CSSS 569 Visualizing Data and Models

Lab 1: Supplemental R resource

Ramses Llobet[1]

Department of Political Science, UW

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[1]Originally provided by former TA Brian Leung.

Useful R resources

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  - TidyTuesday Project: https://github.com/rfordatascience/tidytuesday

R boot camp

- R is a language and environment for statistical computing and graphics

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  - tools for plotting, history, debugging and workspace management
- Let's open RStudio and a plain R Script

Running R code and operators

```
# Arithmetic Operators
1 + 1
```

```
## [1] 2
```

```
2 * 8
```

```
## [1] 16
```

```
9 / 3
```

```
## [1] 3
```

```
2^3
```

```
## [1] 8
```

Running R code and operators

```
# Relational Operators
10 > 8
```

```
## [1] TRUE
```

```
7 <= 6
```

```
## [1] FALSE
```

```
(2 * 5) == 10
```

```
## [1] TRUE
```

```
1 != 2
```

```
## [1] TRUE
```

Objects in R: vectors and assignment

```
# Concatenate vectors into a new vector
c(1, 2, 3)
```

```
## [1] 1 2 3
```

```
# Assign them to a new object for manipulation
x <- c(1, 2, 3)
print(x) # or simply, x
```

```
## [1] 1 2 3
```

```
# Operators on vector
x + 1
```

```
## [1] 2 3 4
```

```
x == 1
```

```
## [1]  TRUE FALSE FALSE
```

Objects in R: vectors and functions

```
# Use an object as input to a function
x <- c(1, 2, 3)

class(x)
```

```
## [1] "numeric"
```

```
length(x)
```

```
## [1] 3
```

```
mean(x)
```

```
## [1] 2
```

Objects in R: three beginner tips

1. Unless you assign (<-) some operations or transformations to an object, those chances will not be registered

```
x <- c(1, 2, 3)
print(x + 1)
```

```
## [1] 2 3 4
```

```
print(x)
```

```
## [1] 1 2 3
```

```
x <- x + 1
print(x)
```

```
## [1] 2 3 4
```

Objects in R: three beginner tips

2. New assignment will overwrite the original values if you assign some values to an existing object. It is a **major** source of errors. One advise is to keep distinct object names

```
x <- c(1, 2, 3)
length(x)
```

```
## [1] 3
```

```
x <- c(1, 2, 3, 4, 5)
length(x)
```

```
## [1] 5
```

Objects in R: three beginner tips

3. When using functions, we often bump into unexpected outputs, or error messages:

```r
y <- c(1, 2, 3, NA)
mean(y)
```

```
## [1] NA
```

```r
# It's essential to know how to seek help:
help(mean)
```

```
## starting httpd help server ... done
```

```r
?mean

# Specify appropriate arguments for functions:
mean(y, na.rm = TRUE)
```

```
## [1] 2
```

Objects in R: atomic vectors

- What are vectors exactly?

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  - (Atomic) vectors are the most basic units of data in R

Objects in `R`: atomic vectors

- What are vectors exactly?
  - (Atomic) vectors are the most basic units of data in `R`
  - Most common types of atomic vectors: **numeric (integer, double)**, **logical**, **character**

Objects in R: atomic vectors

- Most common types of atomic vectors: **numeric (integer, double)**, **logical**, **character**

```
x <- c(1, 2, 3)
class(x)
```

```
## [1] "numeric"
```

```
y <- c(TRUE, FALSE, FALSE)
class(y)
```

```
## [1] "logical"
```

```
names <- c("Peter", "Paul", "Mary")
class(names)
```

```
## [1] "character"
```

Objects in R: atomic vectors

- You can also coerce one type of vector into another:

```r
x <- c(1, 2, 3)
x <- as.character(x)

print(x)
```

```
## [1] "1" "2" "3"
```

```r
class(x)
```

```
## [1] "character"
```

Objects in R: matrix and data frame

- To deal with massive data, we need efficient data structures to store and manipulate vectors: **matrices** and **data frames**

Objects in R: matrix and data frame

- To create a matrix:

```
# Create a vector
numbers <- 1:12
print(numbers)
```

```
##  [1]  1  2  3  4  5  6  7  8  9 10 11 12
```

```
# Store it as a matrix
matrix1 <- matrix(data = numbers, nrow = 3, byrow = TRUE)
print(matrix1)
```

```
##      [,1] [,2] [,3] [,4]
## [1,]    1    2    3    4
## [2,]    5    6    7    8
## [3,]    9   10   11   12
```

Objects in R: matrix and data frame

```r
# Basic information
class(matrix1)
```

```
## [1] "matrix" "array"
```

```r
dim(matrix1) # dimensions
```

```
## [1] 3 4
```

Objects in R: matrix and data frame

```r
# We can change the row/column names of matrices
rownames(matrix1)
```

```
## NULL
```

```r
rownames(matrix1) <- c("row1", "row2", "row3")
print(matrix1)
```

```
##      [,1] [,2] [,3] [,4]
## row1    1    2    3    4
## row2    5    6    7    8
## row3    9   10   11   12
```

Objects in R: matrix and data frame

```r
# Automate any repetitive process
col_names <- paste0("column", 1:4)
print(col_names)
```

```
## [1] "column1" "column2" "column3" "column4"
```

```r
colnames(matrix1) <- col_names
print(matrix1)
```

```
##      column1 column2 column3 column4
## row1       1       2       3       4
## row2       5       6       7       8
## row3       9      10      11      12
```

Objects in R: matrix and data frame

```r
# To augment the matrix with new column
column5 <- c(13, 14, 15)
matrix1 <- cbind(matrix1, column5)
print(matrix1)
```

```
##      column1 column2 column3 column4 column5
## row1       1       2       3       4      13
## row2       5       6       7       8      14
## row3       9      10      11      12      15
```

Objects in R: matrix and data frame

```
# To augment the matrix with new row
row4 <- c("a", "b", "c", "d", "e")
matrix1 <- rbind(matrix1, row4)
print(matrix1)
```

```
##      column1 column2 column3 column4 column5
## row1 "1"     "2"     "3"     "4"     "13"
## row2 "5"     "6"     "7"     "8"     "14"
## row3 "9"     "10"    "11"    "12"    "15"
## row4 "a"     "b"     "c"     "d"     "e"
```

Why do all vectors become characters?

Objects in R: matrix and data frame

- Matrices vs. data frames

Objects in `R`: matrix and data frame

- Matrices vs. data frames
  - Matrices can only contain one **homogenous** type of vectors

Objects in `R`: matrix and data frame

- Matrices vs. data frames
  - Matrices can only contain one **homogenous** type of vectors
  - Data frames can contain **heterogeneous** types of vectors, and thus are more flexible

Objects in R: matrix and data frame

- Data frames can contain **heterogeneous** types of vectors, and thus are more flexible

```
df1 <- data.frame(
  names = c("Peter", "Paul", "Mary"),
  age = c(14, 15, 16),
  female = c(FALSE, FALSE, TRUE),
  stringsAsFactors = FALSE
)

print(df1)
```

```
##   names age female
## 1 Peter  14  FALSE
## 2  Paul  15  FALSE
## 3  Mary  16   TRUE
```

Objects in R: matrix and data frame

```r
# Basic information
class(df1)
```

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

```r
dim(df1)
```

```
## [1] 3 3
```

```r
str(df1)
```

```
## 'data.frame':    3 obs. of  3 variables:
##  $ names : chr  "Peter" "Paul" "Mary"
##  $ age   : num  14 15 16
##  $ female: logi  FALSE FALSE TRUE
```

Objects in R: subsetting data

- There are several ways to subset data: row/column indices, variable names, or evaluations

```
# 1) Subsetting by row/column indices
# For the element in row 1, column 1
df1[1, 1]
```

```
## [1] "Peter"
```

```
# For all elements in row 1, regardless of columns
df1[1, ]
```

```
##   names age female
## 1 Peter  14  FALSE
```

```
# For all elements in column 1, regardless of rows
df1[, 1]
```

```
## [1] "Peter" "Paul"  "Mary"
```

Objects in R: subsetting data

```r
# 2) Subsetting by variable names
df1$names
```

```
## [1] "Peter" "Paul"  "Mary"
```

```r
df1$age
```

```
## [1] 14 15 16
```

```r
df1$female
```

```
## [1] FALSE FALSE  TRUE
```

Objects in R: subsetting data

```
# 3) Subsetting by evaluations
df1[df1$age >= 15, ]
```

```
##   names age female
## 2  Paul  15  FALSE
## 3  Mary  16   TRUE
```

```
df1[df1$female == TRUE, ]
```

```
##   names age female
## 3  Mary  16   TRUE
```

```
df1[df1$name %in% c("Peter", "Paul"), ]
```

```
##   names age female
## 1 Peter  14  FALSE
## 2  Paul  15  FALSE
```

Objects in R: creating new variable in data frame

```r
print(df1)
```

```
##   names age female
## 1 Peter  14  FALSE
## 2  Paul  15  FALSE
## 3  Mary  16   TRUE
```

```r
df1$edu
```

```
## NULL
```

```r
df1$edu <- c("hs", "col", "phd")

print(df1)
```

```
##   names age female edu
## 1 Peter  14  FALSE  hs
## 2  Paul  15  FALSE col
## 3  Mary  16   TRUE phd
```

Summary of data structures in `R`

	Homogeneous	Heterogeneous
1d	Atomic vector	List
2d	Matrix	Data frame
nd	Array	

- Another important data structure: `factor` for categorical data, which will be important for visualization purpose

Vector practices

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1. vector1: $\{$a1, a2, a3, b1, b2, b3, c1, c2, c3 $\ldots$ z1, z2, z3$\}$
   - Hint: break downs the question into two parts; check out function `rep(..., times = ..., each = ...)`

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1. vector1: {a1, a2, a3, b1, b2, b3, c1, c2, c3 ... z1, z2, z3}
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   - Hint: check out function `seq(...)`

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   - Subset the 3rd, 16th, and 25th elements of the vector

Vector practices

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1. vector1: {a1, a2, a3, b1, b2, b3, c1, c2, c3 ... z1, z2, z3}
   - Hint: break downs the question into two parts; check out function `rep(..., times = ..., each = ...)`
2. vector2: The sequence from 1 to 49 by an increment of 2
   - Hint: check out function `seq(...)`
   - Subset the 3rd, 16th, and 25th elements of the vector
   - Subset those elements whose values are either smaller than 10, or greater than 40

Vector practices

```r
# Q1
chr <- rep(letters, each = 3)
print(chr)
```

```
##  [1] "a" "a" "a" "b" "b" "b" "c" "c" "c" "d" "d"
## [12] "d" "e" "e" "e" "f" "f" "f" "g" "g" "g" "h"
## [23] "h" "h" "i" "i" "i" "j" "j" "j" "k" "k" "k"
## [34] "l" "l" "l" "m" "m" "m" "n" "n" "n" "o" "o"
## [45] "o" "p" "p" "p" "q" "q" "q" "r" "r" "r" "s"
## [56] "s" "s" "t" "t" "t" "u" "u" "u" "v" "v" "v"
## [67] "w" "w" "w" "x" "x" "x" "y" "y" "y" "z" "z"
## [78] "z"
```

```r
num <- rep(1:3, times = length(letters))
print(num)
```

```
##  [1] 1 2 3 1 2 3 1 2 3 1 2 3 1 2 3 1 2 3 1 2 3 1 2
## [24] 3 1 2 3 1 2 3 1 2 3 1 2 3 1 2 3 1 2 3 1 2 3 1
## [47] 2 3 1 2 3 1 2 3 1 2 3 1 2 3 1 2 3 1 2 3 1 2 3
## [70] 1 2 3 1 2 3 1 2 3
```

Vector practices

```r
# Q1
vector1 <- paste0(chr, num)
print(vector1)
```

```
##  [1] "a1" "a2" "a3" "b1" "b2" "b3" "c1" "c2" "c3"
## [10] "d1" "d2" "d3" "e1" "e2" "e3" "f1" "f2" "f3"
## [19] "g1" "g2" "g3" "h1" "h2" "h3" "i1" "i2" "i3"
## [28] "j1" "j2" "j3" "k1" "k2" "k3" "l1" "l2" "l3"
## [37] "m1" "m2" "m3" "n1" "n2" "n3" "o1" "o2" "o3"
## [46] "p1" "p2" "p3" "q1" "q2" "q3" "r1" "r2" "r3"
## [55] "s1" "s2" "s3" "t1" "t2" "t3" "u1" "u2" "u3"
## [64] "v1" "v2" "v3" "w1" "w2" "w3" "x1" "x2" "x3"
## [73] "y1" "y2" "y3" "z1" "z2" "z3"
```

Vector practices

```
# Q2
vector2 <- seq(from = 1, to = 49, by = 2)
print(vector2)
```

```
##  [1]  1  3  5  7  9 11 13 15 17 19 21 23 25 27 29
## [16] 31 33 35 37 39 41 43 45 47 49
```

```
vector2[c(3, 16, 25)]
```

```
## [1]  5 31 49
```

```
vector2[vector2 < 10 | vector2 > 40]
```

```
##  [1]  1  3  5  7  9 41 43 45 47 49
```

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   - Multiply the values in the first column of matrix 1 by 100; overwrite the original column

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4. df1: a dataframe with two variables:

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   - country = {US, UK, CA, FR, IT}

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4. df1: a dataframe with two variables:
   - country = {US, UK, CA, FR, IT}
   - pop = {327, 66, 37, 67, 60}
   - Subset top-three observations in term of the level of population

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   - Multiply the values in the first column of matrix 1 by 100; overwrite the original column
4. df1: a dataframe with two variables:
   - country = {US, UK, CA, FR, IT}
   - pop = {327, 66, 37, 67, 60}
   - Subset top-three observations in term of the level of population
   - Hint: check out function `order(...)`

Vector practices

```r
# Q3
matrix1 <- matrix(data = vector2, nrow = 5, ncol = 5)
rownames(matrix1) <- paste("row", letters[1:5], sep = "_")
colnames(matrix1) <- paste0("col", 1:5)
matrix1[, 1] <- matrix1[, 1] * 100
print(matrix1)
```

```
##       col1 col2 col3 col4 col5
## row_a  100   11   21   31   41
## row_b  300   13   23   33   43
## row_c  500   15   25   35   45
## row_d  700   17   27   37   47
## row_e  900   19   29   39   49
```

Vector practices

```r
# Q4
df1 <- data.frame(country = c("US", "UK", "CA", "FR", "IT"),
                  pop = c(327, 66, 37, 67, 60))
print(df1)
```

```
##   country pop
## 1      US 327
## 2      UK  66
## 3      CA  37
## 4      FR  67
## 5      IT  60
```

```r
order(df1$pop, decreasing = TRUE)
```

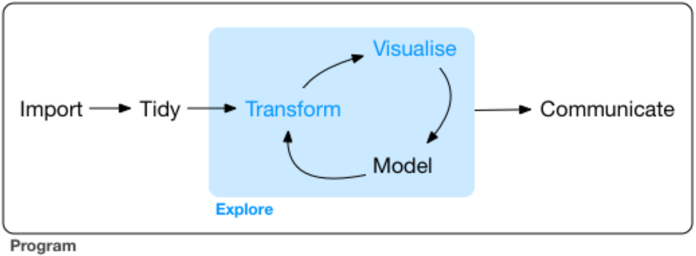
```
## [1] 1 4 2 5 3
```

```r
top3 <- order(df1$pop, decreasing = TRUE)[1:3]
df1[top3, ]
```

```
##   country pop
## 1      US 327
## 4      FR  67
## 2      UK  66
```

Workflow in R

- Usual workflow for data anlaysis (Grolemund and Wickham 2016):



Tidyverse and tidy data

- `Tidyverse` is a collection of packages designed for data science with unified grammar and data structures

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Tidyverse and tidy data

- `Tidyverse` is a collection of packages designed for data science with unified grammar and data structures
- *Tidy data*:
  - Each **variable** must have its own **column**
  - Each **observation** must have its own **row**
  - Each value must have its own cell

Tidyverse and tidy data

- To install `Tidyverse` package, run:

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

- To load a package, run (usually at the top of your R document):

```
library(tidyverse)
```

Importing data in R

```
# Load package
library(tidyverse)
```

```
# Load econ.csv
econ <- read_csv("https://students.washington.edu/rllobet/vis/la
```

```
## Rows: 557 Columns: 4

## -- Column specification ----------------------------
## Delimiter: ","
## chr (1): country
## dbl (3): GWn, year, gdpPercap

##
## i Use `spec()` to retrieve the full column specification for
## i Specify the column types or set `show_col_types = FALSE` to
```

```
# tibble (tbl) is a special class of data frame
class(econ)
```

```
## [1] "spec_tbl_df" "tbl_df"      "tbl"
```

Importing data in R

```
# Get a sense of the dataset
glimpse(econ)
```

```
## Rows: 557
## Columns: 4
## $ country   <chr> "Afghanistan", "Afghanistan", ~
## $ GWn       <dbl> 700, 700, 700, 339, 615, 615, ~
## $ year      <dbl> 1983, 1985, 1991, 2000, 1967, ~
## $ gdpPercap <dbl> 862.5477, 818.9504, 600.5932, ~
```

```
head(econ)
```

```
## # A tibble: 6 x 4
##   country       GWn  year gdpPercap
##   <chr>       <dbl> <dbl>     <dbl>
## 1 Afghanistan   700  1983      863.
## 2 Afghanistan   700  1985      819.
## 3 Afghanistan   700  1991      601.
## 4 Albania       339  2000     2962.
## 5 Algeria       615  1967     1824.
## 6 Algeria       615  1968     1977.
```

Basic data wrangling

- Below are just scratching the surface; check out

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Basic data wrangling

- Below are just scratching the surface; check out
  - Introductory course to tidyverse at DataCamp
  - Cheat sheet for data wrangling
  - *R for Data Science*

Basic data wrangling: count()

Count number of rows in each group:

```
econ %>%
  count(country)
```

```
## # A tibble: 146 x 2
##    country                     n
##    <chr>                   <int>
##  1 Afghanistan                 3
##  2 Albania                     1
##  3 Algeria                     5
##  4 Angola                      3
##  5 Argentina                   5
##  6 Australia                   3
##  7 Austria                     9
##  8 Bahrain                     2
##  9 Bangladesh                  5
## 10 Belarus (Byelorussia)       1
## # ... with 136 more rows
```

Basic data wrangling: %>%

- What is %>% ("pipe")?
  - `x %>% fun(y)` is equivalent to `fun(x, y)`
  - Its advantage will be apparent when you perform numerous steps of manipulation

```
count(econ, country) # Equivalent to econ %>% count(country)
```

```
## # A tibble: 146 x 2
##    country                     n
##    <chr>                   <int>
##  1 Afghanistan                 3
##  2 Albania                     1
##  3 Algeria                     5
##  4 Angola                      3
##  5 Argentina                   5
##  6 Australia                   3
##  7 Austria                     9
##  8 Bahrain                     2
##  9 Bangladesh                  5
## 10 Belarus (Byelorussia)       1
## # ... with 136 more rows
```

Basic data wrangling: arrange()

Order rows by values of column(s) from low to high:

```
econ %>%
  count(country) %>%
  arrange(n) # Rather than: arrange(count(econ, country), n)
```

```
## # A tibble: 146 x 2
##    country                      n
##    <chr>                    <int>
##  1 Albania                      1
##  2 Belarus (Byelorussia)        1
##  3 Cambodia (Kampuchea)         1
##  4 Central African Republic     1
##  5 Chile                        1
##  6 China                        1
##  7 Dominican Republic           1
##  8 Estonia                      1
##  9 Gabon                        1
## 10 Ghana                        1
## # ... with 136 more rows
```

Basic data wrangling: arrange()

Order rows by values of column(s) from high to low:

```
econ %>%
  count(country) %>%
  arrange(desc(n))
```

```
## # A tibble: 146 x 2
##    country                      n
##    <chr>                    <int>
##  1 United States of America   112
##  2 Mexico                      10
##  3 Austria                      9
##  4 Uruguay                      9
##  5 Philippines                  8
##  6 Denmark                      7
##  7 Norway                       7
##  8 Portugal                     7
##  9 Trinidad and Tobago          7
## 10 Venezuela                    7
## # ... with 136 more rows
```

Basic data wrangling: filter()

Extract rows that meet logical criteria:

```
econ %>%
  filter(country == "Brazil")
```

```
## # A tibble: 3 x 4
##   country   GWn  year gdpPercap
##   <chr>   <dbl> <dbl>     <dbl>
## 1 Brazil    140  1954     1848.
## 2 Brazil    140  1989     5224.
## 3 Brazil    140  2002     5481.
```

Basic data wrangling: `filter()`

Extract rows that meet **multiple** logical criteria:

```
econ %>%
  filter(
    country == "Brazil" | country == "Russia (Soviet Union)" |
    country == "India"  | country == "China"
  )
```

```
## # A tibble: 9 x 4
##   country                 GWn  year gdpPercap
##   <chr>                 <dbl> <dbl>     <dbl>
## 1 Brazil                  140  1954     1848.
## 2 Brazil                  140  1989     5224.
## 3 Brazil                  140  2002     5481.
## 4 China                   710  1996     2892.
## 5 India                   750  1943      698.
## 6 India                   750  1961      758.
## 7 India                   750  1992     1350.
## 8 Russia (Soviet Union)   365  1982     6536.
## 9 Russia (Soviet Union)   365  2005     7269.
```

Basic data wrangling: `filter()`

Alternatively:

```
econ %>%
  filter(country %in% c("Brazil", "Russia (Soviet Union)", "India", "China"))
```

```
## # A tibble: 9 x 4
##   country                 GWn  year gdpPercap
##   <chr>                 <dbl> <dbl>     <dbl>
## 1 Brazil                  140  1954     1848.
## 2 Brazil                  140  1989     5224.
## 3 Brazil                  140  2002     5481.
## 4 China                   710  1996     2892.
## 5 India                   750  1943      698.
## 6 India                   750  1961      758.
## 7 India                   750  1992     1350.
## 8 Russia (Soviet Union)   365  1982     6536.
## 9 Russia (Soviet Union)   365  2005     7269.
```

Basic data wrangling: `select()`

Extract columns (variables):

```
econ %>%
  select(country, year, gdpPercap)
```

```
## # A tibble: 557 x 3
##    country      year gdpPercap
##    <chr>       <dbl>     <dbl>
##  1 Afghanistan  1983      863.
##  2 Afghanistan  1985      819.
##  3 Afghanistan  1991      601.
##  4 Albania      2000     2962.
##  5 Algeria      1967     1824.
##  6 Algeria      1968     1977.
##  7 Algeria      1977     2759.
##  8 Algeria      1986     3301.
##  9 Algeria      2006     3386.
## 10 Angola       1953     1126.
## # ... with 547 more rows
```

Basic data wrangling: `filter()` & `select()`

Filter USA observations from 2000 to 2010 with year and `gdpPercap` as the only variables:

```
USAdata <- econ %>%
  filter(country == "United States of America",
         year %in% 2000:2010) %>%
  select(year, gdpPercap)

print(USAdata)
```

```
## # A tibble: 11 x 2
##     year gdpPercap
##    <dbl>     <dbl>
##  1  2000    28702.
##  2  2001    28726.
##  3  2002    28977.
##  4  2003    29459.
##  5  2004    30200.
##  6  2005    30842.
##  7  2006    31358.
##  8  2007    31655.
##  9  2008    31251.
## 10  2009    29899.
## 11  2010    30491.
```

Basic data wrangling: summarize()

Compute table of summaries:

```
USAdata %>%
  summarize(avg_gdpPercap = mean(gdpPercap))
```

```
## # A tibble: 1 x 1
##   avg_gdpPercap
##           <dbl>
## 1        30142.
```

What if we want to calculate the average GDP per capita for all countries in our data set?

Basic data wrangling: group_by() & summarize()

- Create a grouped version of the table with group_by()
  - Subsequent functions will manipulate each group *separately*

```
econ %>%
  group_by(country) %>%
  summarize(avg_gdpPercap = mean(gdpPercap)) %>%
  arrange(desc(avg_gdpPercap))
```

```
## # A tibble: 146 x 2
##    country                        avg_gdpPercap
##    <chr>                                  <dbl>
##  1 Qatar                                 39157.
##  2 Kuwait                                16288.
##  3 German Federal Republic               15739.
##  4 Norway                                14846.
##  5 Ireland                               14353.
##  6 Belarus (Byelorussia)                 13659.
##  7 United States of America              13623.
##  8 United Arab Emirates                  12812.
##  9 Belgium                               12053.
## 10 Austria                               11794.
## # ... with 136 more rows
```

Basic data wrangling: more summarize()

What if we want to know the numbers of distinct countries and years in the data set?

```
econ %>%
  summarize_at(c("country", "year"), n_distinct)
```

```
## # A tibble: 1 x 2
##   country  year
##     <int> <int>
## 1     146   111
```

Basic data wrangling: `mutate()`

Compute new columns (variables):

```
econ %>%
  mutate(
    id = row_number(),
    decade = year %/% 10 * 10
  ) %>%
  select(id, country, GWn, year, decade, gdpPercap)
```

```
## # A tibble: 557 x 6
##       id country       GWn  year decade gdpPercap
##    <int> <chr>       <dbl> <dbl>  <dbl>     <dbl>
##  1     1 Afghanistan   700  1983   1980      863.
##  2     2 Afghanistan   700  1985   1980      819.
##  3     3 Afghanistan   700  1991   1990      601.
##  4     4 Albania       339  2000   2000     2962.
##  5     5 Algeria       615  1967   1960     1824.
##  6     6 Algeria       615  1968   1960     1977.
##  7     7 Algeria       615  1977   1970     2759.
##  8     8 Algeria       615  1986   1980     3301.
##  9     9 Algeria       615  2006   2000     3386.
## 10    10 Angola        540  1953   1950     1126.
## # ... with 547 more rows
```

Basic data wrangling: group_by() & summarize()

What if we want to know countries' average GDP per capita over decades?

```
econ %>%
  mutate(decade = year %/% 10 * 10) %>%
  group_by(country, decade) %>%
  summarize(decAvg_gdp = mean(gdpPercap))
```

```
## `summarise()` has grouped output by 'country'. You can override using the `.

## # A tibble: 382 x 3
## # Groups:   country [146]
##    country     decade decAvg_gdp
##    <chr>        <dbl>      <dbl>
##  1 Afghanistan   1980       841.
##  2 Afghanistan   1990       601.
##  3 Albania       2000      2962.
##  4 Algeria       1960      1901.
##  5 Algeria       1970      2759.
##  6 Algeria       1980      3301.
##  7 Algeria       2000      3386.
##  8 Angola        1950      1161.
##  9 Angola        2000       825.
## 10 Argentina     1900      2992.
## # ... with 372 more rows
```

Saving wrangled data

When you save the wrangled data, don't overwrite the original data with the same file name:

```
write_csv(econ, "econ_wrangled.csv")
```

Intermediate data wranggling: second data set

```
pop <- read_csv("https://students.washington.edu/rllobet/vis/lab1/data/pop.csv"
head(pop)
```

```
## # A tibble: 6 x 5
##   country       GWn  year      pop region
##   <chr>       <dbl> <dbl>    <dbl> <chr>
## 1 Afghanistan   700  1983 15177000 Asia: Southern Asia
## 2 Afghanistan   700  1985 14519000 Asia: Southern Asia
## 3 Afghanistan   700  1991 15403000 Asia: Southern Asia
## 4 Albania       339  2000  3113000 Europe: Southern Europe
## 5 Algeria       615  1967 13078000 Africa: Northern Africa
## 6 Algeria       615  1968 13495000 Africa: Northern Africa
```

```
# Compare with econ
head(econ)
```

```
## # A tibble: 6 x 4
##   country       GWn  year gdpPercap
##   <chr>       <dbl> <dbl>     <dbl>
## 1 Afghanistan   700  1983      863.
## 2 Afghanistan   700  1985      819.
## 3 Afghanistan   700  1991      601.
## 4 Albania       339  2000     2962.
## 5 Algeria       615  1967     1824.
## 6 Algeria       615  1968     1977.
```

Intermediate data wranggling: `join` family

How do we combine two data sets such that:

```
## # A tibble: 559 x 6
##    country       GWn  year gdpPercap      pop region
##    <chr>       <dbl> <dbl>     <dbl>    <dbl> <chr>
##  1 Afghanistan   700  1983      863. 15177000 Asia: Southern Asia
##  2 Afghanistan   700  1985      819. 14519000 Asia: Southern Asia
##  3 Afghanistan   700  1991      601. 15403000 Asia: Southern Asia
##  4 Albania       339  2000     2962.  3113000 Europe: Southern Europe
##  5 Algeria       615  1967     1824. 13078000 Africa: Northern Africa
##  6 Algeria       615  1968     1977. 13495000 Africa: Northern Africa
##  7 Algeria       615  1977     2759. 17058000 Africa: Northern Africa
##  8 Algeria       615  1986     3301. 22520000 Africa: Northern Africa
##  9 Algeria       615  2006     3386. 33749328 Africa: Northern Africa
## 10 Angola        540  1953     1126.       NA NA: NA
## # ... with 549 more rows
```

Intermediate data wranggling: join family

Family of join functions: inner_join, left_join, right_join, full_join...

```
data <- econ %>%
  left_join(pop, by = c("GWn", "year")) %>%
  select(-country.y) %>%
  rename(country = country.x)
```

```
## # A tibble: 559 x 6
##    country       GWn  year gdpPercap      pop region
##    <chr>       <dbl> <dbl>     <dbl>    <dbl> <chr>
##  1 Afghanistan   700  1983      863. 15177000 Asia: Southern Asia
##  2 Afghanistan   700  1985      819. 14519000 Asia: Southern Asia
##  3 Afghanistan   700  1991      601. 15403000 Asia: Southern Asia
##  4 Albania       339  2000     2962.  3113000 Europe: Southern Europe
##  5 Algeria       615  1967     1824. 13078000 Africa: Northern Africa
##  6 Algeria       615  1968     1977. 13495000 Africa: Northern Africa
##  7 Algeria       615  1977     2759. 17058000 Africa: Northern Africa
##  8 Algeria       615  1986     3301. 22520000 Africa: Northern Africa
##  9 Algeria       615  2006     3386. 33749328 Africa: Northern Africa
## 10 Angola        540  1953     1126.       NA NA: NA
## # ... with 549 more rows
```

Intermediate data wranggling: `separate` (or Regex)

How to separate the `region` column into `continent` and `sub_region`?

```
## # A tibble: 559 x 7
##    country       GWn  year gdpPercap      pop continent sub_region
##    <chr>       <dbl> <dbl>     <dbl>    <dbl> <chr>     <chr>
##  1 Afghanistan   700  1983      863. 15177000 Asia      Southern Asia
##  2 Afghanistan   700  1985      819. 14519000 Asia      Southern Asia
##  3 Afghanistan   700  1991      601. 15403000 Asia      Southern Asia
##  4 Albania       339  2000     2962.  3113000 Europe    Southern Europe
##  5 Algeria       615  1967     1824. 13078000 Africa    Northern Africa
##  6 Algeria       615  1968     1977. 13495000 Africa    Northern Africa
##  7 Algeria       615  1977     2759. 17058000 Africa    Northern Africa
##  8 Algeria       615  1986     3301. 22520000 Africa    Northern Africa
##  9 Algeria       615  2006     3386. 33749328 Africa    Northern Africa
## 10 Angola        540  1953     1126.       NA NA        NA
## # ... with 549 more rows
```

Intermediate data wranggling: separate (or Regex)

How to separate the region column into continent and sub_region?

```
data %>%
  separate(region, into = c("continent", "sub_region"), sep = ": ")
```

```
## # A tibble: 559 x 7
##    country       GWn  year gdpPercap      pop continent sub_region
##    <chr>       <dbl> <dbl>     <dbl>    <dbl> <chr>     <chr>
##  1 Afghanistan   700  1983      863. 15177000 Asia      Southern Asia
##  2 Afghanistan   700  1985      819. 14519000 Asia      Southern Asia
##  3 Afghanistan   700  1991      601. 15403000 Asia      Southern Asia
##  4 Albania       339  2000     2962.  3113000 Europe    Southern Europe
##  5 Algeria       615  1967     1824. 13078000 Africa    Northern Africa
##  6 Algeria       615  1968     1977. 13495000 Africa    Northern Africa
##  7 Algeria       615  1977     2759. 17058000 Africa    Northern Africa
##  8 Algeria       615  1986     3301. 22520000 Africa    Northern Africa
##  9 Algeria       615  2006     3386. 33749328 Africa    Northern Africa
## 10 Angola        540  1953     1126.       NA NA        NA
## # ... with 549 more rows
```

Intermediate data wranggling: separate (or Regex)

How to separate the region column into continent and sub_region?

```
# Or using regular expression
data %>%
  mutate(continent = str_extract(region, ".*(?=: )"),
         sub_region = str_extract(region, "(?<=: ).*")) %>%
  select(-region)
```

```
## # A tibble: 559 x 7
##    country       GWn  year gdpPercap      pop continent sub_region
##    <chr>       <dbl> <dbl>     <dbl>    <dbl> <chr>     <chr>
##  1 Afghanistan   700  1983      863. 15177000 Asia      Southern Asia
##  2 Afghanistan   700  1985      819. 14519000 Asia      Southern Asia
##  3 Afghanistan   700  1991      601. 15403000 Asia      Southern Asia
##  4 Albania       339  2000     2962.  3113000 Europe    Southern Europe
##  5 Algeria       615  1967     1824. 13078000 Africa    Northern Africa
##  6 Algeria       615  1968     1977. 13495000 Africa    Northern Africa
##  7 Algeria       615  1977     2759. 17058000 Africa    Northern Africa
##  8 Algeria       615  1986     3301. 22520000 Africa    Northern Africa
##  9 Algeria       615  2006     3386. 33749328 Africa    Northern Africa
## 10 Angola        540  1953     1126.       NA NA        NA
## # ... with 549 more rows
```

Intermediate data wranggling: `case_when`

- How to convert `pop` into a new categorical variable, called `popCat`:

Intermediate data wranggling: `case_when`

- How to convert `pop` into a new categorical variable, called `popCat`:
  - Countries with `pop` value lower than the first quartile of all `pop` is classified as "low"

Intermediate data wranggling: `case_when`

- How to convert `pop` into a new categorical variable, called `popCat`:
  - Countries with `pop` value lower than the first quartile of all `pop` is classified as "low"
  - Countries with `pop` value equal to or higher than the first quartile, but lower than the third quartile is classified as "middle"

Intermediate data wranggling: `case_when`

- How to convert `pop` into a new categorical variable, called `popCat`:
  - Countries with `pop` value lower than the first quartile of all `pop` is classified as "low"
  - Countries with `pop` value equal to or higher than the first quartile, but lower than the third quartile is classified as "middle"
  - Countries with `pop` value equal to or higher than the third quartile is classified as "high"

Intermediate data wranggling: case_when

```r
Qts <- quantile(data$pop, prob = c(0.25, 0.75), na.rm = TRUE)
print(Qts)
```

```
##      25%      75%
##  3805000 81896000
```

```r
Q1 <- Qts[1]
Q3 <- Qts[2]

data <- data %>%
  mutate(popCat = case_when(pop < Q1 ~ "low",
                            pop >= Q1 & pop < Q3 ~ "middle",
                            pop > Q3 ~ "high"))
```

```
## # A tibble: 559 x 8
##    country       GWn  year gdpPercap      pop continent sub_region      popCat
##    <chr>       <dbl> <dbl>     <dbl>    <dbl> <chr>     <chr>           <chr>
##  1 Afghanistan   700  1983      863. 15177000 Asia      Southern Asia   middle
##  2 Afghanistan   700  1985      819. 14519000 Asia      Southern Asia   middle
##  3 Afghanistan   700  1991      601. 15403000 Asia      Southern Asia   middle
##  4 Albania       339  2000     2962.  3113000 Europe    Southern Europe low
##  5 Algeria       615  1967     1824. 13078000 Africa    Northern Africa middle
##  6 Algeria       615  1968     1977. 13495000 Africa    Northern Africa middle
##  7 Algeria       615  1977     2759. 17058000 Africa    Northern Africa middle
##  8 Algeria       615  1986     3301. 22520000 Africa    Northern Africa middle
##  9 Algeria       615  2006     3386. 33749328 Africa    Northern Africa middle
## 10 Angola        540  1953     1126.       NA NA        NA              <NA>
## # ... with 549 more rows
```

Intermediate data wranggling: `mutate` and `lag`

Focus on USA data again. How to create a variable, named `growth`, thats computes the percentage change in `gdpPercap` compared to the immediate last year?

```
## # A tibble: 114 x 4
##    country                    year gdpPercap   growth
##    <chr>                     <dbl>     <dbl>    <dbl>
##  1 United States of America  1900     4091. NA
##  2 United States of America  1901     4464.  0.0912
##  3 United States of America  1902     4421. -0.00969
##  4 United States of America  1903     4551.  0.0295
##  5 United States of America  1904     4410. -0.0311
##  6 United States of America  1905     4642.  0.0528
##  7 United States of America  1906     5079.  0.0941
##  8 United States of America  1907     5065. -0.00280
##  9 United States of America  1908     4561. -0.0996
## 10 United States of America  1909     5017.  0.100
## # ... with 104 more rows
```

Intermediate data wranggling: mutate and lag

```r
# Extract USA data
USAdata <- data %>%
  filter(country == "United States of America") %>%
  select(country, year, gdpPercap)

# Use `lag` to create a column of gdpPercap in past year
USAdata <- USAdata %>%
  mutate(gdpPercap_lag1 = lag(gdpPercap, n = 1))

print(USAdata)
```

```
## # A tibble: 114 x 4
##    country                   year gdpPercap gdpPercap_lag1
##    <chr>                    <dbl>     <dbl>          <dbl>
##  1 United States of America  1900     4091.            NA
##  2 United States of America  1901     4464.          4091.
##  3 United States of America  1902     4421.          4464.
##  4 United States of America  1903     4551.          4421.
##  5 United States of America  1904     4410.          4551.
##  6 United States of America  1905     4642.          4410.
##  7 United States of America  1906     5079.          4642.
##  8 United States of America  1907     5065.          5079.
##  9 United States of America  1908     4561.          5065.
## 10 United States of America  1909     5017.          4561.
## # ... with 104 more rows
```

Intermediate data wranggling: mutate and lag

```r
USAdata <- USAdata %>%
  mutate(growth = (gdpPercap - gdpPercap_lag1) / gdpPercap_lag1)

print(USAdata)
```

```
## # A tibble: 114 x 5
##    country                   year gdpPercap gdpPercap_lag1   growth
##    <chr>                    <dbl>     <dbl>          <dbl>    <dbl>
##  1 United States of America  1900     4091.            NA   NA
##  2 United States of America  1901     4464.          4091.  0.0912
##  3 United States of America  1902     4421.          4464. -0.00969
##  4 United States of America  1903     4551.          4421.  0.0295
##  5 United States of America  1904     4410.          4551. -0.0311
##  6 United States of America  1905     4642.          4410.  0.0528
##  7 United States of America  1906     5079.          4642.  0.0941
##  8 United States of America  1907     5065.          5079. -0.00280
##  9 United States of America  1908     4561.          5065. -0.0996
## 10 United States of America  1909     5017.          4561.  0.100
## # ... with 104 more rows
```

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