About Tidyverse

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10.5

Tibbles

```
library("tidyverse")
```

Exercises

1. How can you tell if an object is a tibble? (Hint: try printing `mtcars`, which is a regular data frame).

```
mtcars
```

```
##                     mpg cyl  disp  hp drat    wt  qsec vs am gear carb
## Mazda RX4          21.0   6 160.0 110 3.90 2.620 16.46  0  1    4    4
## Mazda RX4 Wag      21.0   6 160.0 110 3.90 2.875 17.02  0  1    4    4
## Datsun 710         22.8   4 108.0  93 3.85 2.320 18.61  1  1    4    1
## Hornet 4 Drive     21.4   6 258.0 110 3.08 3.215 19.44  1  0    3    1
## Hornet Sportabout  18.7   8 360.0 175 3.15 3.440 17.02  0  0    3    2
## Valiant            18.1   6 225.0 105 2.76 3.460 20.22  1  0    3    1
## Duster 360         14.3   8 360.0 245 3.21 3.570 15.84  0  0    3    4
## Merc 240D          24.4   4 146.7  62 3.69 3.190 20.00  1  0    4    2
## Merc 230           22.8   4 140.8  95 3.92 3.150 22.90  1  0    4    2
## Merc 280           19.2   6 167.6 123 3.92 3.440 18.30  1  0    4    4
## Merc 280C          17.8   6 167.6 123 3.92 3.440 18.90  1  0    4    4
## Merc 450SE         16.4   8 275.8 180 3.07 4.070 17.40  0  0    3    3
## Merc 450SL         17.3   8 275.8 180 3.07 3.730 17.60  0  0    3    3
## Merc 450SLC        15.2   8 275.8 180 3.07 3.780 18.00  0  0    3    3
## Cadillac Fleetwood 10.4   8 472.0 205 2.93 5.250 17.98  0  0    3    4
## Lincoln Continental 10.4  8 460.0 215 3.00 5.424 17.82  0  0    3    4
## Chrysler Imperial  14.7   8 440.0 230 3.23 5.345 17.42  0  0    3    4
## Fiat 128           32.4   4  78.7  66 4.08 2.200 19.47  1  1    4    1
## Honda Civic        30.4   4  75.7  52 4.93 1.615 18.52  1  1    4    2
## Toyota Corolla     33.9   4  71.1  65 4.22 1.835 19.90  1  1    4    1
## Toyota Corona      21.5   4 120.1  97 3.70 2.465 20.01  1  0    3    1
## Dodge Challenger   15.5   8 318.0 150 2.76 3.520 16.87  0  0    3    2
## AMC Javelin        15.2   8 304.0 150 3.15 3.435 17.30  0  0    3    2
## Camaro Z28         13.3   8 350.0 245 3.73 3.840 15.41  0  0    3    4
## Pontiac Firebird   19.2   8 400.0 175 3.08 3.845 17.05  0  0    3    2
## Fiat X1-9          27.3   4  79.0  66 4.08 1.935 18.90  1  1    4    1
## Porsche 914-2      26.0   4 120.3  91 4.43 2.140 16.70  0  1    5    2
## Lotus Europa       30.4   4  95.1 113 3.77 1.513 16.90  1  1    5    2
## Ford Pantera L     15.8   8 351.0 264 4.22 3.170 14.50  0  1    5    4
## Ferrari Dino       19.7   6 145.0 175 3.62 2.770 15.50  0  1    5    6
## Maserati Bora      15.0   8 301.0 335 3.54 3.570 14.60  0  1    5    8
## Volvo 142E         21.4   4 121.0 109 4.11 2.780 18.60  1  1    4    2
```

```
class(mtcars)
```

```
## [1] "data.frame"
```

```
class(as_tibble(mtcars))
```

```
## [1] "tbl_df"     "tbl"        "data.frame"
```

Tibbles will only print out a limited number of rows and show the class on top of each column. Additionally, tibbles have class `"tbl_df"` and `"tbl_"` in addition to `"data.frame"`.

2. Compare and contrast the following operations on a `data.frame` and equivalent tibble. What is different? Why might the default data frame behaviors cause you frustration?

```
df <- data.frame(abc = 1, xyz = "a")
df$x
```

```
## [1] a
## Levels: a
```

```
df[, "xyz"]
```

```
## [1] a
## Levels: a
```

```
df[, c("abc", "xyz")]
```

```
##   abc xyz
## 1   1   a
```

```
tbl <- as_tibble(df)
tbl$x
```

```
## Warning: Unknown or uninitialised column: 'x'.
```

```
## NULL
```

```
tbl[, "xyz"]
```

```
## # A tibble: 1 x 1
##   xyz
##   <fct>
## 1 a
```

```
tbl[, c("abc", "xyz")]
```

```
## # A tibble: 1 x 2
##     abc xyz
##   <dbl> <fct>
## 1  1.00 a
```

Using `$` a data.frame will partially complete the column. So even though we wrote `df$x` it returned `df$xyz`. This saves a few keystrokes, but can result in accidentally using a different variable than you thought you were using.

With data.frames, with `[` the type of object that is returned differs on the number of columns. If it is one column, it won't return a data.frame, but instead will return a vector. With more than one column, then it will return a data.frame. This is fine if you know what you are passing in, but suppose you did `df[ , vars]` where `vars` was a variable. Then you what that code does depends on `length(vars)` and you'd have to write code to account for those situations or risk bugs.

3. If you have the name of a variable stored in an object, e.g. `var <- "mpg"`, how can you extract the reference variable from a tibble?

You can use the double bracket, like `df[[var]]`. You cannot use the dollar sign, because `df$var` would look for a column named `var`.

4. Practice referring to non-syntactic names in the following data frame by:

    1. Extracting the variable called 1.
    2. Plotting a scatterplot of 1 vs 2.
    3. Creating a new column called 3 which is 2 divided by 1.
    4. Renaming the columns to one, two and three.

```
annoying <- tibble(
  `1` = 1:10,
  `2` = `1` * 2 + rnorm(length(`1`))
)
```

Extract the variable called 1:

```
annoying[["1"]]
```

```
##  [1]  1  2  3  4  5  6  7  8  9 10
```

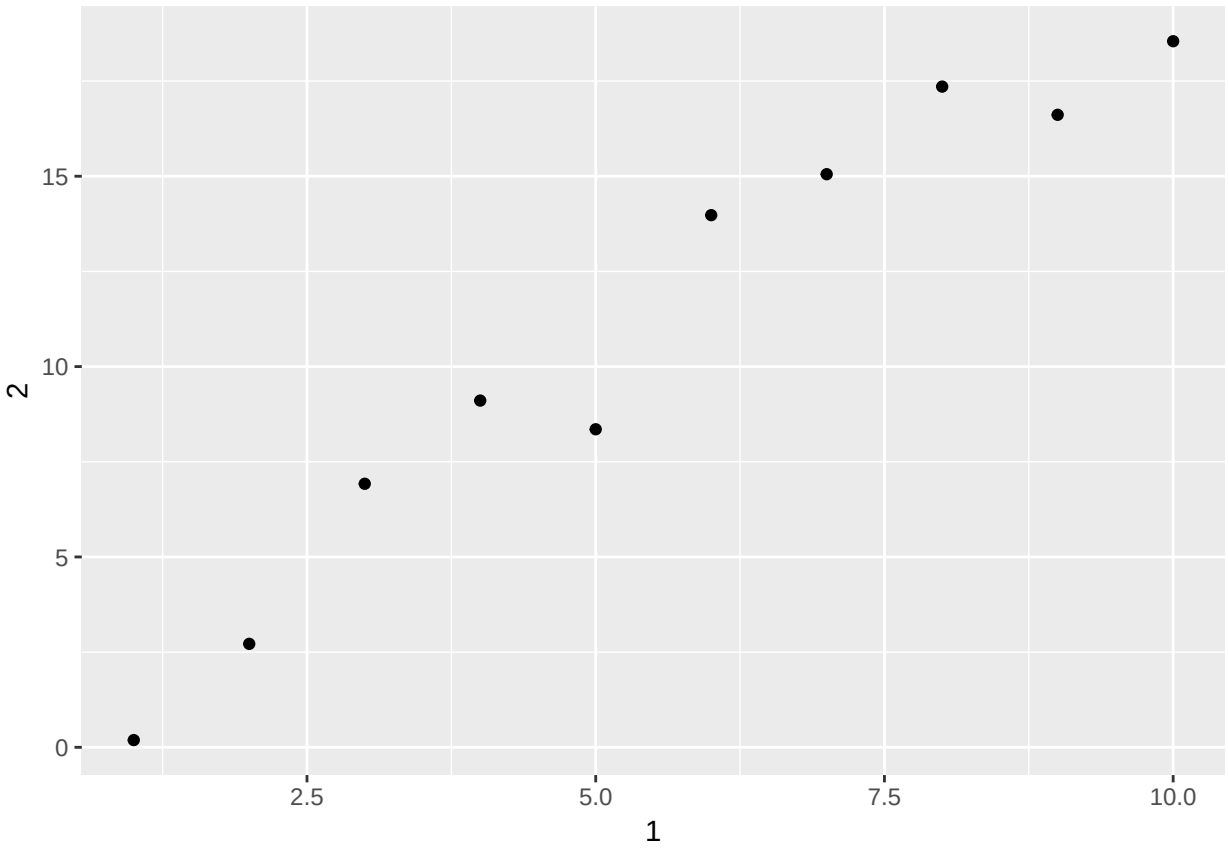
or

```
annoying$`1`
```

```
##  [1]  1  2  3  4  5  6  7  8  9 10
```

A scatter plot of 1 vs. 2:

```
ggplot(annoying, aes(x = `1`, y = `2`)) +
  geom_point()
```



A new column `3` with is `2` divided by `1`:

```
annoying[["3"]] <- annoying$`2` / annoying$`1`
```

or

```
annoying[["3"]] <- annoying[["2"]] / annoying[["1"]]
```

Renaming the columns to `one`, `two`, and `three`:

```
annoying <- rename(annoying, one = `1`, two = `2`, three = `3`)
glimpse(annoying)
```

```
## Observations: 10
## Variables: 3
## $ one   <int> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10
## $ two   <dbl> 0.1894852, 2.7175677, 6.9220044, 9.1073704, 8.3538921, 1...
## $ three <dbl> 0.1894852, 1.3587839, 2.3073348, 2.2768426, 1.6707784, 2...
```

5. What does `tibble::enframe()` do? When might you use it?

It converts named vectors to a data frame with names and values

```
?tibble::enframe
```

```
enframe(c(a = 1, b = 2, c = 3))
```

```
## # A tibble: 3 x 2
##   name  value
##   <chr> <dbl>
## 1 a      1.00
```

```
## 2 b      2.00
## 3 c      3.00
```

6. What option controls how many additional column names are printed at the footer of a tibble?

The print function for tibbles is in `print.tbl_df`:

```
?print.tbl_df
```

The option `n_extra` determines the number of extra columns to print information for.

12.6.1

Case Study

This code is repeated from the chapter because it is needed by the exercises.

```
who1 <- who %>%
  gather(new_sp_m014:newrel_f65, key = "key", value = "cases", na.rm = TRUE)
glimpse(who1)
```

```
## Observations: 76,046
## Variables: 6
## $ country <chr> "Afghanistan", "Afghanistan", "Afghanistan", "Afghanis...
## $ iso2    <chr> "AF", "AF", "AF", "AF", "AF", "AF", "AF", "AF", "AF", ...
## $ iso3    <chr> "AFG", "AFG", "AFG", "AFG", "AFG", "AFG", "AFG", "AFG"...
## $ year    <int> 1997, 1998, 1999, 2000, 2001, 2002, 2003, 2004, 2005, ...
## $ key     <chr> "new_sp_m014", "new_sp_m014", "new_sp_m014", "new_sp_m...
## $ cases   <int> 0, 30, 8, 52, 129, 90, 127, 139, 151, 193, 186, 187, 2...
```

```
who2 <- who1 %>%
 mutate(key = stringr::str_replace(key, "newrel", "new_rel"))
```

```
who3 <- who2 %>%
  separate(key, c("new", "type", "sexage"), sep = "_")
who3
```

```
## # A tibble: 76,046 x 8
##    country     iso2  iso3   year new   type  sexage cases
##    <chr>       <chr> <chr> <int> <chr> <chr> <chr>  <int>
##  1 Afghanistan AF    AFG    1997 new   sp    m014       0
##  2 Afghanistan AF    AFG    1998 new   sp    m014      30
##  3 Afghanistan AF    AFG    1999 new   sp    m014       8
##  4 Afghanistan AF    AFG    2000 new   sp    m014      52
##  5 Afghanistan AF    AFG    2001 new   sp    m014     129
##  6 Afghanistan AF    AFG    2002 new   sp    m014      90
##  7 Afghanistan AF    AFG    2003 new   sp    m014     127
##  8 Afghanistan AF    AFG    2004 new   sp    m014     139
##  9 Afghanistan AF    AFG    2005 new   sp    m014     151
## 10 Afghanistan AF    AFG    2006 new   sp    m014     193
## # ... with 76,036 more rows
```

```
who3 %>%
  count(new)
```

```
## # A tibble: 1 x 2
##   new       n
```

```
##   <chr> <int>
## 1 new   76046
```

```
who4 <- who3 %>%
  select(-new, -iso2, -iso3)
```

```
who5 <- who4 %>%
  separate(sexage, c("sex", "age"), sep = 1)
who5
```

```
## # A tibble: 76,046 x 6
##    country      year type  sex   age   cases
##    <chr>       <int> <chr> <chr> <chr> <int>
##  1 Afghanistan  1997 sp    m     014       0
##  2 Afghanistan  1998 sp    m     014      30
##  3 Afghanistan  1999 sp    m     014       8
##  4 Afghanistan  2000 sp    m     014      52
##  5 Afghanistan  2001 sp    m     014     129
##  6 Afghanistan  2002 sp    m     014      90
##  7 Afghanistan  2003 sp    m     014     127
##  8 Afghanistan  2004 sp    m     014     139
##  9 Afghanistan  2005 sp    m     014     151
## 10 Afghanistan  2006 sp    m     014     193
## # ... with 76,036 more rows
```

1. In this case study I set `na.rm = TRUE` just to make it easier to check that we had the correct values. Is this reasonable? Think about how missing values are represented in this dataset. Are there implicit missing values? What's the difference between an `NA` and zero?

Perhaps? I would need to know more about the data generation process. There are zero's in the data, which means they may explicitly be indicating no cases.

```
who1 %>%
  filter(cases == 0) %>%
  nrow()
```

```
## [1] 11080
```

So it appears that either a country has all its values in a year as non-missing if the WHO collected data for that country, or all its values are non-missing. So it is okay to treat explicitly and implicitly missing values the same, and we don't lose any information by dropping them.

```
gather(who, new_sp_m014:newrel_f65, key = "key", value = "cases") %>%
  group_by(country, year)  %>%
  mutate(missing = is.na(cases)) %>%
  select(country, year, missing) %>%
  distinct() %>%
  group_by(country, year) %>%
  filter(n() > 1)
```

```
## # A tibble: 6,968 x 3
## # Groups:   country, year [3,484]
##    country      year missing
##    <chr>       <int> <lgl>
##  1 Afghanistan  1997 F
##  2 Afghanistan  1998 F
##  3 Afghanistan  1999 F
##  4 Afghanistan  2000 F
```

```
##  5 Afghanistan  2001 F
##  6 Afghanistan  2002 F
##  7 Afghanistan  2003 F
##  8 Afghanistan  2004 F
##  9 Afghanistan  2005 F
## 10 Afghanistan  2006 F
## # ... with 6,958 more rows
```

2. What happens if you neglect the `mutate()` step? (`mutate(key = stringr::str_replace(key, "newrel", "new_rel")`)

`separate` emits the warning "too few values", and if we check the rows for keys beginning with `"newrel_"`, we see that `sexage` is messing, and `type = m014`.

```
who3a <- who1 %>%
  separate(key, c("new", "type", "sexage"), sep = "_")
```

```
## Warning: Expected 3 pieces. Missing pieces filled with `NA` in 2580 rows
## [73467, 73468, 73469, 73470, 73471, 73472, 73473, 73474, 73475, 73476,
## 73477, 73478, 73479, 73480, 73481, 73482, 73483, 73484, 73485, 73486, ...].
```

```
filter(who3a, new == "newrel") %>% head()
```

```
## # A tibble: 6 x 8
##   country     iso2  iso3   year new    type  sexage cases
##   <chr>       <chr> <chr> <int> <chr>  <chr> <chr>  <int>
## 1 Afghanistan AF    AFG    2013 newrel m014  <NA>    1705
## 2 Albania     AL    ALB    2013 newrel m014  <NA>      14
## 3 Algeria     DZ    DZA    2013 newrel m014  <NA>      25
## 4 Andorra     AD    AND    2013 newrel m014  <NA>       0
## 5 Angola      AO    AGO    2013 newrel m014  <NA>     486
## 6 Anguilla    AI    AIA    2013 newrel m014  <NA>       0
```

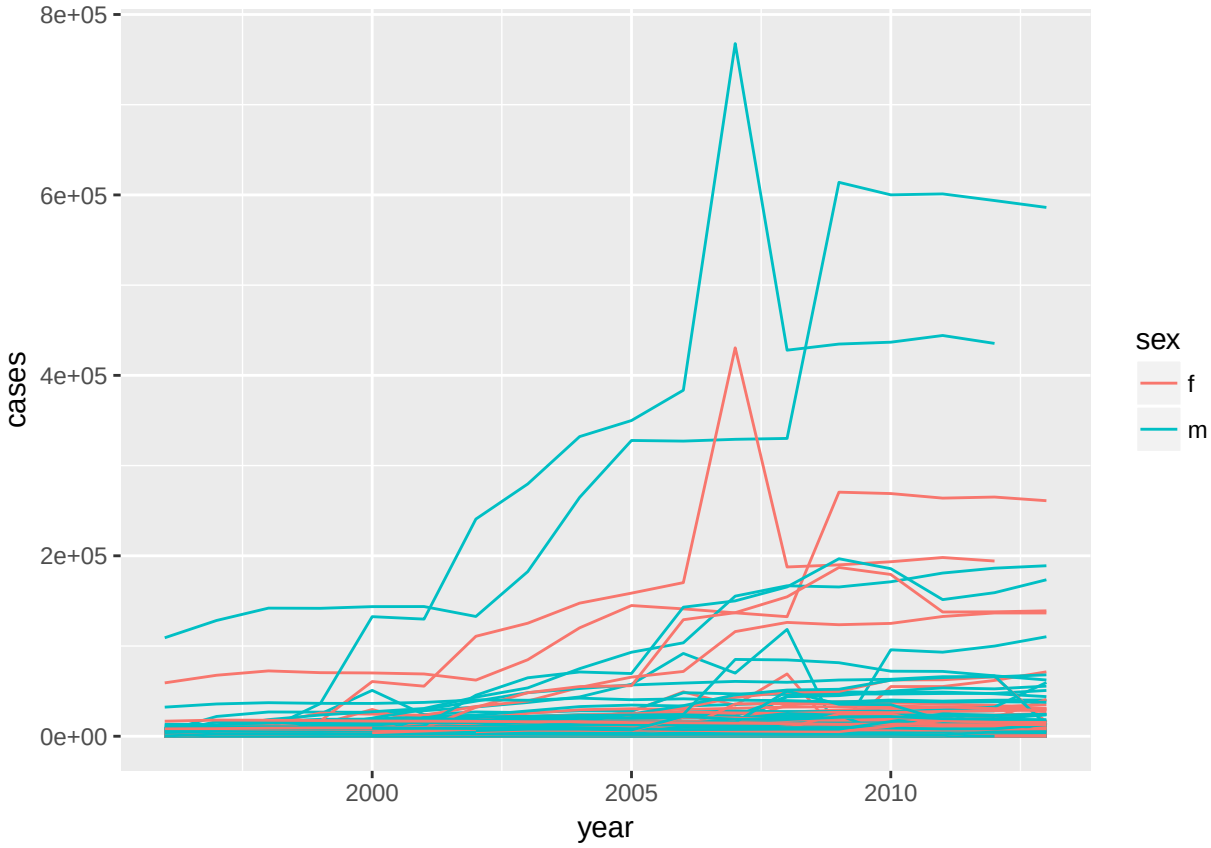
3. I claimed that `iso2` and `iso3` were redundant with country. Confirm this claim.

```
select(who3, country, iso2, iso3) %>%
  distinct() %>%
  group_by(country) %>%
  filter(n() > 1)
```

```
## # A tibble: 0 x 3
## # Groups:   country [0]
## # ... with 3 variables: country <chr>, iso2 <chr>, iso3 <chr>
```

4. For each country, year, and sex compute the total number of cases of TB. Make an informative visualization of the data.

```
who5 %>%
  group_by(country, year, sex) %>%
  filter(year > 1995) %>%
  summarise(cases = sum(cases)) %>%
  unite(country_sex, country, sex, remove = FALSE) %>%
  ggplot(aes(x = year, y = cases, group = country_sex, colour = sex)) +
  geom_line()
```



A small multiples plot faceting by country is difficult given the number of countries. Focusing on those countries with the largest changes or absolute magnitudes after providing the context above is another option.