CWRU DSCI351-351M-451: Week04a Tidy Data Manipulation(CWRU, Pitt, UCF, UTRGV)

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4.1.3.1 Tidyverse Cheatsheets, Functions and Reading Your Code

Look at the Tidyverse Cheatsheet

- **Tidyverse For Beginners Cheatsheet**
  - In the Git/20s-dsci353-353m-453-prof/3-readings/3-CheatSheets/ folder
- **Data Wrangling with dplyr and tidyr Cheatsheet**

Tidyverse Functions & Conventions

```
- The pipe operator `%>%`
- Use `dplyr::filter()` to subset data row-wise.
- Use `dplyr::arrange()`  to sort the observations in a data frame
- Use `dplyr::mutate()` to update or create new columns of a data frame
- Use `dplyr::summarize()` to turn many observations into a single data point
- Use `dplyr::arrange()` to change the ordering of the rows of a data frame
- Use `dplyr::select()` to choose variables from a tibble,
  - keeps only variables you mention
- Use `dplyr::rename()` keeps all the variables and renames variables
  - rename(iris, petal_length = Petal.Length)
- These can be combined using `dplyr::group_by()`
  - which lets you perform operations "by group".
- The `%in%` matches conditions provided by a vector using the c() function
- The **forcats** package has tidyverse functions
  - for factors (categorical variables)
- The **readr** package has tidyverse functions
  - to read_..., melt_... col_..., parse_... data and objects
```

Reading Your Code: Whenever you see

- The assignment operator `<-`, think **"gets"**
- The pipe operator, `%>%`, think **"then"**

```
library(devtools)
```

4.1.3.2 What is a Tidy Data Frame

```
## Loading required package: usethis
```

```
# devtools::install_github("rstudio/EDAWR")
```

4.1.3.2.1 What is data wrangling? Intro, Motivation, Outline, Setup

- Pt. 1 Data Wrangling Introduction
  - Tibbles
  - View
  - Pipe Operator
- Pt 2 Intro to Data Wrangling with R and the Tidyverse

    - What is a Tidy Dataframe?
    - tidyr package for gather and spread
- dplyr – Pt 3 Intro to the Grammar of Data Manipulation with R
- [Working with Two Datasets: Binds, Set Operations, and Joins
- Pt 4 Intro to Data Manipulation](https://youtu.be/AuBgYDCg1Cg?list=WL)

4.1.3.2.2 Buckle your seat belt

- *Ignore if you don't need this bit of support.*

Now is the time to make sure

- you are working in an appropriate directory on your computer,
- probably through the use of an RStudio Project.

To see where you are

- Enter `getwd()` in the Console to see current working directory or,
- in RStudio, this is displayed in the bar at the top of Console.

You should clean out your work space.

- In RStudio, click on the "Clear" broom icon from the Environment tab or
- use *Session > Clear Work space*.
- You can also enter `rm(list = ls())` in the Console to accomplish same.

Now restart R.

- This will ensure you don't have any packages loaded
    - from previous calls to `library()`.
- In RStudio, use *Session > Restart R*.
- Otherwise, quit R with `q()` and re-launch it.

Why do we do this? So that the code you write is complete and re-runnable.

- If you return to a clean slate often,
    - you will root out hidden dependencies
    - where one snippet of code only works
    - because it relies on objects created by code saved elsewhere
    - or, much worse, never saved at all.
- Similarly, an aggressive clean slate approach
    - will expose any usage of packages
    - that have not been explicitly loaded.

Finally, open a new R script

- and develop and run your code from there.
- In RStudio, use *File > New File > R Script*.
    - Save this script with a name ending in `.r` or `.R`,
    - containing no spaces or other funny stuff,
    - and that evokes whatever it is we're doing today.
- Example: `cm004_data-care-feeding.r`.

Another great idea is to do this in an R Markdown document.

4.1.3.2.3 Data frames are awesome

- Whenever you have rectangular, spreadsheet-y data,

    - your default data receptacle in R is a data frame.
    - Do not depart from this without good reason.

Data frames are awesome because…

- Data frames package related variables neatly together,
  - keeping them in sync vis-a-vis row order
  - applying any filtering of observations uniformly.
- Most functions for inference, modeling, and graphing
  - are happy to be passed a data frame via a `data =` argument.
  - This has been true in base R for a long time.
- The set of packages known as the `tidyverse`
  - takes this one step further
  - and explicitly prioritizes the processing of data frames.
- This includes popular packages like `dplyr` and `ggplot2`.
- In fact the tidyverse prioritizes
  - a special flavor of data frame, called a "tibble."

Data frames

- unlike general arrays or, specifically, matrices in R
- can hold variables of different flavors,
  - such as character data (subject ID or name),
  - quantitative data (white blood cell count),
  - and categorical information (treated vs. untreated).
- If you use homogeneous structures,
  - like matrices,
  - for data analysis,
  - you are likely to make the terrible mistake
  - of spreading a data set out over multiple, unlinked objects.
- Why? Because you can't put character data,
  - such as subject name,
  - into the numeric matrix that holds white blood cell count.
- This fragmentation is a Bad Idea.

4.1.3.3 Get the Gapminder data

- What is Gapminder
  - A project of Hans Rosling
  - Gapminder Project

Hans Rosling and Gapminder: 200 years in 4 minutes - BBC News

We will work with some of the data from the Gapminder project.

This is released as an R package,

- so we can install it from CRAN like so:

```
# install.packages("gapminder")
```

Now load the package:

```
library(gapminder)
```

`##### Meet the `gapminder` data frame or "tibble"`

By loading the `gapminder` package,

- we now have access to a data frame by the same name.

Get an overview of this with `str()`,

- which displays the structure of an object.

```
str(gapminder)
## tibble [1,704 x 6] (S3: tbl_df/tbl/data.frame)
##  $ country  : Factor w/ 142 levels "Afghanistan",..: 1 1 1 1 1 1 1 1 1 1 ...
##  $ continent: Factor w/ 5 levels "Africa","Americas",..: 3 3 3 3 3 3 3 3 3 3 ...
##  $ year     : int [1:1704] 1952 1957 1962 1967 1972 1977 1982 1987 1992 1997 ...
##  $ lifeExp  : num [1:1704] 28.8 30.3 32 34 36.1 ...
##  $ pop      : int [1:1704] 8425333 9240934 10267083 11537966 13079460 14880372 12881816 13867957 163
##  $ gdpPercap: num [1:1704] 779 821 853 836 740 ...
```

`str()` will provide a sensible description of almost anything

- and, worst case, nothing bad can actually happen.
- When in doubt, just `str()` some of the recently created objects
  - to get some ideas about what to do next.

We could print the `gapminder` object itself to screen.

- However, if you've used R before, you might be reluctant to do this,
- because large data sets just fill up your Console
  - and provide very little insight.

This is the first big win for **tibbles**.

- The `tidyverse`
- offers a special case of R's default data frame: the "tibble",
  - which is a nod to the actual class of these objects, `tbl_df`.

If you have not already done so,

- install the `tidyverse` meta-package now:

```
# install.packages("tidyverse")
```

Now load it:

```
library(tidyverse)
## -- Attaching packages --------------------------------------- tidyverse 1.3.1 --
## v ggplot2 3.3.6     v purrr   0.3.4
## v tibble  3.1.7     v dplyr   1.0.10
## v tidyr   1.2.1     v stringr 1.4.1
## v readr   2.1.2     v forcats 0.5.2
## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

Now we can boldly print `gapminder` to screen!

- It is a tibble (and also a regular data frame)
- and the `tidyverse` provides a nice print method
  - that shows the most important stuff
  - and doesn't fill up your Console.

```
## see? it's still a regular data frame, but also a tibble
class(gapminder)
## [1] "tbl_df"     "tbl"        "data.frame"
gapminder
## # A tibble: 1,704 x 6
##    country     continent  year lifeExp      pop gdpPercap
##    <fct>       <fct>     <int>   <dbl>    <int>     <dbl>
##  1 Afghanistan Asia       1952    28.8  8425333      779.
```

```
##  2 Afghanistan Asia       1957    30.3  9240934      821.
##  3 Afghanistan Asia       1962    32.0 10267083      853.
##  4 Afghanistan Asia       1967    34.0 11537966      836.
##  5 Afghanistan Asia       1972    36.1 13079460      740.
##  6 Afghanistan Asia       1977    38.4 14880372      786.
##  7 Afghanistan Asia       1982    39.9 12881816      978.
##  8 Afghanistan Asia       1987    40.8 13867957      852.
##  9 Afghanistan Asia       1992    41.7 16317921      649.
## 10 Afghanistan Asia       1997    41.8 22227415      635.
## # ... with 1,694 more rows
```

If you are dealing with plain vanilla data frames,

- you can rein in data frame printing explicitly
    - with `head()` and `tail()`.
- Or turn it into a tibble with `as_tibble()`!

```
head(gapminder)
## # A tibble: 6 x 6
##   country     continent  year lifeExp      pop gdpPercap
##   <fct>       <fct>     <int>   <dbl>    <int>     <dbl>
## 1 Afghanistan Asia       1952    28.8  8425333      779.
## 2 Afghanistan Asia       1957    30.3  9240934      821.
## 3 Afghanistan Asia       1962    32.0 10267083      853.
## 4 Afghanistan Asia       1967    34.0 11537966      836.
## 5 Afghanistan Asia       1972    36.1 13079460      740.
## 6 Afghanistan Asia       1977    38.4 14880372      786.
tail(gapminder)
## # A tibble: 6 x 6
##   country  continent  year lifeExp      pop gdpPercap
##   <fct>    <fct>     <int>   <dbl>    <int>     <dbl>
## 1 Zimbabwe Africa     1982    60.4  7636524      789.
## 2 Zimbabwe Africa     1987    62.4  9216418      706.
## 3 Zimbabwe Africa     1992    60.4 10704340      693.
## 4 Zimbabwe Africa     1997    46.8 11404948      792.
## 5 Zimbabwe Africa     2002    40.0 11926563      672.
## 6 Zimbabwe Africa     2007    43.5 12311143      470.
as_tibble(iris)
## # A tibble: 150 x 5
##    Sepal.Length Sepal.Width Petal.Length Petal.Width Species
##           <dbl>       <dbl>        <dbl>       <dbl> <fct>
##  1          5.1         3.5          1.4         0.2 setosa
##  2          4.9         3            1.4         0.2 setosa
##  3          4.7         3.2          1.3         0.2 setosa
##  4          4.6         3.1          1.5         0.2 setosa
##  5          5           3.6          1.4         0.2 setosa
##  6          5.4         3.9          1.7         0.4 setosa
##  7          4.6         3.4          1.4         0.3 setosa
##  8          5           3.4          1.5         0.2 setosa
##  9          4.4         2.9          1.4         0.2 setosa
## 10          4.9         3.1          1.5         0.1 setosa
## # ... with 140 more rows
```

More ways to query basic info on a data frame:

```r
names(gapminder)
## [1] "country"   "continent" "year"      "lifeExp"   "pop"       "gdpPercap"
ncol(gapminder)
## [1] 6
length(gapminder)
## [1] 6
dim(gapminder)
## [1] 1704    6
nrow(gapminder)
## [1] 1704
```

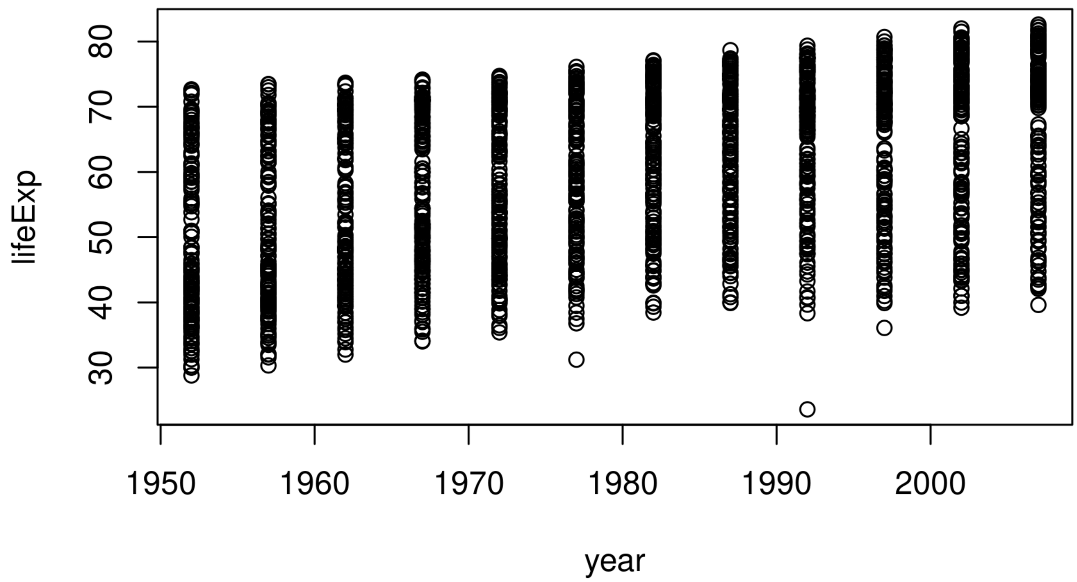
A statistical overview can be obtained with `summary()`

```r
summary(gapminder)
##         country        continent        year         lifeExp
##  Afghanistan:  12   Africa  :624   Min.   :1952   Min.   :23.60
##  Albania    :  12   Americas:300   1st Qu.:1966   1st Qu.:48.20
##  Algeria    :  12   Asia    :396   Median :1980   Median :60.71
##  Angola     :  12   Europe  :360   Mean   :1980   Mean   :59.47
##  Argentina  :  12   Oceania : 24   3rd Qu.:1993   3rd Qu.:70.85
##  Australia  :  12                  Max.   :2007   Max.   :82.60
##  (Other)    :1632
##       pop              gdpPercap
##  Min.   :6.001e+04   Min.   :   241.2
##  1st Qu.:2.794e+06   1st Qu.:  1202.1
##  Median :7.024e+06   Median :  3531.8
##  Mean   :2.960e+07   Mean   :  7215.3
##  3rd Qu.:1.959e+07   3rd Qu.:  9325.5
##  Max.   :1.319e+09   Max.   :113523.1
##
```

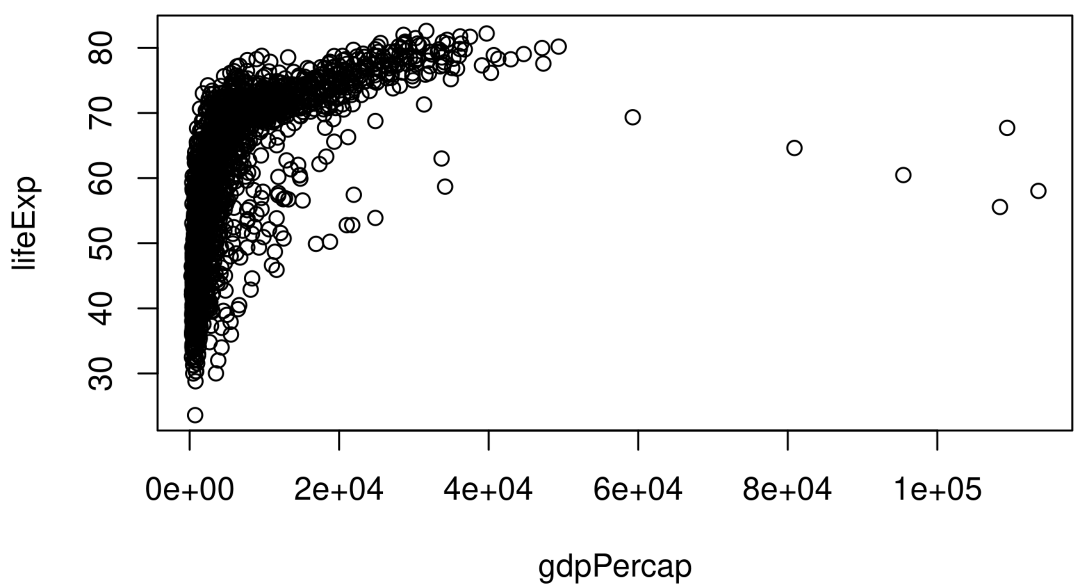
Although we haven't begun our formal coverage of visualization yet,

- it's so important for smell-testing data set
    - that we will make a few figures anyway.
- Here we use only base R graphics, which are very basic.

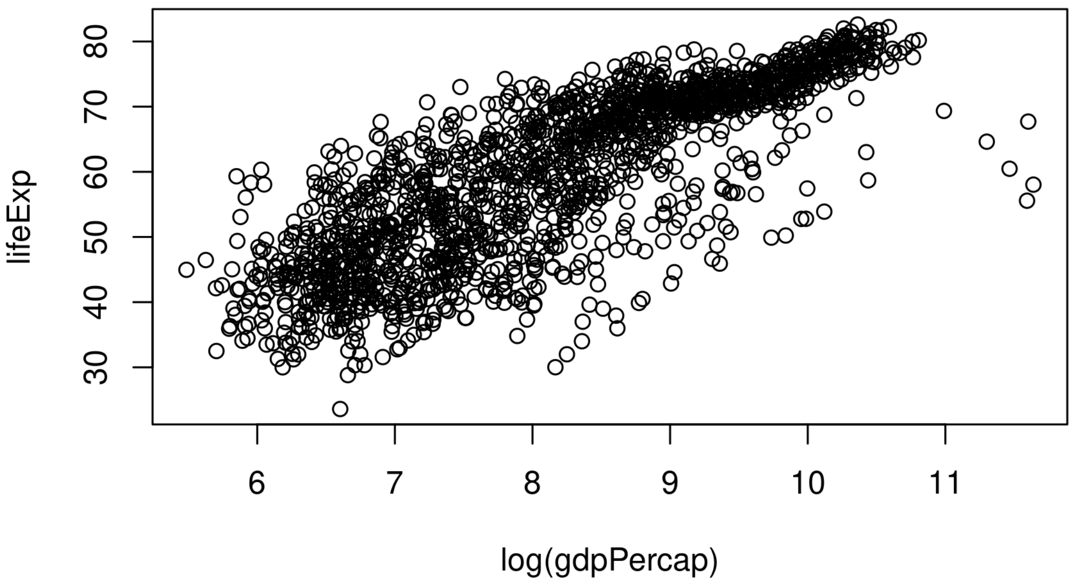
```r
plot(lifeExp ~ year, gapminder)
```




```
plot(lifeExp ~ gdpPercap, gapminder)
```




```
plot(lifeExp ~ log(gdpPercap), gapminder)
```



4.1.3.4 Non-sequitur: The Equals Operator

- Sidebar on equals:
  - A single equal sign `=` is most commonly used
    - to specify values of arguments when calling functions in R,
    - e.g. `group = continent`.
  - It can be used for assignment
    - but we advise against that,
    - in favor of `<-`.
  - A double equal sign `==` is a binary comparison operator,
    - akin to less than `<` or greater than `>`,
    - returning the logical value `TRUE` in the case of equality
    - and `FALSE` otherwise.
  - Although you may not yet understand exactly why,
    - `subset = country == "Colombia"` restricts operation – scatter plotting,
    - in above examples – to observations where the country is Colombia.

Let's go back to the result of `str()` to talk about what a data frame is.

```
str(gapminder)
## tibble [1,704 x 6] (S3: tbl_df/tbl/data.frame)
##  $ country  : Factor w/ 142 levels "Afghanistan",..: 1 1 1 1 1 1 1 1 1 1 ...
##  $ continent: Factor w/ 5 levels "Africa","Americas",..: 3 3 3 3 3 3 3 3 3 3 ...
##  $ year     : int [1:1704] 1952 1957 1962 1967 1972 1977 1982 1987 1992 1997 ...
##  $ lifeExp  : num [1:1704] 28.8 30.3 32 34 36.1 ...
##  $ pop      : int [1:1704] 8425333 9240934 10267083 11537966 13079460 14880372 12881816 13867957 163
##  $ gdpPercap: num [1:1704] 779 821 853 836 740 ...
```

A data frame is a special case of a *list*,

- which is used in R to hold just about anything.

Data frames are a special case

- where the length of each list component is the same.

Data frames are superior to matrices in R

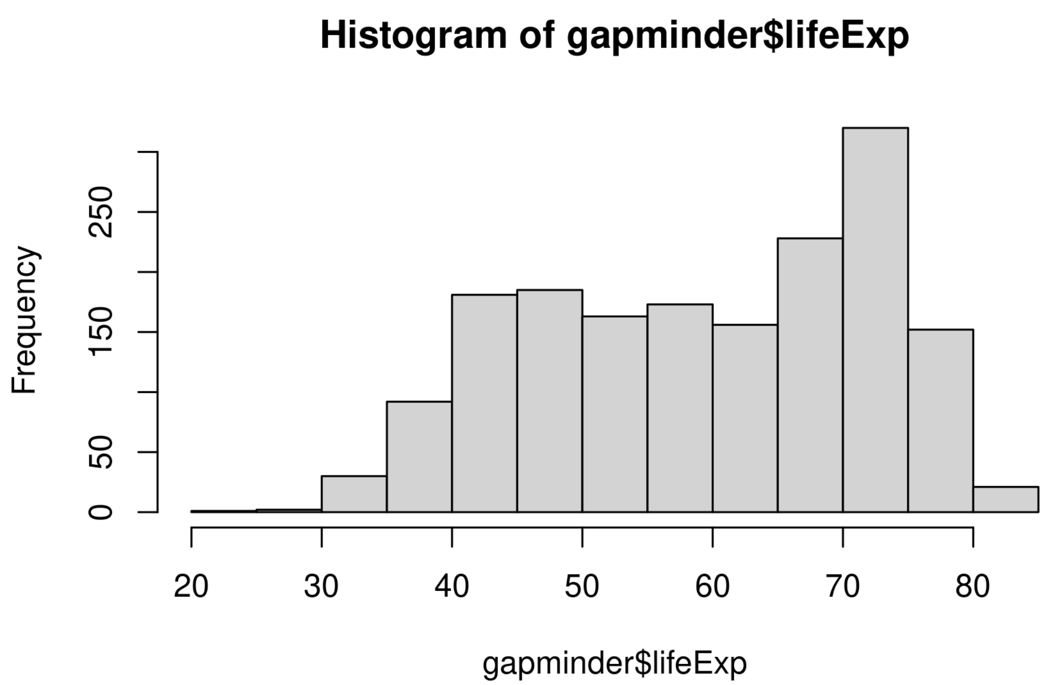
- because they can hold vectors of different flavors,
- e.g. numeric, character, and categorical data can be stored together.
- This comes up a lot!

Look at the variables inside a data frame

- To specify a single variable from a data frame,
  - use the dollar sign `$`.

Let's explore the numeric variable for life expectancy.

```
head(gapminder$lifeExp)
## [1] 28.801 30.332 31.997 34.020 36.088 38.438
summary(gapminder$lifeExp)
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   23.60   48.20   60.71   59.47   70.85   82.60
hist(gapminder$lifeExp)
```



The year variable is an integer variable,

- but since there are so few unique values
- it also functions a bit like a categorical variable.

```
summary(gapminder$year)
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    1952    1966    1980    1980    1993    2007
```

```
table(gapminder$year)
##
## 1952 1957 1962 1967 1972 1977 1982 1987 1992 1997 2002 2007
##  142  142  142  142  142  142  142  142  142  142  142  142
```

The variables for country and continent

- hold truly categorical information,
- which is stored as a *factor* in R.

```
class(gapminder$continent)
## [1] "factor"
summary(gapminder$continent)
##   Africa Americas     Asia   Europe  Oceania
##      624      300      396      360       24
levels(gapminder$continent)
## [1] "Africa"   "Americas" "Asia"     "Europe"   "Oceania"
nlevels(gapminder$continent)
## [1] 5
```

The **levels** of the factor `continent`

- are "Africa", "Americas", etc.
- and this is what's usually presented to your eyeballs by R.

In general, the levels are friendly human-readable character strings,

- like "male/female" and "control/treated".
- But *never ever ever* forget that, under the hood,
  - R is really storing integer codes 1, 2, 3, etc.
- Look at the result from `str(gapminder$continent)`
  - if you are skeptical.

```
str(gapminder$continent)
##  Factor w/ 5 levels "Africa","Americas",..: 3 3 3 3 3 3 3 3 3 3 ...
```

This Janus-like nature of factors

- means they are rich with booby traps for the unsuspecting
- but they are a necessary evil.

I recommend you resolve to learn how to properly care and feed your *factors*

- The pros far outweigh the cons.

Specifically in modeling and figure-making,

- factors are anticipated and accommodated
- by the functions and packages you will want to exploit.

Here we count how many observations are associated with each continent

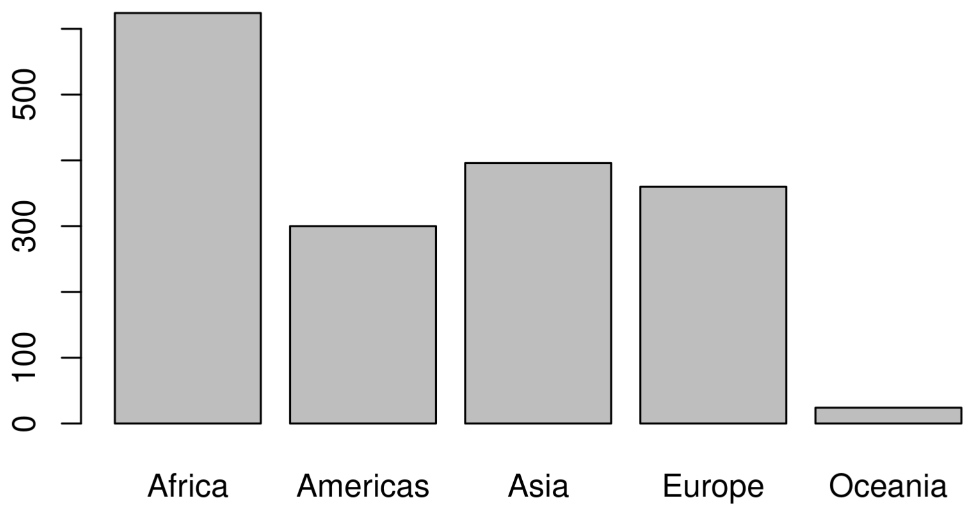
- and, as usual, try to portray that info visually.

This makes it much easier to quickly see

- that African countries are well represented in this data set.

```
table(gapminder$continent)
##
##   Africa Americas     Asia   Europe  Oceania
```

```
##       624       300       396       360        24
barplot(table(gapminder$continent))
```



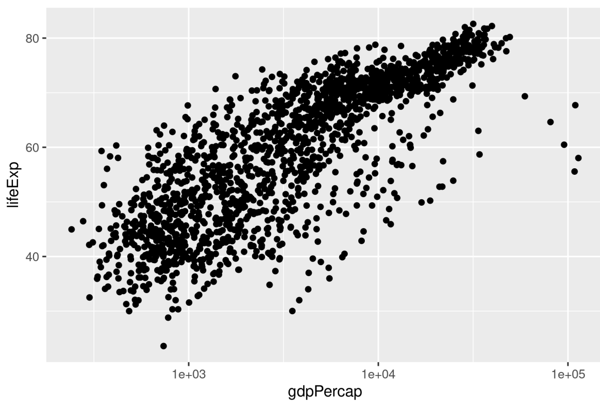
In the figures below, we see how factors

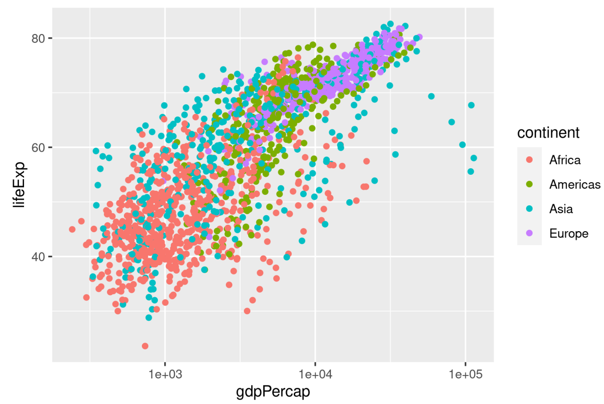
- can be put to work in figures.

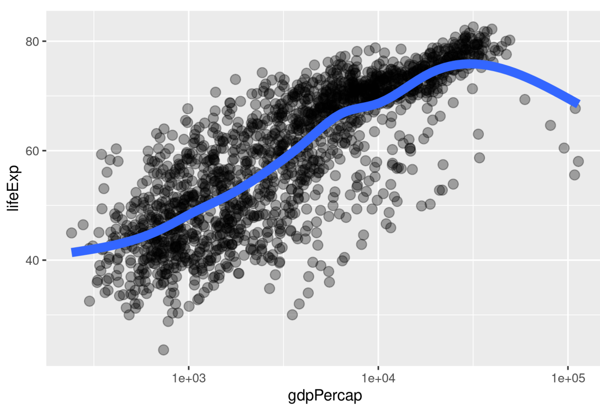
The `continent` factor is easily mapped

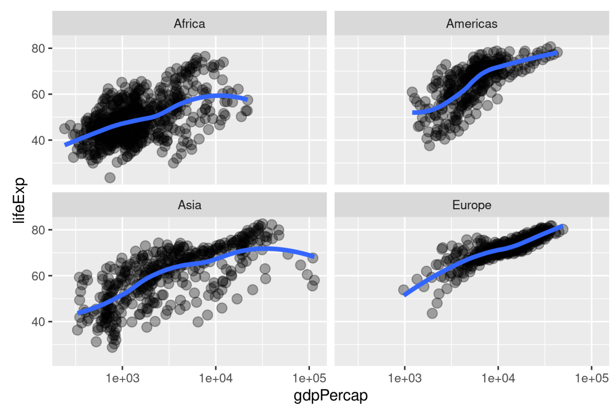
- into "facets" or colors and a legend
  - by the `ggplot2` package.
- *Making figures with `ggplot2` is covered elsewhere
  - so feel free to just sit back and enjoy these plots
  - or blindly copy/paste.*

```
## we exploit the fact that ggplot2 was installed and loaded via the tidyverse
p <- ggplot(filter(gapminder, continent != "Oceania"),
            aes(x = gdpPercap, y = lifeExp)) # just initializes
p <- p + scale_x_log10() # log the x axis the right way
p + geom_point() # scatterplot
p + geom_point(aes(color = continent)) # map continent to color
p + geom_point(alpha = (1 / 3), size = 3) + geom_smooth(lwd = 3, se = FALSE)
## `geom_smooth()` using method = 'gam' and formula 'y ~ s(x, bs = "cs")'
p + geom_point(alpha = (1 / 3), size = 3) + facet_wrap( ~ continent) +
  geom_smooth(lwd = 1.5, se = FALSE)
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```









Recap

- Use data frames!!!
- Use the `tidyverse`!!! This will provide a special type of data frame called a "tibble" that has nice default printing behavior, among other benefits.
- When in doubt, `str()` something or print something.
- Always understand the basic extent of your data frames: number of rows and columns.
- Understand what flavor the variables are.
- Use factors!!! But with intention and care.
- Do basic statistical and visual sanity checking of each variable.
- Refer to variables by name, e.g., `gapminder$lifeExp`, not by column number. Your code will be more robust and readable.

CLASS STOPPED HERE

4.1.3.5 Tidy Manipulation: Introduction to dplyr package

4.1.3.5.1 Intro

- `dplyr` is a package for data manipulation,
  - developed by Hadley Wickham and Romain Francois.
  - It is built to be fast, highly expressive, and open-minded
    - about how your data is stored.
  - It is installed as part of the the `tidyverse` meta-package
    - and, as a core package, it is among those loaded via `library(tidyverse)`.

`dplyr`'s roots are in an earlier package called `plyr`,

- which implements the "split-apply-combine" strategy for data analysis (PDF).

- Where `plyr` covers a diverse set of inputs and outputs
  - (e.g., arrays, data frames, lists),
- `dplyr` has a laser-like focus on data frames
  - or, in the `tidyverse`, "tibbles".
- `dplyr` is a package-level treatment of the `ddply()` function
  - from `plyr`,
- because "data frame in, data frame out"
- proved to be so incredibly important.

Have no idea what I'm talking about? Not sure if you care?

- If you use these base R functions:
  - `subset()`, `apply()`, `[sl]apply()`, `tapply()`, `aggregate()`,
  - `split()`, `do.call()`, `with()`, `within()`,
  - then you should keep reading.
- Also, if you use `for()` loops a lot,
  - you might enjoy learning other ways
  - to iterate over rows or groups of rows
  - or variables in a data frame.

Load `dplyr` and `gapminder`

I choose to load the `tidyverse`,

- which will load `dplyr`,
  - among other packages we use incidentally below.

Also load `gapminder`.

```
# library(gapminder)
# library(tidyverse)
```

Say hello to the Gapminder tibble

- The `gapminder` data frame is a special kind of data frame: a tibble.

```
gapminder
## # A tibble: 1,704 x 6
##    country     continent  year lifeExp      pop gdpPercap
##    <fct>       <fct>     <int>   <dbl>    <int>     <dbl>
##  1 Afghanistan Asia       1952    28.8  8425333      779.
##  2 Afghanistan Asia       1957    30.3  9240934      821.
##  3 Afghanistan Asia       1962    32.0 10267083      853.
##  4 Afghanistan Asia       1967    34.0 11537966      836.
##  5 Afghanistan Asia       1972    36.1 13079460      740.
##  6 Afghanistan Asia       1977    38.4 14880372      786.
##  7 Afghanistan Asia       1982    39.9 12881816      978.
##  8 Afghanistan Asia       1987    40.8 13867957      852.
##  9 Afghanistan Asia       1992    41.7 16317921      649.
## 10 Afghanistan Asia       1997    41.8 22227415      635.
## # ... with 1,694 more rows
```

It's tibble-ness is why we get nice compact printing.

- For a reminder of the problems with base data frame printing,
  - go type `iris` in the R Console
- or, better yet, print a data frame to screen
  - that has lots of columns.

Note how gapminder's `class()` includes `tbl_df`;

- the "tibble" terminology is a nod to this.

```
class(gapminder)
## [1] "tbl_df"     "tbl"        "data.frame"
```

There will be some functions, like `print()`,

- that know about tibbles and do something special.
- There will others that do not, like `summary()`.
- In which case the regular data frame treatment will happen,
  - because every tibble is also a regular data frame.

To turn any data frame into a tibble use `as_tibble()`:

```
as_tibble(iris)
## # A tibble: 150 x 5
##    Sepal.Length Sepal.Width Petal.Length Petal.Width Species
##           <dbl>       <dbl>        <dbl>       <dbl> <fct>
##  1          5.1         3.5          1.4         0.2 setosa
##  2          4.9         3            1.4         0.2 setosa
##  3          4.7         3.2          1.3         0.2 setosa
##  4          4.6         3.1          1.5         0.2 setosa
##  5          5           3.6          1.4         0.2 setosa
##  6          5.4         3.9          1.7         0.4 setosa
##  7          4.6         3.4          1.4         0.3 setosa
##  8          5           3.4          1.5         0.2 setosa
##  9          4.4         2.9          1.4         0.2 setosa
## 10          4.9         3.1          1.5         0.1 setosa
## # ... with 140 more rows
```

4.1.3.5.2 Think before you create excerpts of your data ...

- If you feel the urge to store a little snippet of your data:

```
(canada <- gapminder[241:252, ])
## # A tibble: 12 x 6
##    country continent  year lifeExp      pop gdpPercap
##    <fct>   <fct>     <int>   <dbl>    <int>     <dbl>
##  1 Canada  Americas   1952    68.8 14785584    11367.
##  2 Canada  Americas   1957    70.0 17010154    12490.
##  3 Canada  Americas   1962    71.3 18985849    13462.
##  4 Canada  Americas   1967    72.1 20819767    16077.
##  5 Canada  Americas   1972    72.9 22284500    18971.
##  6 Canada  Americas   1977    74.2 23796400    22091.
##  7 Canada  Americas   1982    75.8 25201900    22899.
##  8 Canada  Americas   1987    76.9 26549700    26627.
##  9 Canada  Americas   1992    78.0 28523502    26343.
## 10 Canada  Americas   1997    78.6 30305843    28955.
## 11 Canada  Americas   2002    79.8 31902268    33329.
## 12 Canada  Americas   2007    80.7 33390141    36319.
```

Stop and ask yourself ...

> Do I want to create mini data sets for each level of some factor (or unique combination of several factors) ... in order to compute or graph something?
>
> If YES, **use proper data aggregation techniques** or faceting in `ggplot2` – **don't subset the data**. Or, more realistic, only subset the data as a temporary measure while you develop

your elegant code for computing on or visualizing these data subsets.

If NO, then maybe you really do need to store a copy of a subset of the data. But seriously consider whether you can achieve your goals by simply using the `subset =` argument of, e.g., the `lm()` function, to limit computation to your excerpt of choice. Lots of functions offer a `subset =` argument!

Copies and excerpts of your data

- clutter your work space,
  - invite mistakes,
  - and sow general confusion.
- Avoid whenever possible.

Reality can also lie somewhere in between.

- You will find the workflows presented below
  - can help you accomplish your goals
- with minimal creation of temporary, intermediate objects.

4.1.3.5.3 Use `filter()` to subset data row-wise.

- `filter()` takes logical expressions
  - and returns the rows for which all are `TRUE`.

```
filter(gapminder, lifeExp < 29)
## # A tibble: 2 x 6
##   country     continent  year lifeExp     pop gdpPercap
##   <fct>       <fct>     <int>   <dbl>   <int>     <dbl>
## 1 Afghanistan Asia       1952    28.8 8425333      779.
## 2 Rwanda      Africa     1992    23.6 7290203      737.
filter(gapminder, country == "Rwanda", year > 1979)
## # A tibble: 6 x 6
##   country continent  year lifeExp     pop gdpPercap
##   <fct>   <fct>     <int>   <dbl>   <int>     <dbl>
## 1 Rwanda  Africa     1982    46.2 5507565      882.
## 2 Rwanda  Africa     1987    44.0 6349365      848.
## 3 Rwanda  Africa     1992    23.6 7290203      737.
## 4 Rwanda  Africa     1997    36.1 7212583      590.
## 5 Rwanda  Africa     2002    43.4 7852401      786.
## 6 Rwanda  Africa     2007    46.2 8860588      863.
filter(gapminder, country %in% c("Rwanda", "Afghanistan"))
## # A tibble: 24 x 6
##    country     continent  year lifeExp      pop gdpPercap
##    <fct>       <fct>     <int>   <dbl>    <int>     <dbl>
##  1 Afghanistan Asia       1952    28.8  8425333      779.
##  2 Afghanistan Asia       1957    30.3  9240934      821.
##  3 Afghanistan Asia       1962    32.0 10267083      853.
##  4 Afghanistan Asia       1967    34.0 11537966      836.
##  5 Afghanistan Asia       1972    36.1 13079460      740.
##  6 Afghanistan Asia       1977    38.4 14880372      786.
##  7 Afghanistan Asia       1982    39.9 12881816      978.
##  8 Afghanistan Asia       1987    40.8 13867957      852.
##  9 Afghanistan Asia       1992    41.7 16317921      649.
## 10 Afghanistan Asia       1997    41.8 22227415      635.
## # ... with 14 more rows
```

Compare with some base R code to accomplish the same things

```
gapminder[gapminder$lifeExp < 29,] ## repeat `gapminder`, [i, j] indexing is distracting
subset(gapminder, country == "Rwanda") ## almost same as filter; quite nice actually
```

Under no circumstances

- should you subset your data
  - the way I did at first:

```
excerpt <- gapminder[241:252, ]
```

Why is this a terrible idea?

- It is not self-documenting.
  - What is so special about rows 241 through 252?
- It is fragile.
  - This line of code will produce different results
  - if someone changes the row order of `gapminder`,
  - e.g. sorts the data earlier in the script.

```
filter(gapminder, country == "Canada")
```

This call explains itself and is fairly robust.

4.1.3.5.4 Meet the new pipe operator

- Before we go any further,
  - we should exploit the new pipe operator
  - that the tidyverse imports
    - from the magrittr package by Stefan Bache.

This is going to change your data analytic life.

- You no longer need to enact multi-operation commands
  - by nesting them inside each other,
  - like so many Russian nesting dolls.
- This new syntax leads to code
  - that is much easier to write and to read.

Here's what it looks like: `%>%`.

- The RStudio keyboard shortcut:
  - Ctrl + Shift + M (Windows), Cmd + Shift + M (Mac).

Let's demo then I'll explain:

```
gapminder %>% head()
## # A tibble: 6 x 6
##   country     continent  year lifeExp      pop gdpPercap
##   <fct>       <fct>     <int>   <dbl>    <int>     <dbl>
## 1 Afghanistan Asia       1952    28.8  8425333      779.
## 2 Afghanistan Asia       1957    30.3  9240934      821.
## 3 Afghanistan Asia       1962    32.0 10267083      853.
## 4 Afghanistan Asia       1967    34.0 11537966      836.
## 5 Afghanistan Asia       1972    36.1 13079460      740.
## 6 Afghanistan Asia       1977    38.4 14880372      786.
```

This is equivalent to `head(gapminder)`.

- The pipe operator takes the thing on the left-hand-side

    - and **pipes** it into the function call
    - on the right-hand-side
- literally, drops it in as the first argument.

Never fear, you can still specify other arguments to this function!

To see the first 3 rows of Gapminder,

- we could say `head(gapminder, 3)` or this:

```
gapminder %>% head(3)
## # A tibble: 3 x 6
##   country     continent  year lifeExp      pop gdpPercap
##   <fct>       <fct>     <int>   <dbl>    <int>     <dbl>
## 1 Afghanistan Asia       1952    28.8  8425333      779.
## 2 Afghanistan Asia       1957    30.3  9240934      821.
## 3 Afghanistan Asia       1962    32.0 10267083      853.
```

I've advised you to think

- "gets" whenever you see the assignment operator, `<-`.

Similarly, you should think

- "then" whenever you see the pipe operator, `%>%`.

You are probably not impressed yet, but the magic will soon happen.

4.1.3.5.5 Use `select()` to subset the data on variables or columns.

Back to `dplyr` …

Use `select()` to subset the data on variables or columns. Here's a conventional call:

```
select(gapminder, year, lifeExp)
## # A tibble: 1,704 x 2
##     year lifeExp
##    <int>   <dbl>
##  1  1952    28.8
##  2  1957    30.3
##  3  1962    32.0
##  4  1967    34.0
##  5  1972    36.1
##  6  1977    38.4
##  7  1982    39.9
##  8  1987    40.8
##  9  1992    41.7
## 10  1997    41.8
## # ... with 1,694 more rows
```

And here's the same operation,

- but written with the pipe operator
- and piped through `head()`:

```
gapminder %>%
  select(year, lifeExp) %>%
  head(4)
## # A tibble: 4 x 2
##    year lifeExp
##   <int>   <dbl>
## 1  1952    28.8
```

```
## 2  1957    30.3
## 3  1962    32.0
## 4  1967    34.0
```

Think: "Take `gapminder`,

- then select the variables year and lifeExp,
- then show the first 4 rows."

4.1.3.5.6 Revel in the convenience

- Here's the data for Cambodia,
  - but only certain variables:

```
gapminder %>%
  filter(country == "Cambodia") %>%
  select(year, lifeExp)
## # A tibble: 12 x 2
##     year lifeExp
##    <int>   <dbl>
##  1  1952    39.4
##  2  1957    41.4
##  3  1962    43.4
##  4  1967    45.4
##  5  1972    40.3
##  6  1977    31.2
##  7  1982    51.0
##  8  1987    53.9
##  9  1992    55.8
## 10  1997    56.5
## 11  2002    56.8
## 12  2007    59.7
```

and what a typical base R call would look like:

```
gapminder[gapminder$country == "Cambodia", c("year", "lifeExp")]
## # A tibble: 12 x 2
##     year lifeExp
##    <int>   <dbl>
##  1  1952    39.4
##  2  1957    41.4
##  3  1962    43.4
##  4  1967    45.4
##  5  1972    40.3
##  6  1977    31.2
##  7  1982    51.0
##  8  1987    53.9
##  9  1992    55.8
## 10  1997    56.5
## 11  2002    56.8
## 12  2007    59.7
```

4.1.3.5.7 Pure, predictable, pipe able

- We've barely scratched the surface of `dplyr`

  - but I want to point out key principles you may start to appreciate.
  - If you're new to R or "programming with data",
    * feel free skip this section
    * and move on.

`dplyr`'s verbs, such as `filter()` and `select()`,

- are what's called pure functions.
- To quote from Wickham's Advanced R Programming book:

  The functions that are the easiest to understand and reason about are pure functions: functions that always map the same input to the same output and have no other impact on the work space.

  In other words, pure functions have no side effects: they don't affect the state of the world in any way apart from the value they return.

  In fact, these verbs are a special case of pure functions: they take the same flavor of object as input and output.

  Namely, a data frame or one of the other data receptacles `dplyr` supports.

And finally,

- the data is **always**
  - the very first argument of the verb functions.

This set of deliberate design choices,

- together with the new pipe operator,
- produces a highly effective,
  - low friction domain-specific language
  - for data analysis.

Go to the next block, `dplyr` functions for a single dataset, for more `dplyr`!

4.1.3.5.8 Resources

- `dplyr` official stuff

  - package home on CRAN
    * note there are several vignettes, with the introduction being the most relevant right now
    * the one on window functions will also be interesting to you now
  - development home on GitHub

RStudio Data Wrangling cheatsheet, covering `dplyr` and `tidyr`. Remember you can get to these via *Help > Cheat sheets.*

Excellent slides on pipelines and `dplyr` by TJ Mahr, talk given to the Madison R Users Group.

Blog post Hands-on dplyr tutorial for faster data manipulation in R by Data School, that includes a link to an R Markdown document and links to videos

dplyr functions for a single data set

- In the introduction to dplyr, we used two very important verbs and an operator:

  - `filter()` for subsetting data with row logic
  - `select()` for subsetting data variable- or column-wise
  - the pipe operator `%>%`,
    * which feeds the LHS as the first argument
    * to the expression on the RHS

We also discussed dplyr's role inside the tidyverse and tibbles:

- dplyr is a core package in the tidyverse meta-package.
- Since we often make incidental usage of the others,
  - we will load dplyr and the others via `library(tidyverse)`.
- The tidyverse embraces a special flavor of data frame,
  - called a tibble.
- The `gapminder` data set is stored as a tibble.

4.1.3.5.9 Load dplyr and gapminder

- I choose to load the tidyverse, which will load dplyr, among other packages we use incidentally below. Also load gapminder.

```
# library(gapminder)
# library(tidyverse)
```

4.1.3.5.10 Create a copy of gapminder

- We're going to make changes to the `gapminder` tibble.

To eliminate any fear

- that you're damaging the data that comes with the package,
- we create an explicit copy of `gapminder` for our experiments.

```
(my_gap <- gapminder)
## # A tibble: 1,704 x 6
##    country     continent  year lifeExp      pop gdpPercap
##    <fct>       <fct>     <int>   <dbl>    <int>     <dbl>
##  1 Afghanistan Asia       1952    28.8  8425333      779.
##  2 Afghanistan Asia       1957    30.3  9240934      821.
##  3 Afghanistan Asia       1962    32.0 10267083      853.
##  4 Afghanistan Asia       1967    34.0 11537966      836.
##  5 Afghanistan Asia       1972    36.1 13079460      740.
##  6 Afghanistan Asia       1977    38.4 14880372      786.
##  7 Afghanistan Asia       1982    39.9 12881816      978.
##  8 Afghanistan Asia       1987    40.8 13867957      852.
##  9 Afghanistan Asia       1992    41.7 16317921      649.
## 10 Afghanistan Asia       1997    41.8 22227415      635.
## # ... with 1,694 more rows
```

Pay close attention to when we evaluate statements

- but let the output just print to screen:

```
## let output print to screen, but do not store
my_gap %>% filter(country == "Canada")
```

… versus when we assign the output to an object,

- possibly overwriting an existing object.

```
## store the output as an R object
my_precious <- my_gap %>% filter(country == "Canada")
```

4.1.3.5.11 Use `mutate()` to add new variables

- Imagine we wanted to recover each country's GDP.

After all, the Gapminder data

- has a variable for population
  - and GDP per capita.
- Let's multiply them together.

`mutate()` is a function that

- defines and inserts new variables into a tibble.
- You can refer to existing variables by name.

```
my_gap %>%
  mutate(gdp = pop * gdpPercap)
## # A tibble: 1,704 x 7
##    country     continent  year lifeExp      pop gdpPercap          gdp
##    <fct>       <fct>     <int>   <dbl>    <int>     <dbl>        <dbl>
##  1 Afghanistan Asia       1952    28.8  8425333      779.  6567086330.
##  2 Afghanistan Asia       1957    30.3  9240934      821.  7585448670.
##  3 Afghanistan Asia       1962    32.0 10267083      853.  8758855797.
##  4 Afghanistan Asia       1967    34.0 11537966      836.  9648014150.
##  5 Afghanistan Asia       1972    36.1 13079460      740.  9678553274.
##  6 Afghanistan Asia       1977    38.4 14880372      786. 11697659231.
##  7 Afghanistan Asia       1982    39.9 12881816      978. 12598563401.
##  8 Afghanistan Asia       1987    40.8 13867957      852. 11820990309.
##  9 Afghanistan Asia       1992    41.7 16317921      649. 10595901589.
## 10 Afghanistan Asia       1997    41.8 22227415      635. 14121995875.
## # ... with 1,694 more rows
```

Hmmmm … those GDP numbers are almost uselessly large and abstract.

Consider the advice of Randall Munroe of xkcd:

> One thing that bothers me is large numbers presented without context…
>
> 'If I added a zero to this number, would the sentence containing it mean something different to me?'
>
> If the answer is 'no,' maybe the number has no business being in the sentence in the first place."
>
> Maybe it would be more meaningful to consumers of my tables and figures to stick with GDP per capita.
>
> But what if I reported GDP per capita, *relative to some benchmark country.*
>
> Since Canada is my adopted home, I'll go with that.

I need to create a new variable

- that is `gdpPercap` divided by Canadian `gdpPercap`,
  - taking care that I always divide two numbers that pertain to the same year.

How I achieve:

- Filter down to the rows for Canada.
- Create a new temporary variable in `my_gap`:
  - Extract the `gdpPercap` variable from the Canadian data.
  - Replicate it once per country in the data set, so it has the right length.
- Divide raw `gdpPercap` by this Canadian figure.
- Discard the temporary variable of replicated Canadian `gdpPercap`.

```
ctib <- my_gap %>%
  filter(country == "Canada")
## this is a semi-dangerous way to add this variable
## I'd prefer to join on year, but we haven't covered joins yet
```

```
my_gap <- my_gap %>%
  mutate(
    tmp = rep(ctib$gdpPercap, nlevels(country)),
    gdpPercapRel = gdpPercap / tmp,
    tmp = NULL
  )
```

Note that, `mutate()` builds new variables sequentially

- so you can reference earlier ones (like `tmp`)
    - when defining later ones (like `gdpPercapRel`).
- Also, you can get rid of a variable
    - by setting it to `NULL`.

How could we sanity check that this worked?

- The Canadian values for `gdpPercapRel` better all be 1!

```
my_gap %>%
  filter(country == "Canada") %>%
  select(country, year, gdpPercapRel)
## # A tibble: 12 x 3
##    country  year gdpPercapRel
##    <fct>   <int>        <dbl>
##  1 Canada   1952            1
##  2 Canada   1957            1
##  3 Canada   1962            1
##  4 Canada   1967            1
##  5 Canada   1972            1
##  6 Canada   1977            1
##  7 Canada   1982            1
##  8 Canada   1987            1
##  9 Canada   1992            1
## 10 Canada   1997            1
## 11 Canada   2002            1
## 12 Canada   2007            1
```

I perceive Canada to be a "high GDP" country,

- so I predict that the distribution of `gdpPercapRel` is located below 1,
    - possibly even well below.
- Check your intuition!

```
summary(my_gap$gdpPercapRel)
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
## 0.007236 0.061648 0.171521 0.326659 0.446564 9.534690
```

The relative GDP per capita numbers are, in general, well below 1.

We see that most of the countries covered by this data set

- have substantially lower GDP per capita, relative to Canada,
- across the entire time period.

Remember: Trust No One. Including (especially?) yourself.

- Always try to find a way to check that you've done what meant to.
- Prepare to be horrified.

4.1.3.5.12 Use `arrange()` to row-order data in a principled way

- `arrange()` reorders the rows in a data frame.
  - Imagine you wanted this data ordered by year then country,
    * as opposed to by country then year.

```
my_gap %>%
  arrange(year, country)
## # A tibble: 1,704 x 7
##    country     continent  year lifeExp      pop gdpPercap gdpPercapRel
##    <fct>       <fct>     <int>   <dbl>    <int>     <dbl>        <dbl>
##  1 Afghanistan Asia       1952    28.8  8425333      779.       0.0686
##  2 Albania     Europe     1952    55.2  1282697     1601.       0.141
##  3 Algeria     Africa     1952    43.1  9279525     2449.       0.215
##  4 Angola      Africa     1952    30.0  4232095     3521.       0.310
##  5 Argentina   Americas   1952    62.5 17876956     5911.       0.520
##  6 Australia   Oceania    1952    69.1  8691212    10040.       0.883
##  7 Austria     Europe     1952    66.8  6927772     6137.       0.540
##  8 Bahrain     Asia       1952    50.9   120447     9867.       0.868
##  9 Bangladesh  Asia       1952    37.5 46886859      684.       0.0602
## 10 Belgium     Europe     1952    68    8730405     8343.       0.734
## # ... with 1,694 more rows
```

Or maybe you want just the data from 2007,

- sorted on life expectancy?

```
my_gap %>%
  filter(year == 2007) %>%
  arrange(lifeExp)
## # A tibble: 142 x 7
##    country                  continent  year lifeExp      pop gdpPercap gdpPerc~1
##    <fct>                    <fct>     <int>   <dbl>    <int>     <dbl>     <dbl>
##  1 Swaziland                Africa     2007    39.6  1133066     4513.    0.124
##  2 Mozambique               Africa     2007    42.1 19951656      824.    0.0227
##  3 Zambia                   Africa     2007    42.4 11746035     1271.    0.0350
##  4 Sierra Leone             Africa     2007    42.6  6144562      863.    0.0237
##  5 Lesotho                  Africa     2007    42.6  2012649     1569.    0.0432
##  6 Angola                   Africa     2007    42.7 12420476     4797.    0.132
##  7 Zimbabwe                 Africa     2007    43.5 12311143      470.    0.0129
##  8 Afghanistan              Asia       2007    43.8 31889923      975.    0.0268
##  9 Central African Republic Africa     2007    44.7  4369038      706.    0.0194
## 10 Liberia                  Africa     2007    45.7  3193942      415.    0.0114
## # ... with 132 more rows, and abbreviated variable name 1: gdpPercapRel
```

Oh, you'd like to sort on life expectancy

- in **desc**ending order? Then use `desc()`.

```
my_gap %>%
  filter(year == 2007) %>%
  arrange(desc(lifeExp))
## # A tibble: 142 x 7
##    country          continent  year lifeExp       pop gdpPercap gdpPercapRel
##    <fct>            <fct>     <int>   <dbl>     <int>     <dbl>        <dbl>
##  1 Japan            Asia       2007    82.6 127467972    31656.        0.872
##  2 Hong Kong, China Asia       2007    82.2   6980412    39725.        1.09
```

```
##  3 Iceland         Europe     2007    81.8    301931    36181.          0.996
##  4 Switzerland     Europe     2007    81.7   7554661    37506.          1.03 
##  5 Australia       Oceania    2007    81.2  20434176    34435.          0.948
##  6 Spain           Europe     2007    80.9  40448191    28821.          0.794
##  7 Sweden          Europe     2007    80.9   9031088    33860.          0.932
##  8 Israel          Asia       2007    80.7   6426679    25523.          0.703
##  9 France          Europe     2007    80.7  61083916    30470.          0.839
## 10 Canada          Americas   2007    80.7  33390141    36319.          1    
## # ... with 132 more rows
```

I advise that your analyses

- NEVER rely on rows or variables being in a specific order.
- But it's still true that human beings write the code
  - and the interactive development process can be much nicer
  - if you reorder the rows of your data as you go along.
- Also, once you are preparing tables for human eyeballs,
  - it is imperative that you step up
  - and take control of row order.

4.1.3.5.13 Use `rename()` to rename variables

- When I first cleaned this Gapminder excerpt,
  - I was a camelCase person,
  - but now I'm all about snake_case.

So I am vexed by the variable names I chose

- when I cleaned this data years ago.
- Let's rename some variables!

```
my_gap %>%
  rename(life_exp = lifeExp,
         gdp_percap = gdpPercap,
         gdp_percap_rel = gdpPercapRel)
## # A tibble: 1,704 x 7
##    country     continent  year life_exp      pop gdp_percap gdp_percap_rel
##    <fct>       <fct>     <int>    <dbl>    <int>      <dbl>          <dbl>
##  1 Afghanistan Asia       1952     28.8  8425333       779.         0.0686
##  2 Afghanistan Asia       1957     30.3  9240934       821.         0.0657
##  3 Afghanistan Asia       1962     32.0 10267083       853.         0.0634
##  4 Afghanistan Asia       1967     34.0 11537966       836.         0.0520
##  5 Afghanistan Asia       1972     36.1 13079460       740.         0.0390
##  6 Afghanistan Asia       1977     38.4 14880372       786.         0.0356
##  7 Afghanistan Asia       1982     39.9 12881816       978.         0.0427
##  8 Afghanistan Asia       1987     40.8 13867957       852.         0.0320
##  9 Afghanistan Asia       1992     41.7 16317921       649.         0.0246
## 10 Afghanistan Asia       1997     41.8 22227415       635.         0.0219
## # ... with 1,694 more rows
```

I did NOT assign the post-rename object back to `my_gap`

- because that would make the chunks in this practicum
  - harder to copy/paste and run out of order.
- In real life, I would probably assign this back to `my_gap`,
  - in a data preparation script,
  - and proceed with the new variable names.

4.1.3.5.14 `select()` can rename and reposition variables

- You've seen simple use of `select()`.

There are two tricks you might enjoy:

1. `select()` can rename the variables you request to keep.
2. `select()` can be used with `everything()` to hoist a variable up to the front of the tibble.

```
my_gap %>%
  filter(country == "Burundi", year > 1996) %>%
  select(yr = year, lifeExp, gdpPercap) %>%
  select(gdpPercap, everything())
## # A tibble: 3 x 3
##   gdpPercap    yr lifeExp
##       <dbl> <int>   <dbl>
## 1      463.  1997    45.3
## 2      446.  2002    47.4
## 3      430.  2007    49.6
```

`everything()` is one of several helpers for variable selection.

- Read its help to see the rest.

4.1.3.5.15 `group_by()` is a mighty weapon

- I have found ~~friends and family~~ collaborators
  - love to ask seemingly innocuous questions like,
    * "which country experienced the sharpest 5-year drop in life expectancy?".
  - In fact, that is a totally natural question to ask.
    * But if you are using a language that doesn't know about data,
    * it's an incredibly annoying question to answer.

dplyr offers powerful tools to solve this class of problem.

- `group_by()` adds extra structure to your data set – grouping information – which lays the groundwork for computations within the groups.
- `summarize()` takes a data set with n observations, computes requested summaries, and returns a data set with 1 observation.
- Window functions take a data set with n observations and return a data set with n observations.
- `mutate()` and `summarize()` will honor groups.
- You can also do very general computations on your groups with `do()`, though elsewhere in this course, I advocate for other approaches that I find more intuitive, using the `purrr` package.

Combined with the verbs you already know,

- these new tools allow you
  - to solve an extremely diverse set of problems
  - with relative ease.

Counting things up

- Let's start with simple counting.

How many observations do we have per continent?

```
my_gap %>%
  group_by(continent) %>%
  summarize(n = n())
## # A tibble: 5 x 2
##   continent     n
```

```
##   <fct>     <int>
## 1 Africa      624
## 2 Americas    300
## 3 Asia        396
## 4 Europe      360
## 5 Oceania      24
```

Let us pause here to think about the tidyverse.

You could get these same frequencies using `table()` from base R.

```
table(gapminder$continent)
##
##   Africa Americas     Asia   Europe  Oceania
##      624      300      396      360       24
str(table(gapminder$continent))
##  'table' int [1:5(1d)] 624 300 396 360 24
##  - attr(*, "dimnames")=List of 1
##   ..$ : chr [1:5] "Africa" "Americas" "Asia" "Europe" ...
```

But the object of class `table` that is returned

- makes downstream computation a bit fiddlier than you'd like.

For example, it's too bad the continent levels

- come back only as *names*
  - and not as a proper factor,
  - with the original set of levels.

This is an example of how the tidyverse

- smooths transitions where you want
- the output of step i
  - to become the input of step i + 1.

The `tally()` function is a convenience function

- that knows to count rows.
- It honors groups.

```
my_gap %>%
  group_by(continent) %>%
  tally()
## # A tibble: 5 x 2
##   continent     n
##   <fct>     <int>
## 1 Africa      624
## 2 Americas    300
## 3 Asia        396
## 4 Europe      360
## 5 Oceania      24
```

The `count()` function is an even more convenient function

- that does both grouping and counting.

```
my_gap %>%
  count(continent)
## # A tibble: 5 x 2
```

```
##   continent     n
##   <fct>     <int>
## 1 Africa      624
## 2 Americas    300
## 3 Asia        396
## 4 Europe      360
## 5 Oceania      24
```

What if we wanted to add the number of unique countries for each continent?

You can compute multiple summaries inside `summarize()`.

- Use the `n_distinct()` function
  - to count the number of distinct countries
  - within each continent.

```
my_gap %>%
  group_by(continent) %>%
  summarize(n = n(),
            n_countries = n_distinct(country))
## # A tibble: 5 x 3
##   continent     n n_countries
##   <fct>     <int>       <int>
## 1 Africa      624          52
## 2 Americas    300          25
## 3 Asia        396          33
## 4 Europe      360          30
## 5 Oceania      24           2
```

General summarization

- The functions you'll apply within `summarize()`
  - include classical statistical summaries,
    - like `mean()`, `median()`, `var()`, `sd()`, `mad()`,
    - `IQR()`, `min()`, and `max()`.
  - Remember they are functions that take n inputs
    - and distill them down into 1 output.

Although this may be statistically ill-advised,

- let's compute the average life expectancy by continent.

```
my_gap %>%
  group_by(continent) %>%
  summarize(avg_lifeExp = mean(lifeExp))
## # A tibble: 5 x 2
##   continent avg_lifeExp
##   <fct>           <dbl>
## 1 Africa           48.9
## 2 Americas         64.7
## 3 Asia             60.1
## 4 Europe           71.9
## 5 Oceania          74.3
```

`summarize_at()` applies the same summary function(s)

- to multiple variables.
- Let's compute average and median life expectancy and GDP per capita

    - by continent by year …
    - but only for 1952 and 2007.

```
my_gap %>%
  filter(year %in% c(1952, 2007)) %>%
  group_by(continent, year) %>%
  summarize_at(vars(lifeExp, gdpPercap), funs(mean, median))
## # A tibble: 10 x 6
## # Groups:   continent [5]
##    continent  year lifeExp_mean gdpPercap_mean lifeExp_median gdpPercap_median
##    <fct>     <int>        <dbl>          <dbl>          <dbl>            <dbl>
##  1 Africa     1952         39.1          1253.           38.8             987.
##  2 Africa     2007         54.8          3089.           52.9            1452.
##  3 Americas   1952         53.3          4079.           54.7            3048.
##  4 Americas   2007         73.6         11003.           72.9            8948.
##  5 Asia       1952         46.3          5195.           44.9            1207.
##  6 Asia       2007         70.7         12473.           72.4            4471.
##  7 Europe     1952         64.4          5661.           65.9            5142.
##  8 Europe     2007         77.6         25054.           78.6           28054.
##  9 Oceania    1952         69.3         10298.           69.3           10298.
## 10 Oceania    2007         80.7         29810.           80.7           29810.
```

Let's focus just on Asia.

- What are the minimum and maximum life expectancies
- seen by year?

```
my_gap %>%
  filter(continent == "Asia") %>%
  group_by(year) %>%
  summarize(min_lifeExp = min(lifeExp),
            max_lifeExp = max(lifeExp))
## # A tibble: 12 x 3
##     year min_lifeExp max_lifeExp
##    <int>       <dbl>       <dbl>
##  1  1952        28.8        65.4
##  2  1957        30.3        67.8
##  3  1962        32.0        69.4
##  4  1967        34.0        71.4
##  5  1972        36.1        73.4
##  6  1977        31.2        75.4
##  7  1982        39.9        77.1
##  8  1987        40.8        78.7
##  9  1992        41.7        79.4
## 10  1997        41.8        80.7
## 11  2002        42.1        82
## 12  2007        43.8        82.6
```

Of course it would be much more interesting to see

- *which* country contributed these extreme observations.
    - Is the minimum (maximum) always coming from the same country?
- We tackle that with window functions shortly.

4.1.3.5.16 Grouped mutate

- Sometimes you don't want to collapse the n rows for each group into one row.

- You want to keep your groups,
- but compute within them.

Computing with group-wise summaries

- Let's make a new variable that is
  - the years of life expectancy gained (lost) relative to 1952,
    - for each individual country.
  - We group by country
    - and use `mutate()` to make a new variable.
  - The `first()` function extracts the first value from a vector.
  - Notice that `first()` is
    - operating on the vector of life expectancies
    - *within each country group.*

```
my_gap %>%
  group_by(country) %>%
  select(country, year, lifeExp) %>%
  mutate(lifeExp_gain = lifeExp - first(lifeExp)) %>%
  filter(year < 1963)
## # A tibble: 426 x 4
## # Groups:   country [142]
##    country      year lifeExp lifeExp_gain
##    <fct>       <int>   <dbl>        <dbl>
##  1 Afghanistan  1952    28.8         0
##  2 Afghanistan  1957    30.3         1.53
##  3 Afghanistan  1962    32.0         3.20
##  4 Albania      1952    55.2         0
##  5 Albania      1957    59.3         4.05
##  6 Albania      1962    64.8         9.59
##  7 Algeria      1952    43.1         0
##  8 Algeria      1957    45.7         2.61
##  9 Algeria      1962    48.3         5.23
## 10 Angola       1952    30.0         0
## # ... with 416 more rows
```

Within country,

- we take the difference between life expectancy in year i
  - and life expectancy in 1952.
- Therefore we always see zeroes for 1952 and,
  - for most countries,
  - a sequence of positive and increasing numbers.

Window functions

- Window functions
  - take n inputs
    - and give back n outputs.
  - Furthermore, the output depends on all the values.
  - So `rank()` is a window function
    - but `log()` is not.

Here we use window functions

- based on ranks and offsets.

Let's revisit the worst and best life expectancies in Asia over time,

- but retaining info about *which* country
- contributes these extreme values.

```
my_gap %>%
  filter(continent == "Asia") %>%
  select(year, country, lifeExp) %>%
  group_by(year) %>%
  filter(min_rank(desc(lifeExp)) < 2 | min_rank(lifeExp) < 2) %>%
  arrange(year) %>%
  print(n = Inf)
## # A tibble: 24 x 3
## # Groups:   year [12]
##     year country     lifeExp
##    <int> <fct>         <dbl>
##  1  1952 Afghanistan    28.8
##  2  1952 Israel         65.4
##  3  1957 Afghanistan    30.3
##  4  1957 Israel         67.8
##  5  1962 Afghanistan    32.0
##  6  1962 Israel         69.4
##  7  1967 Afghanistan    34.0
##  8  1967 Japan          71.4
##  9  1972 Afghanistan    36.1
## 10  1972 Japan          73.4
## 11  1977 Cambodia       31.2
## 12  1977 Japan          75.4
## 13  1982 Afghanistan    39.9
## 14  1982 Japan          77.1
## 15  1987 Afghanistan    40.8
## 16  1987 Japan          78.7
## 17  1992 Afghanistan    41.7
## 18  1992 Japan          79.4
## 19  1997 Afghanistan    41.8
## 20  1997 Japan          80.7
## 21  2002 Afghanistan    42.1
## 22  2002 Japan          82
## 23  2007 Afghanistan    43.8
## 24  2007 Japan          82.6
```

We see that (min = Afghanistan, max = Japan) is the most frequent result,

- but Cambodia and Israel pop up at least once each
  - as the min or max, respectively.
- That table should make you impatient for our upcoming work
  - on tidying and reshaping data!

Wouldn't it be nice to have one row per year?

- How did that actually work?
- First, I store and view a partial
  - that leaves off the `filter()` statement.
- All of these operations should be familiar.

```
asia <- my_gap %>%
  filter(continent == "Asia") %>%
  select(year, country, lifeExp) %>%
  group_by(year)
```

```
asia
## # A tibble: 396 x 3
## # Groups:   year [12]
##     year country     lifeExp
##    <int> <fct>         <dbl>
##  1  1952 Afghanistan    28.8
##  2  1957 Afghanistan    30.3
##  3  1962 Afghanistan    32.0
##  4  1967 Afghanistan    34.0
##  5  1972 Afghanistan    36.1
##  6  1977 Afghanistan    38.4
##  7  1982 Afghanistan    39.9
##  8  1987 Afghanistan    40.8
##  9  1992 Afghanistan    41.7
## 10  1997 Afghanistan    41.8
## # ... with 386 more rows
```

Now we apply a window function – `min_rank()`.

- Since `asia` is grouped by year,
    - `min_rank()` operates within mini-data sets,
    - each for a specific year.
- Applied to the variable `lifeExp`, `min_rank()`
    - returns the rank of each country's observed life expectancy.
- FYI, the `min` part just specifies how ties are broken.
- Here is an explicit peek at these within-year life expectancy ranks,
    - in both the (default) ascending and descending order.

For concreteness, I use `mutate()`

- to actually create these variables,
    - even though I dropped this in the solution above.
- Let's look at a bit of that.

```
asia %>%
  mutate(le_rank = min_rank(lifeExp),
         le_desc_rank = min_rank(desc(lifeExp))) %>%
  filter(country %in% c("Afghanistan", "Japan", "Thailand"), year > 1995)
## # A tibble: 9 x 5
## # Groups:   year [3]
##    year country     lifeExp le_rank le_desc_rank
##   <int> <fct>         <dbl>   <int>        <int>
## 1  1997 Afghanistan    41.8       1           33
## 2  2002 Afghanistan    42.1       1           33
## 3  2007 Afghanistan    43.8       1           33
## 4  1997 Japan          80.7      33            1
## 5  2002 Japan          82        33            1
## 6  2007 Japan          82.6      33            1
## 7  1997 Thailand       67.5      12           22
## 8  2002 Thailand       68.6      12           22
## 9  2007 Thailand       70.6      12           22
```

Afghanistan tends to present 1's in the `le_rank` variable,

- Japan tends to present 1's in the `le_desc_rank` variable
- and other countries,
    - like Thailand,

    – present less extreme ranks.

You can understand the original `filter()` statement now:

```
# filter(min_rank(desc(asia$lifeExp)) < 2 | min_rank(asia$lifeExp) < 2)
```

These two sets of ranks are formed on-the-fly, within year group,

- and `filter()` retains rows with rank less than 2,
    - which means … the row with rank = 1.
- Since we do for ascending and descending ranks,
    - we get both the min and the max.
- If we had wanted just the min OR the max,
    - an alternative approach using `top_n()`
    - would have worked.

```
my_gap %>%
  filter(continent == "Asia") %>%
  select(year, country, lifeExp) %>%
  arrange(year) %>%
  group_by(year) %>%
  #top_n(1, wt = lifeExp)        ## gets the min
  top_n(1, wt = desc(lifeExp)) ## gets the max
## # A tibble: 12 x 3
## # Groups:   year [12]
##     year country     lifeExp
##    <int> <fct>         <dbl>
##  1  1952 Afghanistan    28.8
##  2  1957 Afghanistan    30.3
##  3  1962 Afghanistan    32.0
##  4  1967 Afghanistan    34.0
##  5  1972 Afghanistan    36.1
##  6  1977 Cambodia       31.2
##  7  1982 Afghanistan    39.9
##  8  1987 Afghanistan    40.8
##  9  1992 Afghanistan    41.7
## 10  1997 Afghanistan    41.8
## 11  2002 Afghanistan    42.1
## 12  2007 Afghanistan    43.8
```

4.1.3.5.17 Grand Finale

- So let's answer that "simple" question:
    - which country experienced the sharpest 5-year drop in life expectancy?
    - Recall that this excerpt of the Gapminder data
        - only has data every five years, e.g. for 1952, 1957, etc.
    - So this really means looking at life expectancy changes
        - between adjacent time points.
    - At this point, that's just too easy,
        - so let's do it by continent while we're at it.

```
my_gap %>%
  select(country, year, continent, lifeExp) %>%
  group_by(continent, country) %>%
  ## within country, take (lifeExp in year i) - (lifeExp in year i - 1)
  ## positive means lifeExp went up, negative means it went down
```

```
  mutate(le_delta = lifeExp - lag(lifeExp)) %>%
  ## within country, retain the worst lifeExp change = smallest or most negative
  summarize(worst_le_delta = min(le_delta, na.rm = TRUE)) %>%
  ## within continent, retain the row with the lowest worst_le_delta
  top_n(-1, wt = worst_le_delta) %>%
  arrange(worst_le_delta)
## `summarise()` has grouped output by 'continent'. You can override using the
## `.groups` argument.
## # A tibble: 5 x 3
## # Groups:   continent [5]
##   continent country     worst_le_delta
##   <fct>     <fct>                <dbl>
## 1 Africa    Rwanda              -20.4
## 2 Asia      Cambodia             -9.10
## 3 Americas  El Salvador          -1.51
## 4 Europe    Montenegro           -1.46
## 5 Oceania   Australia             0.170
```

Ponder that for a while.

The subject matter and the code.

Mostly you're seeing what genocide looks like

- in dry statistics
- on average life expectancy.

Break the code into pieces,

- starting at the top,
- and inspect the intermediate results.

That's certainly how I was able to *write* such a thing.

These commands do not leap fully formed

- out of anyone's forehead
- they are built up gradually,
  - with lots of errors and refinements along the way.
- I'm not even sure it's a great idea
  - to do so much manipulation in one fell swoop.

Is the statement above really hard for you to read?

- If yes, then by all means
  - break it into pieces
  - and make some intermediate objects.
- Your code should be easy
  - to write and read
  - when you're done.

In later practicums, we'll explore more of dplyr,

- such as operations based on two data sets.

4.1.3.5.18 Resources

- `dplyr` official stuff
  - package home on CRAN
    - note there are several vignettes, with the introduction being the most relevant right now

        * the one on window functions will also be interesting to you now
    - development home on GitHub
    - tutorial HW delivered (note this links to a DropBox folder) at useR! 2014 conference

RStudio Data Wrangling cheatsheet, covering `dplyr` and `tidyr`. Remember you can get to these via *Help > Cheatsheets.*

Data transformation chapter of R for Data Science

Excellent slides on pipelines and `dplyr` by TJ Mahr, talk given to the Madison R Users Group.

Blog post Hands-on dplyr tutorial for faster data manipulation in R by Data School, that includes a link to an R Markdown document and links to videos

4.1.3.6 File I/O: Getting data into and out of R

4.1.3.6.1 File I/O overview

- We've been loading the Gapminder data
    - as a data.frame from the `gapminder` data package.

We haven't been explicitly writing any data or derived results to file.

In real life, you'll bring rectangular data

- into and out of R all the time.

Sometimes you'll need to do same for non-rectangular objects.

How do you do this? What issues should you think about?

4.1.3.6.2 Data import mindset

- Data import generally feels one of two ways:
    - "Surprise me!"
        * This is the attitude you must adopt when you first get a dataset.
        * You are just happy to import without an error.
        * You start to explore.
        * You discover flaws in the data and/or the import.
        * You address them.
        * Lather, rinse, repeat.
    - "Another day in paradise."
        * This is the attitude when you bring in a tidy dataset
        * you have maniacally cleaned in one or more cleaning scripts.
        * There should be no surprises.
        * You should express your expectations about the data
        * in formal assertions at the very start of these downstream scripts.

In the second case, and as the first cases progresses,

- you actually know a lot about how the data is / should be.

My main import advice:

- **use the arguments of your import function**
- **to get as far as you can,**
- **as fast as possible**.

Novice code often has a great deal of

- unnecessary post import fussing around.

- Read the docs for the import functions
    - and take maximum advantage of the arguments
    - to control the import.

4.1.3.6.3 Data export mindset

- There will be many occasions when you need to write data from R.

Two main examples:

- a tidy ready-to-analyze data set that you heroically created from messy data
- a numerical result from data aggregation or modeling or statistical inference

First tip: **today's outputs are tomorrow's inputs**.

- Think back on all the pain you have suffered importing data
- and don't inflict such pain on yourself!

Second tip: don't be too cute or clever.

- A plain text file that is readable by a human being in a text editor
    - should be your default
    - until you have **actual proof** that this will not work.
- Reading and writing to exotic or proprietary formats
    - will be the first thing to break
    - in the future or on a different computer.
- It also creates barriers for anyone
    - who has a different toolkit than you do.
    - Be software-agnostic.
    - Aim for future-proof and moron-proof.

How does this fit with our emphasis on dynamic reporting via R Markdown?

- There is a time and place for everything.
- There are projects and documents
    - where the scope and personnel will allow you
    - to geek out with `knitr` and R Markdown.
- But there are lots of good reasons why
    - (parts of) an analysis
    - should not (only) be embedded in a dynamic report.
- Maybe you are just doing data cleaning
    - to produce a valid input data set.
- Maybe you are making a small
    - but crucial contribution to a giant multi-author paper. Etc.
- Also remember there are other tools and workflows
    - for making something reproducible.
    - I'm looking at you, make.

4.1.3.6.4 Load the tidyverse, for readr and forcats

- The main tidyverse package we will be using is readr,

    - which provides drop-in substitutes for `read.table()` and friends.

However, to make some points about data export and import,

- it is nice to reorder factor levels.
- For that, we will also use function
    - from the forcats package.

```r
library(tidyverse)
```

4.1.3.6.5 Locate the Gapminder data

- We could load the data from the package as usual,
  - but instead we will load it from tab delimited file.
  - The gapminder package includes the data
    * normally found in the `gapminder` data frame as a `.tsv`.
    * So let's get the path to that file on *your* system.

```r
(gap_tsv <- system.file("extdata/gapminder.tsv", package = "gapminder"))
## [1] "/home/frenchrh/R/x86_64-pc-linux-gnu-library/4.2/gapminder/extdata/gapminder.tsv"
```

4.1.3.6.6 Bring rectangular data in

- The workhorse data import function of readr is `read_delim()`.
  - Here we'll use a variant, `read_tsv()`,
    * that anticipates tab-delimited data:

```r
gapminder <- NULL
gapminder <- read_tsv(gap_tsv)
## Rows: 1704 Columns: 6
## -- Column specification --------------------------------------------------------
## Delimiter: "\t"
## chr (2): country, continent
## dbl (4): year, lifeExp, pop, gdpPercap
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
str(gapminder, give.attr = FALSE)
## spec_tbl_df [1,704 x 6] (S3: spec_tbl_df/tbl_df/tbl/data.frame)
##  $ country  : chr [1:1704] "Afghanistan" "Afghanistan" "Afghanistan" "Afghanistan" ...
##  $ continent: chr [1:1704] "Asia" "Asia" "Asia" "Asia" ...
##  $ year     : num [1:1704] 1952 1957 1962 1967 1972 ...
##  $ lifeExp  : num [1:1704] 28.8 30.3 32 34 36.1 ...
##  $ pop      : num [1:1704] 8425333 9240934 10267083 11537966 13079460 ...
##  $ gdpPercap: num [1:1704] 779 821 853 836 740 ...
```

For full flexibility re: specifying the delimiter,

- you can always use `readr::read_delim()`.

There's a similar convenience wrapper

- for comma-separated values, `read_csv()`.

The most noticeable difference between

- the readr functions and base
  - is that readr
  - does NOT convert strings to factors by default.
- In the grand scheme of things,
  - this is better default behavior,
  - although we go ahead and convert them to factor here.
- Do not be deceived – in general,
  - you will do less post-import fussing if you use readr.

```
gapminder <- gapminder %>%
  mutate(country = factor(country),
         continent = factor(continent))
str(gapminder)
## tibble [1,704 x 6] (S3: tbl_df/tbl/data.frame)
##  $ country  : Factor w/ 142 levels "Afghanistan",..: 1 1 1 1 1 1 1 1 1 1 ...
##  $ continent: Factor w/ 5 levels "Africa","Americas",..: 3 3 3 3 3 3 3 3 3 3 ...
##  $ year     : num [1:1704] 1952 1957 1962 1967 1972 ...
##  $ lifeExp  : num [1:1704] 28.8 30.3 32 34 36.1 ...
##  $ pop      : num [1:1704] 8425333 9240934 10267083 11537966 13079460 ...
##  $ gdpPercap: num [1:1704] 779 821 853 836 740 ...
```

Bring rectangular data in – summary

- Default to `readr::read_delim()` and friends.
  - Use the arguments!

The Gapminder data is too clean and simple

- to show off the great features of readr,
- so I encourage you to check out the vignette on column types.
- There are many variable types
  - that you will be able to parse correctly upon import,
  - thereby eliminating a great deal of post-import fussing.

4.1.3.6.7 Compute something worthy of export

- We need to compute something worth writing to file.

Let's create a country-level summary

- of maximum life expectancy.

```
gap_life_exp <- gapminder %>%
  group_by(country, continent) %>%
  summarise(life_exp = max(lifeExp)) %>%
  ungroup()
## `summarise()` has grouped output by 'country'. You can override using the
## `.groups` argument.
gap_life_exp
## # A tibble: 142 x 3
##    country     continent life_exp
##    <fct>       <fct>        <dbl>
##  1 Afghanistan Asia          43.8
##  2 Albania     Europe        76.4
##  3 Algeria     Africa        72.3
##  4 Angola      Africa        42.7
##  5 Argentina   Americas      75.3
##  6 Australia   Oceania       81.2
##  7 Austria     Europe        79.8
##  8 Bahrain     Asia          75.6
##  9 Bangladesh  Asia          64.1
## 10 Belgium     Europe        79.4
## # ... with 132 more rows
```

The `gap_life_exp` data frame

- is an example of an intermediate result
- that we want to store for the future
  - for downstream analyses
  - or visualizations.

4.1.3.6.8 Write rectangular data out

- The workhorse export function

  - for rectangular data in readr is `write_delim()` and friends.
  - Let's use `write_csv()` to get a comma-delimited file.

```
write_csv(gap_life_exp, "./data/gap_life_exp.csv")
```

Let's look at the first few lines of `gap_life_exp.csv`.

If you're following along,

- you should be able to open this file
- or, in a shell, use `head` on it.

```
country,continent,life_exp
Afghanistan,Asia,43.828
Albania,Europe,76.423
Algeria,Africa,72.301
Angola,Africa,42.731
Argentina,Americas,75.32
```

This is pretty decent looking,

- though there is no visible alignment or separation into columns.
- Had we used the base function `read.csv()`,
  - we would be seeing row names and lots of quotes,
  - unless we had explicitly shut that down.
- Nicer default behavior is the main reason we are using
  - `readr::write_csv()` over `write.csv()`.

It's not really fair to complain about the lack of visible alignment.

- Remember we are "writing data for computers".
- If you really want to browse around the file,
  - use `View()` in RStudio
  - but don't succumb to the temptation
    * to start doing artisanal data manipulations in Excel
    * get back to R and construct commands
    * that you can re-run the next 15 times you
    * import/clean/aggregate/export the same data set.
    * Trust me, it will happen.

4.1.3.6.9 Invertibility

- It turns out these self-imposed rules are often in conflict with one another

  - Write to plain text files
  - Break analysis into pieces:
    * the output of script `i` is an input for script `i + 1`
  - Be the boss of factors:
    * order the levels in a meaningful, usually non-alphabetical way
  - Avoid duplication of code and data

Example: after performing the country-level summarization,

- we reorder the levels of the country factor,
  - based on life expectancy.
- This reordering operation is conceptually important
  - and must be embodied in R commands stored in a script.
- However, as soon as we write `gap_life_exp` to a plain text file,
  - that meta-information about the countries is lost.
- Upon re-import with `read_delim()` and friends,
  - we are back to alphabetically ordered factor levels.
- Any measure we take to avoid this loss
  - immediately breaks another one of our rules.

So what do I do?

- I must admit I save (and re-load) R-specific binary files.
- Right after I save the plain text file. Belt and suspenders.

I have toyed with the idea of writing import helper functions

- for a specific project,
  - that would re-order factor levels in principled ways.
- They could be defined in one file and called from many.
- This would also have a very natural implementation within a workflow where each analytical project is an R package.
- But so far it has seemed too much like yak shaving.
- I'm intrigued by a recent discussion of putting such information in YAML frontmatter (see Martin Fenner blog post Using YAML frontmatter with CSV).

4.1.3.6.10 Reordering the levels of the country factor

- The topic of factor level reordering is covered elsewhere,
  - so let's Just. Do. It.
  - I reorder the country factor levels
    - according to the life expectancy summary
    - we've already computed.

```
head(levels(gap_life_exp$country)) # alphabetical order
## [1] "Afghanistan" "Albania"     "Algeria"     "Angola"      "Argentina"
## [6] "Australia"
gap_life_exp <- gap_life_exp %>%
  mutate(country = fct_reorder(country, life_exp))
head(levels(gap_life_exp$country)) # in increasing order of maximum life expectancy
## [1] "Sierra Leone" "Angola"       "Afghanistan"  "Liberia"      "Rwanda"
## [6] "Mozambique"
head(gap_life_exp)
## # A tibble: 6 x 3
##   country     continent life_exp
##   <fct>       <fct>        <dbl>
## 1 Afghanistan Asia          43.8
## 2 Albania     Europe        76.4
## 3 Algeria     Africa        72.3
## 4 Angola      Africa        42.7
## 5 Argentina   Americas      75.3
## 6 Australia   Oceania       81.2
```

Note that the **row order of `gap_life_exp` has not changed**.

I could choose to reorder the rows of the data frame

- if, for example, I was about to prepare a table to present to people.
- But I'm not, so I won't.

4.1.3.6.11 `saveRDS()` and `readRDS()`

- If you have a data frame AND
  - you have exerted yourself to rationalize the factor levels,
  - you have my blessing to save it to file
    - in a way that will preserve this hard work upon re-import.
  - Use `saveRDS()`.

```
saveRDS(gap_life_exp, "./data/gap_life_exp.rds")
```

`saveRDS()` serializes an R object to a binary file.

- It's not a file you will able to
  - open in an editor,
  - diff nicely with Git(Hub),
  - or share with non-R friends.
- It's a special purpose, limited use function
  - that I use in specific situations.

The opposite of `saveRDS()` is `readRDS()`.

- You must assign the return value to an object.
- I highly recommend you assign back to the same name as before.
  - Why confuse yourself?!?

```
rm("./data/gap_life_exp")
gap_life_exp
## # A tibble: 142 x 3
##    country     continent life_exp
##    <fct>       <fct>        <dbl>
##  1 Afghanistan Asia          43.8
##  2 Albania     Europe        76.4
##  3 Algeria     Africa        72.3
##  4 Angola      Africa        42.7
##  5 Argentina   Americas      75.3
##  6 Australia   Oceania       81.2
##  7 Austria     Europe        79.8
##  8 Bahrain     Asia          75.6
##  9 Bangladesh  Asia          64.1
## 10 Belgium     Europe        79.4
## # ... with 132 more rows
gap_life_exp <- readRDS("./data/gap_life_exp.rds")
gap_life_exp
## # A tibble: 142 x 3
##    country     continent life_exp
##    <fct>       <fct>        <dbl>
##  1 Afghanistan Asia          43.8
##  2 Albania     Europe        76.4
##  3 Algeria     Africa        72.3
##  4 Angola      Africa        42.7
##  5 Argentina   Americas      75.3
##  6 Australia   Oceania       81.2
```

```
##  7 Austria     Europe        79.8
##  8 Bahrain     Asia          75.6
##  9 Bangladesh  Asia          64.1
## 10 Belgium     Europe        79.4
## # ... with 132 more rows
```

`saveRDS()` has more arguments,

- in particular `compress` for controlling compression,
  - so read the help for more advanced usage.
- It is also very handy for saving non-rectangular objects,
  - like a fitted regression model,
  - that took a nontrivial amount of time to compute.

You will eventually hear about

- `save()` + `load()` and even `save.image()`.
- You may even see them in documentation and tutorials,
  - but don't be tempted. Just say no.
- These functions encourage unsafe practices,
  - like storing multiple objects together
  - and even entire work spaces.
- There are legitimate uses of these functions,
  - but not in your typical data analysis.

4.1.3.6.12 Retaining factor levels upon re-import

- Concrete demonstration of
  - how non-alphabetical factor level order is lost
    * with `write_delim()` / `read_delim()` workflows
    * but maintained with `saveRDS()` / `readRDS()`.

```
(
  country_levels <-
    tibble(original = head(levels(
      gap_life_exp$country
    )))
)
## # A tibble: 6 x 1
##   original
##   <chr>
## 1 Sierra Leone
## 2 Angola
## 3 Afghanistan
## 4 Liberia
## 5 Rwanda
## 6 Mozambique
write_csv(gap_life_exp, "./data/gap_life_exp.csv")
saveRDS(gap_life_exp, "./data/gap_life_exp.rds")
rm(gap_life_exp)
# head(gap_life_exp) # will cause error! proving gap_life_exp is really gone
gap_via_csv <- read_csv("./data/gap_life_exp.csv") %>%
  mutate(country = factor(country))
## Rows: 142 Columns: 3
## -- Column specification --------------------------------------------------------
## Delimiter: ","
```

```
## chr (2): country, continent
## dbl (1): life_exp
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
gap_via_rds <- readRDS("./data/gap_life_exp.rds")
country_levels <- country_levels %>%
  mutate(via_csv = head(levels(gap_via_csv$country)),
         via_rds = head(levels(gap_via_rds$country)))
country_levels
## # A tibble: 6 x 3
##   original     via_csv     via_rds
##   <chr>        <chr>       <chr>
## 1 Sierra Leone Afghanistan Sierra Leone
## 2 Angola       Albania     Angola
## 3 Afghanistan  Algeria     Afghanistan
## 4 Liberia      Angola      Liberia
## 5 Rwanda       Argentina   Rwanda
## 6 Mozambique   Australia   Mozambique
```

Note how the original, post-reordering country factor levels

- are restored using the `saveRDS()` / `readRDS()` strategy
- but revert to alphabetical ordering using `write_csv()` / `read_csv()`.

4.1.3.6.13 `dput()` and `dget()`

- One last method of saving and restoring data deserves a mention:
  - `dput()` and `dget()`. `dput()`
    - offers this odd combination of features:
    - it creates a plain text representation of an R object
    - which still manages to be quite opaque.
  - If you use the `file =` argument,
    - `dput()` can write this representation to file
    - but you won't be tempted to actually read that thing.
    - `dput()` creates an R-specific-but-not-binary representation.
  - Let's try it out.

```
## first restore gap_life_exp with our desired country factor level order
gap_life_exp <- readRDS("./data/gap_life_exp.rds")
dput(gap_life_exp, "gap_life_exp-dput.txt")
```

Now let's look at the first few lines of the file `gap_life_exp-dput.txt`.

```
structure(list(country = structure(c(3L, 107L, 74L, 2L, 98L,
138L, 128L, 102L, 49L, 125L, 26L, 56L, 96L, 47L, 75L, 85L, 18L,
12L, 37L, 24L, 133L, 13L, 16L, 117L, 84L, 82L, 53L, 9L, 28L,
120L, 22L, 104L, 114L, 109L, 115L, 23L, 73L, 97L, 66L, 71L, 15L,
29L, 20L, 122L, 134L, 40L, 35L, 123L, 38L, 126L, 60L, 25L, 7L,
39L, 59L, 141L, 86L, 140L, 51L, 63L, 64L, 52L, 121L, 135L, 132L,
```

Huh? Don't worry about it.

- Remember we are "writing data for computers".
- The partner function `dget()` reads this representation back in.

```
gap_life_exp_dget <- dget("gap_life_exp-dput.txt")
country_levels <- country_levels %>%
  mutate(via_dput = head(levels(gap_life_exp_dget$country)))
country_levels
## # A tibble: 6 x 4
##   original     via_csv     via_rds      via_dput
##   <chr>        <chr>       <chr>        <chr>
## 1 Sierra Leone Afghanistan Sierra Leone Sierra Leone
## 2 Angola       Albania     Angola       Angola
## 3 Afghanistan  Algeria     Afghanistan  Afghanistan
## 4 Liberia      Angola      Liberia      Liberia
## 5 Rwanda       Argentina   Rwanda       Rwanda
## 6 Mozambique   Australia   Mozambique   Mozambique
```

Note how the original, post-reordering country factor levels

- are restored using the `dput()` / `dget()` strategy.

But why on earth would you ever do this?

The main application of this is the creation of highly portable, self-contained minimal examples.

- For example, if you want to pose a question
  - on a forum or directly to an expert,
  - it might be required or just plain courteous
  - to NOT attach any data files.
- You will need a monolithic, plain text blob
  - that defines any necessary objects and has the necessary code.
- `dput()` can be helpful for producing
  - the piece of code that defines the object.
- If you `dput()` without specifying a file,
  - you can copy the return value from Console
  - and paste into a script.
- Or you can write to file
  - and copy from there
  - or add R commands below.

4.1.3.6.14 Other types of objects to use `dput()` or `saveRDS()` on

- My special dispensation to abandon human-readable, plain text files
  - is even broader than I've let on.
  - Above, I give my blessing to store data.frames
    - via `dput()` and/or `saveRDS()`,
    - when you've done some rational factor level re-ordering.
  - The same advice and mechanics apply a bit more broadly:
    - you're also allowed to use R-specific file formats
    - to save vital non-rectangular objects,
    - such as a fitted nonlinear mixed effects model
    - or a classification and regression tree.

4.1.3.6.15 Clean up

- We've written several files in this practicum.
  - Some of them are not of lasting value or have confusing file names.
  - I choose to delete them,

    - while demonstrating some of the many functions R offers
    - for interacting with the file system.
  - It's up to you whether you want to submit this command or not.

```
file.remove(list.files(pattern = "^gap_life_exp"))
## [1] TRUE
```

4.1.3.6.16 Pitfalls of delimited files

- If a delimited file
  - contains fields where a human being has typed,
    - be crazy paranoid because people do really nutty things.
  - Especially people who aren't in the business of programming
    - and have never had to compute on text.
  - Claim: a person's regular expression skill
    - is inversely proportional to the skill
    - required to handle the files they create.
  - Implication: if someone has never heard of regular expressions,
    - prepare for lots of pain working with their files.

When the header fields

- (often, but not always, the variable names)
  - or actual data contain the delimiter,
  - it can lead to parsing and import failures.
- Two popular delimiters are the comma `,` and the TAB `\t`
  - and humans tend to use these when typing.
- If you can design this problem away during data capture,
  - such as by using a drop down menu on an input form,
  - by all means do so.
- Sometimes this is impossible or undesirable
  - and you must deal with fairly free form text.
- That's a good time to allow/force text to be protected with quotes,
  - because it will make parsing the delimited file go more smoothly.

Sometimes, instead of rigid tab-delimiting,

- white space is used as the delimiter.
- That is, in fact, the default
  - for both `read.table()` and `write.table()`.
- Assuming you will write/read variable names from the first line
  - (a.k.a. the `header` in `write.table()` and `read.table()`),
  - they must be valid R variable names …
  - or they will be coerced into something valid.
- So, for these two reasons,
  - it is good practice to use "one word" variable names whenever possible.
- If you need to evoke multiple words,
  - use `snake_case` or `camelCase` to cope.
- Example: the header entry for the field holding the subject's last name
  - should be `last_name` or `lastName`
  - NOT `last name`.
- With the `readr` package,
  - "column names are left as is,
  - not munged into valid R identifiers
  - (i.e. there is no `check.names = TRUE`)".
- So you can get away with white space in variable names

    - and yet I recommend that you do not.

4.1.3.6.17 References

- Data import chapter of R for Data Science by Hadley Wickham and Garrett Grolemund.

Nine simple ways to make it easier to (re)use your data by Ethan P White, Elita Baldridge, Zachary T. Brym, Kenneth J. Locey, Daniel J. McGlinn, Sarah R. Supp.

- First appeared here: PeerJ PrePrints 1:e7v2 http://dx.doi.org/10.7287/peerj.preprints.7v2
- Published here: Ideas in Ecology and Evolution 6(2): 1?10, 2013. doi:10.4033/iee.2013.6b.6.f http://library.queensu.ca/ojs/index.php/IEE/article/view/4608
- Section 4 "Use Standard Data Formats" is especially good reading.

Tidy data by Hadley Wickham.

- In the Journal of Statistical Software Vol 59 (2014), Issue 10, 10.18637/jss.v059.i10: http://www.jstatsoft.org/article/view/v059i10
- PDF also available here: http://vita.had.co.nz/papers/tidy-data.pdf

4.1.3.7 Links

- Jenny Bryan, RStudio software engineer
- Stats Prof at U British Columbia
    - https://twitter.com/JennyBryan