Exploratory Data Analysis

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Graphing with `ggplot2`

The R library `ggplot2` is very powerful for plotting but you may find the syntax little strange. There are plenty of examples at the `ggplot2` online help website. The `ggplot2` package is loaded as part of the `tidyverse` set of packages.

Advantages of `ggplot2` are the following:

- employs the "grammar of graphics" of [1]
- plotting involves a high level of abstraction
- very flexible and complete graphics system
- theme system for getting attractive plots
- Fast growing and actively developed

Some disadvantages of `ggplot2` are the following:

- 3-dimensional graphics (opt for `rgl` package instead)
- Graph-theory type graphs (nodes/edges layout; opt for `igraph` and other packages)
- Interactive graphics (opt for `plotly`, `ggvis` and other packages)

Grammar of Graphics

The main idea behind the grammar of graphics of [1] is to mimic the manual graphing approach by defining building blocks and combining them to create the figure.

The building blocks of a graph are:

- data
- aesthetic mapping

- geometric object
- transformation or re-expression of data
- scales
- coordinate system
- position adjustments
- faceting

Aesthetic Mapping (`aes`)

In ggplot land *aesthetic* means visualisation features or aesthetics. These are

- position (i.e., on the x and y axes)
- color ("outside" color)
- fill ("inside" color)
- shape (of points)
- linetype
- size

Aesthetic mappings are set with the `aes()` function.

Geometric Objects (`geom`)

Geometric objects or `geoms` are the actual marking or inking on a plot such as:

- points (`geom_point`, for scatter plots, dot plots, etc)
- lines (`geom_line`, for time series, trend lines, etc)
- boxplot (`geom_boxplot`, for boxplots)

A plot must have at least one `geom` *but there is no upper limit.* In order to add a `geom` to a plot, the `+` operator is employed. A list of available geometric objects can be obtained by typing `geom_<tab>` in Rstudio. The following command can also be used which will open a Help window.

```
help.search("geom_", package = "ggplot2")
```

ggplot2 in the tidyverse

`ggplot2` is now part of the `tidyverse`. We have installed `tidyverse` in a previous workshop so you will not need to install it again.

We can now load the `ggplot2` library with the commands:

```
library(tidyverse)
```

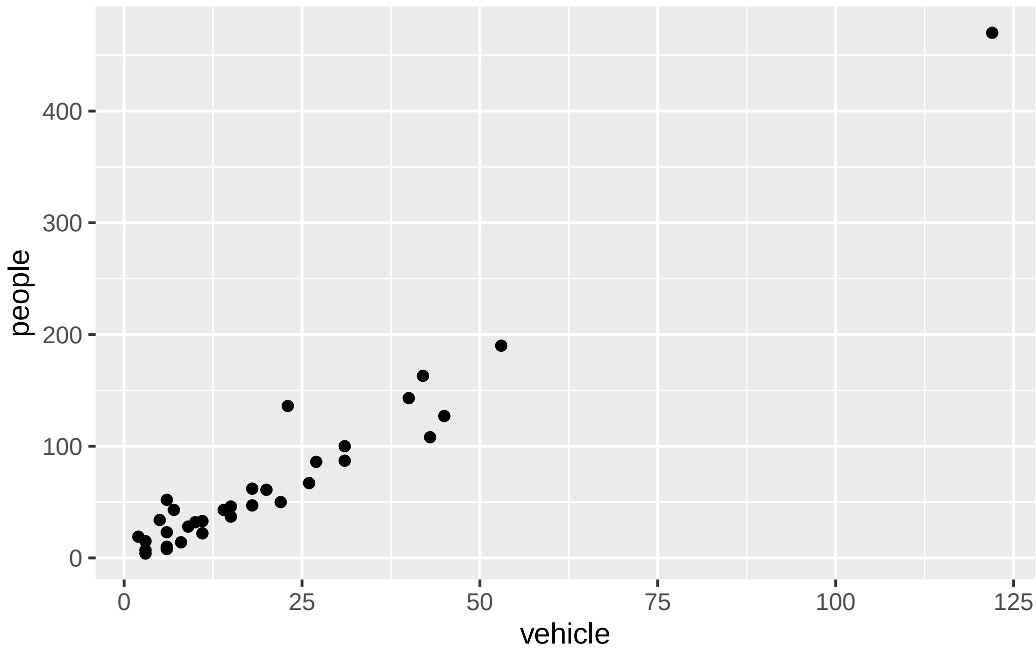
```
-- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
v dplyr     1.1.4     v readr     2.1.5
v forcats   1.0.0     v stringr   1.5.1
v ggplot2   3.5.1     v tibble    3.2.1
v lubridate 1.9.3     v tidyr     1.3.1
v purrr     1.0.4
-- Conflicts ------------------------------------------ tidyverse_conflicts() --
x dplyr::filter() masks stats::filter()
x dplyr::lag()    masks stats::lag()
i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to becom
```

In order to work with `ggplot2`, we must have a `data frame` or a `tibble` containing our data. We need to specify the `aesthetics` or how the columns of our data frame can be translated into positions, colours, sizes, and shapes of graphical elements.

Let's start with the rangitikei data we used in an earlier workshop

```
rangitikei <- read.csv(
  "../data/rangitikei.csv",
  header=TRUE,
  row.names = 1
  )
```

```
ggplot(rangitikei) +
  aes(x = vehicle, y = people) +
  geom_point()
```



The `aes` part defines the "aesthetics", which is how columns of the dataframe map to graphical attributes such as x and y position, colour, size, etc. An aesthetic can be either numeric or categorical and an appropriate scale will be used. After this, we add layers of graphics called `geom_`s. `geom_point` layer is employed to map x and y and we need not specify all the options for `geom_point`.

Exercise 2.1

Why does the following give an error and how would you fix it?

```
ggplot(data = rangitikei) +
  geom_point()
```

Adding layers

ggplot works by adding layers to your plots. Your plots must include `aes()` and a `geom_`; after that we can add extras.

We can add a title using *labs()* or *ggtitle()* functions. Try-

```
ggplot(rangitikei) +
  aes(x = vehicle, y = people, color = river) +
  geom_point() +
  ggtitle("No. of people vs No. of vehicles")
```

or

```
ggplot(rangitikei)+
  aes(x = vehicle, y = people) +
  geom_point() +
  labs(title = "No. of people vs No. of vehicles")
```

Note that *labs()* allows captions and subtitles. Check out `?labs()` for all the options.

Exercise 2.2

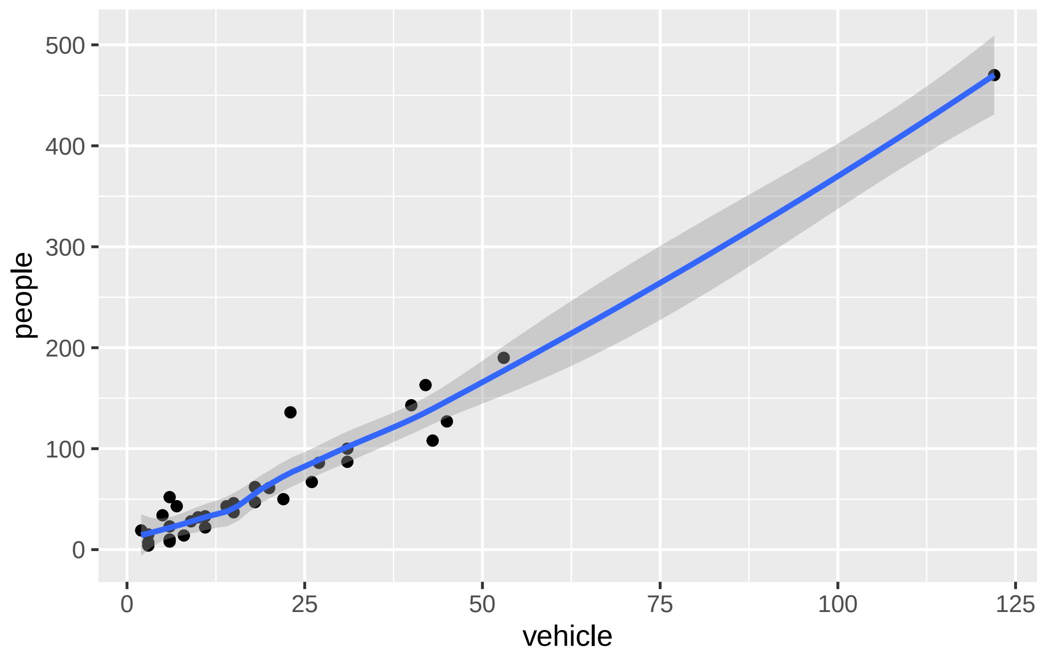
Remake the above graph, adjusting the x axis to say `Vehicles` using the `labs()` function.

```
# your code goes here
```

`geom_smooth` is additionally used to show trends.

```
ggplot(rangitikei) +
  aes(x = vehicle, y = people) +
  geom_point() +
  geom_smooth()
```

```
`geom_smooth()` using method = 'loess' and formula = 'y ~ x'
```



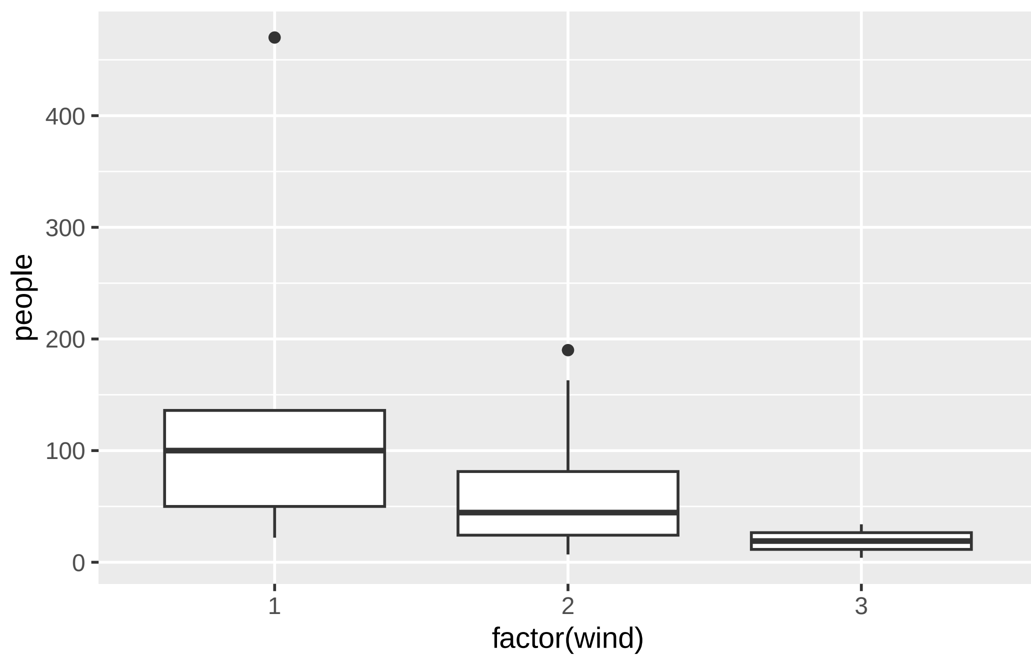
Exercise 2.3

Run this code in your head and predict what the output will look like. Then, run the code in R and check your predictions.

```
ggplot(rangitikei) +
  aes(x = vehicle, y = people) +
  geom_point()+
  geom_smooth(se = FALSE)
```

Similar to `geom_smooth`, a variety of other `geoms` are available. For example, `geom_boxplot()`:

```
ggplot(rangitikei) +
  aes(x = factor(wind), y = people) +
  geom_boxplot()
```



You can add additional information to your graph by using multiple `geoms`. Each `geom` accepts a particular set of mappings; for example `geom_text()` accepts a `labels` mapping. Try-

```
ggplot(rangitikei) +
  aes(x = vehicle, y = people) +
  geom_point() +
  geom_text(aes(label = w.e),
            size = 5)
```

Exercise 2.4

Will these two graphs look different? Why/why not? What happens when you run the code?

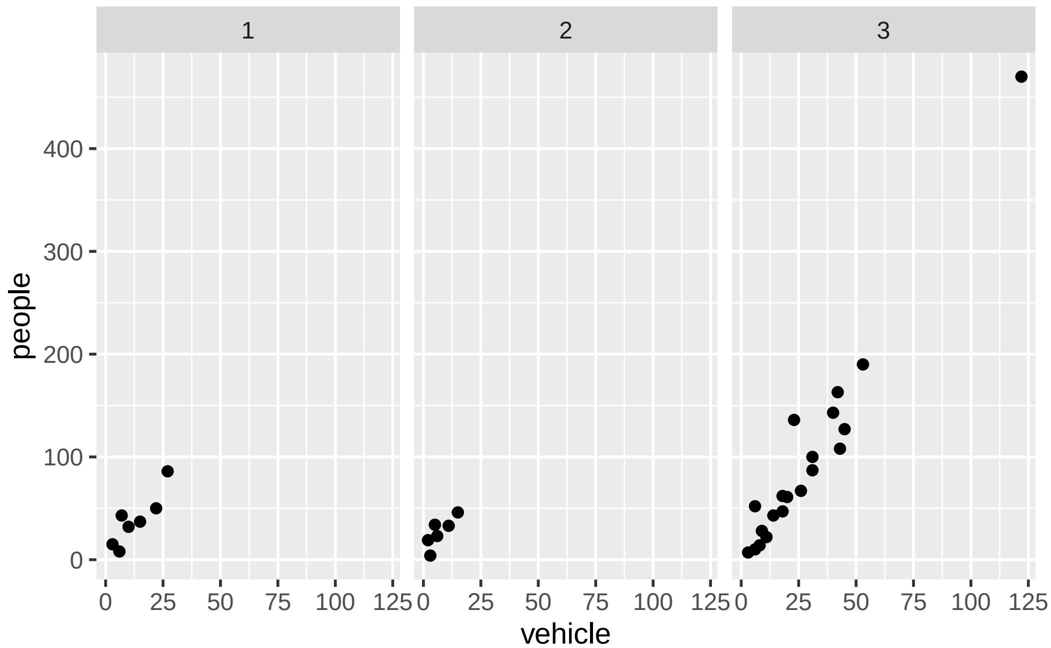
```
ggplot(
  data = rangitikei,
  mapping = aes(x = vehicle, y = people)
) +
  geom_point() +
  geom_smooth()

ggplot() +
  geom_point(
    data = rangitikei,
    mapping = aes(x = vehicle, y = people)
  ) +
  geom_smooth(
    data = rangitikei,
    mapping = aes(x = vehicle, y = people)
  )
```

Explore multiple `geom`s and thing about how different types of data might be displayed in each.

Panels

The faceting option allows a collection of small plots with the same scales. Try-

```
ggplot(rangitikei) +
  aes(x=vehicle, y=people) +
  geom_point() +
  facet_wrap(~ river)
```



Faceting is the `ggplot2` option to create separate graphs for subsets of data. `ggplot2` offers two functions for creating small multiples:

1. `facet_wrap()`: define subsets as the levels of a single grouping variable
2. `facet_grid()`: define subsets as the crossing of two grouping variables

The following arguments are common to most scales in `ggplot2`:

- **name:** the first argument gives the axis or legend title
- **limits:** the minimum and maximum of the scale
- **breaks:** the points along the scale where labels should appear
- **labels:** the labels that appear at each break

Adjusting scales

Specific scale functions may have additional arguments. Some of the available Scales are:

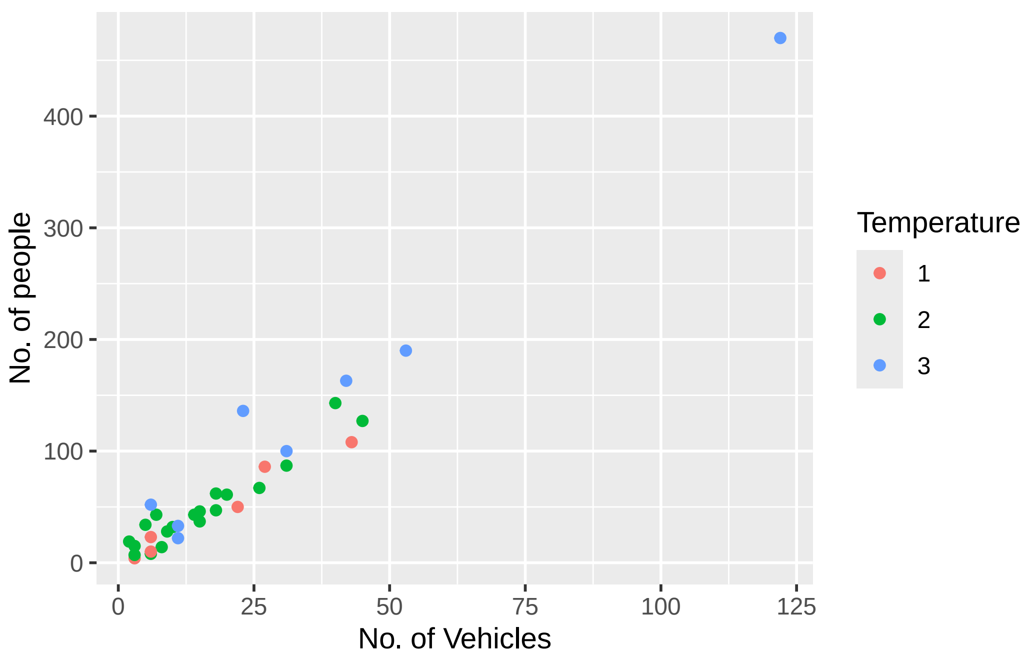
Scale	**Examples**
`scale_color_`	`scale_color_discrete`
`scale_fill_`	`scale_fill_continuous`
`scale_size_`	`scale_size_manual`
	`scale_size_discrete`

Scale	Examples
scale_shape_	scale_shape_discrete
	scale_shape_manual
scale_linetype_	scale_linetype_discrete
scale_x_	scale_x_continuous
	scale_x_log
	scale_x_date
scale_y_	scale_y_reverse
	scale_y_discrete
	scale_y_datetime

In RStudio, we can type `scale_` followed by TAB to get the whole list of available scales.

Try-

```
ggplot(rangitikei) +
  aes(x = vehicle, y = people, color = factor(temp)) +
  geom_point() +
  scale_x_continuous(name = "No. of Vehicles") +
  scale_y_continuous(name = "No. of people") +
  scale_color_discrete(name = "Temperature")
```



The other coding option is shown below:

```
ggplot(rangitikei) +
  aes(x = vehicle, y = people, color = factor(temp)) +
  geom_point() +
  xlab("No. of Vehicles") +
  ylab("No. of people") +
  labs(colour="Temperature")
```

Note that a desired graph can be obtained in more than one way.

In both of the above graphs adding color adds a third layer of data that can be plotted.

Themes

Themes can help adjust different pieces of your graphs to make them publication or presentation ready. Here you can adjust font, size, axis features, etc.

The `ggplot2` theme system handles plot elements (not data based) such as

- Axis labels
- Plot background
- Facet label background
- Legend appearance

Built-in themes include:

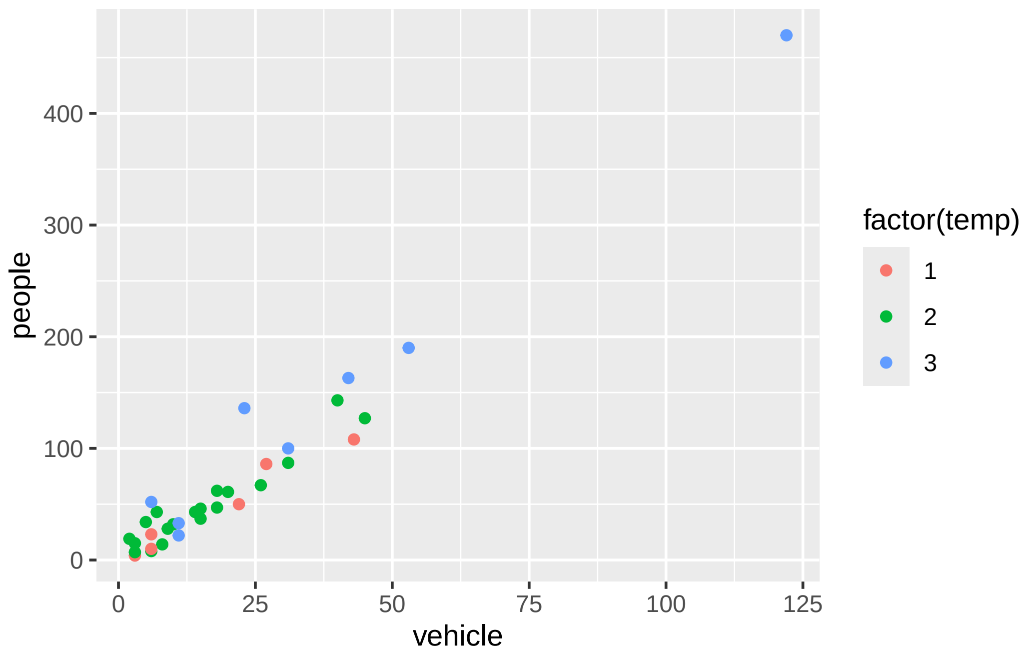
- `theme_gray()` (default)
- `theme_bw()`
- `theme_minimal()`
- `theme_classic()`

```
p1 <- ggplot(rangitikei) +
  aes(x = vehicle, y = people, color = factor(temp)) +
  geom_point()
```

Note that the graph is assigned an object name `p1` and nothing will be printed unless we then print the object `p1`. Here, the plot is assigned to an object to make applying and comparing different themes simple.

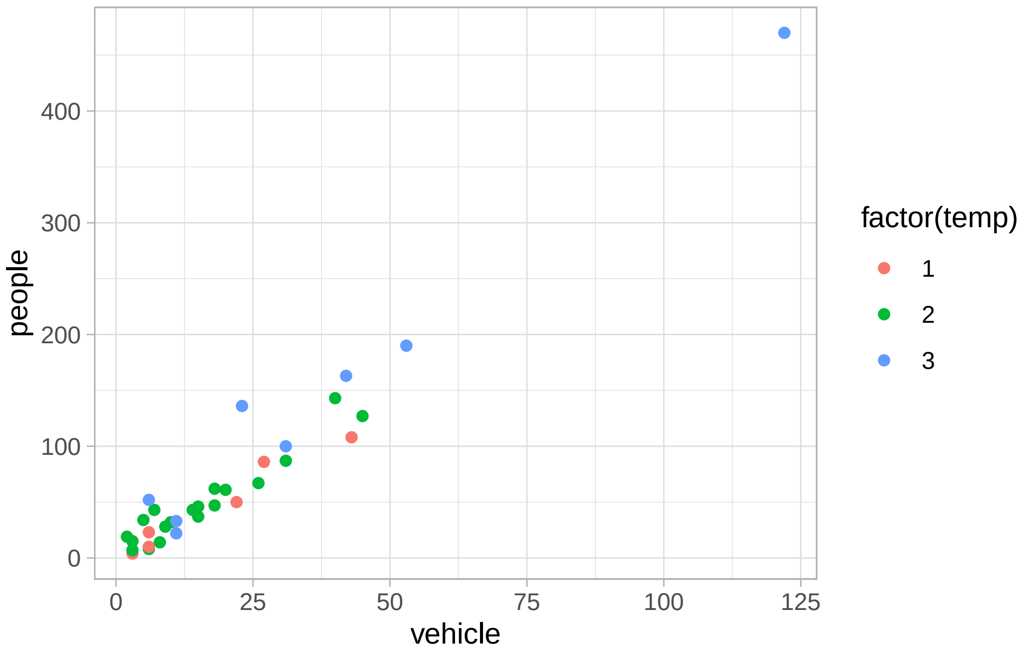
```
p1 <- ggplot(rangitikei) +
  aes(x = vehicle, y = people, color = factor(temp)) +
  geom_point()
```

```
p1
```

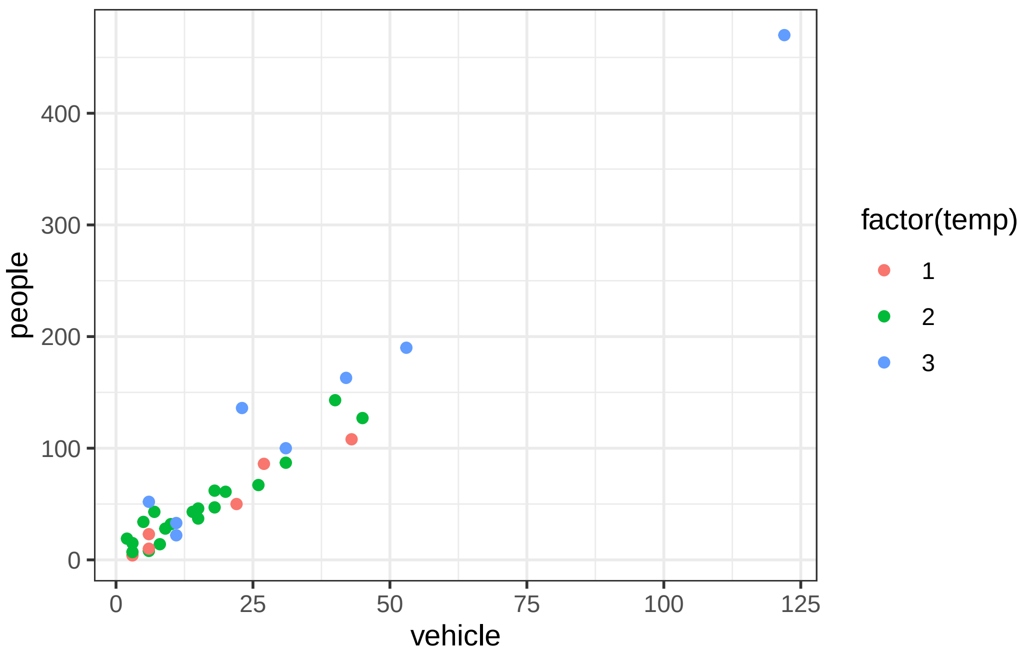


Try-

```
p1 + theme_light()
```

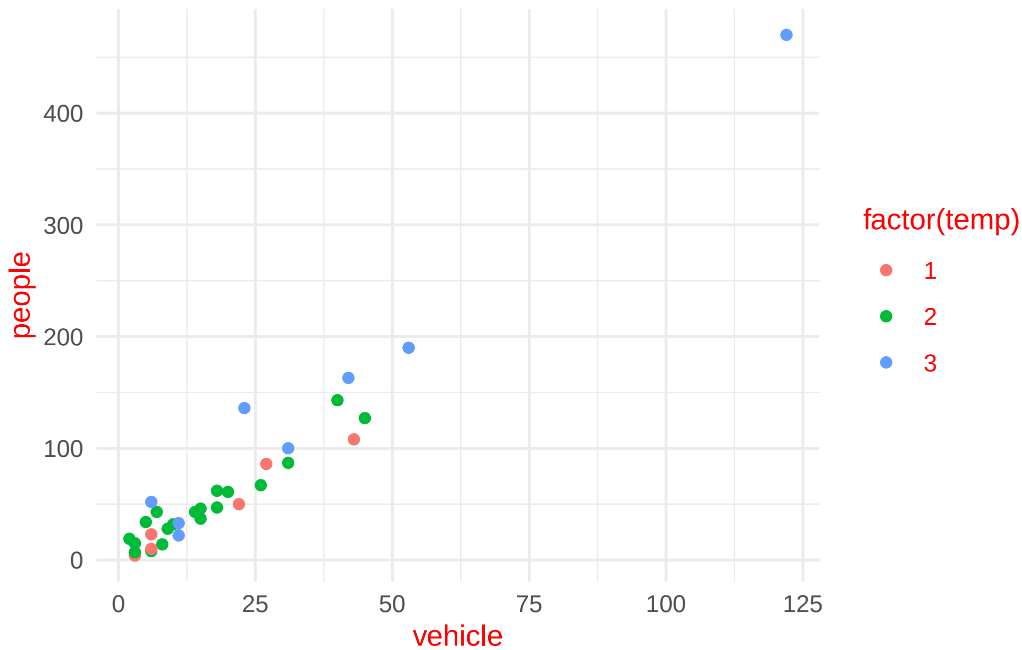



```
p1 + theme_bw()
```



Specific theme elements can be overridden using `theme()`. For example:

```r
p1 + theme_minimal() +
  theme(text = element_text(color = "red"))
```



All theme options can be seen with `?theme`.

To specify a theme for a whole document, use

```r
theme_set(theme_minimal())
```

A cheat sheet for `ggplot2` is available at https://www.rstudio.com/resources/cheatsheets/ (optional to download). There are many other packages which incorporate `ggplot2` based graphs or dependent on it.

Multiple plots

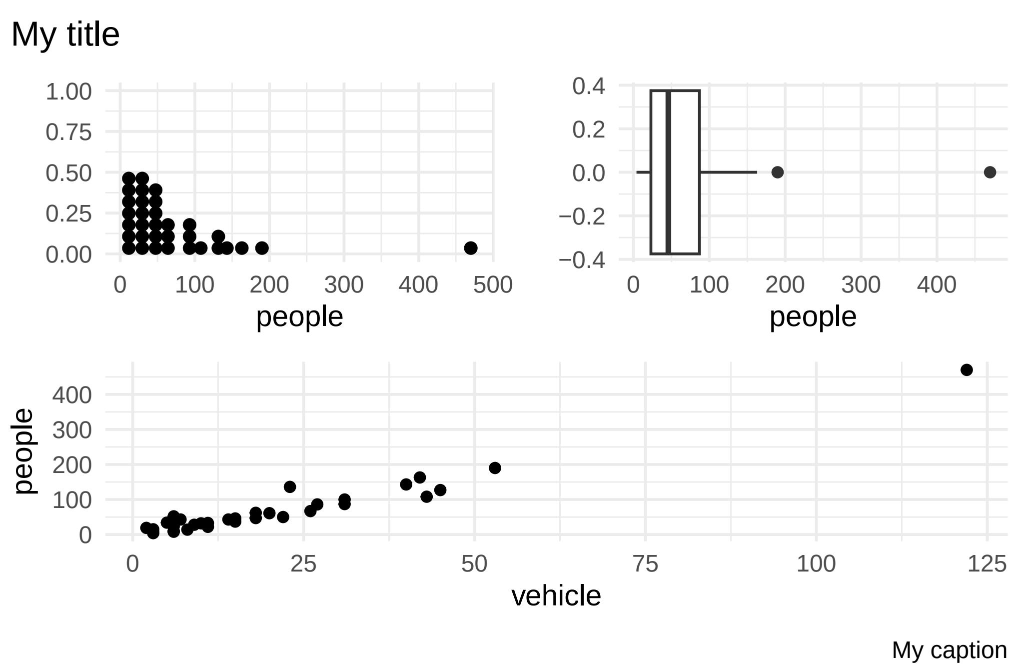
Sometimes you want to create a figure with multiple plots. Rather than trying to combine the data and then faceting, you may need to save each as an object and combine with a helper library. The library *patchwork* allows complex composition arbitrary plots, which are not produced using the faceting option. Try

```r
library(patchwork)

p1 <- qplot(people, data = rangitikei, geom = "dotplot") # change this to a ggplot
```

```
Warning: `qplot()` was deprecated in ggplot2 3.4.0.
```

```r
p2 <- qplot(people, data = rangitikei, geom = "boxplot")
p3 <- ggplot(rangitikei, aes(x = vehicle, y = people)) + geom_point()

(p1 + p2) / p3 +
  plot_annotation("My title", caption = "My caption")
```

```
Bin width defaults to 1/30 of the range of the data. Pick better value with
`binwidth`.
```



Have a quick google of the library `ggpubr` for the function `ggarrange` as another option for combining plots.

Dataset `Prestige`

As you work through this workshop, you can copy the code and paste it into a code chunk. Write notes and observations to your self as you go.

We will be using a well-known dataset called `Prestige` from the `car` R package. This dataset deals with prestige ratings of Canadian occupations. The `Prestige` dataset has 102 rows and 6 columns. Each row (or 'observation') is an occupation.

This data frame contains the following columns:

- `education` - Average education of occupational incumbents, years, in 1971.
- `income` - Average income of incumbents, dollars, in 1971.
- `women` - Percentage of incumbents who are women.
- `prestige` - Pineo-Porter prestige score for occupation, from a social survey conducted in the mid-1960s.
- `census` - Canadian Census occupational code.
- `type` - Type of occupation. A factor with levels: bc, Blue Collar; prof, Professional, Managerial, and Technical; wc, White Collar. (includes four missing values).

First we'll load the data. The dataset sits in the `car` package, so you need to load the `car` package first.

```
library(car)
data(Prestige)
```

Exercise 2.5

Draw a bar chart for `type`. These plots show the count or relative frequency of blue collar (`bc`), professional (`prof`), and white collar (`wc`) professions in the dataset.

```
# your code goes here
```

Exercise 2.6

Draw a histogram of `prestige`.

```
# your code goes here
```

Below demonstrates the flexibility of `ggplot` code. You can specify the `data` argument by piping it into `ggplot`, or by putting it as an argument to `ggplot` or a `geom_`. Likewise, the `mapping` or `aes` information, which determines which variables are used where, can be added as an extra line or specified inside the `ggplot` or `geom_` function.

```
Prestige |>
  ggplot() +
  aes(x = prestige) +
  geom_histogram()
```

Now, this histogram, where the number of bins has been chosen for us, looks a bit "spiky" to my eye. You can control the number of bins by adding an argument `bins = 10`.

```
Prestige |>
  ggplot() +
  aes(x = prestige) +
  geom_histogram(bins=10)
```

`ggplot` is very flexible as to where you put the data and the `aes` information; all of these methods give the same result.

```
Prestige |>
  ggplot() +
  aes(x = prestige) +
  geom_histogram(bins=10)
```

```
ggplot(
  data = Prestige,
  mapping = aes(x = prestige)
  ) +
```

```
  geom_histogram(bins=10)
```

```
ggplot(Prestige) +
  aes(x = prestige) +
  geom_histogram(bins=10)
```

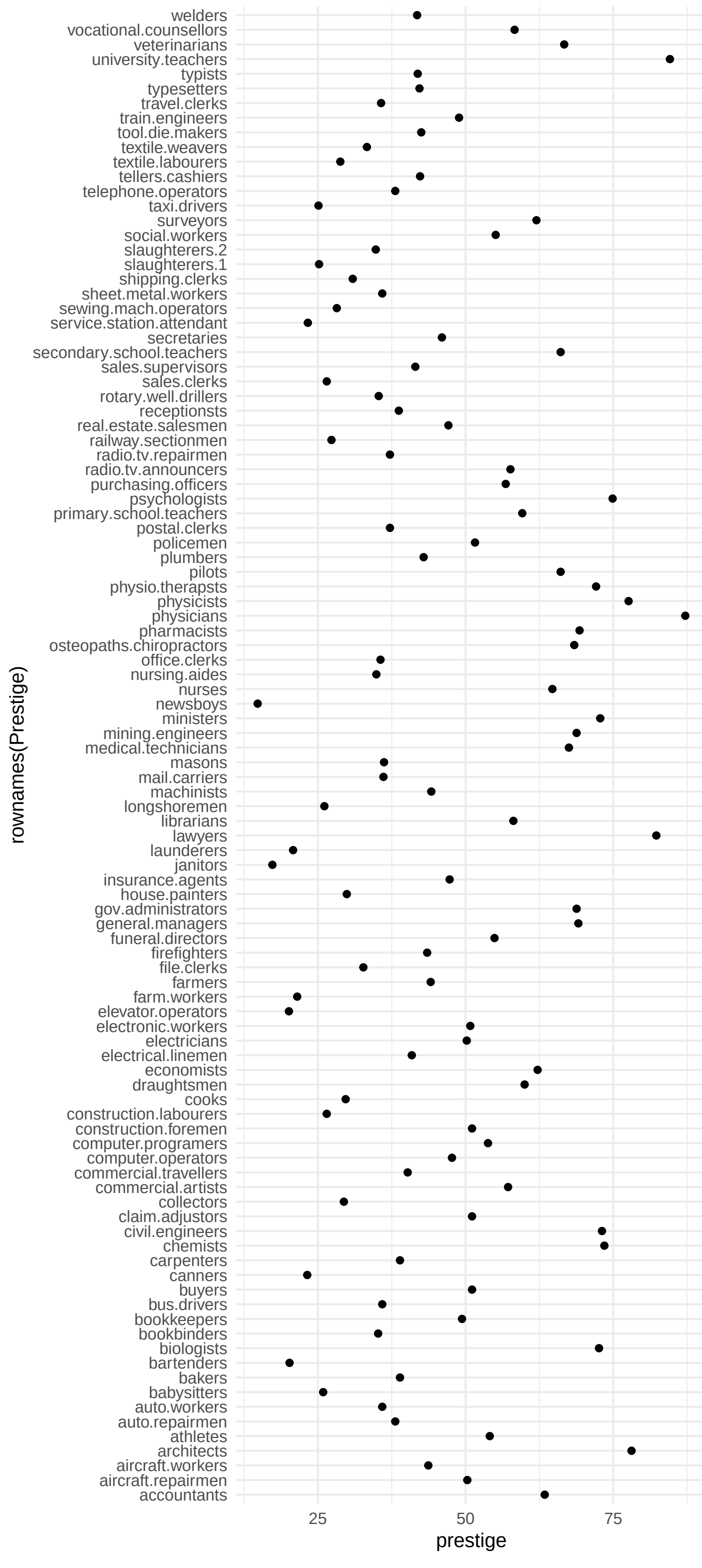
```
ggplot() +
  geom_histogram(
    data = Prestige,
    mapping = aes(x = prestige),
    bins = 10
    )
```

```
# or
# hist(Prestige$prestige)
```

Now let's display the prestige scores for each profession as a dot plot.

Note that I'm including the code-chunk option `#| fig-height: 12` at the beginning of my code chunk so that the plot is big enough to show all the professions without overlap.

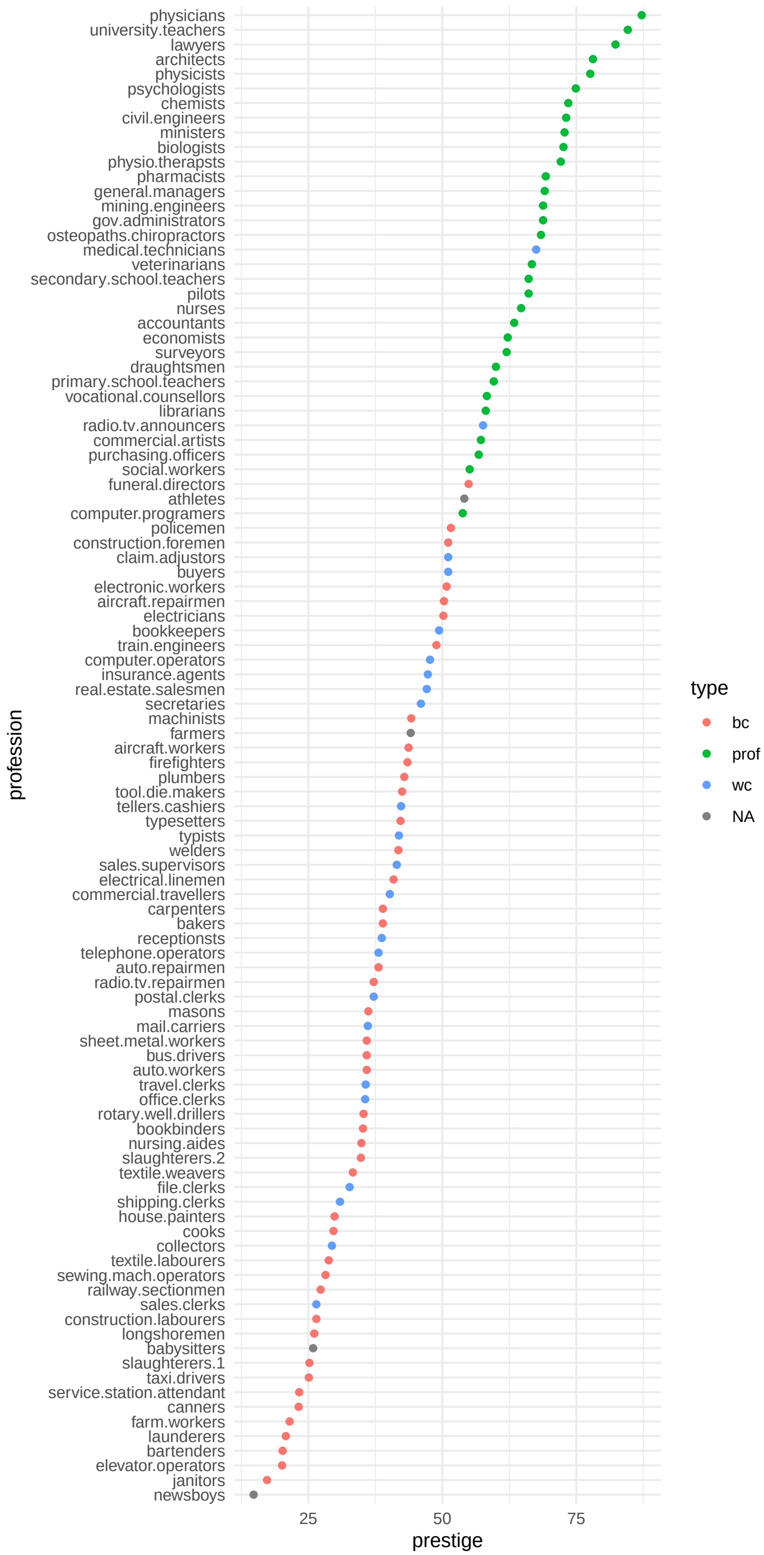
```
Prestige |>
  ggplot() +
  aes(x = rownames(Prestige), y = prestige) +
  geom_point() +
  coord_flip()
```


welders
vocational.counsellors
veterinarians
university.teachers
typists
typesetters
travel.clerks
train.engineers
tool.die.makers
textile.weavers
textile.labourers
tellers.cashiers
telephone.operators
taxi.drivers
surveyors
social.workers
slaughterers.2
slaughterers.1
shipping.clerks
sheet.metal.workers
sewing.mach.operators
service.station.attendant
secretaries
secondary.school.teachers
sales.supervisors
sales.clerks
rotary.well.drillers
receptionsts
real.estate.salesmen
railway.sectionmen
radio.tv.repairmen
radio.tv.announcers
purchasing.officers
psychologists
primary.school.teachers
postal.clerks
policemen
plumbers
pilots
physio.therapsts
physicists
physicians
pharmacists
osteopaths.chiropractors
office.clerks
nursing.aides
nurses
newsboys
ministers
mining.engineers
medical.technicians
masons
mail.carriers
machinists
longshoremen
librarians
lawyers
launderers
janitors
insurance.agents
house.painters
gov.administrators
general.managers
funeral.directors
firefighters
file.clerks
farmers
farm.workers
elevator.operators
electronic.workers
electricians
electrical.linemen
economists
draughtsmen
cooks
construction.labourers
construction.foremen
computer.programers
computer.operators
commercial.travellers
commercial.artists
collectors
claim.adjustors
civil.engineers
chemists
carpenters
canners
buyers
bus.drivers
bookkeepers
bookbinders
biologists
bartenders
bakers
babysitters
auto.workers
auto.repairmen
athletes
architects
aircraft.workers
aircraft.repairmen
accountants
rownames(Prestige)
25
50
75
prestige

What a mess!

We can tidy it up by ordering the professions on the plot according to `prestige`. First, we move the professions from rownames to a variable. Then, we `fct_reorder` the professions using the `prestige` scores. Then, the resulting data gets piped into `ggplot`.

```
Prestige |>
  rownames_to_column(var = "profession") |>
  mutate(
    profession = fct_reorder(profession, prestige)
    ) |>
  ggplot() +
  aes(x = profession, y = prestige, colour = type) +
  geom_point() +
  coord_flip()
```


physicians
university.teachers
lawyers
architects
physicists
psychologists
chemists
civil.engineers
ministers
biologists
physio.therapsts
pharmacists
general.managers
mining.engineers
gov.administrators
osteopaths.chiropractors
medical.technicians
veterinarians
secondary.school.teachers
pilots
nurses
accountants
economists
surveyors
draughtsmen
primary.school.teachers
vocational.counsellors
librarians
radio.tv.announcers
commercial.artists
purchasing.officers
social.workers
funeral.directors
athletes
computer.programers
policemen
construction.foremen
claim.adjustors
buyers
electronic.workers
aircraft.repairmen
electricians
bookkeepers
train.engineers
computer.operators
insurance.agents
real.estate.salesmen
secretaries
machinists
farmers
aircraft.workers
firefighters
plumbers
tool.die.makers
tellers.cashiers
typesetters
typists
welders
sales.supervisors
electrical.linemen
commercial.travellers
carpenters
bakers
receptionists
telephone.operators
auto.repairmen
radio.tv.repairmen
postal.clerks
masons
mail.carriers
sheet.metal.workers
bus.drivers
auto.workers
travel.clerks
office.clerks
rotary.well.drillers
bookbinders
nursing.aides
slaughterers.2
textile.weavers
file.clerks
shipping.clerks
house.painters
cooks
collectors
textile.labourers
sewing.mach.operators
railway.sectionmen
sales.clerks
construction.labourers
longshoremen
babysitters
slaughterers.1
taxi.drivers
service.station.attendant
canners
farm.workers
launderers
bartenders
elevator.operators
janitors
newsboys
profession
25
50
75
prestige
type
bc
prof
wc
NA

Exercise 2.7

a) Obtain some summary statistics for `prestige`. There are a few options for this.

```
# your code goes here
```

b) Make a summary dataset, average variable for each type of occupation.

```
# your code goes here
```

Exercise 2.8

Make a boxplot of `prestige ~ type`:

```
# your code goes here
```

Exercise 2.9

Obtain the Empirical Cumulative Distribution Function (ECDF) graphs of `prestige ~ type`:

```
Prestige |>
  ggplot() +
  aes(prestige, colour=type) +
  stat_ecdf()
```

```
Prestige |>
  ggplot() +
  aes(prestige) +
  stat_ecdf() +
  facet_wrap(~type)
```

```
Prestige |>
  ggplot() +
  aes(
    x = prestige, # these aes settings are used
    col = type    # by both geoms
    ) +
  geom_density(
    aes(fill = type), # the 'fill' aes goes here because
    alpha = .2        # geom_rug doesn't use 'fill'
    ) +
  geom_rug()
```

With which plot – the ECDF or the density plot – is it easier to compare the distributions of prestige scores among these groups?

Exercise 2.10

Obtain the $\{0.05, 0.1, 0.25, 0.5, 0.75, 0.9, 0.95\}$ quantiles of `prestige`:

```
# your code goes here
```

Exercise 2.11

Obtain the scatter plot (with and without marginal boxplots) **prestige vs. education** : How can you describe the relationship implied by the pattern?

```
# your code goes here
```

Exercise 2.12

Make a bubble or balloon plot **prestige vs. education vs. income** with income forming the bubble size.

Make a different scatter plot using the same three variables. Keep `x = education, y = prestige` but use a different option to illustrate the influence of income.

```
# your code goes here
```

Exercise 2.13

Create `prestige ~ education | type` graphs. That is, `prestige ~ education` grouped by `type` as colours and/or panels.

```
# your code goes here
```

Select answers: # Answer: Exercise 2.5 {-}

```
p <- Prestige |>
  ggplot() +
  aes(type) +
  geom_bar()

p
```

Answer: Exercise 2.7a

```r
summary(Prestige)
```

```
   education          income          women           prestige    
 Min.   : 6.380   Min.   :  611   Min.   : 0.000   Min.   :14.80  
 1st Qu.: 8.445   1st Qu.: 4106   1st Qu.: 3.592   1st Qu.:35.23  
 Median :10.540   Median : 5930   Median :13.600   Median :43.60  
 Mean   :10.738   Mean   : 6798   Mean   :28.979   Mean   :46.83  
 3rd Qu.:12.648   3rd Qu.: 8187   3rd Qu.:52.203   3rd Qu.:59.27  
 Max.   :15.970   Max.   :25879   Max.   :97.510   Max.   :87.20  
     census       type   
 Min.   :1113   bc  :44  
 1st Qu.:3120   prof:31  
 Median :5135   wc  :23  
 Mean   :5402   NA's: 4  
 3rd Qu.:8312            
 Max.   :9517            
```

```r
library(psych)

describe(Prestige)
```

```
          vars   n    mean      sd  median trimmed     mad     min      max
education    1 102   10.74    2.73   10.54   10.63    3.15    6.38    15.97
income       2 102 6797.90 4245.92 5930.50 6161.49 3060.83  611.00 25879.00
women        3 102   28.98   31.72   13.60   24.74   18.73    0.00    97.51
prestige     4 102   46.83   17.20   43.60   46.20   19.20   14.80    87.20
census       5 102 5401.77 2644.99 5135.00 5393.87 4097.91 1113.00  9517.00
type*        6  98    1.79    0.80    2.00    1.74    1.48    1.00     3.00
             range skew kurtosis     se
education     9.59 0.32    -1.03   0.27
income    25268.00 2.13     6.29 420.41
women        97.51 0.90    -0.68   3.14
```

```
prestige     72.40 0.33    -0.79   1.70
census     8404.00 0.11    -1.49 261.89
type*         2.00 0.40    -1.36   0.08
```

```r
describeBy(education + income + women + prestige ~ type,
           data = Prestige)
```

```
 Descriptive statistics by group
type: bc
          vars  n    mean      sd  median trimmed     mad     min     max
education    1 44    8.36    1.16    8.35    8.32    1.14    6.38   10.93
income       2 44 5374.14 2004.33 5216.50 5338.56 2275.05 1656.00 8895.00
women        3 44   18.97   26.15    4.72   14.48    7.01    0.00   90.67
prestige     4 44   35.53   10.02   35.90   35.46   11.34   17.30   54.90
            range skew kurtosis     se
education    4.55 0.34    -0.76   0.18
income    7239.00 0.17    -1.00 302.16
women       90.67 1.36     0.51   3.94
prestige    37.60 0.05    -1.03   1.51
------------------------------------------------------------
type: prof
          vars  n     mean      sd  median trimmed     mad     min      max
education    1 31    14.08    1.39   14.44   14.16    1.22   11.09    15.97
income       2 31 10559.45 5422.82 8865.00 9700.04 3955.58 4614.00 25879.00
women        3 31    25.51   28.37   11.68   21.03   13.86    0.58    96.12
prestige     4 31    67.85    8.68   68.40   67.34    9.19   53.80    87.20
             range  skew kurtosis     se
education     4.88 -0.47    -0.93   0.25
income    21265.00  1.37     1.36 973.97
women        95.54  1.14    -0.04   5.09
prestige     33.40  0.36    -0.67   1.56
------------------------------------------------------------
type: wc
          vars  n    mean      sd  median trimmed     mad     min     max
education    1 23   11.02    0.92   11.13   11.03    0.68    9.17   12.79
income       2 23 5052.30 1944.32 4741.00 4960.53 2342.51 2448.00 8780.00
women        3 23   52.83   33.11   56.10   53.19   47.77    3.16   97.51
prestige     4 23   42.24    9.52   41.50   41.61    8.60   26.50   67.50
            range  skew kurtosis     se
education    3.62 -0.20    -0.27   0.19
income    6332.00  0.44    -1.18 405.42
```

```
women        94.35 -0.10     -1.58   6.90
prestige     41.00  0.63      0.18   1.98
```

Answer: Exercise 2.8

```
Prestige |>
  ggplot() +
  aes(y=prestige, x=type) +
  geom_boxplot()
```

```
# as violin plots
Prestige |>
  ggplot() +
  aes(y=prestige, x=type) +
  geom_violin()
```

```
# Or put it all together
Prestige |>
  ggplot() +
  aes(y=prestige, x=type) +
  geom_violin() +
  geom_boxplot(col = 2, alpha = .2) +
  geom_jitter(alpha = .2, width = .2, height = 0, colour = 4)
```

Answer: Exercise 2.10

```
pr <- c(0.01, 0.05, 0.1, 0.25, 0.5, 0.75, 0.9, 0.95, 0.99)

Prestige |>
  summarise(
    probs = pr,
    quants = quantile(prestige, pr)
    )

# or simply
quantile(Prestige$prestige, pr)
```

Answer: Exercise 2.11

```
library(ggExtra)

p1 <- Prestige |>
  ggplot() +
  aes(x = education, y = prestige) +
  geom_point() +
  geom_smooth(col = 2) +
  geom_smooth(method = "lm", se = FALSE)

ggMarginal(p1, type="boxplot")
```

```
library(car)

scatterplot(education ~ prestige, data = Prestige)
```

The later plot will show prediction interval ribbon while the first plot will show the confidence interval ribbon.

Answer: Exercise 2.12

```r
library(ggplot2)

Prestige |>
  ggplot() +
  aes(x = education, y = prestige, size = income) +
  geom_point()
```

Answer: Exercise 2.13

```
Prestige |>
  ggplot() +
  aes(x = education, y = prestige, colour = type) +
  geom_point() +
  facet_wrap(~ type)
```

```
p <- Prestige |>
  ggplot() +
  aes(x = education, y = prestige, color = type) +
  geom_point()

p
```

More graphing examples are here (R code file).

Bibliography

[1] L. Wilkinson. *The Grammar of Graphics*. Berlin, Heidelberg: Springer-Verlag, 2005. ISBN: 0387245448.