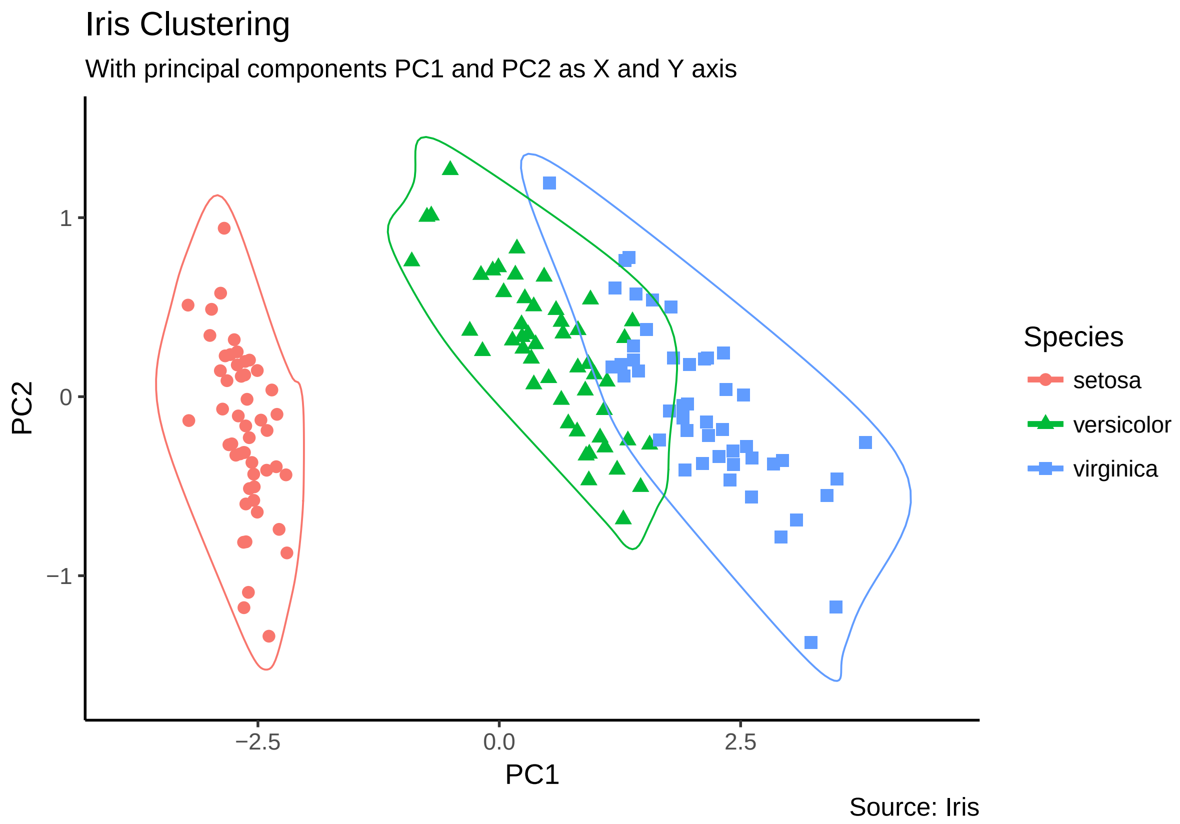
blank

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))
```



REFERENCE: http://r-statistics.co/Top50-Ggplot2-Visualizations-MasterList-R-Code.html