Homework 4

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```
library(tidyverse)
```

```
## -- Attaching packages ---------------------------------- tidyverse 1.2.1 --
```

```
## ✓ ggplot2 2.2.1     ✓ purrr   0.2.4
## ✓ tibble  1.4.2     ✓ dplyr   0.7.4
## ✓ tidyr   0.8.0     ✓ stringr 1.2.0
## ✓ readr   1.1.1     ✓ forcats 0.2.0
```

```
## -- Conflicts ------------------------------------- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

```
library(knitr)
library(tibble)
```

10.5 Exercises

1. How can you tell if an object is a tibble?

```
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"
```

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 the $ with the data frame completes the column, but with a tibble it produces a warning message. With data frames the [returns what we have assigned to the object, so 'a'. With the tibble, the [returns the full object 'xyz'.

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?

From a tibble, you have to use the double bracket because the $ looks for a column named var.

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

1. Extracting the variable called 1.

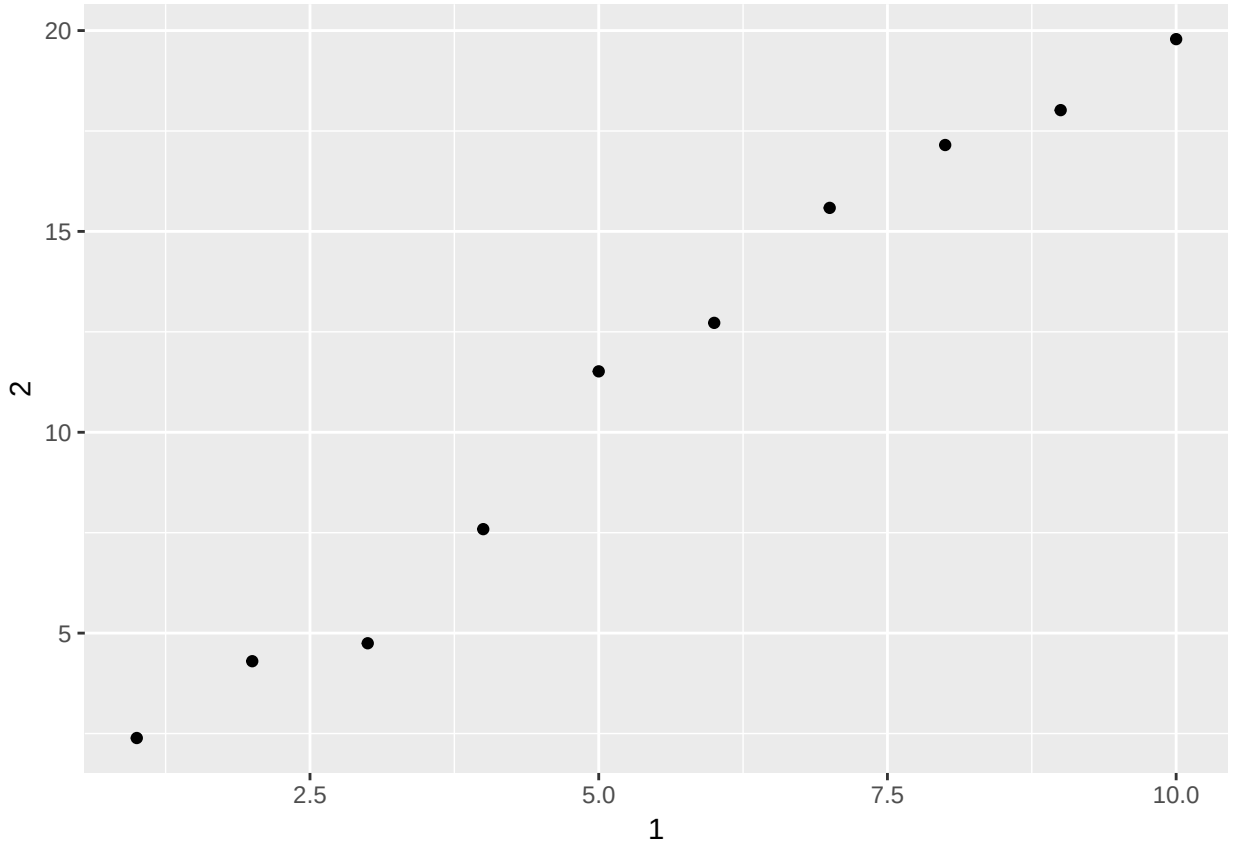
```
annoying <- tibble(
  `1` = 1:10,
  `2` = `1` * 2 + rnorm(length(`1`))
)

annoying[["1"]]
```

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

2. Plotting a scatterplot of 1 vs 2.

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



3. Creating a new column called 3 which is 2 divided by 1.

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

```
##  [1] 2.388772 2.150277 1.582447 1.897025 2.303365 2.120630 2.226587
##  [8] 2.143874 2.002132 1.978667
```

4. 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> 2.388772, 4.300555, 4.747341, 7.588100, 11.516823, 12.72...
## $ three <dbl> 2.388772, 2.150277, 1.582447, 1.897025, 2.303365, 2.1206...
```

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

Tibble::enframe() converts named vectors to a data frame with names and values. You could use it when you want to convert a tibble to data to make a graph.

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

The print command for tibbles is print.tbl_df and the option n_extra determines the number of columns to print.

12.6.1 Exercises

```
#code needed from chapter
who %>%
  gather(code, value, new_sp_m014:newrel_f65, na.rm = TRUE) %>%
  mutate(code = stringr::str_replace(code, "newrel", "new_rel")) %>%
  separate(code, c("new", "var", "sexage")) %>%
  select(-new, -iso2, -iso3) %>%
  separate(sexage, c("sex", "age"), sep = 1)
```

```
## # A tibble: 76,046 x 6
##    country      year var   sex   age   value
##    <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
```

```
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?

This may not be reasonable because there are zeros in the data.

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

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

It appears that the if the data is missing it is either because there is some or all missing data. So, in this case there is no difference between NA and zero.

```
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")))

If you neglect the mutate() step separate gives us the warning of missing pieces filled with "NA".

```
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
```

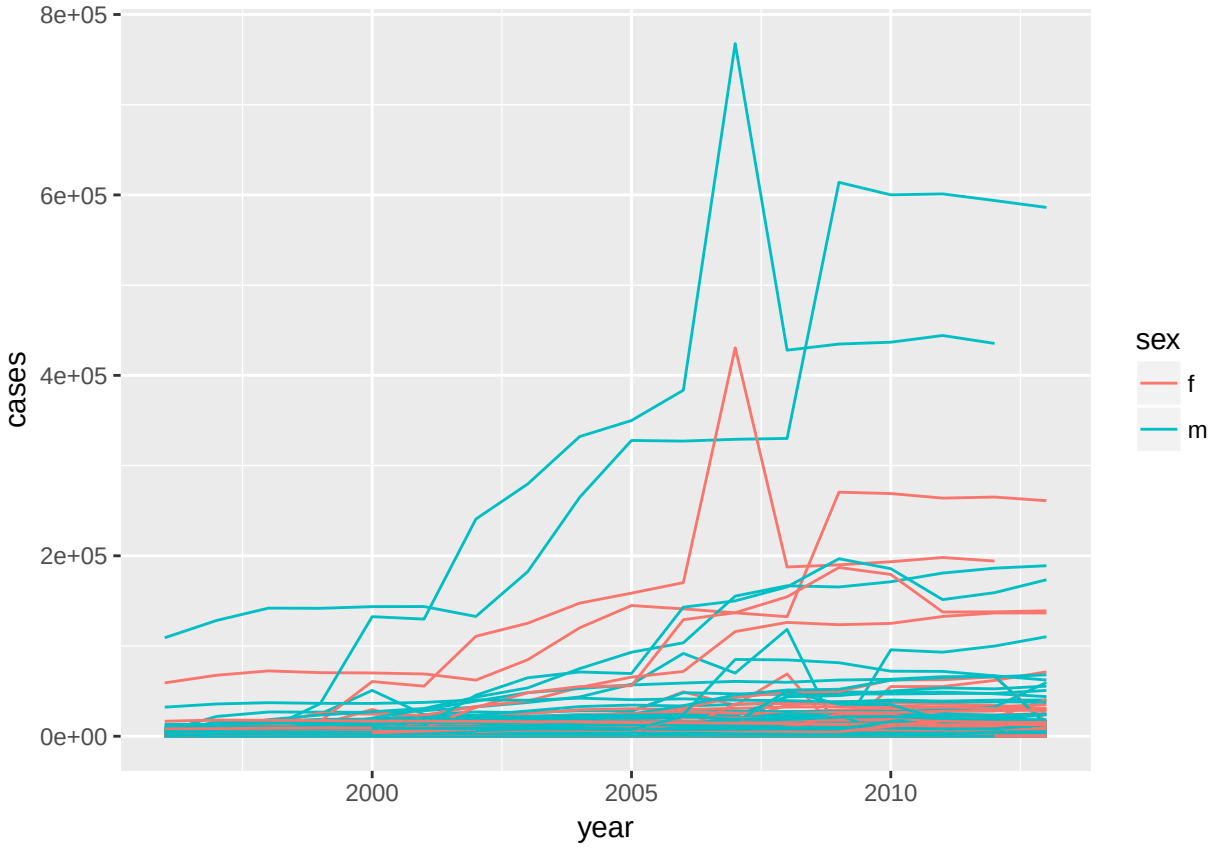
3. I claimed that iso2 and iso3 were redundant with country. Confirm this claim.

```
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()
```



It appears that there are too many countries being analyzed by this graph. The bottom is hard to read. We should focus on the countried with the biggest changes.