DSC 3091- ADVANCED STATISTICS APPLICATIONS I

S/18/406 P K K N S JAYATHILAKE

2023-08-02

Handling Missing Values and Data Visualisation

Handling Missing Values

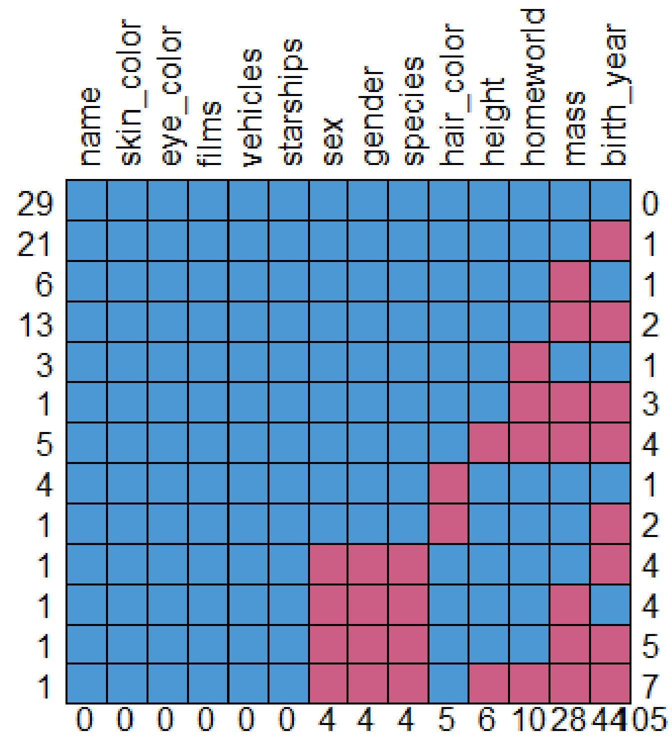
- After importing data, we have to clean them before visualizing or analysing them. A part of data cleaning we have discussed in the previous lectures.
- When cleaning data, identification of the missing values is also important. To do this, first find the proportion of missing values in each variable.
- Consider the `starwars` data set in the `dplyr` package, and obtain the proportion of missing values in each variable.

```
library(dplyr)

propmiss <- colSums(is.na(starwars))/nrow(starwars)
round(propmiss, 2)

##       name     height       mass hair_color skin_color  eye_color birth_ye
ar
##       0.00       0.07       0.32       0.06       0.00       0.00       0.
51
##        sex     gender  homeworld    species      films   vehicles  starshi
ps
##       0.05       0.05       0.11       0.05       0.00       0.00       0.
00
```

Note that 51% of the birth_year values are missing. If this variable is not important for the data analysis, you can drop this variable.

To visualize the missing values, use the function `md.pattern()` in `mice` package as below:

```r
library(mice)

md.pattern(starwars, rotate.names = T)
```



```
##    name skin_color eye_color films vehicles starships sex gender species
## 29    1          1         1     1        1         1   1      1       1
## 21    1          1         1     1        1         1   1      1       1
## 6     1          1         1     1        1         1   1      1       1
## 13    1          1         1     1        1         1   1      1       1
## 3     1          1         1     1        1         1   1      1       1
## 1     1          1         1     1        1         1   1      1       1
## 5     1          1         1     1        1         1   1      1       1
## 4     1          1         1     1        1         1   1      1       1
## 1     1          1         1     1        1         1   1      1       1
## 1     1          1         1     1        1         1   0      0       0
## 1     1          1         1     1        1         1   0      0       0
## 1     1          1         1     1        1         1   0      0       0
## 1     1          1         1     1        1         1   0      0       0
##       0          0         0     0        0         0   4      4       4
##    hair_color height homeworld mass birth_year
## 29          1      1         1    1          1   0
## 21          1      1         1    1          0   1
## 6           1      1         1    0          1   1
## 13          1      1         1    0          0   2
## 3           1      1         0    1          1   1
## 1           1      1         0    0          0   3
## 5           1      0         0    0          0   4
## 4           0      1         1    1          1   1
## 1           0      1         1    1          0   2
## 1           1      1         1    1          0   4
## 1           1      1         1    0          1   4
## 1           1      1         1    0          0   5
## 1           1      0         0    0          0   7
##             5      6        10   28         44 105
```

The missing values in a data set can be handled in two ways.

(i) **Listwise deletion** : Delete all observations which contain missing values.

First, we remove birth_year variable, since it contains 51% of the missing values, and then delete observations in the other variables which contain missing values.

```
newstar1 <- starwars %>%
  select(-birth_year)
newstar1 <- na.omit(newstar1)
propmiss <- colSums(is.na(newstar1 ))/nrow(newstar1)
round(propmiss, 2)
```

```
##       name     height       mass hair_color skin_color  eye_color         s
ex
##          0          0          0          0          0          0
0
##     gender  homeworld    species      films   vehicles  starships
##          0          0          0          0          0          0
```

(ii) **Imputation** : Replace missing values with suitable values. Refer R packages as `VIM`, `mice`, `Amelia`, `Hmisc`, `mi` and `missForest` for possible options. A details tutorial of using these packages are given here.

In the following example, we use `VIM` package which impute missing values using the 5 nearest neighbors. Since, films, vehicles and starships are lists, we remove those variables from the data set before impute values.

```
newstar2 <- starwars %>%
  select(-films, -vehicles, -starships)
library(VIM)

newstar2 <- kNN(newstar2, k=5)
propmiss <- colSums(is.na(newstar2))/nrow(newstar2)
round(propmiss, 2)

##            name          height            mass      hair_color      skin_color
##               0               0               0               0               0
##       eye_color      birth_year             sex          gender       homeworld
##               0               0               0               0               0
##         species        name_imp      height_imp        mass_imp hair_color_imp
##               0               0               0               0               0
## skin_color_imp   eye_color_imp birth_year_imp         sex_imp      gender_imp
##               0               0               0               0               0
##   homeworld_imp     species_imp
##               0               0
```

Data Visualization Using `ggplot2`

- The R package `ggplot2` produces publication quality graphics which has an underlying grammar that allows you to create graphs by combining independent components.

- The graphics of `ggplot2` start with a **layer** that shows the raw data. Then, you can add the other layers which are the collection of geometric elements and statistical transformations.

- Geometric elements are identified as **geom**s, which usually represent points, lines, polygons, etc in the plot.

- Statistical transformations are given as **stat**s which summarise the data.

- The coordinate system of the graph is represented by **coord**, which also provides axes and gridlines of the graph.

- The term **facet** is used to break up and display subsets of data.

- For the graph, a **theme** also can be used with specific font size and background colour etc.

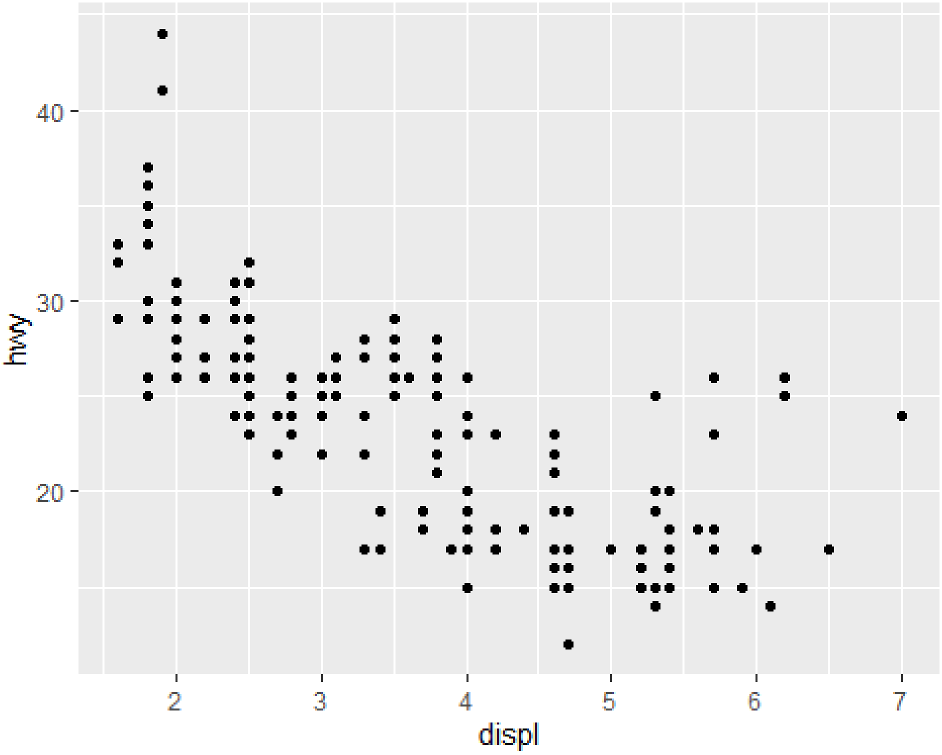
- To understand the concepts of `ggplot2`, we use the `mpg` data set in `ggplot2` package. This data set includes the fuel economy of popular car models in 1999 and 2008, collected by the US Environmental Protection Agency.

- Check the variables of the data set, and find whether there are any missing values.

- Any ggplot2 plot has **data**, a set of **aesthetic mappings** and at least one layer with a **geom** function.

Suppose we want to draw a scatter plot for engine size (displ) vs. fuel economy (hwy).

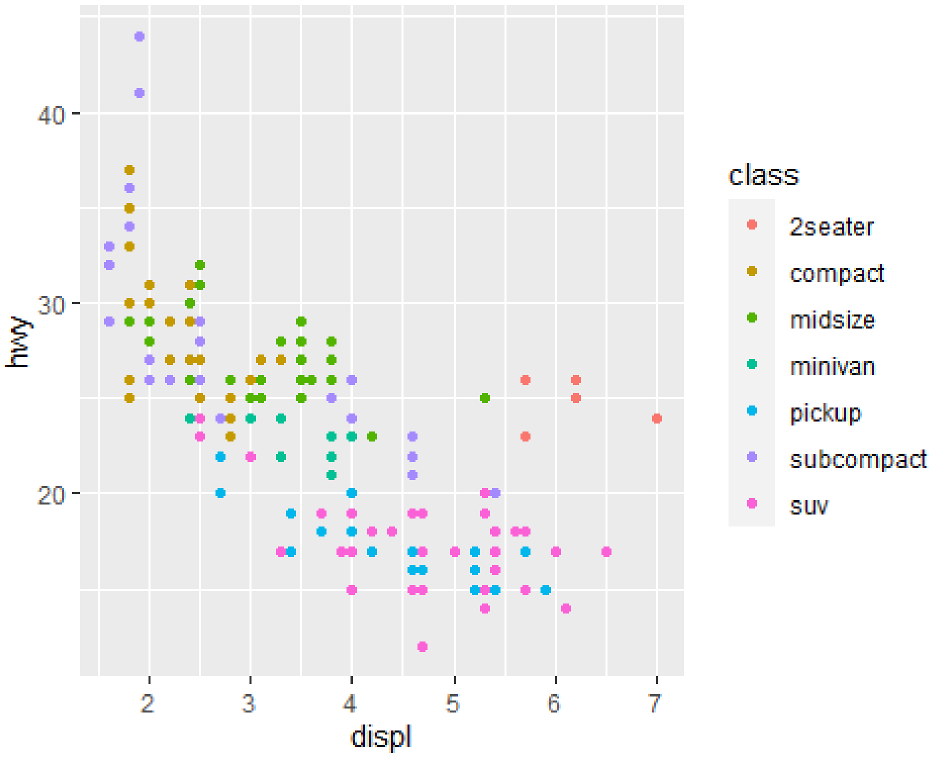
```
library(ggplot2)
mpg %>%
  ggplot(aes(x = displ, y = hwy)) +
  geom_point()
```



Here, we call data first, and then aesthetic mappings are given in ggplot() function. Then, **geom** layer is added using + sign. Refer the other **geom** elements here: https://ggplot2.tidyverse.org/reference/index.html.

To add more variables to the plot, we can use **colour, size,** and **shape** as other aesthetics.

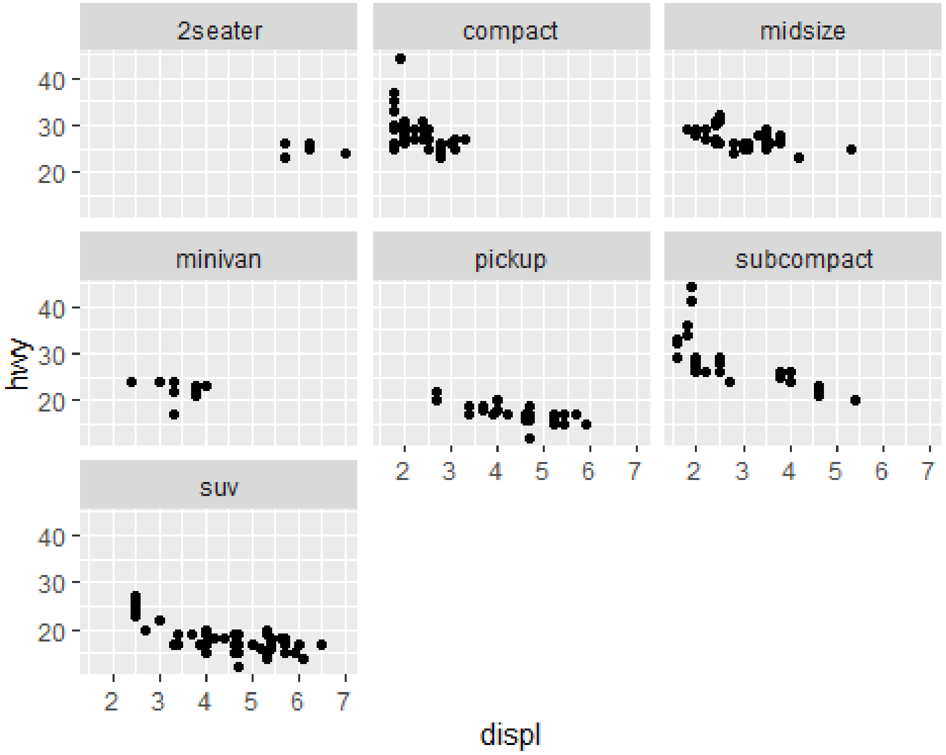
```
mpg %>%
  ggplot(aes(displ, hwy, colour = class)) +
  geom_point()
```



- Change the previous plot using `shape = drv` or `size = cyl` as aesthetics.
- Don't add many aesthetics to the same plot. Instead, draw simple plots to understand the relationships.
- The aesthetics **colour** and **shape** work well with categorical variables, and the aesthetics **size** works well for continuous variables.
- Also, if you have a large data set or you need to compare distributions separately for different categories, use faceting.
- To display additional **categorical** variable on a plot, we can use faceting. This is useful when having a large number of observations.
- Faceting creates a set of graphics by splitting the data into subsets and displaying them in the same graph.

There are two types of faceting: (i) grid faceting and (ii) wrapped faceting.

```
mpg %>%
  ggplot(aes(displ, hwy)) +
  geom_point() +
  facet_wrap(~class)
```

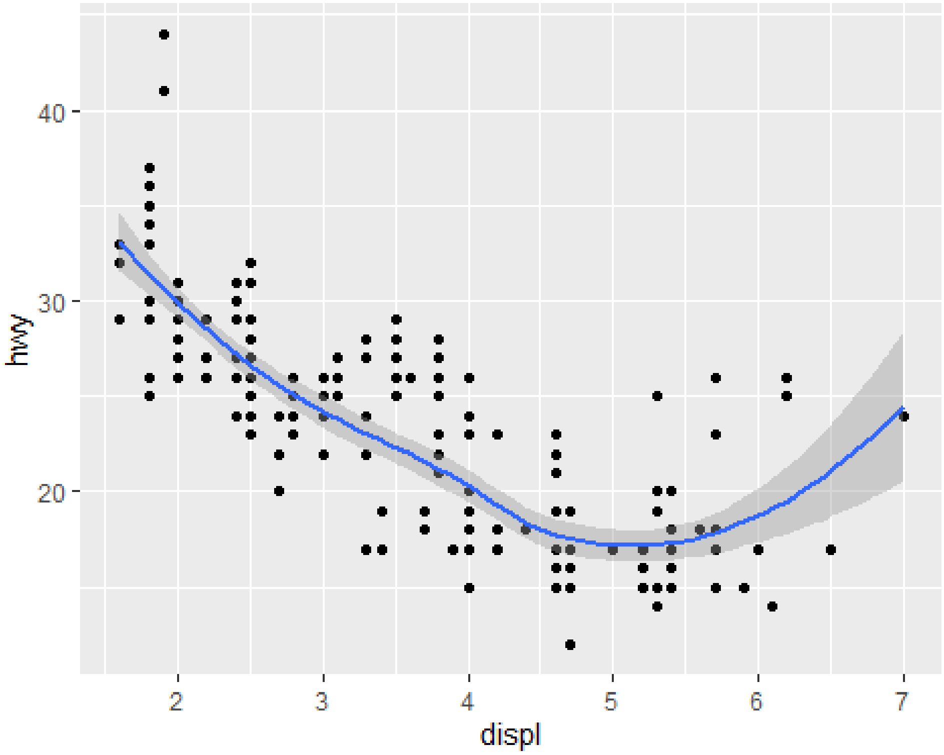


Other geom() Functions

Function	Description
geom_smooth	Add a smooth curve to the scatter plot with its standard error.
geom_boxplot()	Draw a box and whisker plot.
geom_histogram() and geom_freqpoly()	Draw a histogram and a frequency polygon.
geom_bar()	Draw Bar Charts for categorical variables.
geom_path() and geom_line()	Draw path and line plots to connect data points.

Adding a smooth curve with confidence interval

```
mpg %>%
  ggplot(aes(displ, hwy)) +
  geom_point() +
  geom_smooth()
```



- Here, the final layer is the smooth curve with confidence interval. If you want to hide the confidence interval, use `geom_smooth(se = FALSE)`.
- The default method of the smooth curve fitting is `method = "loess"`, which uses a smooth local polynomial regression, when n <= 1000.
- For large n (n > 1000), an alternative smoothing algorithm is used.

`method = "lm"` fits a linear model,

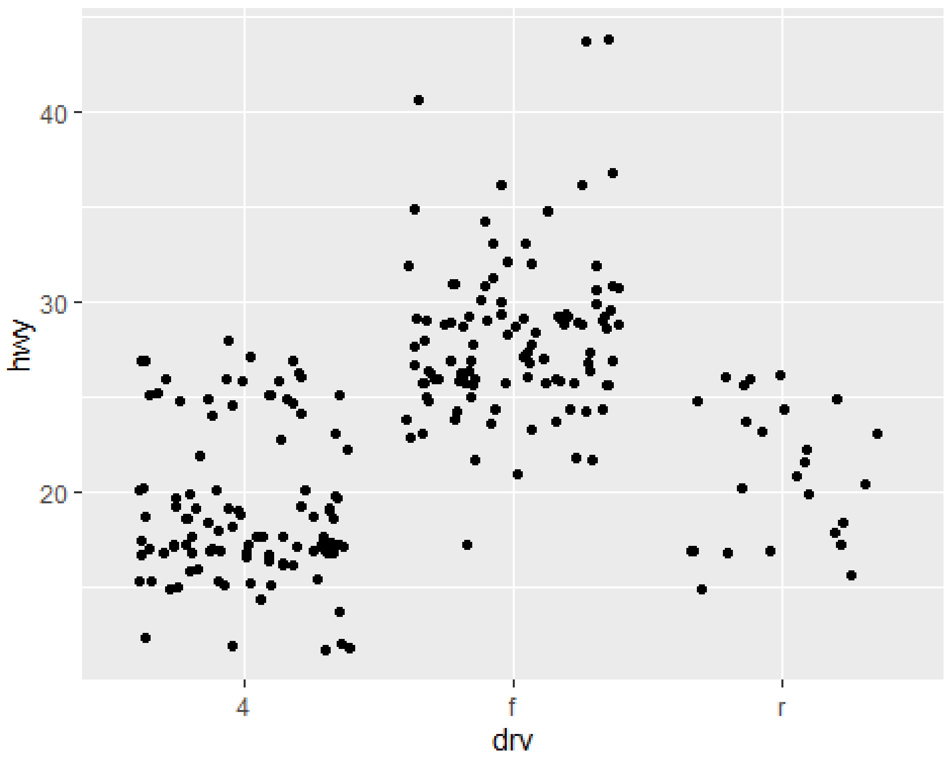
`method = "rlm"` fits a robust fitting of linear models in which the outliers does not affect the fit. Load **MASS** package if you use this method.

Refer the other options of `geom_smooth()`:
https://ggplot2.tidyverse.org/reference/geom_smooth.html

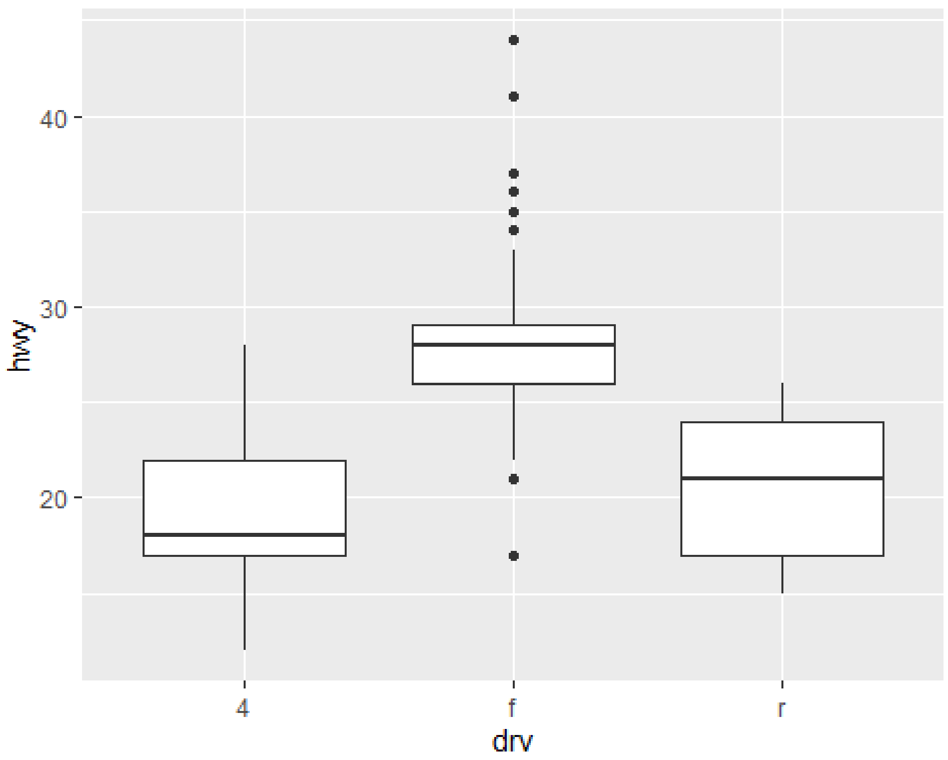
To compare the distribution of continuous variable among categories of a categorical variable, draw jittered plots, box-and-whisker plots and violin plots .

Jittered plots show all observations, and hence it is good for a relatively small datasets.

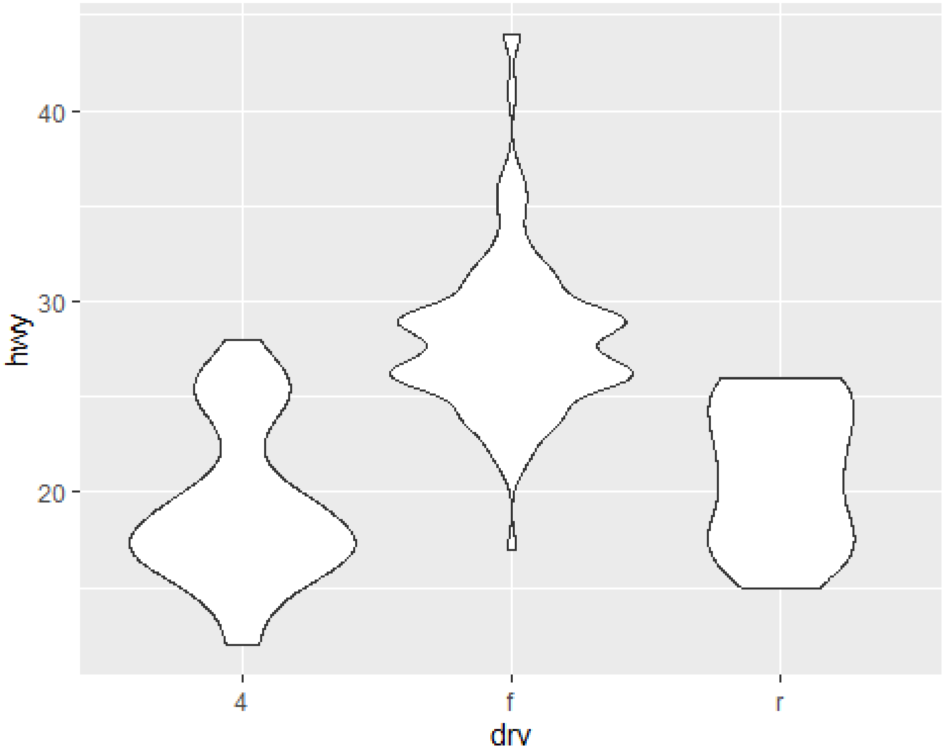
```
mpg %>%
  ggplot(aes(drv, hwy)) + geom_jitter()
```



```
mpg %>%
  ggplot(aes(drv, hwy)) + geom_boxplot()
```



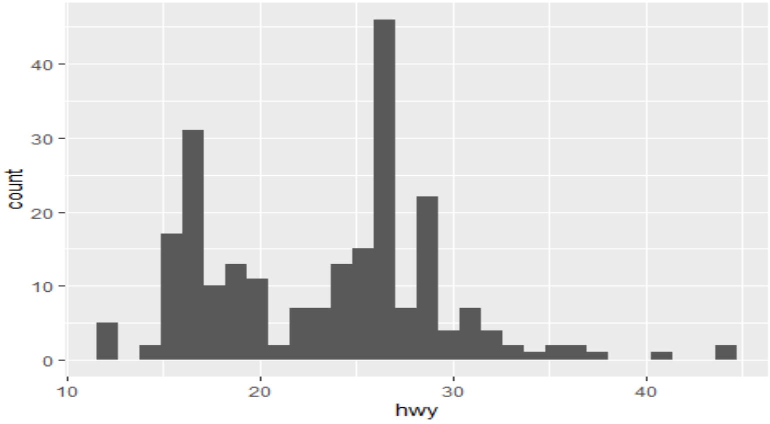
```
mpg %>%
  ggplot(aes(drv, hwy)) + geom_violin()
```



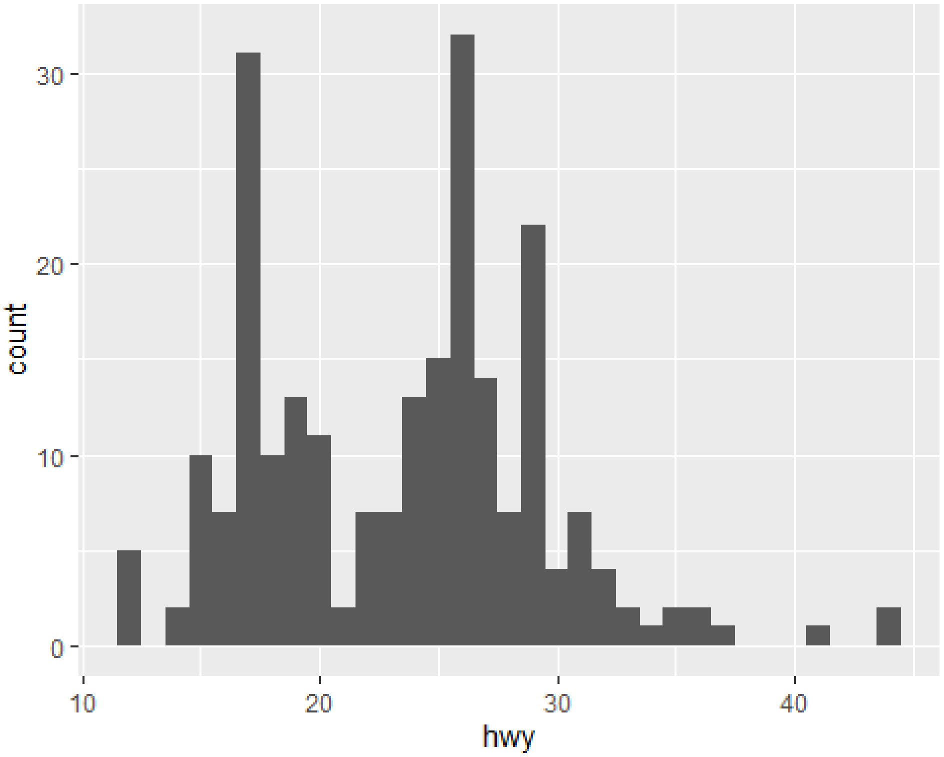
To show the distribution of a single variable, draw a histogram or frequency polygon.

The default number of bins is 30 in the `geom_histogram()` function. You can change this by setting the width of the bins with the `binwidth` argument.

```
mpg %>%
  ggplot(aes(hwy)) +
  geom_histogram()
```



```
mpg %>%
  ggplot(aes(hwy)) +
  geom_histogram(binwidth = 1)
```



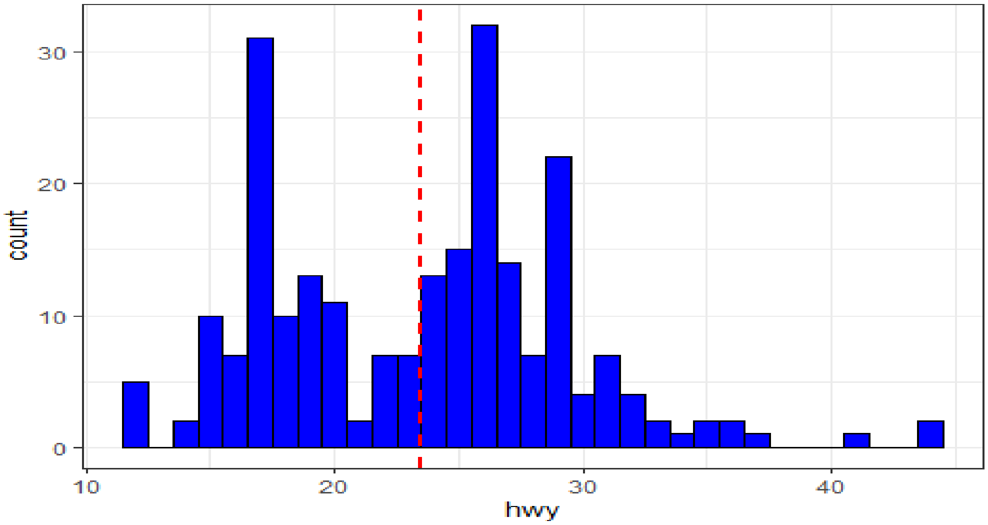
Themes

Themes is used to control over the non-data elements like fonts, ticks, panel strips, and backgrounds of your plot.

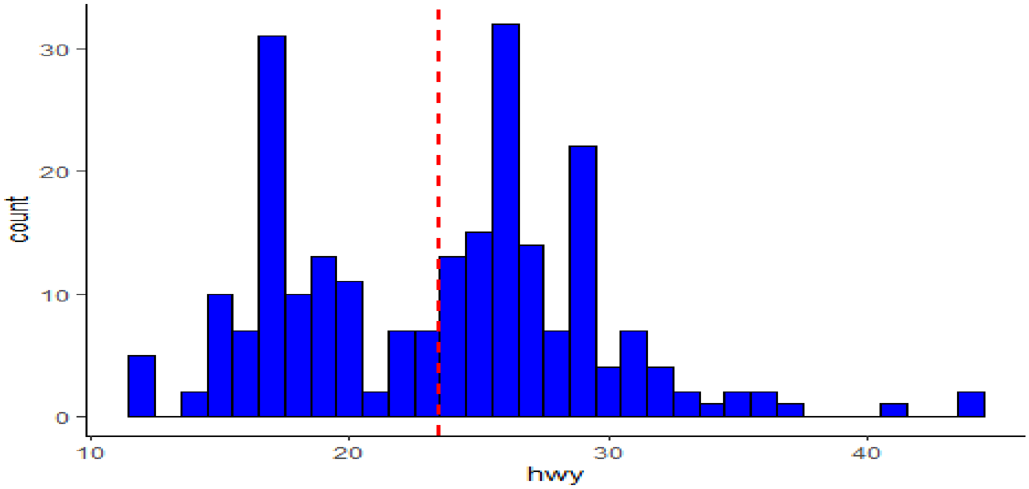
1. **theme_gray** : gray background color and white grid lines
2. **theme_bw** : white background and gray grid lines
3. **theme_linedraw** : black lines around the plot
4. **theme_light** : light gray lines and axis
5. **theme_minimal**: no background annotations
6. **theme_classic** : theme with axis lines and no grid lines
7. **theme_void**: Empty theme
8. **theme_dark**(): dark background designed to make colours

Consider the following two plots

```
mpg %>%
  ggplot(aes(hwy)) +
  geom_histogram(color="black", fill="blue", binwidth = 1)+
  geom_vline(aes(xintercept=mean(hwy)),color="red", linetype="dashed", size=1
)+
  theme_bw()
```



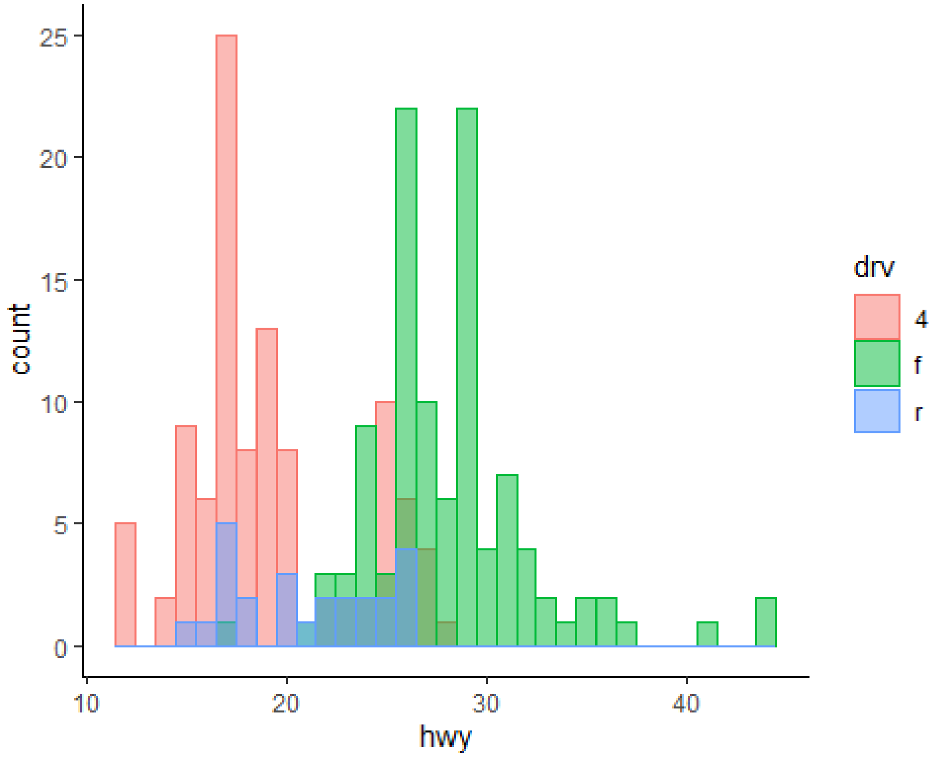
```
mpg %>%
  ggplot(aes(hwy)) +
  geom_histogram(color="black", fill="blue",binwidth = 1)+
  geom_vline(aes(xintercept=mean(hwy)),color="red", linetype="dashed", size=1
)+
  theme_classic()
```



Use the other background themes and see the difference.

In the mpg data set, the variable drv represents the drive type (f=front wheel, r=rear wheel, 4=4 wheel) of vehicles. We can draw histograms of hwy variable separately for the drive type in the same graph as below:

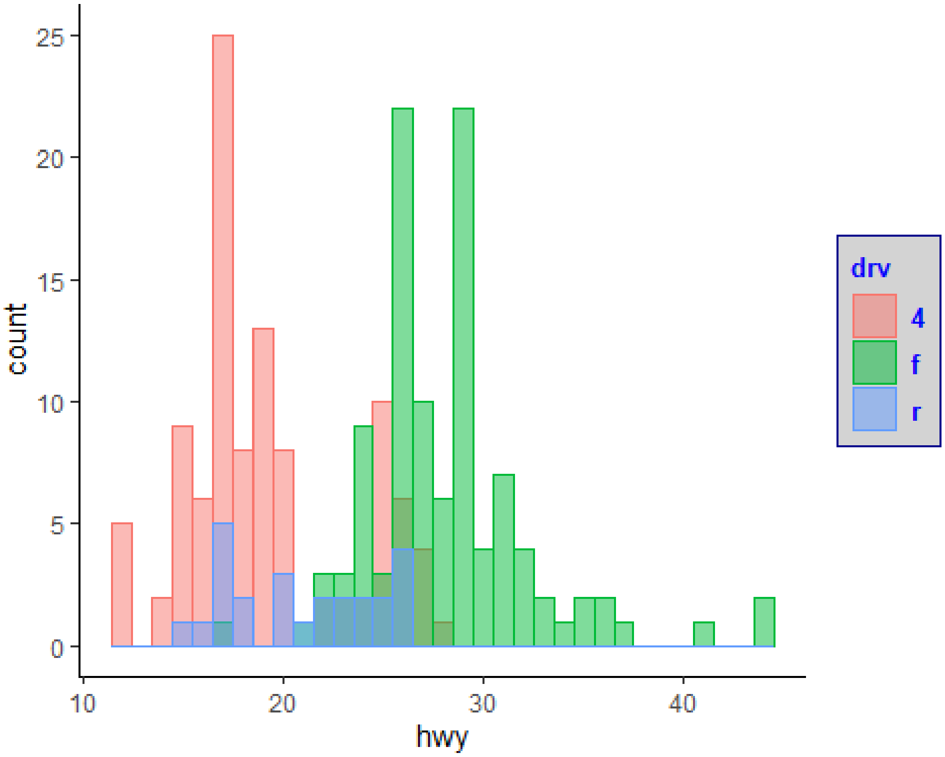
```
mpg %>%
  ggplot(aes(x=hwy, fill=drv, color=drv)) +
  geom_histogram(alpha=0.5, position="identity", binwidth = 1)+
      theme_classic()
```



- You can change the position argument in a plot to use for overlapping points on the layer. The default value is "stack".Other possible values for the argument position are "identity"and "dodge".
- The default legend position is right in ggplot. Some of the options to change the legend position are given below:
- `theme(legend.position="top") theme(legend.position="bottom")`
  `theme(legend.position="none") theme(legend.position = c(0.8, 0.2))`
- Change the legend position of the previous plot using the above codes.

To change the legend title, text font style, and the background colour of the legend box, use the following codes:

```
p<-mpg %>%
  ggplot(aes(x=hwy, fill=drv, color=drv)) +
  geom_histogram(alpha=0.5, position="identity", binwidth = 1)+
          theme_classic()
p1<-p+theme(legend.title = element_text(colour="blue", size=10, face="bold"))

p2<-p1+theme(legend.text = element_text(colour="blue", size=10, face="bold"))

p2+theme(legend.background = element_rect(fill="lightgray",size=0.5, linetype
="solid", colour ="darkblue"))
```



Saving Your Plot

Save your plot by assigning it to a plot object as below:

```
p <- mpg %>%
    ggplot(aes(displ, hwy, colour = factor(cyl))) +
  geom_point()

# Save the plot as png
ggsave("plot.png", p, width = 5, height = 5)
```

To see the data sets in a loaded R package, go to

Environment tab —-> Global Environment

Then, select the specific package. Now, you can see the list of data sets in that package.

OR else use the `datasets` function in the `vcdExtra` package as below:

```
library(vcdExtra)

vcdExtra::datasets("ggplot2")

##              Item      class      dim
## 1        diamonds data.frame 53940x10
## 2       economics data.frame    574x6
## 3  economics_long data.frame   2870x4
## 4       faithfuld data.frame   5625x3
## 5     luv_colours data.frame    657x4
## 6         midwest data.frame   437x28
## 7             mpg data.frame   234x11
## 8          msleep data.frame    83x11
## 9    presidential data.frame     12x4
## 10          seals data.frame   1155x4
## 11      txhousing data.frame   8602x9
##                                                                 Title
## 1                           Prices of over 50,000 round cut diamonds
## 2                                            US economic time series
## 3                                            US economic time series
## 4                           2d density estimate of Old Faithful data
## 5                                            'colors()' in Luv space
## 6                                               Midwest demographics
## 7  Fuel economy data from 1999 to 2008 for 38 popular models of cars
## 8       An updated and expanded version of the mammals sleep dataset
## 9                    Terms of 12 presidents from Eisenhower to Trump
## 10                                    Vector field of seal movements
## 11                                               Housing sales in TX
```

More Details

- `mice` R package: https://datascienceplus.com/imputing-missing-data-with-r-mice-package/
- ggplot2 by Hadley Wickham, Danielle Navarro, and Thomas Lin Pedersen: https://ggplot2-book.org/index.html

- Graphic Design with ggplot2, rstudio::conf(2022) Workshop by Cdric Scherer: https://rstudio-conf-2022.github.io/ggplot2-graphic-design/
- ggplot themes and background colour: http://www.sthda.com/english/wiki/ggplot2-themes-and-background-colors-the-3-elements
- ggplot2 legends: http://www.sthda.com/english/wiki/ggplot2-legend-easy-steps-to-change-the-position-and-the-appearance-of-a-graph-legend-in-r-software
- ggplot legend title, position and labels: https://www.datanovia.com/en/blog/ggplot-legend-title-position-and-labels/
- Data Visualization with ggplot2: https://www.publichealth.columbia.edu/sites/default/files/media/fdawg_ggplot2.html
- ggplot2 - Essentials: http://www.sthda.com/english/wiki/ggplot2-essentials
- Colortool: http://www.sthda.com/english/wiki/the-elements-of-choosing-colors-for-great-data-visualization-in-r
- Gramme of Graphics: https://pkg.garrickadenbuie.com/gentle-ggplot2/#1
- Dealing with missing values: https://medium.com/coinmonks/dealing-with-missing-data-using-r-3ae428da2d17