Applied R for Social Scientists

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April 2016

This Class

This class

- Assumption of *some* previous exposure to R
- We're not explaining assignment, packages, calling functions, etc
- Will *not* be covering statistics
- Alex will start with some common data tasks: loading, variable creation, merging, etc
- Daniel will take the second part to talk about tables and visualization

Getting the data

- `source()` runs a file through R
- This one checks if you have the data already and tries to download it if not
- The dataset we're using is the General Social Survey spanning 1972-2014

```r
source("check-gss-and-maybe-download.R")
```

```
## [1] "GSS file exists!"
```

- R can read almost any data
- Here are some of the most common types:

package	function	file formats
foreign	**`read.*`**	dta, spss, etc
haven	**`read_*`**	dta (13+) files and others
readr	**`read_csv`**	csv files

Read data

- We have stata data (`*.dta`)
- `convert.factors = FALSE` ensures that R doesn't convert the values to the labels that stata uses

```
GSS <- foreign::read.dta("./data/GSS7214_R5.DTA",
                         convert.factors = FALSE)
```

Data management

- Let's get a sense of the data we're working with
- Do you want more, less, or about the same spending? (education and social security)

```
table(GSS$nateduc, GSS$natsoc, exclude = NULL)
```

```
##
##              1     2     3  <NA>
##   1       8540  4335   699  7939
##   2       2062  2288   296  5005
##   3        353   457   210  1317
##   <NA>   11841  7408  1282  5567
```

- `cor` gives us (by default) the pearson's *r* between two variables
- Without setting `use`, R tries to use the whole data, some of which are missing and thus results in `NA`

```
cor(GSS$nateduc,
    GSS$natsoc,
    use = "complete.obs")
```

```
## [1] 0.1965368
```

- Let's make an indicator variable for whether a respondent is black or not
- Here's the `race` variable
- I also like to make sure that I'm not going to overwrite an existing variable

```
table(GSS$race)
```

```
##
##     1     2     3
## 48240  8312  3047
```

```
table(GSS$black)
```

```
## < table of extent 0 >
```

- Using `ifelse` to create a variable conditional on other var's values

```
GSS$black <- ifelse(GSS$race == 2, TRUE, FALSE)
table(GSS$black)
```

```
##
## FALSE  TRUE
## 51287  8312
```

- Now let's check to see if that correlation is different for black people
- Note how ugly this looks!

```
cor(GSS$nateduc[GSS$black == TRUE],
    GSS$natsoc[GSS$black == TRUE],
    use="complete.obs")
```

```
## [1] 0.1772446
```

- `dplyr` is an R package that makes data management *much* easier
- Different functions for data munging:
- `filter()`, `select()`, `mutate()`
- It introduces the pipe operator `%>%` to the language
- Functions for merging data
- `*_join`: full, inner, left, right
- `group_by`, which lets us perform operations on groups of the data
- Because I'll use `tidyr` later and it gets angry if you load it after `dplyr`, I'm loading it now

```r
library(tidyr)
suppressPackageStartupMessages(library(dplyr))
```

- The pipe (`%>%`) "pipes" the output of the last thing into the first argument of the next thing
- `summarize` (or `summarise`) from `dplyr` returns a `data.frame`

```
with(filter(GSS, black == TRUE),
     cor(nateduc, natsoc,
         use = "complete.obs"))
```

```
## [1] 0.1772446
```

```
GSS %>%
  filter(black == TRUE) %>%
  summarize(mycor =
                cor(nateduc, natsoc,
                    use = "complete.obs"))
```

```
##       mycor
## 1 0.1772446
```

- 1972 doesn't have any observations we're interested in (our spending variables weren't asked), so let's drop it
- Again, we can use `filter`, but this time we assign the result back to `GSS`:

```
GSS <- GSS %>%
  filter(year != 1972)
```

- Variables with categories can be represented as factors in R
- If you want R to think they're ordered, you can use `ordered` TRUE= as an argument

```
table(GSS$sex)
```

```
##
##     1     2
## 25479 32507
```

```
GSS <- GSS %>%
  mutate(sex = factor(sex,
                      levels = c(1, 2),
                      labels = c("M", "F")))

table(GSS$sex)
```

```
##
##     M     F
## 25479 32507
```

- dplyr provides group_by
- Lets us perform operations to grouped data

```
thecors <- GSS %>%
  group_by(sex, black) %>%
  summarize(thecor = cor(nateduc, natsoc,
                        use = "complete.obs"),
            n = n())
```

```r
print(thecors)
```

```
## Source: local data frame [4 x 4]
## Groups: sex [?]
##
##       sex black    thecor     n
##    (fctr) (lgl)     (dbl) (int)
## 1       M FALSE 0.1918454 22446
## 2       M  TRUE 0.1674413  3033
## 3       F FALSE 0.1786193 27489
## 4       F  TRUE 0.1820090  5018
```

- Maybe we're interested in preferences by year?

```
gss_yearly <- GSS %>%
  group_by(year) %>%
  summarize(educ = mean(nateduc,
                        na.rm = TRUE),
            soc = mean(natsoc,
                       na.rm = TRUE))
```

```r
head(gss_yearly)
```

```
## Source: local data frame [6 x 3]
##
##    year     educ   soc
##   (int)    (dbl) (dbl)
## 1  1973 1.582287   NaN
## 2  1974 1.562059   NaN
## 3  1975 1.604930   NaN
## 4  1976 1.579020   NaN
## 5  1977 1.605854   NaN
## 6  1978 1.576766   NaN
```

- Means are nice, but there are other ways to summarize data
- What if we want to look at the proportion of people who support more spending minus the proportion who support less?

```
netsupport <- function(thedata){
  prop_more <- mean(thedata == 1, na.rm = TRUE)
  prop_less <- mean(thedata == 3, na.rm = TRUE)
  prop_more - prop_less
}
```

```r
GSS %>%
  group_by(year) %>%
  summarize(support_educ = netsupport(nateduc),
            support_soc = netsupport(natsoc))
```

```
## Source: local data frame [29 x 3]
##
##     year support_educ support_soc
##    (int)        (dbl)       (dbl)
## 1   1973    0.4177127          NA
## 2   1974    0.4379408          NA
## 3   1975    0.3950704          NA
## 4   1976    0.4209800          NA
## 5   1977    0.3941457          NA
```

- The `ggplot2` package provides the `economics` data.frame that has US economic data starting in July 1967
- `?economics` gives more info

```
library(ggplot2)
head(economics, 3)
```

```
## Source: local data frame [3 x 6]
##
##         date   pce    pop psavert uempmed unemploy
##       (date) (dbl)  (int)   (dbl)   (dbl)    (int)
## 1 1967-07-01 507.4 198712    12.5     4.5     2944
## 2 1967-08-01 510.5 198911    12.5     4.7     2945
## 3 1967-09-01 516.3 199113    11.7     4.6     2958
```

- Let's make an unemployment rate by unemploy*pop

```
economics <- economics %>%
  mutate(unemp_rate = unemploy / pop)
```

- Note `mutate` is from dplyr, this is base R:

```
economics$unemp_rate <- economics$unemploy / economics$pop
```

- The `economics` data is monthly and our GSS data is yearly, so we need to aggregate

```
economics_yearly <- economics %>%
  mutate(year = format(date, "%Y")) %>%
  group_by(year) %>%
  summarize(unemp = mean(unemp_rate))
```

- Let's see what our data looks like now!

```r
head(economics_yearly)
```

```
## Source: local data frame [6 x 2]
##
##      year      unemp
##     (chr)      (dbl)
## 1  1967 0.01512179
## 2  1968 0.01394202
## 3  1969 0.01396464
## 4  1970 0.02012547
## 5  1971 0.02418970
## 6  1972 0.02323808
```

- Now we have two data.frame objects — `gss_yearly` and `economics_yearly` — that we want to join together
- `dplyr` provides a really easy way of doing this
- The jargon comes from SQL, a programming language used to store data
- What you probably call a “merge” dplyr calls a “join”
- `*_join` where `*` is either `full`, `inner`, `left`, or `right`
- We’ll use `left_join` since the economics data contains years that aren’t in the GSS

```
gss_yearly <- left_join(gss_yearly,
                        economics_yearly,
                        by = "year")
```

```
## Error in eval(expr, envir, enclos): cannot join on columns 'year' x 'year': C
```

- Error: cannot join on columns 'year' x 'year': Can't join on 'year' x 'year' because of incompatible types (character / integer)

- The error on the last slide indicates that the `year` variable in the two datasets is different
- Let's verify that:

```
class(gss_yearly$year)
```

```
## [1] "integer"
```

```
class(economics_yearly$year)
```

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

- Solution: change `economics_yearly$year` to an integer

```
economics_yearly$year <- as.integer(economics_yearly$year)

gss_yearly <- left_join(gss_yearly,
                        economics_yearly,
                        by="year")
```

```r
head(gss_yearly)
```

```
## Source: local data frame [6 x 4]
##
##     year     educ   soc      unemp
##    (int)    (dbl) (dbl)      (dbl)
## 1  1973 1.582287   NaN 0.02057710
## 2  1974 1.562059   NaN 0.02418823
## 3  1975 1.604930   NaN 0.03677624
## 4  1976 1.579020   NaN 0.03393594
## 5  1977 1.605854   NaN 0.03164388
## 6  1978 1.576766   NaN 0.02780555
```

- Maybe you want to save this new data so you don't have to re-run the merging whenever you want to

package	function	result
readr	`write_csv`	csv file
utils	`write.csv`	csv file
base	`save`	Rdata file
xlsx	`write.xlsx`	excel file

- R can also write to stata/SPSS/SAS files through `foreign` or `haven`

- Let's save a csv file
- If the `data/` subfolder doesn't exist, this will produce an error
- The script that we ran at the beginning created this if it didn't already exist

```
readr::write_csv(gss_yearly, "data/gss-yearly-data.csv")
```

Tidying data

- Sometimes the data you get aren't *tidy*
- Tidy data are data where each row is an observation, each column a variable, and each cell a value
- Most of the strategies I showed you above assume that you're dealing with tidy data
- Remember I loaded tidyr earlier, so there's no need to call `library` again

```r
messy1 <- data_frame(
  country = c("Afghanistan", "Albania", "Algeria"),
  "2007" = c(43.82, 76.42, 72.30),
  "2002" = c(42.13, 75.65, 70.99))
```

```r
print(messy1)
```

```
## Source: local data frame [3 x 3]
##
##         country  2007  2002
##           (chr) (dbl) (dbl)
## 1 Afghanistan 43.82 42.13
## 2     Albania 76.42 75.65
## 3     Algeria 72.30 70.99
```

Use gather when you have non-variable columns

- `gather` can also turn wide to long

```
gather(messy1, "year", "life_expect", 2:3)
```

```
## Source: local data frame [6 x 3]
##
##       country  year life_expect
##         (chr) (chr)       (dbl)
## 1 Afghanistan  2007       43.82
## 2     Albania  2007       76.42
## 3     Algeria  2007       72.30
## 4 Afghanistan  2002       42.13
## 5     Albania  2002       75.65
## 6     Algeria  2002       70.99
```

```r
messy2 <- data.frame(
  country = c(rep("Afghanistan", 4), rep("Albania", 4), rep("Algeria", 4)),
  year = c(rep(2002, 2), rep(2007, 2)),
  variable = c("life_expect", "pop"),
  value = c(42.12, 25268405, 43.82, 31889923,
            75.65, 3508512, 76.42, 3600523,
            70.99, 31287142, 72.30, 33333216)
)
```

```r
head(messy2)
```

```
##         country year    variable       value
## 1 Afghanistan 2002 life_expect       42.12
## 2 Afghanistan 2002         pop 25268405.00
## 3 Afghanistan 2007 life_expect       43.82
## 4 Afghanistan 2007         pop 31889923.00
## 5     Albania 2002 life_expect       75.65
## 6     Albania 2002         pop  3508512.00
```

- `spread` can also turn long to wide

```r
spread(messy2, key = variable, value)
```

```
##       country year life_expect      pop
## 1 Afghanistan 2002       42.12 25268405
## 2 Afghanistan 2007       43.82 31889923
## 3     Albania 2002       75.65  3508512
## 4     Albania 2007       76.42  3600523
## 5     Algeria 2002       70.99 31287142
## 6     Algeria 2007       72.30 33333216
```

- If you have two variables in one column, use `separate`
- For example, a rate of # of people with a trait / total population in each country
- One variable across two columns? use `unite`
- one column for century (19, 20) and another for year (00... 09)

Iteration: Loops and apply

DRY

- DRY (*Don’t Repeat Yourself*) is an acronym from computer science
- Repeating yourself makes your code harder to deal with:
- Intent is less clear
- Harder to spot bugs

- For loops get lots of hate online because people think they're slow (they aren't)
- They can be hard to read, though

```
thedata <- data_frame(
  one = rnorm(100), two = rnorm(100),
  three = rnorm(100), four = rnorm(100)
)
```

```r
output <- list()
output[[1]] <- median(thedata$one)
output[[2]] <- median(thedata$two)
output[[3]] <- median(thedata$three)
output[[4]] <- median(thedata$four)
print(output); rm(output)
```

```
## [[1]]
## [1] -0.155124
##
## [[2]]
## [1] 0.02774598
##
## [[3]]
```

```r
output <- list()
for (i in 1:4) {
  output[[i]] <- median(thedata[[i]])
}
print(output); rm(output)
```

```
## [[1]]
## [1] -0.155124
##
## [[2]]
## [1] 0.02774598
##
## [[3]]
## [1] -0.01962174
```

- Of course, we oftentimes need to perform an operation across many columns
- This is where the map family (from purrr) steps in:

```
library(purrr)
```

```
##
## Attaching package: 'purrr'

## The following object is masked from 'package:dplyr':
##
##     order_by
```

```
map(thedata, median)
```

```
## $one
```

```r
map_dbl(thedata, median)
```

```
##         one         two       three        four
## -0.15512399  0.02774598 -0.01962174 -0.02395900
```

Nested data

- Some data is nested in a hierarchical way
- the **gapminder** data are a good example[1]

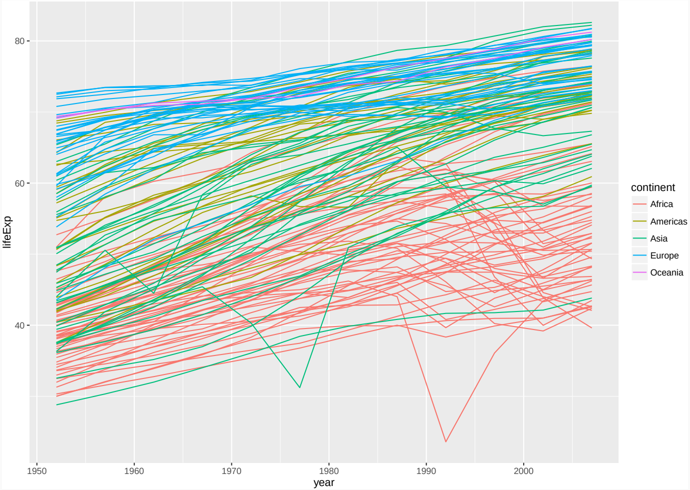
```
library(gapminder); library(ggplot2)
head(gapminder, 3)
```

```
## Source: local data frame [3 x 6]
##
##       country continent  year lifeExp      pop gdpPercap
##        (fctr)    (fctr) (int)   (dbl)    (int)     (dbl)
## 1 Afghanistan      Asia  1952  28.801  8425333  779.4453
## 2 Afghanistan      Asia  1957  30.332  9240934  820.8530
## 3 Afghanistan      Asia  1962  31.997 10267083  853.1007
```

[1] This example taken from the blog post

```r
ggplot(gapminder, aes(x = year, y = lifeExp,
                      color = continent, by = country)) +
  geom_line()
```

LIFE EXPECTANCY OVER TIME



```r
by_country <- gapminder %>%
  group_by(continent, country) %>%
  nest()
```

- Now we have a data frame with one row per group and a column where each cell is itself a whole data frame

```
head(by_country,3)
```

```
## Source: local data frame [3 x 3]
##
##   continent     country                data
##      (fctr)      (fctr)               (chr)
## 1      Asia Afghanistan <tbl_df [12,4]>
## 2    Europe     Albania <tbl_df [12,4]>
## 3    Africa     Algeria <tbl_df [12,4]>
```

NEST

- So for example the first element of the `data` column contains the whole data frame for Afghanistan

```
by_country$data[[1]]
```

```
## Source: local data frame [12 x 4]
##
##     year lifeExp      pop gdpPercap
##    (int)   (dbl)    (int)     (dbl)
## 1   1952  28.801  8425333  779.4453
## 2   1957  30.332  9240934  820.8530
## 3   1962  31.997 10267083  853.1007
## 4   1967  34.020 11537966  836.1971
## 5   1972  36.088 13079460  739.9811
```

- You can create a linear model for each country then:

```
by_country <- by_country %>%
  mutate(model = map(data,
                     ~ lm(lifeExp ~ year, data = .)))
```

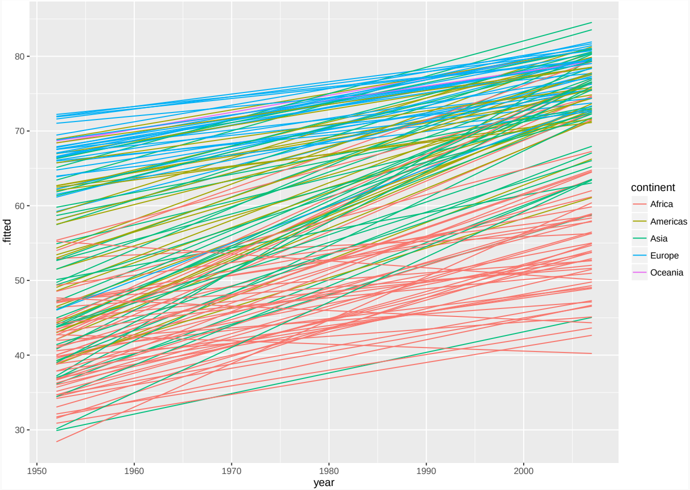
```r
head(by_country, 3)
```

```
## Source: local data frame [3 x 4]
##
##   continent     country              data   model
##      (fctr)      (fctr)             (chr)   (chr)
## 1      Asia Afghanistan <tbl_df [12,4]> <S3:lm>
## 2    Europe     Albania <tbl_df [12,4]> <S3:lm>
## 3    Africa     Algeria <tbl_df [12,4]> <S3:lm>
```

- Here we can extract the fitted values and plot a lint of the fitted values
- By continent, country

```
by_country %>% unnest(model %>% map(broom::augment)) %>%
  select(continent, country, year, .fitted) %>%
  ggplot(aes(x = year, y = .fitted,
             by = country, color = continent)) +
  geom_line()
```

NEST


80
70
60
50
40
30
.fitted
1950
1960
1970
1980
1990
2000
year
continent
Africa
Americas
Asia
Europe
Oceania