understanding data visualization

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Introduction to data visualization

With ever increasing volume of data, it is impossible to tell stories without visualizations. Data visualization is an art of how to turn numbers into useful knowledge. Before the technical implementations of the visualization, let's see first how to select the right chart type.

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.
2. Aesthetics supports information rather that overshadow it.
3. Is not overloaded with information.

Questions to ask when deciding which chart to use

Q1. Do you want to compare values?

To create a comparison chart, use these types of graphs:

- Column
- Bar
- Circular Area
- Line
- Scatter Plot

Q2. Do you want to show the composition?

To show composition, use these charts:

- Stacked Bar
- Stacked Column
- Area

Q3. Do you want to understand the distribution of your data?

To show distributions, use these charts:

- Scatter plot
- Line
- Bar
- Column

Q3. Are you interested in analyzing trends in your data?

- Line
- Column

Q4. Do you want to understand the relationship between the variables in your dataset?

- Scatter plot
- Bubble
- Line

Selecting the Right Chart Type

Primarily, there are 07 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 7 categories.

In your day-to-day activities, you'll come across the below listed 7 charts most of the time.

1. Correlation

- Scatterplot
- Scatterplot With Encircling
- Jitter Plot
- Bubble Plot
- Correlogram

2. Deviation

- Diverging Bars
- Area Chart

3. Ranking

- Ordered Bar Chart
- Dot Plot

4. Distribution

- Histogram on a continuous variable
- Histogram on a categorical variable
- Density Plot
- Box Plot
- Dot + Box Plot

5. Composition

- Bar Chart

6. Change

- Time Series Plots

7. Groups

- Dendrogram
- Clusters

Load the required libraries

```
options(scipen = 999) # turn-off scientific notation like 1e+48
library(ggplot2)
library(ggalt)
library(gapminder)
library(ggExtra)
library(ggcorrplot)
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.
```

```
library(xts)
library(scales)
library(ggthemes)
library(lubridate)
```

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

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

```
library(ggdendro)
```

Set the background theme.

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

1. Correlation

A. Scatter Plot

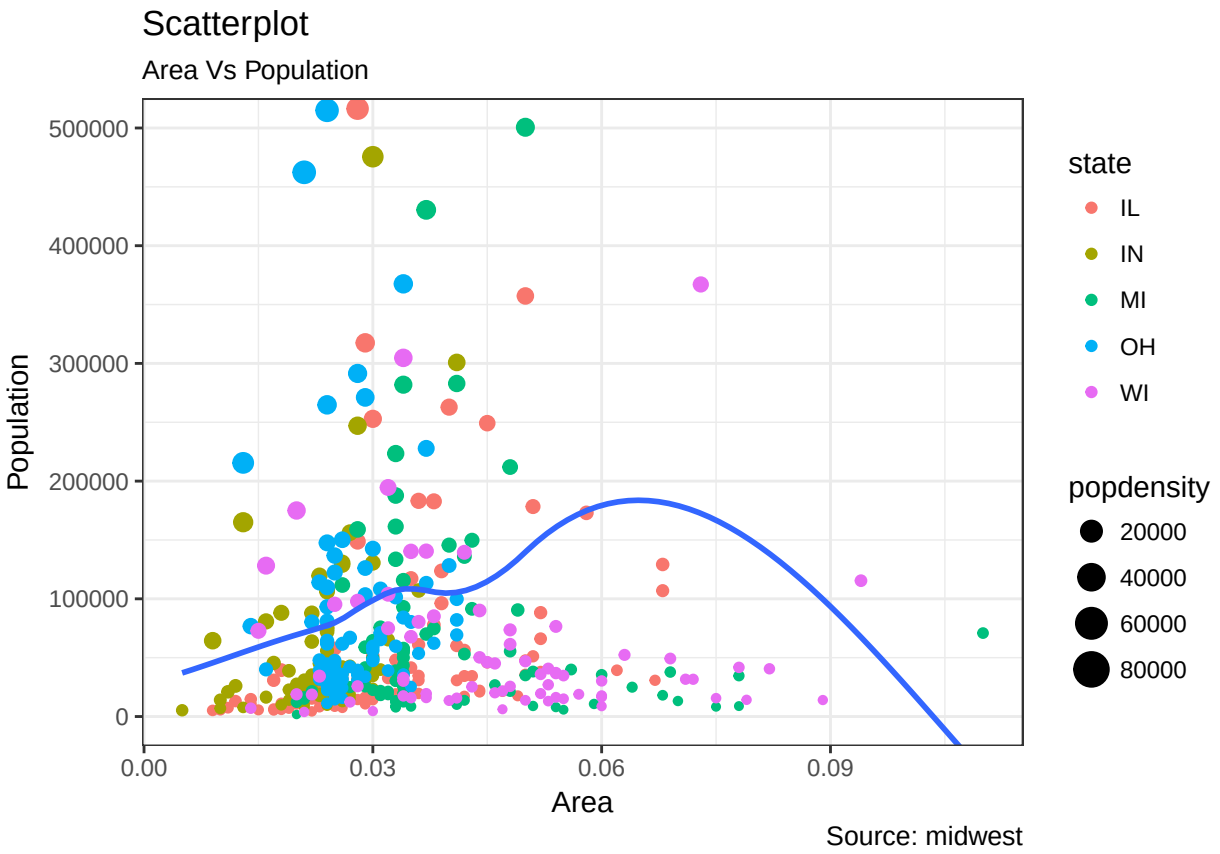
When to use: Scatter Plot is used to see the relationship between two continuous variables.

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'`.

```
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) +
  coord_cartesian(ylim = c(0, 500000))+
  labs(subtitle="Area Vs Population",
       y="Population",
       x="Area",
       title="Scatterplot",
       caption = "Source: midwest")

plot(gg)
```



A categorical variable can be used in a scatterplot to show the characterstics of the plotted variables. So, the above code can be modified as,

B. Scatterplot With Encircling

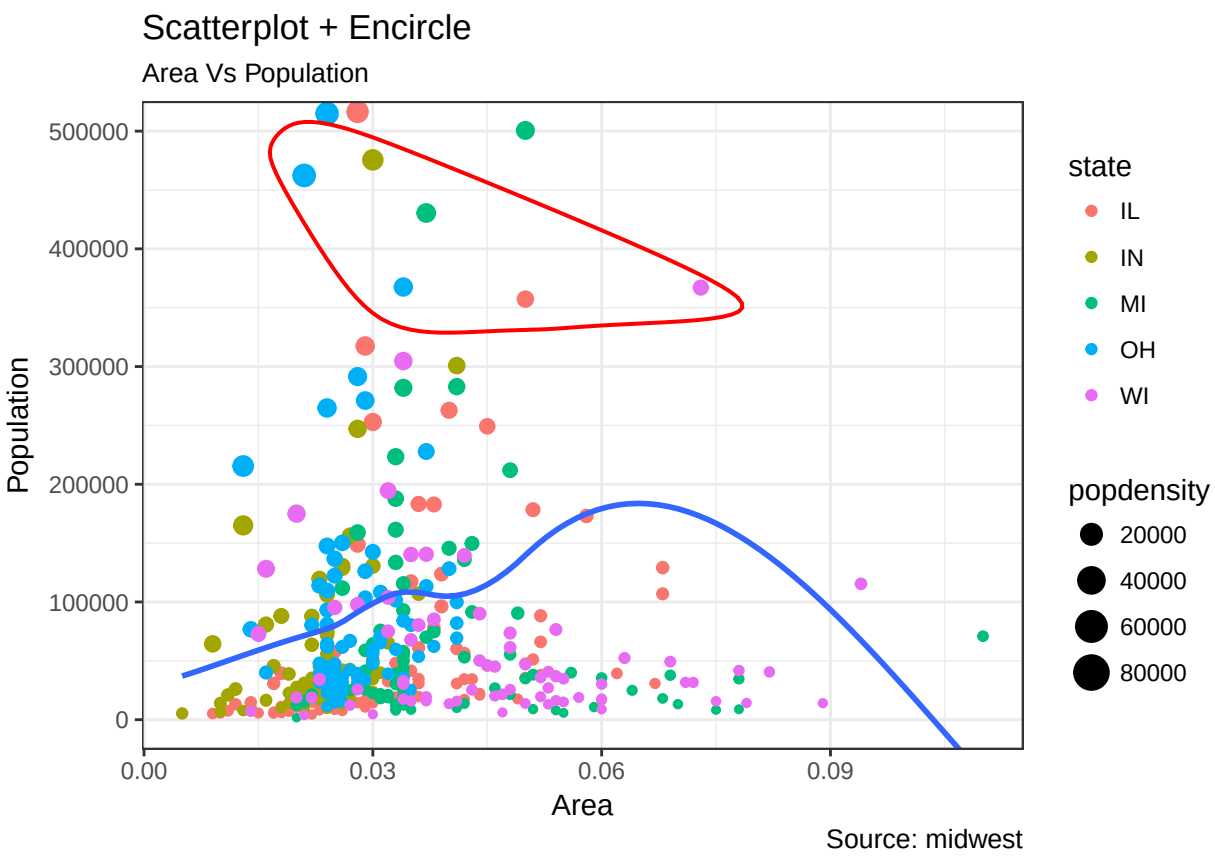
When presenting the results, sometimes I would encirlce certain special group of points or region in the chart so as to draw the attention to those peculiar cases. This can be conveniently done using the `geom_encircle()` in `ggalt` package.

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.

```
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, 0.6)) +
  #ylim(c(0, 500000)) +   # draw smoothing line
  coord_cartesian(ylim = c(0, 500000))+
  geom_encircle(aes(x=area, y=poptotal),
                data=midwest_select,
```

```
                color="red",
                size=2,
                expand=0.06) +   # encircle
  labs(subtitle="Area Vs Population",
       y="Population",
       x="Area",
       title="Scatterplot + Encircle",
       caption="Source: midwest")
```

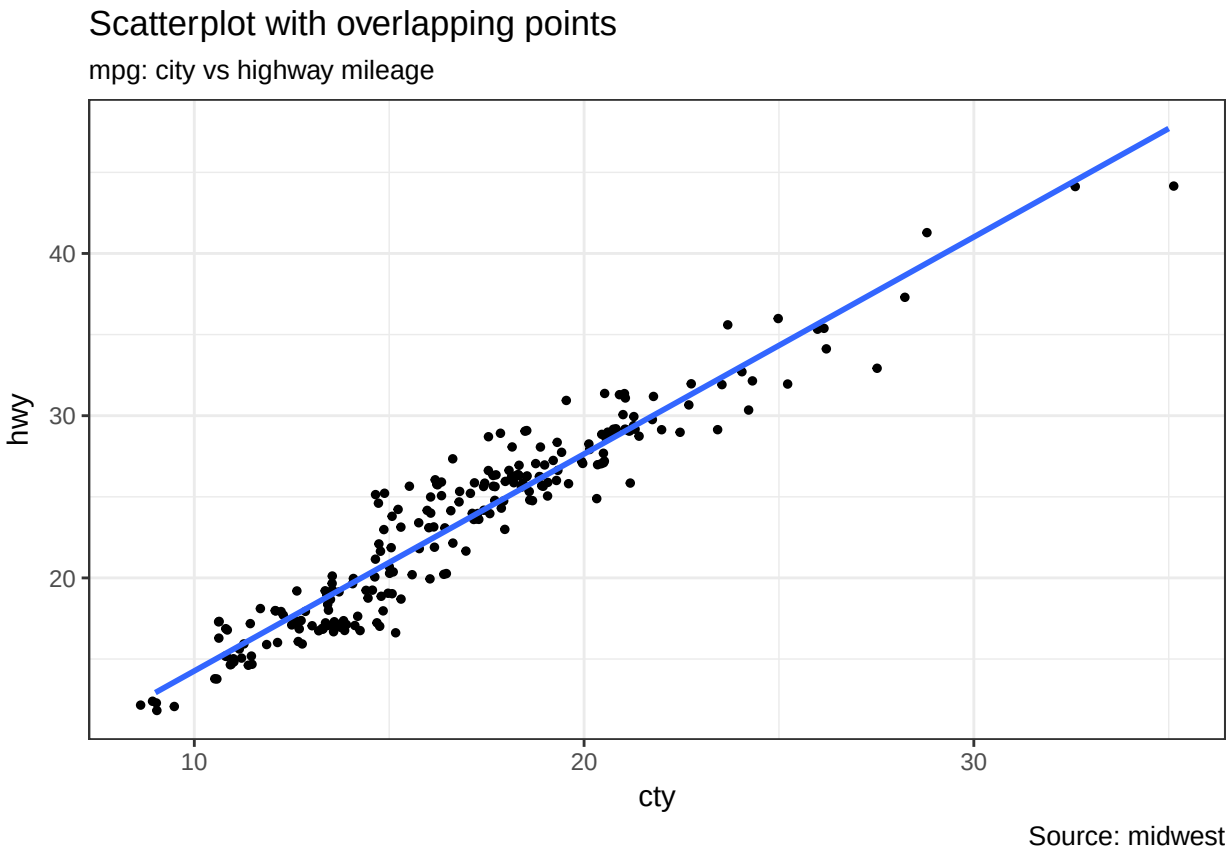


C. Jitter Plot

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`).

```
g <- ggplot(data=mpg, aes(cty, hwy))

# Scatterplot
g + geom_jitter(width = 0.5, size=1) +
  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")
```



D. 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:

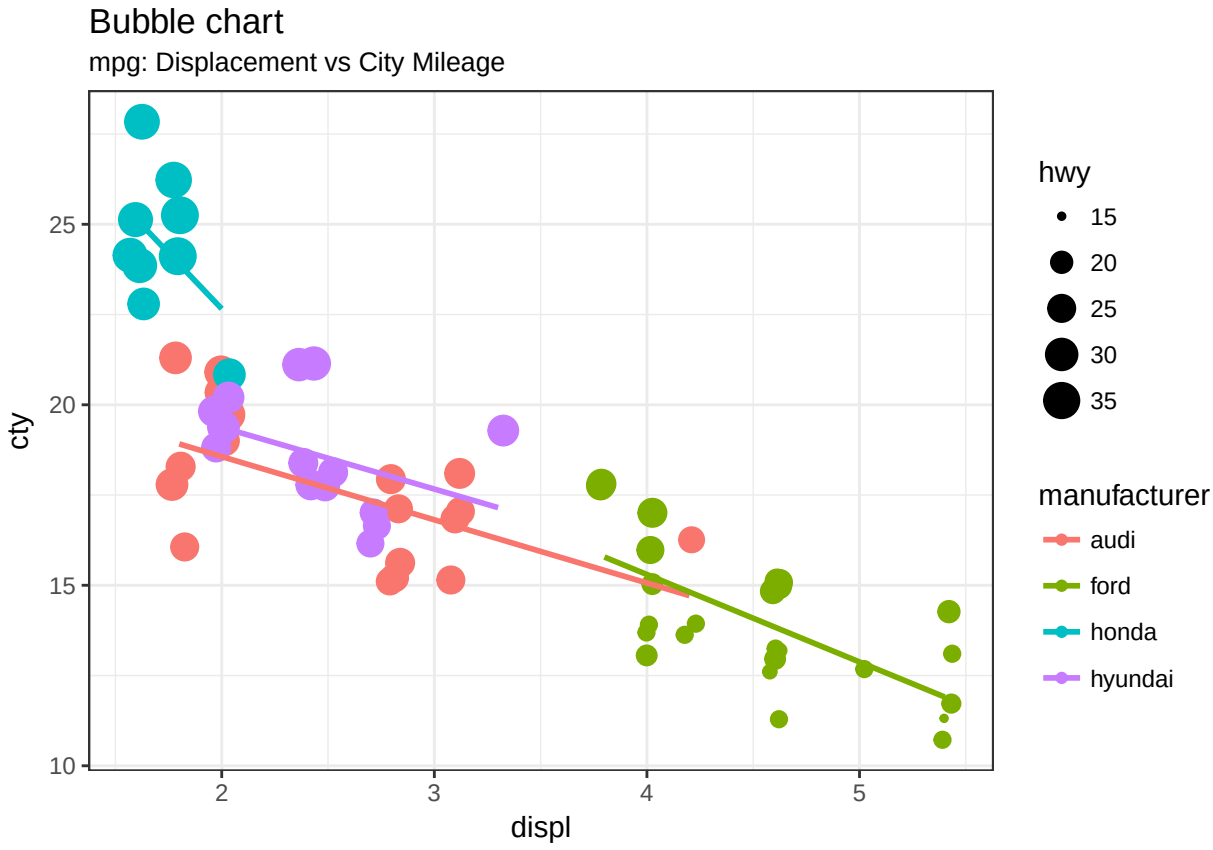
1. A Categorical variable (by changing the color) and
2. Another continuous variable (by changing the size of points).

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).

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

# Scatterplot
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)
```

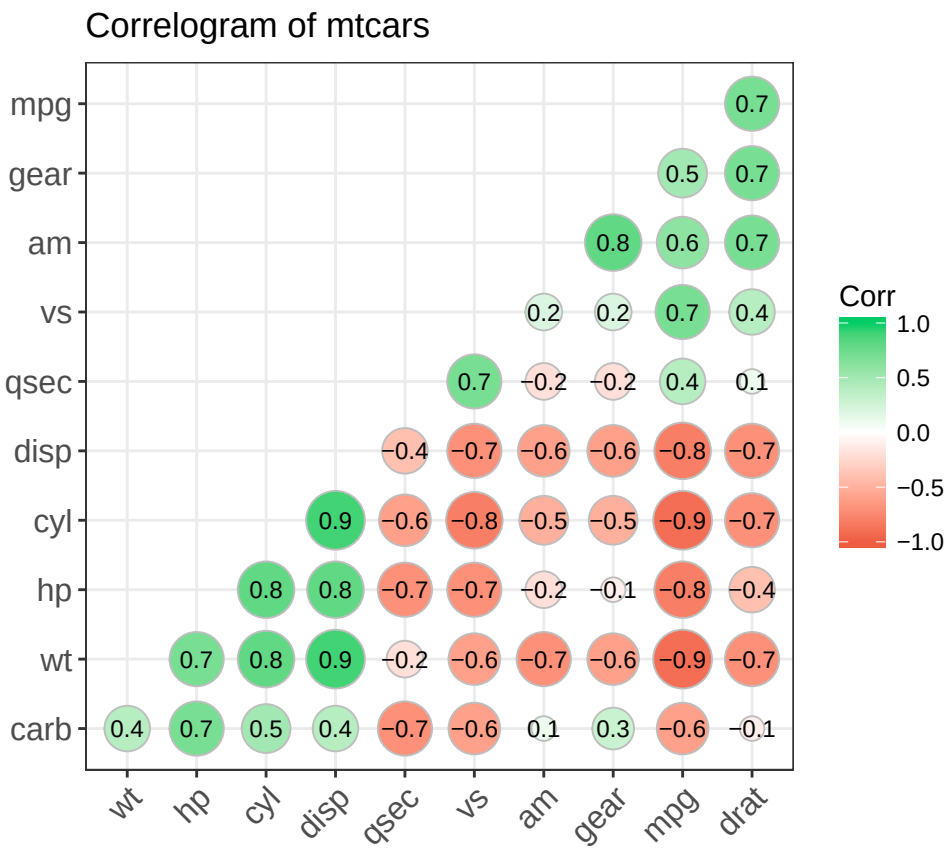


E. Correlogram

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

```
# 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.

F. 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.

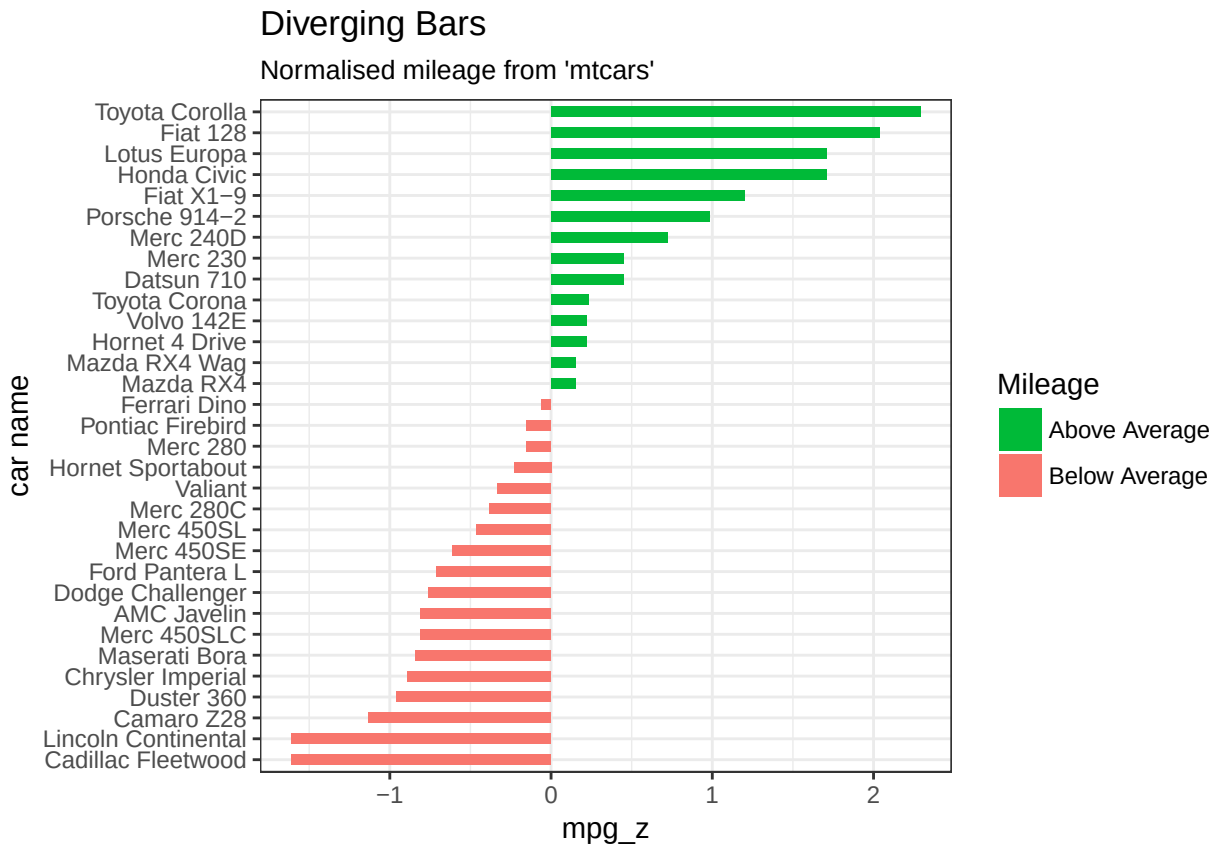
a. Set `stat=identity`

b. 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.

```
# 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
```

```r
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 reta

# 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()
```



G. 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.

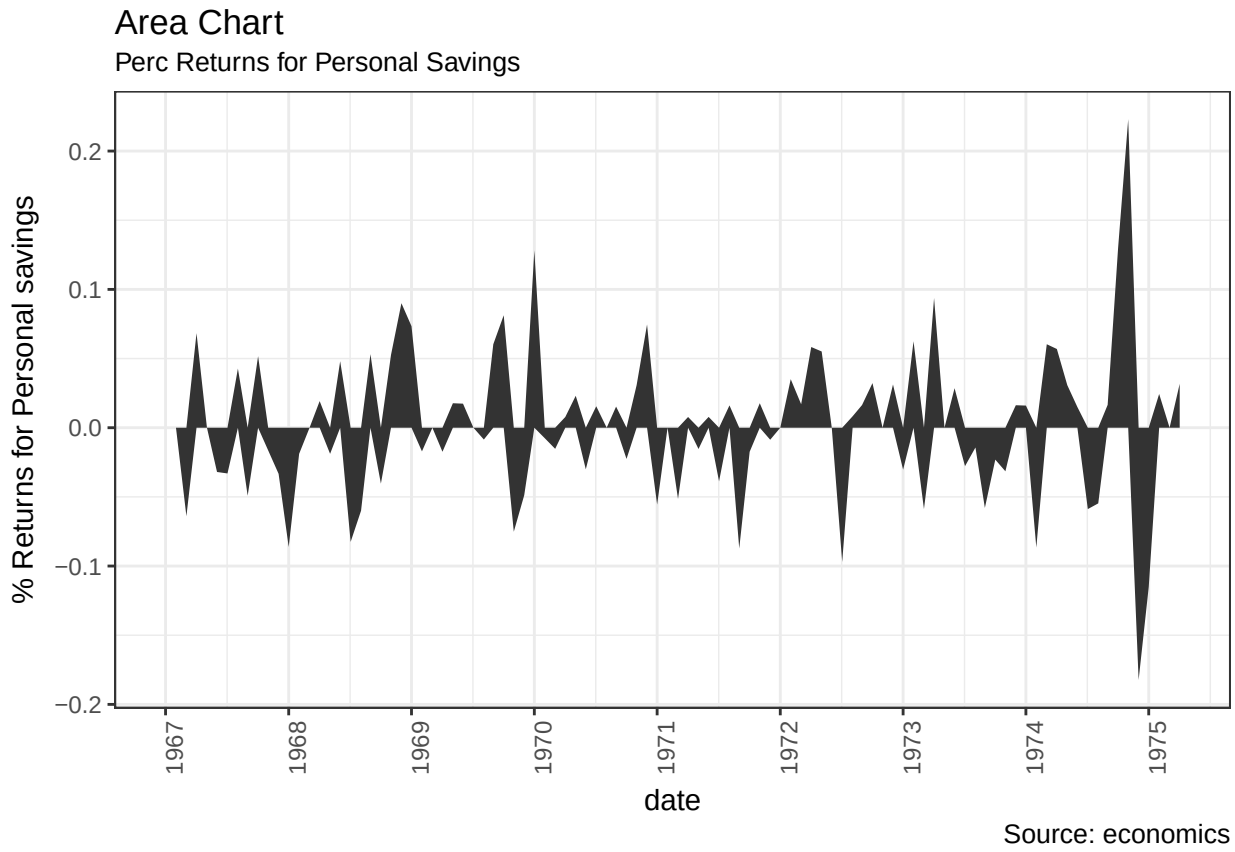
```r
data("economics", package = "ggplot2")

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

# Create break points and labels for axis ticks
```

```r
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")
```



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.

H. 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.

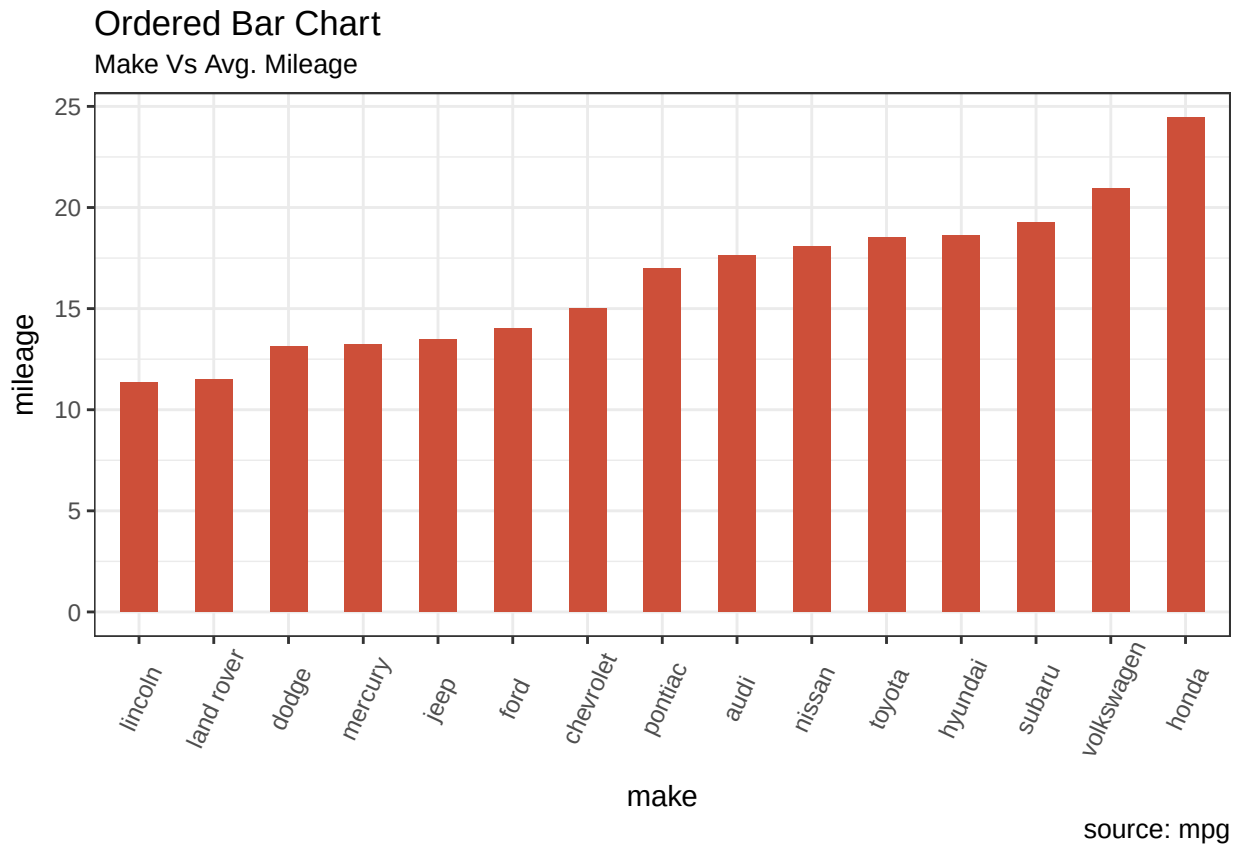
Let's plot the mean city mileage for each manufacturer from mpg dataset. First, aggregate the data and sort it before you draw the plot. Finally, the X variable is converted to a factor.

```
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   11.33
## 8  land rover   11.50
## 3       dodge   13.14
## 10    mercury   13.25
```

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

```
# 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))
```

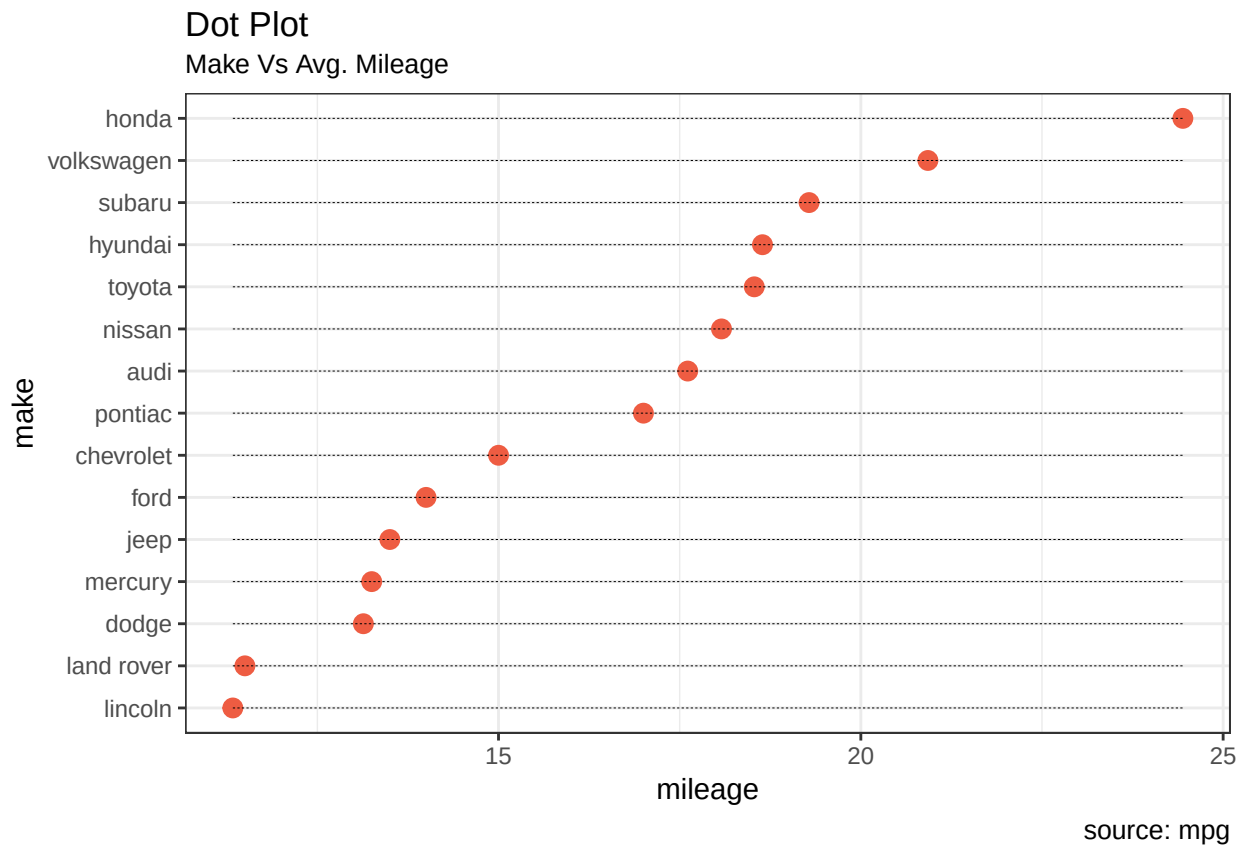


I. Dot Plot

Dot plots 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.

```
# 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()
```



4. Distribution

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

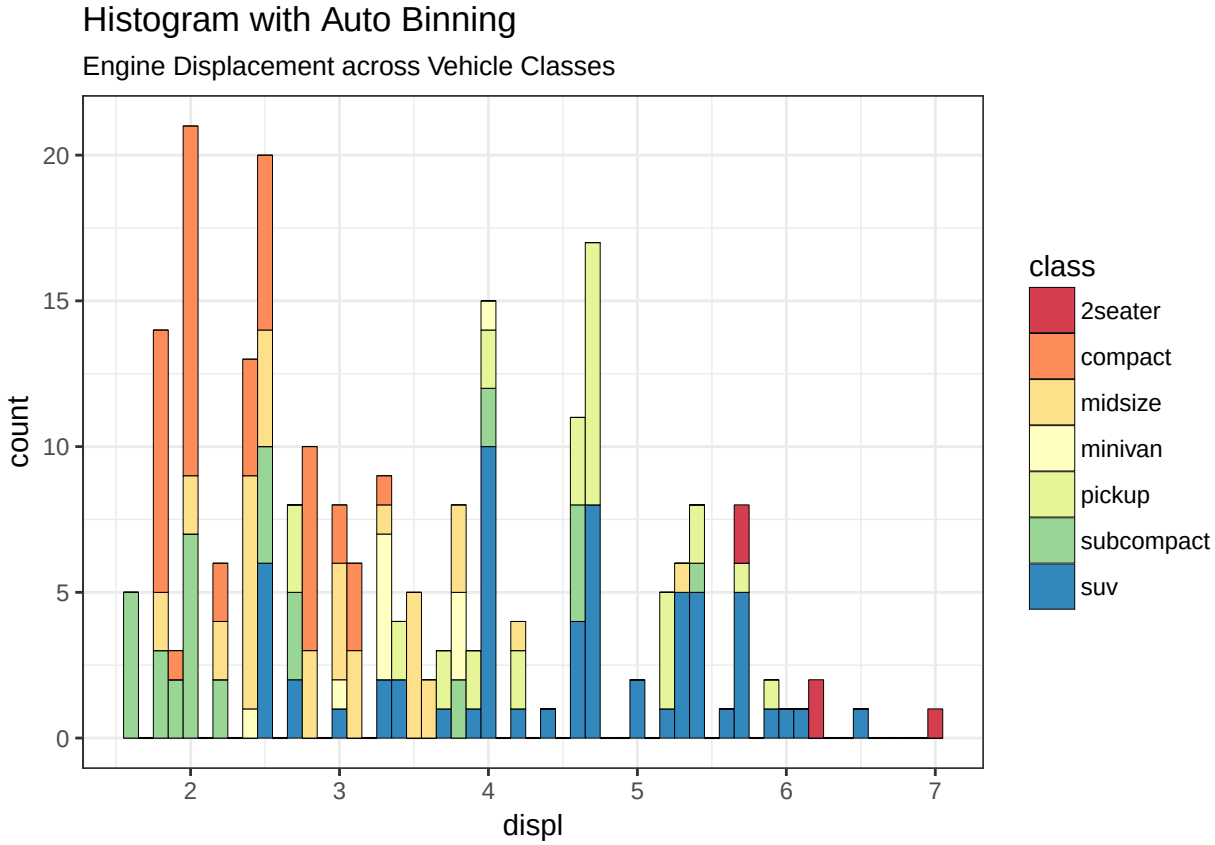
Histogram

J. Histogram on a continuous variable

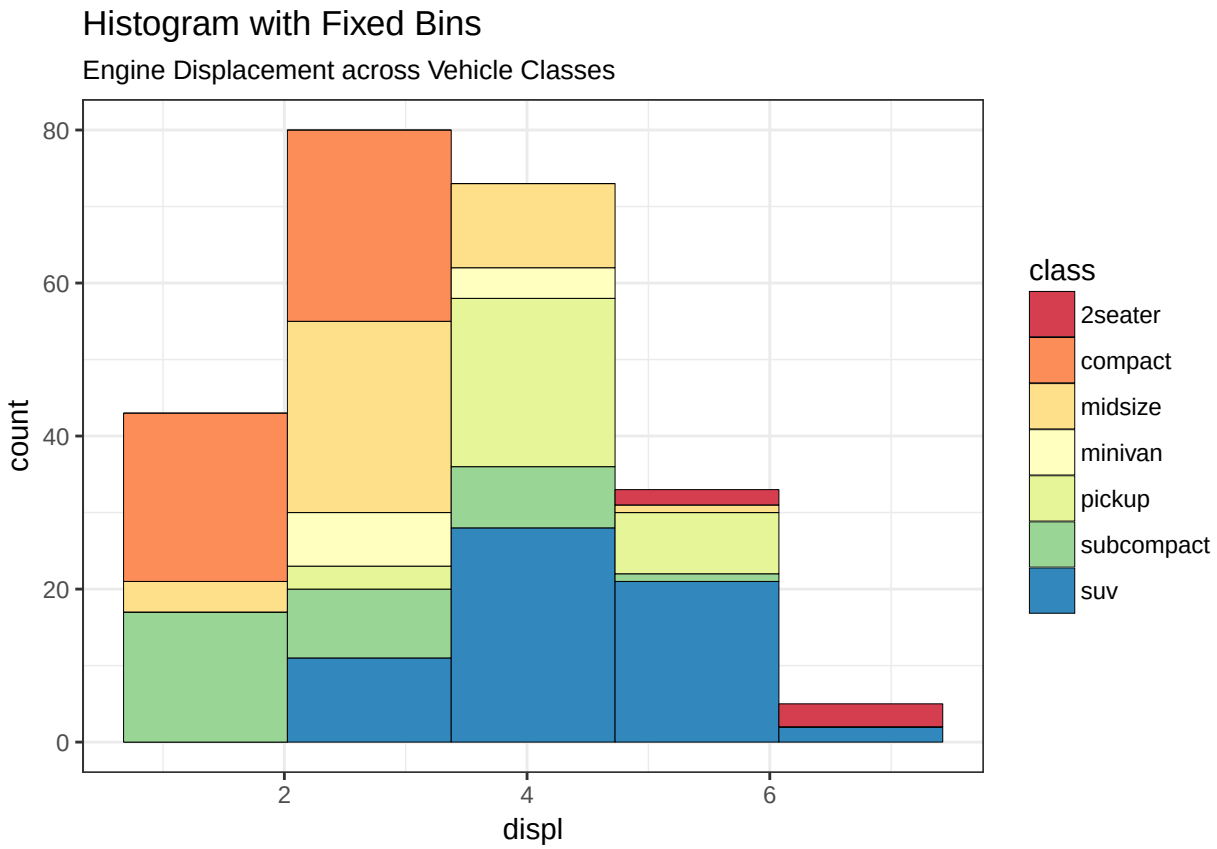
Histogram on a continuous variable can be accomplished using either `geom_bar()` or `geom_histogram()`. When using `geom_histogram()`, you can control the number of bars using the `bins` option. Else, you can set the range covered by each bin using `binwidth`. The value of binwidth is on the same scale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

```
# 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")
```



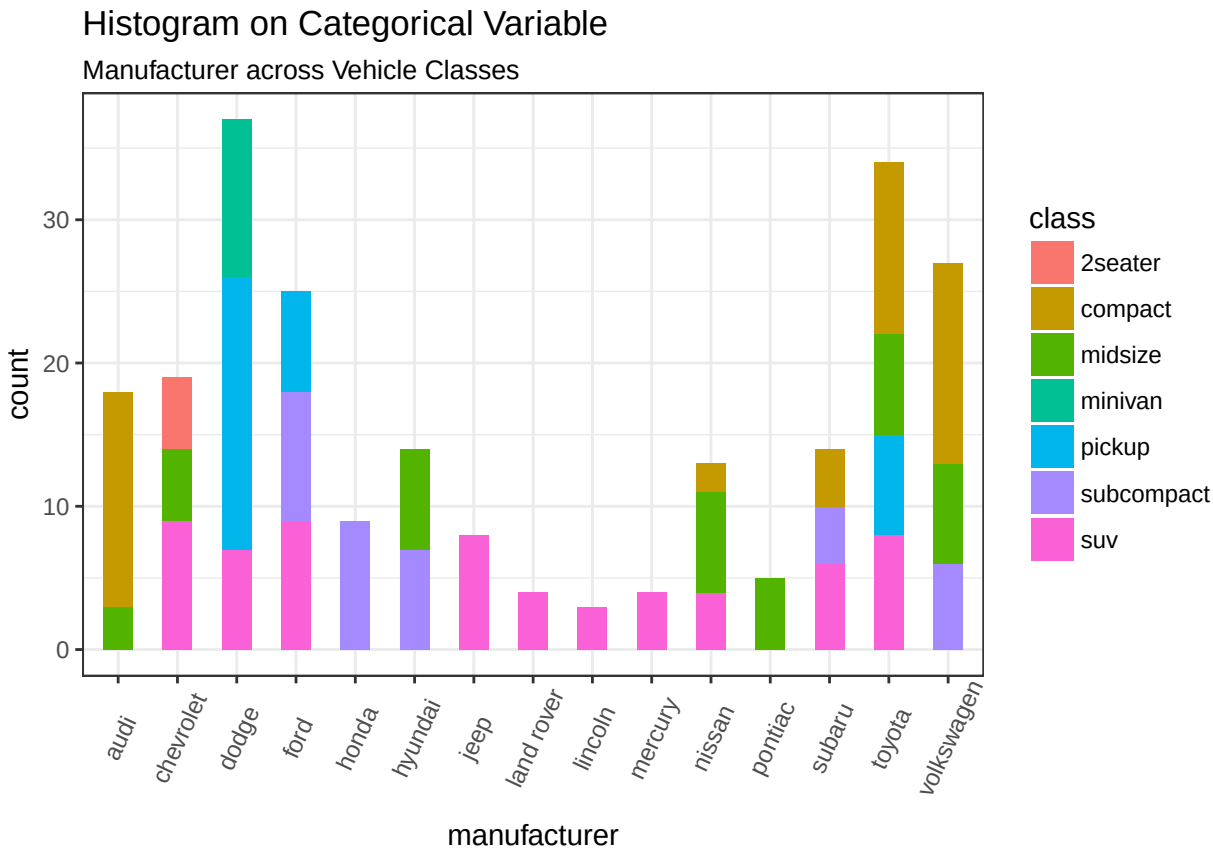

```
g + geom_histogram(aes(fill=class),
                   bins=5,
                   col="black",
                   size=.1) +   # change number of bins
  labs(title="Histogram with Fixed Bins",
       subtitle="Engine Displacement across Vehicle Classes")
```



K. Histogram on a categorical variable

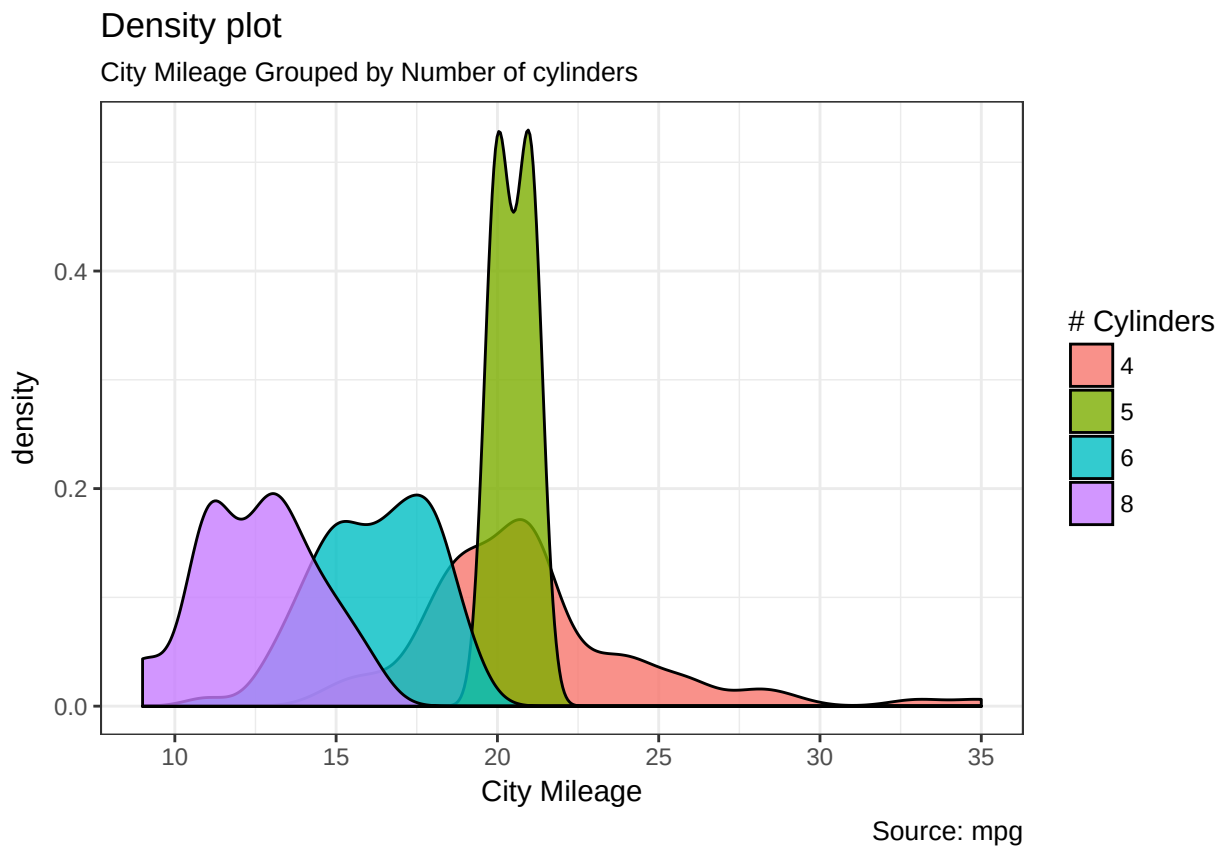
Histogram on a categorical variable would result in a frequency chart showing bars for each category. By adjusting width, you can adjust the thickness of the bars.

```
# 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")
```



L. Density Plot

```
# 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")
```



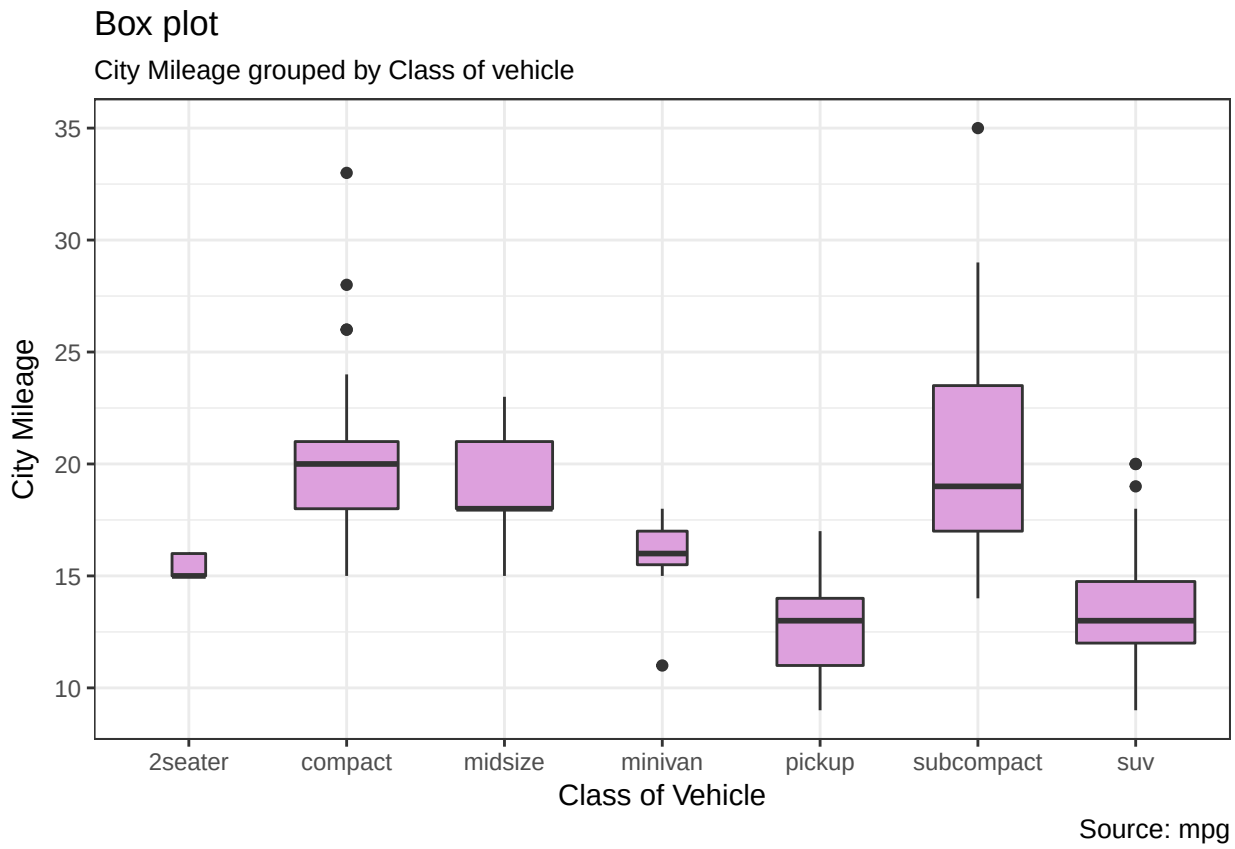
M. Box Plot

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.

```
# 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")
```

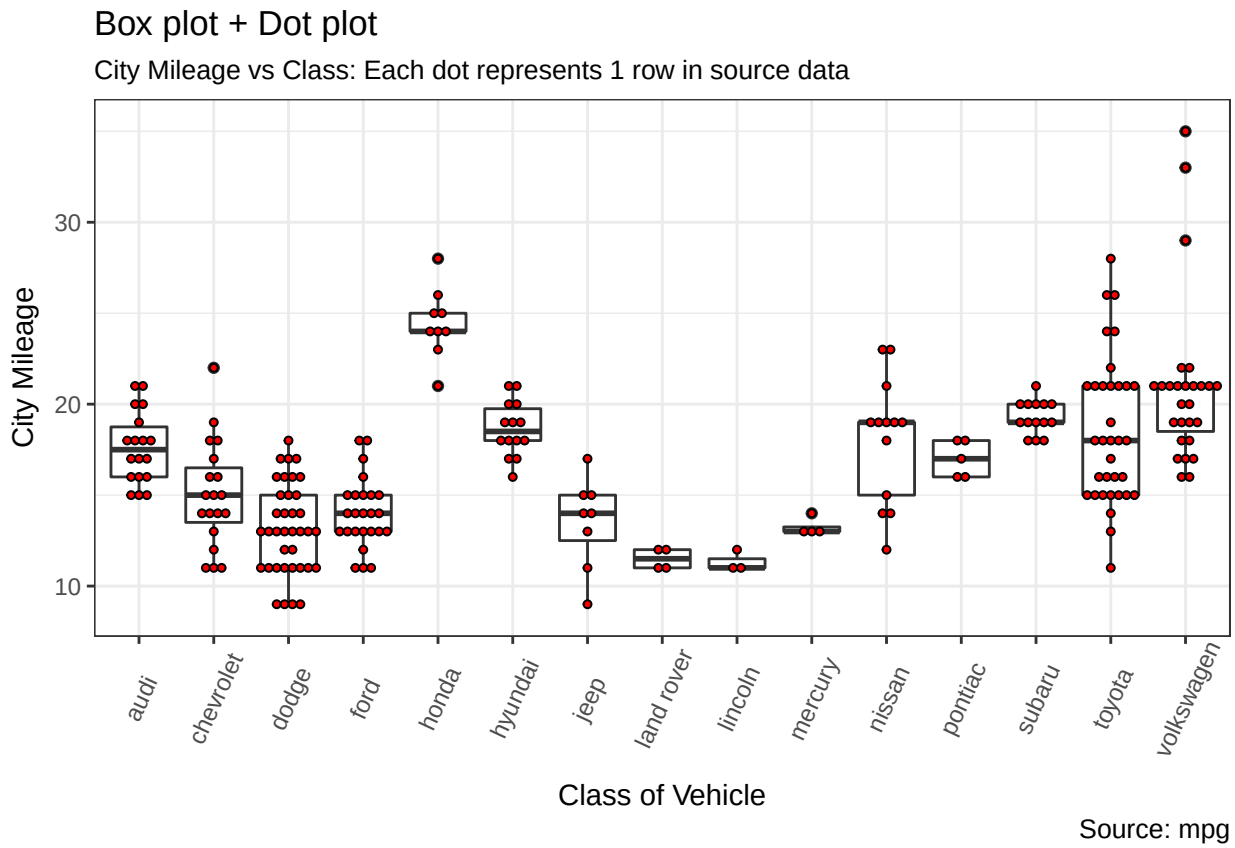


N. Dot + Box Plot

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.

```
# 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`.
```



5. Composition

O. 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.

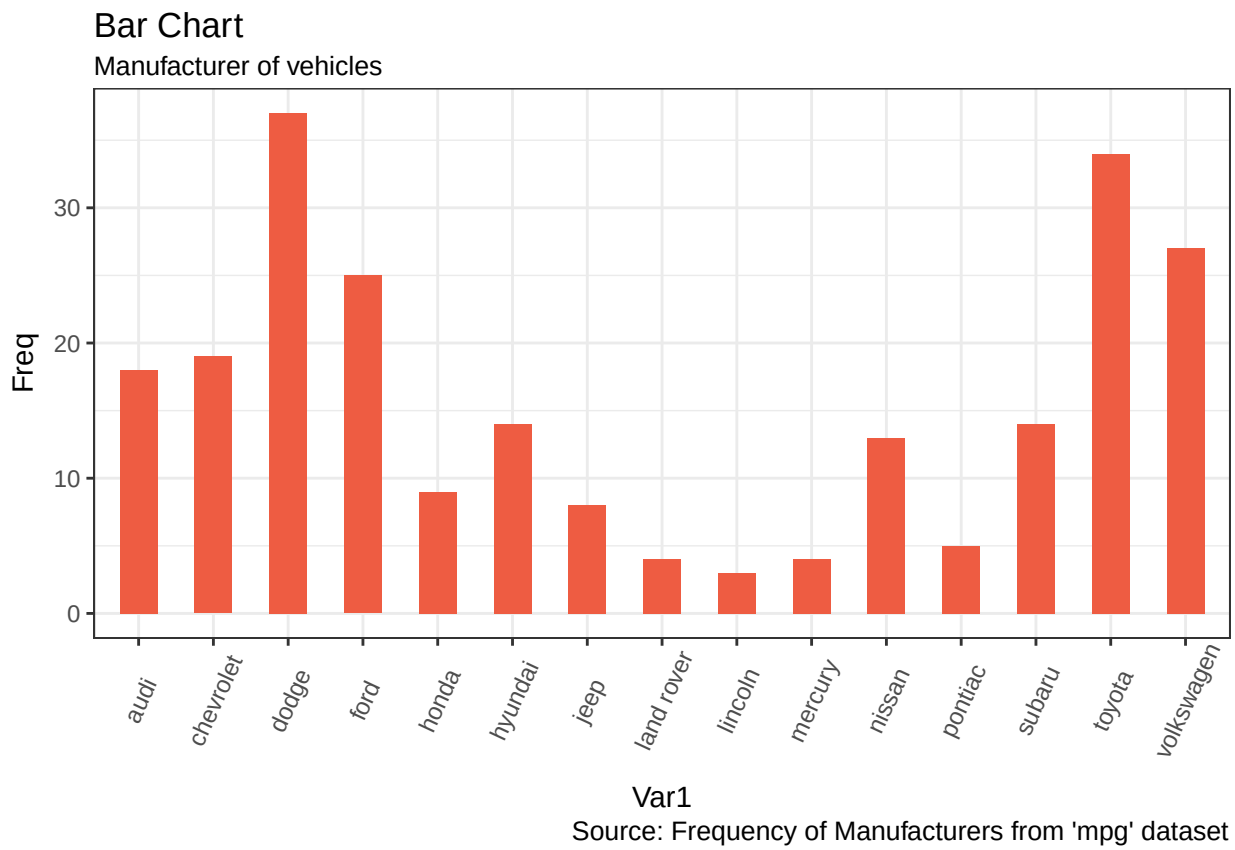
a. Set `stat=identity`
b. Provide both `x` and `y` inside `aes()` where, `x` is either `character` or `factor` and `y` is `numeric`.

```
# 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
```

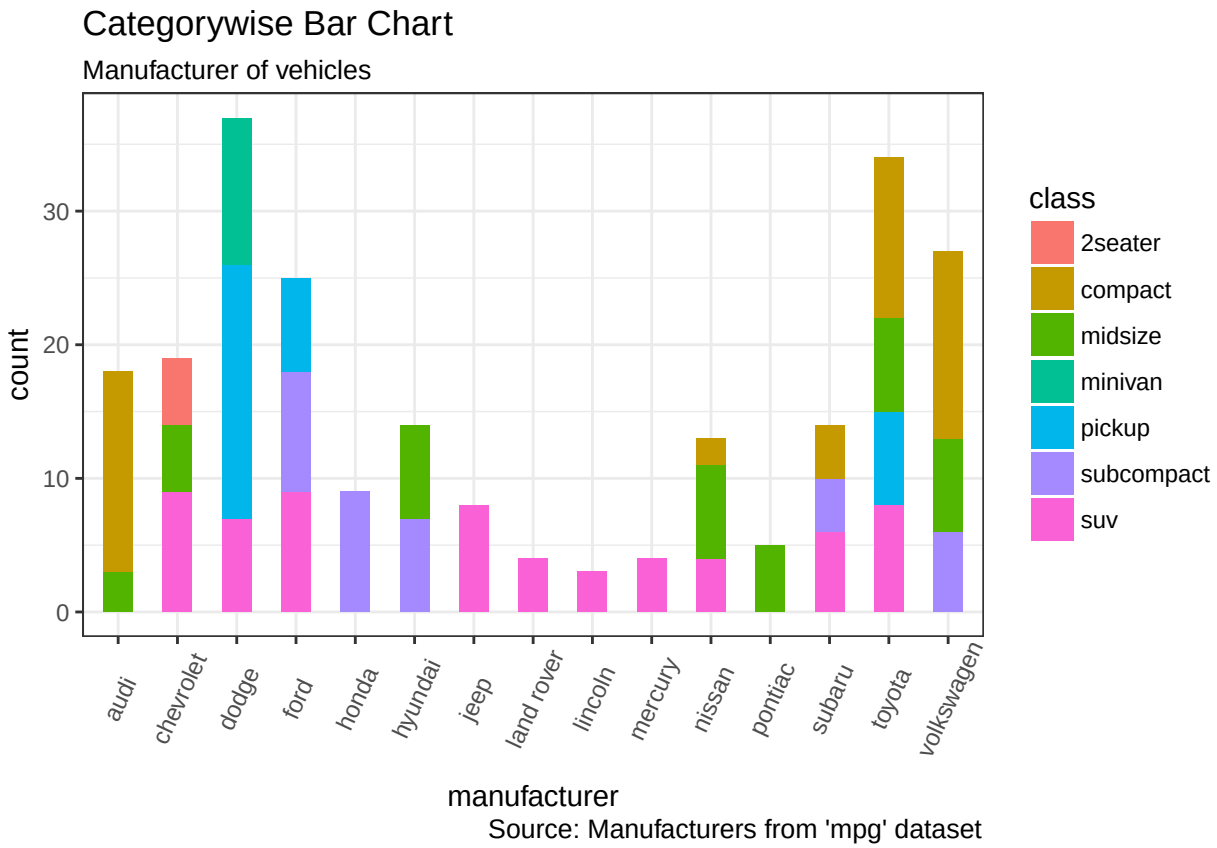
```
g <- ggplot(df, aes(Var1, Freq))
g + geom_bar(stat="identity", width = 0.5, fill="tomato2") +
      labs(title="Bar Chart",
```

```
          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")
```



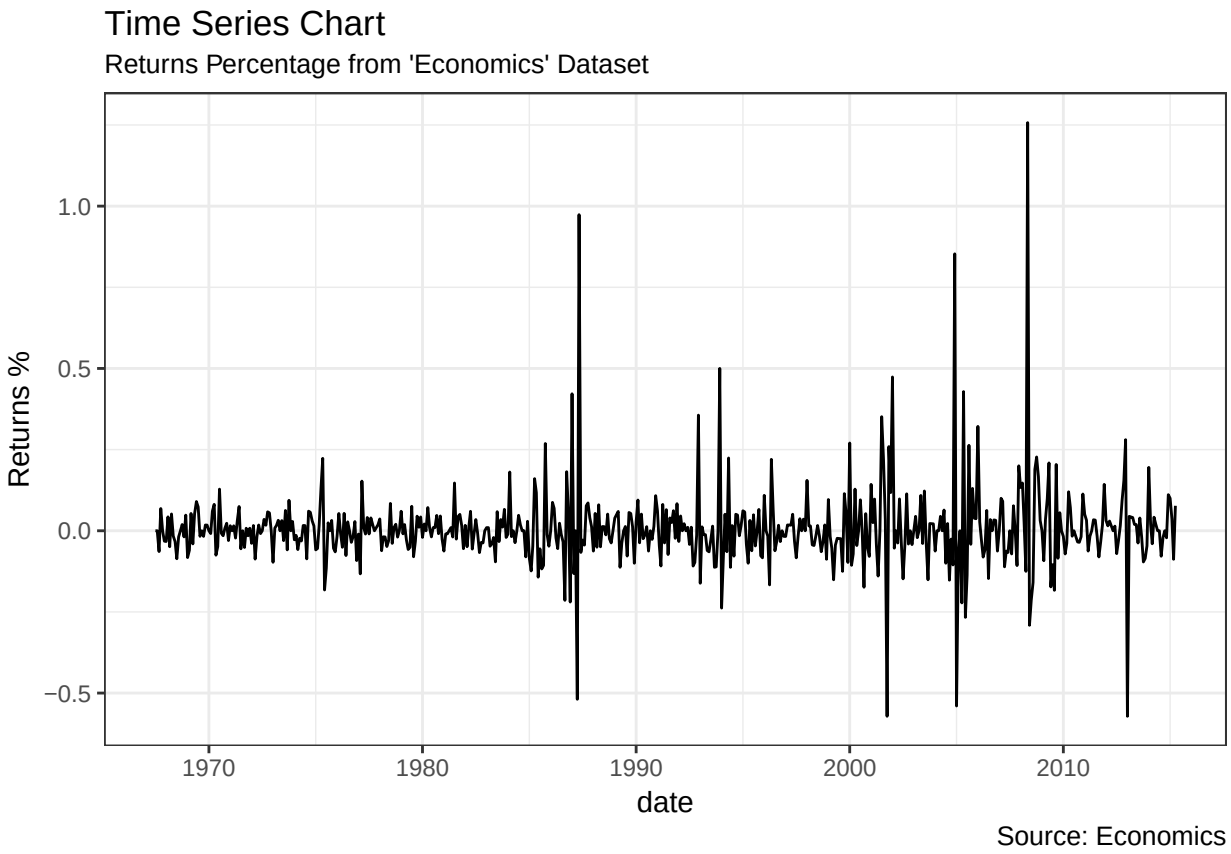
6. Change

P. Time Series Plots

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.

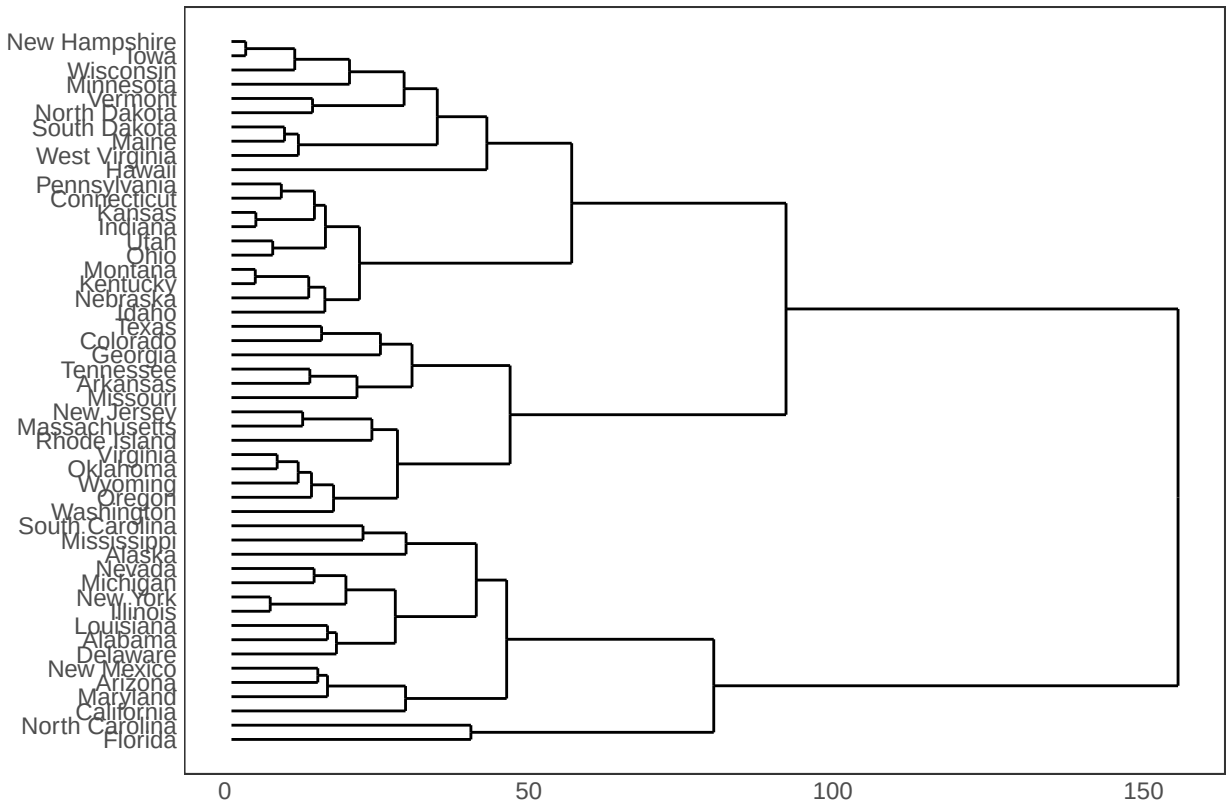
```
ggplot(economics, aes(x=date)) +
  geom_line(aes(y=returns_perc)) +
  labs(title="Time Series Chart",
       subtitle="Returns Percentage from 'Economics' Dataset",
       caption="Source: Economics",
       y="Returns %")
```



7. Groups

Q. Hierarchical Dendrogram

```
library(ggplot2)
library(ggdendro)
hc <- hclust(dist(USArrests), "ave")  # hierarchical clustering
# plot
ggdendrogram(hc, rotate = TRUE, size = 2)
```



R. 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.

```
library(ggplot2)
library(ggalt)
library(ggfortify)

# 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))
```