CSSS 508, Lecture 3

Manipulating and Summarizing Data

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(based on slides from Chuck Lanfear)

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UW CS&SS

Topics

Last time, we learned about,

1. Useful coding tips: packages, directories, and saving data
2. Basics of ggplot: layers and aesthetics
3. Advanced ggplot tools

Today, we will cover,

1. Building blocks
2. Subsetting data
3. Modifying data
4. Summarizing data
5. Merging together data

Death to Spreadsheets

Tools like *Excel* or *Google Sheets* lets you manipulate spreadsheets using functions.

- Spreads are *not reproducible*: It's hard to know how someone changed the raw data!
- It's hard to catch mistakes when you use spreadsheets. Don't be the next sad Research Assistant who makes headlines with an Excel error! (Reinhart & Rogoff, 2010)

Today, we'll use R to manipulate data more *transparently* and *reproducibly*.

1. Building Blocks

1. Logical Operators (`!=`, `==`, `>`, `<=`, etc.)
2. Combining Logical Operators (`&`, `|`)

Logical Operators

Logical operators refer to base functions which allow us to **test a connection** between two objects.

For example, we may test

- Is A equal to B?
- Is A greater than B?
- Is A within B?

and many others!

Logical Operators in Code

- `==`: is equal to (note: there are TWO equal signs here!)
- `!=`: not equal to
- `>`, `>=`, `<`, `<=`: less than, less than or equal to, etc.
- `%in%`: used with checking equal to one of several values

Examples of Logical Operators

Let's create two objects, `A` and `B`

```
A <- c(5,10,15)
B <- c(5,15,25)
```

```
A == B
```

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

```
A >  B
```

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

```
A %in% B
```

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

Combining Logical Operators

We have three main ways to combine logical operators:

- `&`: **both** conditions need to hold (AND)
- `|`: **at least one** condition needs to hold (OR)
- `!`: **inverts** a logical condition (`TRUE` becomes `FALSE`, `FALSE` becomes `TRUE`)

Examples

```
A <- c(5,10,15); B <- c(5,15,25)
```

```
A > 5 & A <= B
```

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

```
B < 10 | B > 20
```

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

```
!(A == 10)
```

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

Aside: `dplyr`

Today, we'll use tools from the `dplyr` package to manipulate data!

- Like `ggplot2`, `dplyr` is part of the , a modern collection of data science tools introduced by Hadley Wickham.
- You can read more about the tidyverse on its website.

To get started, let's install (in the console) and load (in an R/Rmd file) dplyr. (We also load `gapminder`!)

```
# install.packages("dplyr")
library(dplyr)

library(gapminder)
```

Building Block of `dplyr`: Pipes

`dplyr` allows us to use the "pipe" data between functions using the (`%>%`) operator. So instead of nesting functions like this:

```
log(mean(gapminder$pop))
```

```
## [1] 17.20333
```

We can **pipe** them like this:

```
gapminder$pop %>% mean() %>% log()
```

```
## [1] 17.20333
```

- Pipes read "left to right" (intuitive)
- Nested functions read "inside to out." (kinda weird)

2. Subsetting data

- `filter()`
- `select()`
- `distinct()`

Subset Rows: `filter`

We often get *big* datasets, and we only want some of the entries. We can subset rows using `filter`.

```
gapminder %>% filter(country == "China") %>%
  head(4) # display first four rows
```

```
## # A tibble: 4 × 6
##   country continent  year lifeExp       pop gdpPercap
##   <fct>   <fct>     <int>   <dbl>     <int>     <dbl>
## 1 China   Asia       1952    44   556263527      400.
## 2 China   Asia       1957    50.5 637408000      576.
## 3 China   Asia       1962    44.5 665770000      488.
## 4 China   Asia       1967    58.4 754550000      613.
```

```
China <- gapminder %>% filter(country == "China")
```

(Now, `China` is an object in our environment which contains rows corresponding to China.)

Subset Columns: `select`

What if we want to keep each entry, but only use certain variables? Use `select`!

```
gapminder %>% select(country,continent,year,lifeExp) %>% head(4)
```

```
## # A tibble: 4 × 4
##   country     continent  year lifeExp
##   <fct>       <fct>     <int>   <dbl>
## 1 Afghanistan Asia       1952    28.8
## 2 Afghanistan Asia       1957    30.3
## 3 Afghanistan Asia       1962    32.0
## 4 Afghanistan Asia       1967    34.0
```

Dropping columns with `select`

Alternatively, we can use `select()` to drop variables using a `-` sign:

```
gapminder %>% select(-continent, -pop, -lifeExp) %>% head(4)
```

```
## # A tibble: 4 × 3
##   country      year gdpPercap
##   <fct>       <int>     <dbl>
## 1 Afghanistan  1952      779.
## 2 Afghanistan  1957      821.
## 3 Afghanistan  1962      853.
## 4 Afghanistan  1967      836.
```

Finding Unique Rows: `distinct`

You may want to find the unique combinations of variables in a dataset. Use `distinct`

```
gapminder %>% distinct(continent, year) %>% head(6)
```

```
## # A tibble: 6 × 2
##   continent  year
##   <fct>     <int>
## 1 Asia       1952
## 2 Asia       1957
## 3 Asia       1962
## 4 Asia       1967
## 5 Asia       1972
## 6 Asia       1977
```

`distinct` drops variables!

By default, `distinct()` drops unused variables. If you don't want to drop them, add the argument `.keep_all=TRUE`:

```
gapminder %>% distinct(continent, year, .keep_all=TRUE) %>% head(6)
```

```
## # A tibble: 6 × 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.
```

3. Modifying data

- `arrange()`
- `rename()`
- `mutate()`

Sorting data by rows: `arrange`

Sometimes it's useful to sort rows in your data, in ascending (low to high) or descending (high to low) order. We do that with `arrange`.

```
US_and_Canada <- gapminder %>%
  filter(country %in% c("United States","Canada"))
US_and_Canada %>% arrange(year,lifeExp) %>% head(4)
```

```
## # A tibble: 4 × 6
##   country       continent  year lifeExp       pop gdpPercap
##   <fct>         <fct>     <int>   <dbl>     <int>     <dbl>
## 1 United States Americas   1952    68.4 157553000    13990.
## 2 Canada        Americas   1952    68.8  14785584    11367.
## 3 United States Americas   1957    69.5 171984000    14847.
## 4 Canada        Americas   1957    70.0  17010154    12490.
```

Sorting data by rows: `arrange`

To sort in descending order, using `desc()` within `arrange`

```
US_and_Canada %>% arrange(desc(pop)) %>% head(4)
```

```
## # A tibble: 4 × 6
##   country       continent  year lifeExp       pop gdpPercap
##   <fct>         <fct>     <int>   <dbl>     <int>     <dbl>
## 1 United States Americas   2007    78.2 301139947    42952.
## 2 United States Americas   2002    77.3 287675526    39097.
## 3 United States Americas   1997    76.8 272911760    35767.
## 4 United States Americas   1992    76.1 256894189    32004.
```

Rename variables: `rename`

You may receive data with unintuitive variable names. You can change them using `rename()`.

```
US_and_Canada %>% rename(life_expectancy = lifeExp) %>%
  head(4)
```

```
## # A tibble: 4 × 6
##   country continent  year life_expectancy      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.
```

(NOTE 1: I did *not* re-save the object `US_and_Canada`, so the name change is *not* permanent!)

(NOTE 2: I recommend **against** using spaces in a name! It makes things *really hard* sometimes!!)

Create new columns: `mutate`

You can add new columns to a data frame using `mutate()`.

For example, perhaps we wish to state the population in millions:

```
US_and_Canada %>% select(country, year, pop) %>%
    mutate(pop_millions = pop / 1000000) %>%
    head(5)
```

```
## # A tibble: 5 × 4
##   country  year      pop pop_millions
##   <fct>   <int>    <int>        <dbl>
## 1 Canada   1952 14785584         14.8
## 2 Canada   1957 17010154         17.0
## 3 Canada   1962 18985849         19.0
## 4 Canada   1967 20819767         20.8
## 5 Canada   1972 22284500         22.3
```

4. Summarizing data

- `summarize()`
- `group_by()`

Summarizing data: `summarize`

`summarize()` calculates summaries of variables in your data:

- Count the number of rows
- Calculate the mean
- Calculate the sum
- Find the minimum or maximum value

You can use any function inside `summarize()` that aggregates *multiple values* into a *single value* (like `sd()`, `mean()`, or `max()`).

`summarize()` Example

For the year 1982, let's summarize some values in `gapminder`

```
gapminder %>% filter(year == 1982) %>%
  summarize(number_observations = n(),
            max_lifeexp = max(lifeExp),
            mean_pop = mean(pop),
            sd_pop = sd(pop))
```

```
## # A tibble: 1 × 4
##   number_observations max_lifeexp  mean_pop     sd_pop
##                 <int>       <dbl>     <dbl>      <dbl>
## 1                 142        77.1 30207302. 105098650.
```

Summarizing data by groups: `group_by`

What if we want to summarize data by category? Use `group_by` **and** `summarize`

Functions after `group_by()` are computed *within each group* as defined by variables given, rather than over all rows at once.

`group_by()` Example

```r
US_and_Canada %>% group_by(year) %>%
  summarize(total_pop = sum(pop)) %>%
  head(4)
```

```
## # A tibble: 4 × 2
##    year total_pop
##   <int>     <int>
## 1  1952 172338584
## 2  1957 188994154
## 3  1962 205523849
## 4  1967 219531767
```

Because we did `group_by()` with `year` then used `summarize()`, we get *one row per value of `year`*!

5. Merging together data

- `left_join()`
- `full_join()`

Why merge?!

In practice, we often collect data from different sources. To analyze the data, we usually must first combine (merge) them.

For example, imagine you would like to study county-level patterns with respect to age and grocery spending. However, you can only find,

- County level age data from the US Census, and
- County level grocery spending data from the US Department of Agriculture

Merge the data!!

Merging in Concept

When merging datasets `A` and `B`, ask yourself the following two questions:

- Which **rows** do I want to keep?
  - All rows in `A`?
  - All rows in both `A` and `B`?
- How do my datasets **connect**?
  - Is there a specific variable they have in common?
  - Multiple variables they have in common?

Which Rows to Keep:

We'll focus on two types of joins:[1]...

- `A %>% left_join(B)`: keeps `A` and adds variables from `B` after matching.
- `A %>% full_join(B)`: keeps all of `A` and `B`, but combines rows when possible.

[1] Other types include `right_join`, `inner_join`, `semi_join`, and `anti_join`, but we won't study those here.

Matching Criteria

We have to tell R **which variables** to use when merging datasets! Rows are matched when the values in matching variables are equivalent.

- `by = c("County")`: Both datasets have a `County` variable, match on this!
- `by = c("CountyName" = "County_Name")`: Match `CountyName` in `A` with `County_Name` in `B`

Example: `nycflights13` Data

The `nycflights13` package includes five data frames, some of which contain missing data (`NA`):

- `flights`: flights leaving JFK, LGA, or EWR in 2013
- `airlines`: airline abbreviations
- `airports`: airport metadata
- `planes`: airplane metadata
- `weather`: hourly weather data for JFK, LGA, and EWR

```r
# install.packages("nycflights13")
library(nycflights13)
```

Join Example 1

`flights` has one row per flight, with abbreviated airline names.

```
flights %>% select(flight,origin,dest,carrier) %>% head(2)
```

```
## # A tibble: 2 × 4
##   flight origin dest  carrier
##    <int> <chr>  <chr> <chr>
## 1   1545 EWR    IAH   UA
## 2   1714 LGA    IAH   UA
```

`airlines` has one row per airline, with airline abbreviations *and* full names

```
airlines %>% head(2)
```

```
## # A tibble: 2 × 2
##   carrier name
##   <chr>   <chr>
## 1 9E      Endeavor Air Inc.
## 2 AA      American Airlines Inc.
```

Join Example 1 (continued)

Let's left join `flights` with `airlines` to add full airline name to each flight record!

```
flights %>% select(flight,origin,dest,carrier) %>%
  left_join(airlines, by = "carrier")  %>%
  head(5)
```

```
## # A tibble: 5 × 5
##   flight origin dest  carrier name
##    <int> <chr>  <chr> <chr>   <chr>
## 1   1545 EWR    IAH   UA      United Air Lines Inc.
## 2   1714 LGA    IAH   UA      United Air Lines Inc.
## 3   1141 JFK    MIA   AA      American Airlines Inc.
## 4    725 JFK    BQN   B6      JetBlue Airways
## 5    461 LGA    ATL   DL      Delta Air Lines Inc.
```

We now have one row per flight, with both carrier abbreviations and full names!

Join Example #2

`flights` also includes a `tailnum` variable for each plane's tail number.

```
flights %>% select(flight,origin,dest,tailnum) %>% head(2)
```

```
## # A tibble: 2 × 4
##   flight origin dest  tailnum
##    <int> <chr>  <chr> <chr>
## 1   1545 EWR    IAH   N14228
## 2   1714 LGA    IAH   N24211
```

`planes` includes a row for each plane type, including the manufacturer.

```
planes %>% select(tailnum,year,manufacturer,model) %>% head(2)
```

```
## # A tibble: 2 × 4
##   tailnum  year manufacturer     model
##   <chr>   <int> <chr>            <chr>
## 1 N10156   2004 EMBRAER          EMB-145XR
## 2 N102UW   1998 AIRBUS INDUSTRIE A320-214
```

Join Example 2 (continued)

Let's left join `flights` with `planes` to add manufacture to each flight record!

```
flights %>% select(flight,origin,dest,tailnum) %>%
  left_join(planes, by = "tailnum")  %>%
  head(5)
```

```
## # A tibble: 5 × 12
##   flight origin dest  tailnum  year type            manuf…¹ model engines se
##    <int> <chr>  <chr> <chr>   <int> <chr>           <chr>   <chr>   <int> <i
## 1   1545 EWR    IAH   N14228   1999 Fixed wing m… BOEING  737-…       2
## 2   1714 LGA    IAH   N24211   1998 Fixed wing m… BOEING  737-…       2
## 3   1141 JFK    MIA   N619AA   1990 Fixed wing m… BOEING  757-…       2
## 4    725 JFK    BQN   N804JB   2012 Fixed wing m… AIRBUS  A320…       2
## 5    461 LGA    ATL   N668DN   1991 Fixed wing m… BOEING  757-…       2
## # … with abbreviated variable name ¹manufacturer
```

A bunch of columns from `planes` are now in the dataset!

Join Example 2 (continued)

Let's remove some of the "spare" columns

```
flights %>% select(flight,origin,dest,tailnum) %>%
  left_join(planes, by = "tailnum")  %>%
  select(flight,origin,dest,manufacturer,model) %>%
  head(5)
```

```
## # A tibble: 5 × 5
##   flight origin dest  manufacturer model
##    <int> <chr>  <chr> <chr>        <chr>
## 1   1545 EWR    IAH   BOEING       737-824
## 2   1714 LGA    IAH   BOEING       737-824
## 3   1141 JFK    MIA   BOEING       757-223
## 4    725 JFK    BQN   AIRBUS       A320-232
## 5    461 LGA    ATL   BOEING       757-232
```

Summary

1. Logical Operators (`&, |, ==, <, %in%,` etc.)
2. Subsetting (`filter, select, distinct`)
3. Modifying (`arrange, rename, mutate`)
4. Summarizing (`summarize, group_by`)
5. Merging (`left_join, full_join`)

Let's take a 10-minute break, then come back together to practice!

Activity

1. Create a new object that contains `gapminder` (1) observations from China, India, and United States after 1980, and (2) variables corresponding to country, year, population, and life expectancy.
2. How many rows and columns does the object contain?
3. Save over your object after sorting the rows by year (ascending order) and population (descending order). Print the first 6 rows.
4. Add a new variable that contains population in billions.
5. By year, calculate the total population (in billions) across these three countries
6. In ggplot, create a line plot showing life expectancy over time by country. Make the plot visually appealing!

My Answers

Question 1:

```
subset_gapminder <- gapminder %>%
  filter(country %in% c("China","India","United States"),
         year >1980 ) %>%
  select(country, year, pop, lifeExp)
```

Question 2:

```
c(nrow(subset_gapminder),ncol(subset_gapminder))
```

```
## [1] 18  4
```

My Answers

Question 3:

```
subset_gapminder <- subset_gapminder %>% arrange(year,desc(pop))
subset_gapminder %>% head(6)
```

```
## # A tibble: 6 × 4
##   country        year        pop lifeExp
##   <fct>         <int>      <int>   <dbl>
## 1 China          1982 1000281000    65.5
## 2 India          1982  708000000    56.6
## 3 United States  1982  232187835    74.6
## 4 China          1987 1084035000    67.3
## 5 India          1987  788000000    58.6
## 6 United States  1987  242803533    75.0
```

Question 4:

```
subset_gapminder <- subset_gapminder %>%
  mutate(pop_billions = pop/1000000000)
```

My Answers

Question 5:

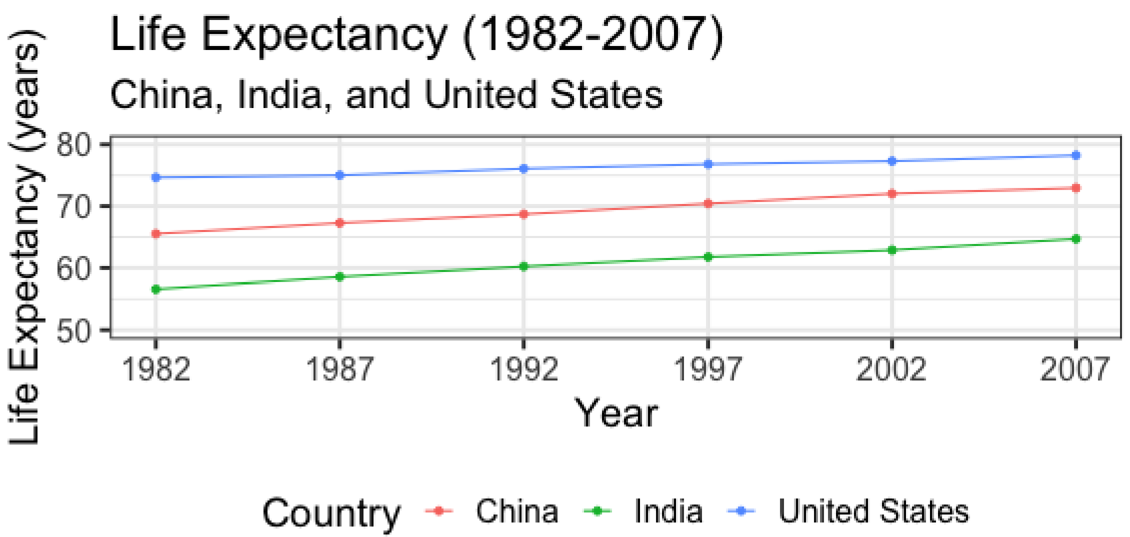
```
subset_gapminder %>% group_by(year) %>%
  summarize(TotalPop_Billions = sum(pop_billions))
```

```
## # A tibble: 6 × 2
##    year TotalPop_Billions
##   <int>             <dbl>
## 1  1982              1.94
## 2  1987              2.11
## 3  1992              2.29
## 4  1997              2.46
## 5  2002              2.60
## 6  2007              2.73
```

My Answers

Question 6

```r
library(ggplot2)
ggplot(subset_gapminder,aes(year,lifeExp,color=country,group=country))+
  theme_bw(base_size=20)+geom_point()+geom_line()+
  xlab("Year")+ylab("Life Expectancy (years)")+
  ggtitle("Life Expectancy (1982-2007)","China, India, and United States")+
  scale_x_continuous(breaks=c(1982,1987,1992,1997,2002,2007),minor_breaks = c())+
  ylim(c(50,80))+scale_color_discrete(name="Country")+theme(legend.position = "bottom")
```



Homework 3

Create an RMarkdown file (from scratch this time!) in which you answer each of the following questions. Be sure to display **all your code in the knitted** version (use throughout `echo=TRUE`).

Remember, the package `nycflights13` contains data on flights originating in NYC during the year 2013. There are three airports servicing NYC: JFK, LGA ("LaGuardia"), and EWR ("Newark").

1. Choose an airport outside New York, and count how many flights went to that airport from NYC in 2013. How many of those flights started at JFK, LGA, and EWR? (Hint: Use `filter`, `group_by`, and `summarize`)
2. The variable `arr_delay` contains arrival delays in minutes (negative values represent early arrivals). Make a `ggplot` histogram displaying arrival delays for 2013 flights from NYC to the airport you chose.
3. Use `left_join` to add weather data at departure to the subsetted data (Hint 1: Match on `origin`, `year`, `month`, `day`, **and** `hour`!!). Calculate the mean temperature by month at departure (`temp`) across all flights (Hint 2: Use `mean(temp,na.rm=T)` to have R calculate an average after ignoring missing data values).
4. Investigate if there is a relationship between departure delay (`dep_delay`) and wind speed (`wind_speed`). Is the relationship different between JFK, LGA, and EWR? I suggest answering this question by making a plot and writing down a one-sentence interpretation.

As always, submit both the .Rmd and knitted .html to Canvas.