Tidy data

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tidyr

By the phrase `tidy data`, it is meant the preferred way of arranging data that is easy to analyse. The principles of tidy data are:

- Each variable forms a column.
- Each observation forms a row.
- Each type of observational unit forms a table.

Simple Manipulations

There is always more than one-way of manipulating the data, producing summaries and tables from raw data.

One of the simplest manipulations on a batch of data we may do is to change the data type say numeric to character. For example, the television viewing time data in the text file `tv.csv` is read into a dataframe by the command line

```
my.data <- read.csv(
  "https://www.massey.ac.nz/~anhsmith/data/tv.csv",
  header =TRUE
  )
```

We can improve the `read.csv` command to recognise the data type while reading the table as follows, using the `read_csv` command from the `readr` package:

```
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
```

```
my.data <- read_csv(
  "https://www.massey.ac.nz/~anhsmith/data/tv.csv",
  col_types = "nfcc"
  )
```

The argument `col_types = "nfcc"` stands for {`numeric`, `factor`, `character`, `character`}, to match the order of the columns.

```
my.data
```

```
# A tibble: 46 x 4
   TELETIME SEX   SCHOOL STANDARD
      <dbl> <fct> <chr>  <chr>
 1     1482 1     1      4
 2     2018 1     1      4
 3     1849 1     1      4
 4      857 1     1      4
 5     2027 2     1      4
 6     2368 2     1      4
 7     1783 2     1      4
 8     1769 2     1      4
 9     2534 1     1      3
10     2366 1     1      3
# i 36 more rows
```

We often do a summary of a numerical variable for a given categorical variable. For example, we like to see obtain the summary statistics of TV viewing times for various schools. The commands

```
by(my.data$TELETIME, my.data$SCHOOL, summary)
```

We employed the `by()` command above and instead, we may also use `tapply()` `aggregate()` functions:

`tapply(my.data$TELETIME, my.data$SCHOOL, summary)`

`aggregate(my.data$TELETIME, list(my.data$SCHOOL), summary)`

A tabulated summary of categorical data is obtained using the `table()` command.

```
my.data <- read.csv(
  "https://www.massey.ac.nz/~anhsmith/data/rangitikei.csv",
  header=TRUE
```

```
  )

wind <- my.data |> pull(wind)
river <- my.data |> pull(river)

table(wind, river)
```

It is sometimes convenient to work with matrices for some R functions such as `apply()`. For example, the number of admissions data in `hospital.txt` data can be formed as a matrix. Note that this is possible because we have the same number of observations for each hospital location.

```
data <- read.table(
  "https://www.massey.ac.nz/~anhsmith/data/hospital.txt",
  header=TRUE,
  sep=",")

M <- data |>
  select(NORTH1, NORTH2, NORTH3,
         SOUTH1, SOUTH2, SOUTH3) |>
  sqrt()

means <- apply(M, 1, mean)
sds <- apply(M, 1, sd)

plot(means, sds)
```

Introduction to the tidyverse

We will be largely using the `tidyverse` suite of packages for data organisation, summarizing, and plotting; see https://www.tidyverse.org/.

Let's load that package now: Remember if you have not installed it you will need to use `install.packages()` first.

```r
library(tidyverse)
```

Datset

For this workshop we will use some tidyverse built in datasets. Each dataset below shows the same values of four variables: country, year, population, and number of documented cases of TB (tuberculosis), but each dataset organizes the values in a different way. Take a look at these datasets by typing their names into a code chunk or directly into the console. You can also try your hand at the functions `head()` and `summary()`.

```
table1
```

```
# A tibble: 6 x 4
  country      year  cases population
  <chr>       <dbl>  <dbl>      <dbl>
1 Afghanistan  1999    745   19987071
2 Afghanistan  2000   2666   20595360
3 Brazil       1999  37737  172006362
4 Brazil       2000  80488  174504898
5 China        1999 212258 1272915272
6 China        2000 213766 1280428583
```

```
table2
```

```
# A tibble: 12 x 4
   country      year type            count
   <chr>       <dbl> <chr>           <dbl>
 1 Afghanistan  1999 cases             745
 2 Afghanistan  1999 population   19987071
 3 Afghanistan  2000 cases            2666
 4 Afghanistan  2000 population   20595360
 5 Brazil       1999 cases           37737
 6 Brazil       1999 population  172006362
 7 Brazil       2000 cases           80488
 8 Brazil       2000 population  174504898
 9 China        1999 cases          212258
10 China        1999 population 1272915272
```

```
11 China        2000 cases          213766
12 China        2000 population 1280428583
```

```r
table3
```

```
# A tibble: 6 x 3
  country      year rate
  <chr>       <dbl> <chr>
1 Afghanistan  1999 745/19987071
2 Afghanistan  2000 2666/20595360
3 Brazil       1999 37737/172006362
4 Brazil       2000 80488/174504898
5 China        1999 212258/1272915272
6 China        2000 213766/1280428583
```

Exercise 1.1

For each of the sample tables, describe what each observation and each column represents. Which is the most `tidy`?

Piping

> **Tip**
>
> **The piping operation is a fundamental aspect of computer programming. The semantics of pipes is taking the output from the left-hand side and passing it as input to the right-hand side.**

The `R` package `magrittr` introduced the pipe operator `%>%` and can be pronounced as "then". In RStudio windows/Linux versions, press `Ctrl+Shift+M` to insert the pipe operator. On a Mac, use `Cmd+Shift+M`.

`R` also has its own pipe, `|>`, which is an alternative to `%>%`. You will see both used in this course. If you want to change the pipe inserted automatically with `Ctrl+Shift+M`, find on the menu **Tools > Global Options**, then click on **Code** and check the box that says "**Use Native Pipe Operator**".

Consider the study guide dataset `rangitikei.txt` (Recreational Use of the Rangitikei river). The first 10 rows of this dataset are shown below:

```
   id loc time w.e cl wind temp river people vehicle
1   1   1    2   1  1    2    2     1     37      15
2   2   1    1   1  1    2    1     2     23       6
3   3   1    2   1  1    2    2     3     87      31
4   4   2    2   1  1    2    1     1     86      27
5   5   2    1   1  1    2    2     2     19       2
6   6   2    2   1  2    1    3     3    136      23
7   7   1    2   2  2    2    2     3     14       8
8   8   1    2   1  2    2    2     3     67      26
9   9   1    1   2  1    3    1     2      4       3
10 10   2    2   1  2    2    2     3    127      45
```

Try the following examples after loading the `rangitikei` dataset.

`select()`

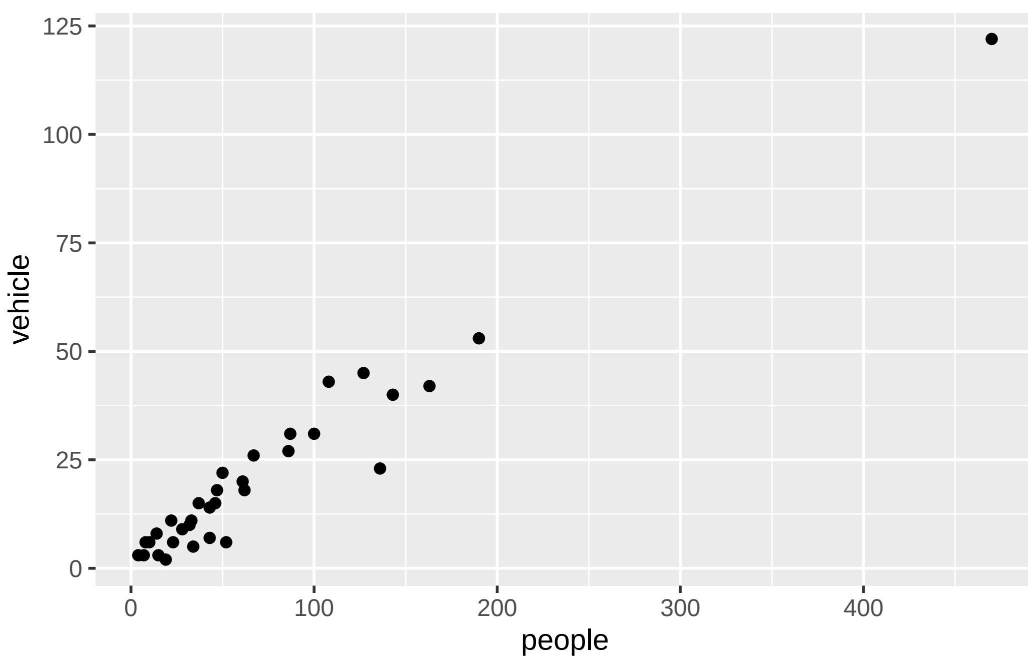
```
new.data <- my.data |>
  select(people, vehicle)

names(new.data)
```

```
[1] "people"  "vehicle"
```

What does `select()` do?

```
my.data |>
  select(people, vehicle) |> # select columns
  ggplot() + # make a plot using those columns
  aes(x=people, y=vehicle) +
  geom_point()
```

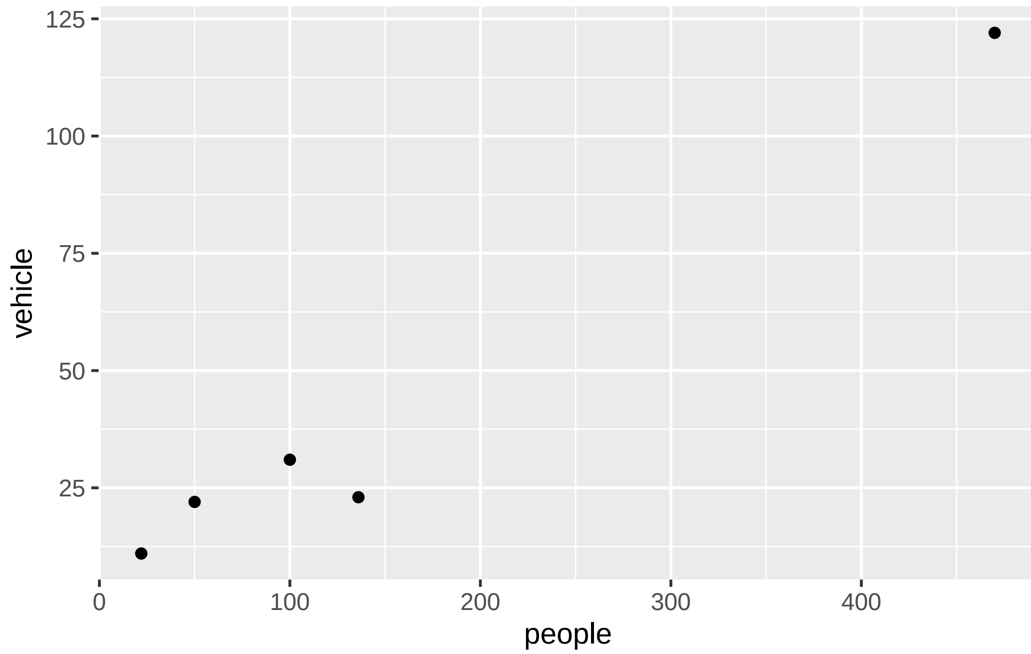


We select two columns and create a scatter plot with the above commands.

Now try another function:

`filter()`

```
my.data |>
  filter(wind==1) |>
  select(people, vehicle) |>
  ggplot() +
  aes(x=people, y=vehicle) +
  geom_point()
```



What does `filter()` do?

The above commands filter the data for the low wind days and plots vehicle against people. `filter()` subsets the data for all observations matching a specified criteria.

`arrange()`

```
my.data |>
  filter(wind==1) |>
  arrange(w.e) |>
  select(w.e, people, vehicle)
```

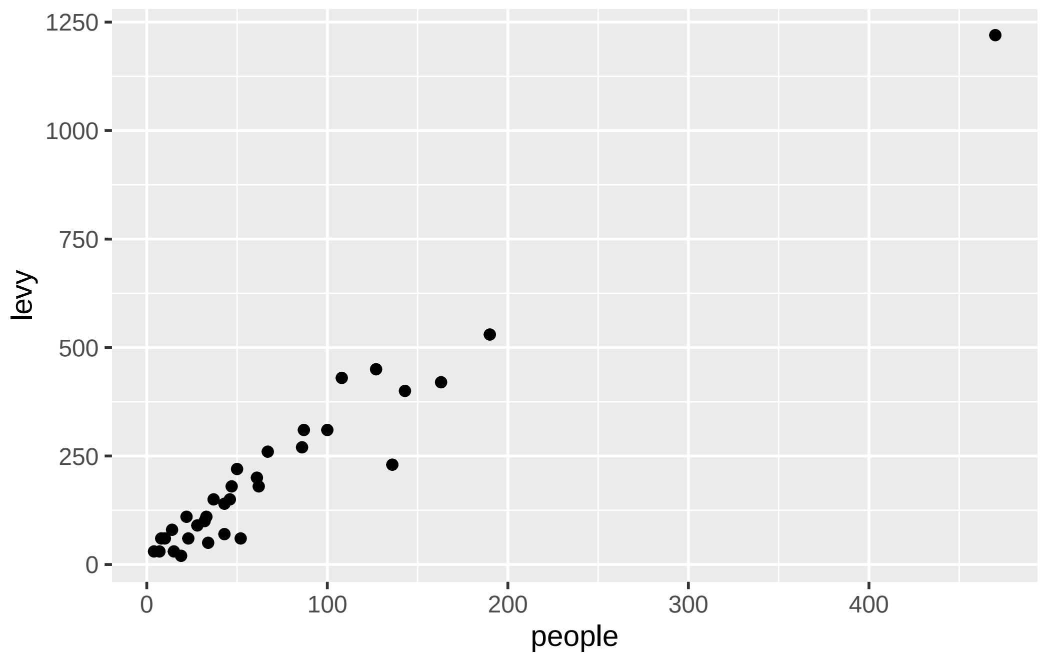
```
  w.e people vehicle
1   1    136      23
```

```
2    1      50       22
3    1     100       31
4    1     470      122
5    2      22       11
```

`mutate()`

Assume that a $10 levy is collected for each vehicle. We can create this new `levy` column as follows.

```
my.data |>
  mutate(levy = vehicle*10) |>
  select(people, levy) |>
  ggplot() +
  aes(x = people, y=levy) +
  geom_point()
```



Note that the pipe operation was used to create a scatter plot using the newly created column.

`summarise()`

```r
my.data |>
  summarise(total = n(),
            avg = mean(people)
            )
```

```
  total      avg
1    33 71.72727
```

We obtain the selected summary measures namely the total and the mean number of people. Try-

```r
my.data |>
  filter(wind == 1) |>
  summarise(total = n(),
            avg = mean(people)
            )
```

```
  total   avg
1     5 155.6
```

`group_by()`

We obtain the wind group-wise summaries below:

```r
my.data |>
  group_by(wind) |>
  summarise(total=n(),
            avg=mean(people))
```

```
# A tibble: 3 x 3
   wind total   avg
  <int> <int> <dbl>
1     1     5 156.
2     2    26  59.7
3     3     2  19
```

There are many more commands such as the `transmute` function which conserves the only the needed columns. Try

```r
my.data |>
  group_by(wind, w.e) |>
  transmute(total=n(),
            avg=mean(people))
```

```
# A tibble: 33 x 4
# Groups:   wind, w.e [6]
    wind   w.e total   avg
   <int> <int> <int> <dbl>
 1     2     1    18  72.1
 2     2     1    18  72.1
 3     2     1    18  72.1
 4     2     1    18  72.1
 5     2     1    18  72.1
 6     1     1     4 189
 7     2     2     8  31.8
 8     2     1    18  72.1
 9     3     2     1   4
10     2     1    18  72.1
# i 23 more rows
```

A simple frequency table is found using `count()`. Try-

```r
my.data |>
  group_by(wind, w.e) |>
  count(temp)
```

```
# A tibble: 10 x 4
# Groups:   wind, w.e [6]
    wind   w.e  temp     n
   <int> <int> <int> <int>
 1     1     1     1     1
 2     1     1     3     3
 3     1     2     3     1
 4     2     1     1     4
 5     2     1     2    12
 6     2     1     3     2
 7     2     2     2     6
 8     2     2     3     2
 9     3     1     2     1
10     3     2     1     1
```

```r
my.data |>
  group_by(wind, w.e) |>
  count(temp, river)
```

```
# A tibble: 16 x 5
# Groups:   wind, w.e [6]
    wind   w.e  temp river     n
   <int> <int> <int> <int> <int>
 1     1     1     1     1     1
 2     1     1     3     3     3
 3     1     2     3     3     1
 4     2     1     1     1     1
 5     2     1     1     2     1
 6     2     1     1     3     2
 7     2     1     2     1     3
 8     2     1     2     2     2
 9     2     1     2     3     7
10     2     1     3     3     2
11     2     2     2     1     2
12     2     2     2     3     4
13     2     2     3     2     1
14     2     2     3     3     1
15     3     1     2     2     1
16     3     2     1     2     1
```

The `count()` is useful to check the balanced nature of the data when many subgroups are involved.

Now let's practice using these functions.

Exercise 1.2

Using `table1`, compute rate of TB cases per 10,000 and the total cases per year

```
table1 |>
  mutate(rate = cases / population * 10000)
```

```
# A tibble: 6 x 5
  country      year  cases population  rate
  <chr>       <dbl>  <dbl>      <dbl> <dbl>
1 Afghanistan  1999    745   19987071 0.373
2 Afghanistan  2000   2666   20595360 1.29
3 Brazil       1999  37737  172006362 2.19
4 Brazil       2000  80488  174504898 4.61
5 China        1999 212258 1272915272 1.67
6 China        2000 213766 1280428583 1.67
```

```
table1 |>
  group_by(year) |>
  summarize(total_cases = sum(cases))
```

```
# A tibble: 2 x 2
   year total_cases
  <dbl>       <dbl>
1  1999      250740
2  2000      296920
```

Exercise 1.3

For `table2`, write pseudo-code for how you would perform the following actions. Sketch/describe how you would do these.

a) Extract the number of TB cases per country per year.

b) Extract the matching population per country per year.

c) Divide cases by population, and multiply by 10000.

d) Store back in the appropriate place.

Dataset *diamonds*

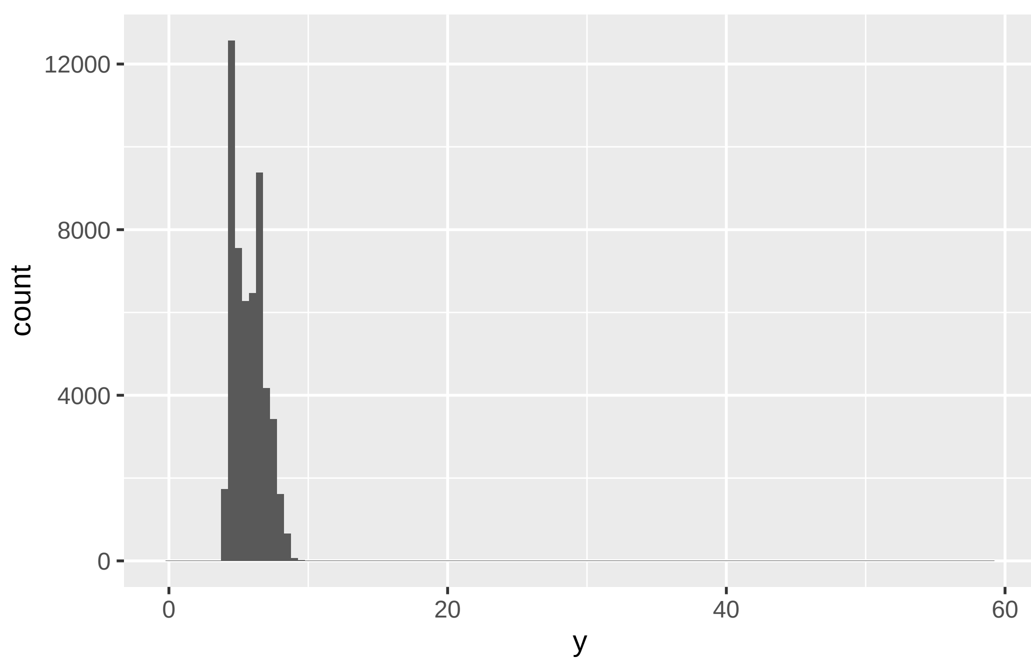
We will now use the built in dataset on diamond price and measurements for some more exercises. See`?diamonds` more information.

Exercise 1.4

Outliers are observations that are unusual; data points that don't seem to fit the pattern. Sometimes outliers are data entry errors, sometimes they are simply values at the extremes that happened to be observed in this data collection, and other times they suggest important new discoveries.

Describe the distribution of the y variable from the diamonds dataset.

```
ggplot(diamonds) +
  aes(x = y) +
  geom_histogram(binwidth = 0.5)
```

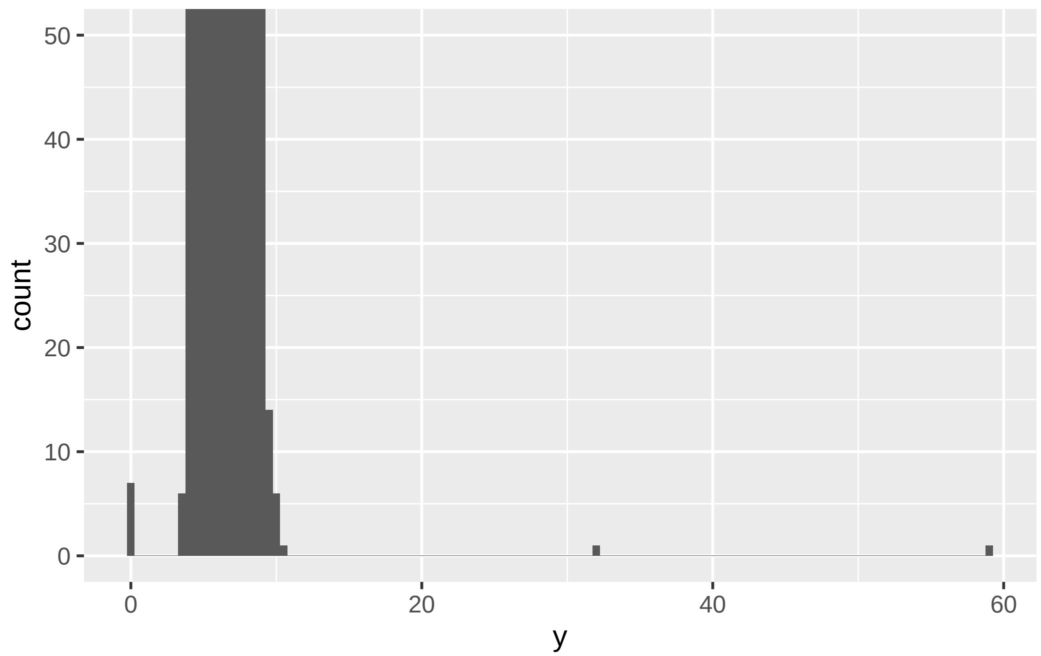


The only evidence of outliers is the unusually wide limits on the x-axis.

There are so many observations in the common bins that the rare bins are very short, making it very difficult to see them (although maybe if you stare intently at 0 you'll spot something).

We can change the `binwidth=` to help with this. We can also zoom in on the y axis using `coord_cartesian()`.

```
ggplot(diamonds) +
  aes(x = y) +
  geom_histogram(binwidth = 0.5) +
  coord_cartesian(ylim = c(0, 50)) # also has an xlim() option
```



Exercise 1.5

Make a new dataset that includes these unusual values using dplyr.

```
unusual <- diamonds |>
  filter(y < 3 | y > 20) |>
  select(price, x, y, z) |>
  arrange(y)
unusual
```

```
# A tibble: 9 x 4
  price     x     y     z
  <int> <dbl> <dbl> <dbl>
1  5139  0      0    0
2  6381  0      0    0
3 12800  0      0    0
4 15686  0      0    0
5 18034  0      0    0
6  2130  0      0    0
7  2130  0      0    0
8  2075  5.15  31.8  5.12
9 12210  8.09  58.9  8.06
```

Exercise 1.6

How many diamonds are 0.99 carat? How many are 1 carat? What do you think is the cause of the difference?

```
# your code goes here
```

Exercise 1.7

What does `na.rm = TRUE` do in mean() and sum()?

```
# your code goes here
```

Tidying data

Most real analyses will require at least a little tidying. You'll begin by figuring out what the underlying variables and observations are. Sometimes this is easy; other times you'll need to consult with the people who originally generated the data. Next, you'll pivot your data into a tidy form, with variables in the columns and observations in the rows.

The `billboard` dataset records the billboard rank of songs in the year 2000:

```
billboard
```

```
# A tibble: 317 x 79
   artist     track date.entered   wk1   wk2   wk3   wk4   wk5   wk6   wk7   wk8
   <chr>      <chr> <date>       <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
 1 2 Pac      Baby~ 2000-02-26      87    82    72    77    87    94    99    NA
 2 2Ge+her    The ~ 2000-09-02      91    87    92    NA    NA    NA    NA    NA
 3 3 Doors D~ Kryp~ 2000-04-08      81    70    68    67    66    57    54    53
 4 3 Doors D~ Loser 2000-10-21      76    76    72    69    67    65    55    59
 5 504 Boyz   Wobb~ 2000-04-15      57    34    25    17    17    31    36    49
 6 98^0       Give~ 2000-08-19      51    39    34    26    26    19     2     2
 7 A*Teens    Danc~ 2000-07-08      97    97    96    95   100    NA    NA    NA
 8 Aaliyah    I Do~ 2000-01-29      84    62    51    41    38    35    35    38
 9 Aaliyah    Try ~ 2000-03-18      59    53    38    28    21    18    16    14
10 Adams, Yo~ Open~ 2000-08-26      76    76    74    69    68    67    61    58
# i 307 more rows
# i 68 more variables: wk9 <dbl>, wk10 <dbl>, wk11 <dbl>, wk12 <dbl>,
#   wk13 <dbl>, wk14 <dbl>, wk15 <dbl>, wk16 <dbl>, wk17 <dbl>, wk18 <dbl>,
#   wk19 <dbl>, wk20 <dbl>, wk21 <dbl>, wk22 <dbl>, wk23 <dbl>, wk24 <dbl>,
#   wk25 <dbl>, wk26 <dbl>, wk27 <dbl>, wk28 <dbl>, wk29 <dbl>, wk30 <dbl>,
#   wk31 <dbl>, wk32 <dbl>, wk33 <dbl>, wk34 <dbl>, wk35 <dbl>, wk36 <dbl>,
#   wk37 <dbl>, wk38 <dbl>, wk39 <dbl>, wk40 <dbl>, wk41 <dbl>, wk42 <dbl>, ...
```

In this dataset, each observation is a song. The first three columns (artist, track and date.entered) are variables that describe the song. Then we have 76 columns (wk1-wk76) that describe the rank of the song in each week. Here, the column names are one variable (the week) and the cell values are another (the rank).

Exercise 1.8

Use `pivot_longer()` to tidy this data

```
# your code goes here
```

Combining datasets

Two tables can be connected through a pair of keys, within each table.

Every join involves a pair of keys: a primary key and a foreign key. A primary key is a variable or set of variables that uniquely identifies each observation. When more than one variable is needed, the key is called a compound key.

There are four types of joins, we will illustrate them using a simple example:

First lets make some data:

```
df1 <- tibble(x = c(1, 2), y = 2:1)
df2 <- tibble(x = c(3, 1), a = 10, b = "a")
```

Now join the two datasets using the different join functions:

```
df1 %>% inner_join(df2)
```

```
Joining with `by = join_by(x)`
```

```
# A tibble: 1 x 4
      x     y     a b
  <dbl> <int> <dbl> <chr>
1     1     2    10 a
```

```
df1 %>% left_join(df2)
```

```
Joining with `by = join_by(x)`

# A tibble: 2 x 4
      x     y     a b    
  <dbl> <int> <dbl> <chr>
1     1     2    10 a    
2     2     1    NA <NA> 
```

```r
df1 %>% right_join(df2)
```

```
Joining with `by = join_by(x)`

# A tibble: 2 x 4
      x     y     a b    
  <dbl> <int> <dbl> <chr>
1     1     2    10 a    
2     3    NA    10 a    
```

```r
df2 %>% left_join(df1)
```

```
Joining with `by = join_by(x)`

# A tibble: 2 x 4
      x     a b         y
  <dbl> <dbl> <chr> <int>
1     3    10 a        NA
2     1    10 a         2
```

```r
df1 %>% full_join(df2)
```

```
Joining with `by = join_by(x)`

# A tibble: 3 x 4
      x     y     a b    
  <dbl> <int> <dbl> <chr>
1     1     2    10 a    
2     2     1    NA <NA> 
3     3    NA    10 a    
```

What are the differences between the join functions?

Specifying join keys

By default, left_join() will use all variables that appear in both data frames as the join key, but it doesn't always work.

For example lets look at some airline data:

```r
library(nycflights13) # data package

flights2 <- flights |>
  select(year, time_hour, origin, dest, tailnum, carrier)
flights2
```

```
# A tibble: 336,776 x 6
    year time_hour           origin dest  tailnum carrier
   <int> <dttm>              <chr>  <chr> <chr>   <chr>
 1  2013 2013-01-01 05:00:00 EWR    IAH   N14228  UA
 2  2013 2013-01-01 05:00:00 LGA    IAH   N24211  UA
 3  2013 2013-01-01 05:00:00 JFK    MIA   N619AA  AA
 4  2013 2013-01-01 05:00:00 JFK    BQN   N804JB  B6
 5  2013 2013-01-01 06:00:00 LGA    ATL   N668DN  DL
 6  2013 2013-01-01 05:00:00 EWR    ORD   N39463  UA
 7  2013 2013-01-01 06:00:00 EWR    FLL   N516JB  B6
 8  2013 2013-01-01 06:00:00 LGA    IAD   N829AS  EV
 9  2013 2013-01-01 06:00:00 JFK    MCO   N593JB  B6
10  2013 2013-01-01 06:00:00 LGA    ORD   N3ALAA  AA
# i 336,766 more rows
```

```r
planes
```

```
# A tibble: 3,322 x 9
   tailnum  year type               manufacturer model engines seats speed engine
   <chr>   <int> <chr>              <chr>        <chr>   <int> <int> <int> <chr>
 1 N10156   2004 Fixed wing multi~ EMBRAER      EMB-~       2    55    NA Turbo~
 2 N102UW   1998 Fixed wing multi~ AIRBUS INDU~ A320~       2   182    NA Turbo~
```

```
 3 N103US   1999 Fixed wing multi~ AIRBUS INDU~ A320~       2   182    NA Turbo~
 4 N104UW   1999 Fixed wing multi~ AIRBUS INDU~ A320~       2   182    NA Turbo~
 5 N10575   2002 Fixed wing multi~ EMBRAER      EMB-~       2    55    NA Turbo~
 6 N105UW   1999 Fixed wing multi~ AIRBUS INDU~ A320~       2   182    NA Turbo~
 7 N107US   1999 Fixed wing multi~ AIRBUS INDU~ A320~       2   182    NA Turbo~
 8 N108UW   1999 Fixed wing multi~ AIRBUS INDU~ A320~       2   182    NA Turbo~
 9 N109UW   1999 Fixed wing multi~ AIRBUS INDU~ A320~       2   182    NA Turbo~
10 N110UW   1999 Fixed wing multi~ AIRBUS INDU~ A320~       2   182    NA Turbo~
# i 3,312 more rows
```

We are going to try to going flight data to data about types of planes

```r
flights2 |>
  left_join(planes)
```

```
Joining with `by = join_by(year, tailnum)`
```

```
# A tibble: 336,776 x 13
    year time_hour           origin dest  tailnum carrier type  manufacturer
   <int> <dttm>              <chr>  <chr> <chr>   <chr>   <chr> <chr>
 1  2013 2013-01-01 05:00:00 EWR    IAH   N14228  UA      <NA>  <NA>
 2  2013 2013-01-01 05:00:00 LGA    IAH   N24211  UA      <NA>  <NA>
 3  2013 2013-01-01 05:00:00 JFK    MIA   N619AA  AA      <NA>  <NA>
 4  2013 2013-01-01 05:00:00 JFK    BQN   N804JB  B6      <NA>  <NA>
 5  2013 2013-01-01 06:00:00 LGA    ATL   N668DN  DL      <NA>  <NA>
 6  2013 2013-01-01 05:00:00 EWR    ORD   N39463  UA      <NA>  <NA>
 7  2013 2013-01-01 06:00:00 EWR    FLL   N516JB  B6      <NA>  <NA>
 8  2013 2013-01-01 06:00:00 LGA    IAD   N829AS  EV      <NA>  <NA>
 9  2013 2013-01-01 06:00:00 JFK    MCO   N593JB  B6      <NA>  <NA>
10  2013 2013-01-01 06:00:00 LGA    ORD   N3ALAA  AA      <NA>  <NA>
# i 336,766 more rows
# i 5 more variables: model <chr>, engines <int>, seats <int>, speed <int>,
#   engine <chr>
```

We get a lot of missing matches because our join is trying to use tailnum and year as a compound key. Both flights and planes have a year column but they mean different things: `flights$year` is the year the flight occurred and `planes$year` is the year the plane was built.

Since these represent different types of data and we might want to keep both, we can be explicit about how to join the two data tables:

```r
flights2 |>
  left_join(planes, join_by(tailnum))
```

```
# A tibble: 336,776 x 14
   year.x time_hour           origin dest  tailnum carrier year.y type
    <int> <dttm>              <chr>  <chr> <chr>   <chr>    <int> <chr>
 1   2013 2013-01-01 05:00:00 EWR    IAH   N14228  UA        1999 Fixed wing mu~
 2   2013 2013-01-01 05:00:00 LGA    IAH   N24211  UA        1998 Fixed wing mu~
 3   2013 2013-01-01 05:00:00 JFK    MIA   N619AA  AA        1990 Fixed wing mu~
 4   2013 2013-01-01 05:00:00 JFK    BQN   N804JB  B6        2012 Fixed wing mu~
 5   2013 2013-01-01 06:00:00 LGA    ATL   N668DN  DL        1991 Fixed wing mu~
 6   2013 2013-01-01 05:00:00 EWR    ORD   N39463  UA        2012 Fixed wing mu~
 7   2013 2013-01-01 06:00:00 EWR    FLL   N516JB  B6        2000 Fixed wing mu~
 8   2013 2013-01-01 06:00:00 LGA    IAD   N829AS  EV        1998 Fixed wing mu~
 9   2013 2013-01-01 06:00:00 JFK    MCO   N593JB  B6        2004 Fixed wing mu~
10   2013 2013-01-01 06:00:00 LGA    ORD   N3ALAA  AA          NA <NA>
# i 336,766 more rows
# i 6 more variables: manufacturer <chr>, model <chr>, engines <int>,
#   seats <int>, speed <int>, engine <chr>
```

Now by default there is a year.x and year.y coming from the flights and planes data respectively. You can change this using the `suffix` argument in join or by renaming the columns after the join.

Exercise 1.9

Imagine you've found the top 10 most popular destinations using this code:

```
top_dest <- flights2 |>
  count(dest, sort = TRUE) |>
  head(10)
```

How can you find all flights to those destinations?

```
# your code goes here
```

Exercise 1.10

What do the tail numbers that don't have a matching record in planes have in common? (Hint: one variable explains ~90% of the problems.)

case_when()

Sometimes you want to add a new variable to your data based on existing variables.

dplyr's case_when() is inspired by SQL's CASE statement and provides a flexible way of performing different computations for different conditions. It has a special syntax that unfortunately looks like nothing else you'll use in the tidyverse. It takes pairs that look like condition ~ output. condition must be a logical vector; when it's TRUE, output will be used.

This can take the place of if_else() statements.

For example:

```
flights |>
  mutate(
    status = case_when( # make a new variable status based on the flights arrival delay
      is.na(arr_delay)      ~ "cancelled",
      arr_delay < -30       ~ "very early",
      arr_delay < -15       ~ "early",
      abs(arr_delay) <= 15  ~ "on time",
      arr_delay < 60        ~ "late",
      arr_delay < Inf       ~ "very late",
    ),
    .keep = "used"
  )
```

```
# A tibble: 336,776 x 2
   arr_delay status
       <dbl> <chr>
 1        11 on time
 2        20 late
 3        33 late
 4       -18 early
 5       -25 early
 6        12 on time
 7        19 late
 8       -14 on time
 9        -8 on time
```

```
10         8 on time
# i 336,766 more rows
```

Exercise 1.11

Write a case_when() statement that uses the month and day columns from flights to label a selection of important US holidays (e.g., New Years Day, 4th of July, Thanksgiving, and Christmas). First create a logical column that is either TRUE or FALSE, and then create a character column that either gives the name of the holiday or is NA.