CSSS508, Week 3

Manipulating and Summarizing Data

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October 13, 2021

Updated: Oct 13, 2021

Death to Spreadsheets

Today we'll talk more about `dplyr`: a package that does in R just about any calculation you've tried to do in Excel, but more *transparently*, *reproducibly*, and *safely*.

Don't be the next sad research assistant who makes headlines with an Excel error (Reinhart & Rogoff, 2010)

Modifying Data Frames with `dplyr`

But First, Pipes (%>%)

`dplyr` uses the `magrittr` forward pipe operator, usually called simply a **pipe**. We write pipes like `%>%` (`Ctrl+Shift+M`).

Pipes take the object on the *left* and apply the function on the *right*:

`object %>% function(argument = y)` is the same as

`function(object, argument = y)`.

Read aloud the `%>%` is "and then".

But First, Pipes (%>%)

```
library(dplyr)
library(gapminder)
gapminder %>% filter(country == "Canada") %>% head(4)
```

```
## # A tibble: 4 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.
```

Pipes save us typing, make code readable, and allow chaining like above, so we use them *all the time* when manipulating data frames.

Using Pipes

Pipes are clearer to read when you have each function on a separate line (inconsistent in these slides because of space constraints).

```
take_these_data %>%
    do_first_thing(with = this_value) %>%
    do_next_thing(using = that_value) %>% ...
```

Stuff to the left of the pipe is passed to the *first argument* of the function on the right. Other arguments go on the right in the function.

If you ever find yourself piping a function where data are not the first argument, use `.` in the data argument instead.

```
gapminder %>% lm(pop ~ year, data = .)
```

Pipe Assignment

When creating a new object from the output of piped functions, place the assignment operator at the beginning.

```
lm_pop_year <- gapminder %>%
  filter(continent == "Americas") %>%
  lm(pop ~ year, data = .)
```

No matter how long the chain of functions is, assignment is always done at the top.[1]

[1] Note this is just a stylistic convention: If you prefer, you *can* do assignment at the end of the chain.

Filtering Rows (subsetting)

Recall last week we used the `filter()` command to subset data like so:

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

```
## # A tibble: 6 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.
```

Excel analogue: Filter!

Another Operator: `%in%`

Common use case: Filter rows to things in some *set*.

We can use `%in%` like `==` but for matching *any element* in the vector on its right[1].

```
former_yugoslavia <- c("Bosnia and Herzegovina", "Croatia",
                       "Montenegro", "Serbia", "Slovenia")

yugoslavia <- gapminder %>% filter(country %in% former_yugoslavia)
slice(yugoslavia, 12:14)
```

```
## # A tibble: 3 x 6
##   country                continent  year lifeExp     pop gdpPercap
##   <fct>                  <fct>     <int>   <dbl>   <int>     <dbl>
## 1 Bosnia and Herzegovina Europe     2007    74.9 4552198     7446.
## 2 Croatia                Europe     1952    61.2 3882229     3119.
## 3 Croatia                Europe     1957    64.8 3991242     4338.
```

[1] The `c()` function is how we make **vectors** in R, which are an important data type.

`distinct()`

You can see all the *unique values* in your data for combinations of columns using `distinct()`:

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

```
## # A tibble: 60 x 2
##    continent  year
##    <fct>     <int>
##  1 Asia       1952
##  2 Asia       1957
##  3 Asia       1962
##  4 Asia       1967
##  5 Asia       1972
##  6 Asia       1977
##  7 Asia       1982
##  8 Asia       1987
##  9 Asia       1992
## 10 Asia       1997
## # ... with 50 more rows
```

`distinct()` drops unused variables!

Note that the default behavior of `distinct()` is to drop all unspecified columns. If you want to get distinct rows by certain variables without dropping the others, use `distinct(.keep_all=TRUE)`:

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

```
## # A tibble: 60 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 50 more rows
```

Sampling Rows: `sample_n()`

We can also filter *at random* to work with a smaller dataset using `sample_n()` or `sample_frac()`.

```
set.seed(789) # makes random numbers repeatable
yugoslavia %>% sample_n(size = 6, replace = FALSE)
```

```
## # A tibble: 6 x 6
##   country                continent  year lifeExp      pop gdpPercap
##   <fct>                  <fct>     <int>   <dbl>    <int>     <dbl>
## 1 Serbia                 Europe     1992    71.7  9826397     9325.
## 2 Serbia                 Europe     2007    74.0 10150265     9787.
## 3 Bosnia and Herzegovina Europe     2007    74.9  4552198     7446.
## 4 Slovenia               Europe     1967    69.2  1646912     9405.
## 5 Serbia                 Europe     1977    70.3  8686367    12981.
## 6 Montenegro             Europe     1957    61.4   442829     3682.
```

Use `set.seed()` to make all random numbers in a file come up *exactly the same* each time it is run. Read *Details* in `?set.seed` if you like your brain to hurt.

Sorting: `arrange()`

Along with filtering the data to see certain rows, we might want to sort it:

```
yugoslavia %>% arrange(year, desc(pop))
```

```
## # A tibble: 60 x 6
##    country                continent  year lifeExp     pop gdpPercap
##    <fct>                  <fct>     <int>   <dbl>   <int>     <dbl>
##  1 Serbia                 Europe     1952    58.0 6860147     3581.
##  2 Croatia                Europe     1952    61.2 3882229     3119.
##  3 Bosnia and Herzegovina Europe     1952    53.8 2791000      974.
##  4 Slovenia               Europe     1952    65.6 1489518     4215.
##  5 Montenegro             Europe     1952    59.2  413834     2648.
##  6 Serbia                 Europe     1957    61.7 7271135     4981.
##  7 Croatia                Europe     1957    64.8 3991242     4338.
##  8 Bosnia and Herzegovina Europe     1957    58.4 3076000     1354.
##  9 Slovenia               Europe     1957    67.8 1533070     5862.
## 10 Montenegro             Europe     1957    61.4  442829     3682.
## # ... with 50 more rows
```

The data are sorted by ascending `year` and descending `pop`.

Keeping Columns: `select()`

Not only can we limit rows, but we can include specific columns (and put them in the order listed) using `select()`.

```
yugoslavia %>% select(country, year, pop) %>% head(4)
```

```
## # A tibble: 4 x 3
##   country                 year     pop
##   <fct>                  <int>   <int>
## 1 Bosnia and Herzegovina  1952 2791000
## 2 Bosnia and Herzegovina  1957 3076000
## 3 Bosnia and Herzegovina  1962 3349000
## 4 Bosnia and Herzegovina  1967 3585000
```

Dropping Columns: `select()`

We can instead drop only specific columns with `select()` using `-` signs:

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

```
## # A tibble: 4 x 3
##   country                  year gdpPercap
##   <fct>                   <int>     <dbl>
## 1 Bosnia and Herzegovina  1952      974.
## 2 Bosnia and Herzegovina  1957     1354.
## 3 Bosnia and Herzegovina  1962     1710.
## 4 Bosnia and Herzegovina  1967     2172.
```

Helper Functions for `select()`

`select()` has a variety of helper functions like `starts_with()`, `ends_with()`, and `contains()`, or can be given a range of contiguous columns `startvar:endvar`. See `?select` for details.

These are very useful if you have a "wide" data frame with column names following a pattern or ordering.

```
# A tibble: 6 x 292
  married10 married11 married12 married13 married14 married15 married16 married17 married18 married19 married20
      <dbl>     <dbl>     <dbl>     <dbl>     <dbl>     <dbl>     <dbl>     <dbl>     <dbl>     <dbl>     <dbl>
1        NA        NA         0         0         0         0         0         0         0         0         0
2        NA        NA        NA        NA         0         0         0         0         1         1        NA
3        NA        NA         0        NA         0         0         0         0         0         0        NA
4        NA        NA        NA        NA         0         0         0         0         0         0         0
5        NA        NA         0         0         0         0         0         0         0         0         0
6        NA        NA         0         0         0         0         0         0         0         0         0
# ... with 281 more variables: married21 <dbl>, married22 <dbl>, married23 <dbl>, married24 <dbl>,
#   married25 <dbl>, married26 <dbl>, in_school10 <dbl>, in_school11 <dbl>, in_school12 <dbl>, in_school13 <dbl>,
#   in_school14 <dbl>, in_school15 <dbl>, in_school16 <dbl>, in_school17 <dbl>, in_school18 <dbl>,
#   in_school19 <dbl>, in_school20 <dbl>, in_school21 <dbl>, in_school22 <dbl>, in_school23 <dbl>,
```

```
DYS %>% select(starts_with("married"))
DYS %>% select(ends_with("18"))
```

`select(where())`

An especially useful helper for `select()` is `where()` which can be used for selecting columns based on functions that check column types.

```
gapminder %>% select(where(is.numeric)) %>% head(3)
```

```
## # A tibble: 3 x 4
##    year lifeExp      pop gdpPercap
##   <int>   <dbl>    <int>     <dbl>
## 1  1952    28.8  8425333      779.
## 2  1957    30.3  9240934      821.
## 3  1962    32.0 10267083      853.
```

```
gapminder %>% select(where(is.factor)) %>% head(3)
```

```
## # A tibble: 3 x 2
##   country     continent
##   <fct>       <fct>
## 1 Afghanistan Asia
## 2 Afghanistan Asia
## 3 Afghanistan Asia
```

`int` (integer) and `dbl` (double) are both types of `numeric` data.

Renaming Columns with `select()`

We can rename columns using `select()`, but that drops everything that isn't mentioned:

```
yugoslavia %>%
    select(Life_Expectancy = lifeExp) %>%
    head(4)
```

```
## # A tibble: 4 x 1
##   Life_Expectancy
##             <dbl>
## 1            53.8
## 2            58.4
## 3            61.9
## 4            64.8
```

Safer: Rename Columns with `rename()`

`rename()` renames variables using the same syntax as `select()` without dropping unmentioned variables.

```
yugoslavia %>%
    select(country, year, lifeExp) %>%
    rename(Life_Expectancy = lifeExp) %>%
    head(4)
```

```
## # A tibble: 4 x 3
##   country                 year Life_Expectancy
##   <fct>                  <int>           <dbl>
## 1 Bosnia and Herzegovina  1952            53.8
## 2 Bosnia and Herzegovina  1957            58.4
## 3 Bosnia and Herzegovina  1962            61.9
## 4 Bosnia and Herzegovina  1967            64.8
```

Column Naming Practices

- *Good* column names will be self-describing. Don't use inscrutable abbreviations to save typing. RStudio's autocompleting functions take away the pain of long variable names: Hit `TAB` while writing code to autocomplete.

- *Valid* "naked" column names can contain upper or lowercase letters, numbers, periods, and underscores. They must start with a letter or period and not be a special reserved word (e.g. `TRUE`, `if`).

- Names are case-sensitive: `Year` and `year` are not the same thing!

- You can include spaces or use reserved words if you put backticks around the name. Spaces can be worth including when preparing data for `ggplot2` or `pander` since you don't have to rename axes or table headings.

Column Name with Space Example

```
library(pander)
```

```
## Warning: package 'pander' was built under R version 4.0.5
```

```
yugoslavia %>% filter(country == "Serbia") %>%
    select(year, lifeExp) %>%
    rename(Year = year, `Life Expectancy` = lifeExp) %>%
    head(5) %>%
    pander(style = "rmarkdown", caption = "Serbian life expectancy")
```

Year	Life Expectancy
1952	58
1957	61.69
1962	64.53
1967	66.91
1972	68.7

Table: Serbian life expectancy

Create New Columns: `mutate()`

In `dplyr`, you can add new columns to a data frame using `mutate()`.

```
yugoslavia %>% filter(country == "Serbia") %>%
    select(year, pop, lifeExp) %>%
    mutate(pop_million = pop / 1000000,
           life_exp_past_40 = lifeExp - 40) %>%
    head(5)
```

```
## # A tibble: 5 x 5
##    year     pop lifeExp pop_million life_exp_past_40
##   <int>   <int>   <dbl>       <dbl>            <dbl>
## 1  1952 6860147    58.0        6.86             18.0
## 2  1957 7271135    61.7        7.27             21.7
## 3  1962 7616060    64.5        7.62             24.5
## 4  1967 7971222    66.9        7.97             26.9
## 5  1972 8313288    68.7        8.31             28.7
```

Note you can create multiple variables in a single `mutate()` call by separating the expressions with commas.

`ifelse()`

A common function used in `mutate()` (and in general in R programming) is `ifelse()`. It returns a vector of values depending on a logical test.

```
ifelse(test = x==y, yes = first_value , no = second_value)
```

Output from `ifelse()` if `x==y` is...

- `TRUE`: `first_value` - the value for `yes =`
- `FALSE`: `second_value` - the value for `no =`
- `NA`: `NA` - because you can't test for NA with an equality!

For example:

```
example <- c(1, 0, NA, -2)
ifelse(example > 0, "Positive", "Not Positive")
```

```
## [1] "Positive"     "Not Positive" NA             "Not Positive"
```

`ifelse()` Example

```
yugoslavia %>% mutate(short_country =
                 ifelse(country == "Bosnia and Herzegovina",
                        "B and H", as.character(country))) %>%
    select(country, short_country, year, pop) %>%
    arrange(year, short_country) %>% head(3)
```

```
## # A tibble: 3 x 4
##   country                short_country  year     pop
##   <fct>                  <chr>         <int>   <int>
## 1 Bosnia and Herzegovina B and H        1952 2791000
## 2 Croatia                Croatia        1952 3882229
## 3 Montenegro             Montenegro     1952  413834
```

Read this as "For each row, if `country` equals 'Bosnia and Herzegovina', make `short_country` equal to 'B and H', otherwise make it equal to that row's value of `country`."

This is a simple way to change some values but not others!

Note: `country` is a factor--use `as.character()` to convert to character.

recode()

`recode()` is another useful function to use inside `mutate()`. Use `recode()` to change specific values to other values, particularly with factors. You can change multiple values at the same time. Note if a value has spaces in it, you'll need to put it in backticks!

```
yugoslavia %>%
  mutate(country = recode(country,
                          `Bosnia and Herzegovina`="B and H",
                          Montenegro="M")) %>%
  distinct(country)
```

```
## # A tibble: 5 x 1
##   country
##   <fct>
## 1 B and H
## 2 Croatia
## 3 M
## 4 Serbia
## 5 Slovenia
```

`case_when()`

`case_when()` performs multiple `ifelse()` operations at the same time. `case_when()` allows you to create a new variable with values based on multiple logical statements. This is useful for making categorical variables or variables from combinations of other variables.

```
gapminder %>%
  mutate(gdpPercap_ordinal =
    case_when(
      gdpPercap <  700 ~ "low",
      gdpPercap >= 700 & gdpPercap < 800 ~ "moderate",
      TRUE ~ "high" )) %>% # Value when all other statements are FALSE
  slice(6:9) # get rows 6 through 9
```

```
## # A tibble: 4 x 7
##   country     continent  year lifeExp      pop gdpPercap gdpPercap_ordinal
##   <fct>       <fct>     <int>   <dbl>    <int>     <dbl> <chr>
## 1 Afghanistan Asia       1977    38.4 14880372      786. moderate
## 2 Afghanistan Asia       1982    39.9 12881816      978. high
## 3 Afghanistan Asia       1987    40.8 13867957      852. high
## 4 Afghanistan Asia       1992    41.7 16317921      649. low
```

`pull()`

Sometimes you want to extract a single column from a data frame as a *vector* (or single value).

`pull()` *pulls* a column of a data frame out as a vector.

```
gapminder %>% pull(lifeExp) %>% head(4)
```

```
## [1] 28.801 30.332 31.997 34.020
```

```
gapminder %>% select(lifeExp) %>% head(4)
```

```
## # A tibble: 4 x 1
##   lifeExp
##     <dbl>
## 1    28.8
## 2    30.3
## 3    32.0
## 4    34.0
```

Note the difference between these two operations: The second yields only one column but is still a data frame.

In-Line `pull()`

`pull()` is particularly useful when you want to use a vector-only command in a `dplyr` chain of functions (say, in an in-line expression).

This in-line code...

`The average life expectancy in Afghanistan from 1952 to 2007 was `r gapminder %>% filter(country=="Afghanistan") %>% pull(lifeExp) %>% mean() %>% round(1)` years.`

... will produce this output:

The average life expectancy in Afghanistan from 1952 to 2007 was 37.5 years.

`mean()` can only take a *vector* input, not a dataframe, so this won't work with `select(lifeExp)` instead of `pull(lifeExp)`.

Summarizing with `dplyr`

General Aggregation: `summarize()`

`summarize()`[1] takes your column(s) of data and computes something using every row:

- Count how many rows there are
- Calculate the mean
- Compute the sum
- Obtain a minimum or maximum value

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

[1] Note: Can also be written `summarise()`

`summarize()` Example

For the year 1982, let's get the number of observations, total population, mean life expectancy, and range of life expectancy for former Yugoslavian countries.

```
yugoslavia %>%
    filter(year == 1982) %>%
    summarize(n_obs          = n(),
              total_pop      = sum(pop),
              mean_life_exp  = mean(lifeExp),
              range_life_exp = max(lifeExp) - min(lifeExp))
```

```
## # A tibble: 1 x 4
##   n_obs total_pop mean_life_exp range_life_exp
##   <int>     <int>         <dbl>          <dbl>
## 1     5  20042685          71.3           3.94
```

These new variables are calculated using *all of the rows* in `yugoslavia`

Avoiding Repetition

`summarize(across())`

Maybe you need to calculate the mean and standard deviation of a bunch of columns. With `across()`, put the variables to compute (using `c()` or `select()` syntax) and put the functions to use in a `list()` after.

```
yugoslavia %>%
  filter(year == 1982) %>%
  summarize(across(c(lifeExp, pop), list(avg = ~mean(.), sd = ~sd(.))))
```

```
## # A tibble: 1 x 4
##   lifeExp_avg lifeExp_sd pop_avg   pop_sd
##         <dbl>      <dbl>   <dbl>    <dbl>
## 1        71.3       1.60 4008537 3237282.
```

Note it automatically names the summarized variables based on the names given in `list()`.

Whoa, too many `(` and `)`

It can get hard to read code with lots of **nested** functions--functions inside others.

Break things up when it gets confusing!

```
yugoslavia %>%
  filter(year == 1982) %>%
  summarize(
    across(
      c(lifeExp, pop),
      list(
        avg = ~mean(.),
        sd = ~sd(.)
      )
    )
  )
```

RStudio also helps you by tracking parentheses: Put your cursor after a `)` and see! Or set [rainbow parentheses](#)

Avoiding Repetition

There are additional ways to use `across()` for repetitive operations:

- `across(everything())` will summarize / mutate *all* variables sent to it in the same way. For instance, getting the mean and standard deviation of an entire dataframe:

```
dataframe %>%
  summarize(across(everything(), list(mean = ~mean(.), sd = ~sd(.))))
```

- `across(where())` will summarize / mutate all variables that satisfy some logical condition. For instance, summarizing every numeric column in a dataframe at once:

```
dataframe %>%
  summarize(across(where(is.numeric), list(mean = ~mean(.), sd = ~sd(.))))
```

You can use all of these to avoid typing out the same code repeatedly!

`group_by()`

The special function `group_by()` changes how functions operate on the data, most importantly `summarize()`.

Functions after `group_by()` are computed *within each group* as defined by variables given, rather than over all rows at once. Typically the variables you group by will be integers, factors, or characters, and not continuous real values.

Excel analogue: pivot tables

	A	B	C	D	E	F	G	H	I	J
1	Category	(All)								
2										
3	**Sum of Amount**	**Column**								
4	**Row Labels**	**Apple**	**Banana**	**Beans**	**Broccoli**	**Carrots**	**Mango**	**Orange**	**Grand Total**	
5	Australia	20634	52721	14433	17953	8106	9186	8680	131713	
6	Canada	24867	33775		12407		3767	19929	94745	
7	France	80193	36094	680	5341	9104	7388	2256	141056	
8	Germany	9082	39686	29905	37197	21636	8775	8887	155168	
9	New Zealand	10332	40050		4390			12010	66782	
10	United Kingdom	17534	42908	5100	38436	41815	5600	21744	173137	
11	United States	28615	95061	7163	26715	56284	22363	30932	267133	
12	**Grand Total**	**191257**	**340295**	**57281**	**142439**	**136945**	**57079**	**104438**	**1029734**	
13										

`group_by()` example

```
yugoslavia %>%
  group_by(year) %>%
    summarize(num_countries     = n_distinct(country),
              total_pop         = sum(pop),
              total_gdp_per_cap = sum(pop*gdpPercap)/total_pop) %>%
    head(5)
```

```
## # A tibble: 5 x 4
##    year num_countries total_pop total_gdp_per_cap
##   <int>         <int>     <int>             <dbl>
## 1  1952             5  15436728             3030.
## 2  1957             5  16314276             4187.
## 3  1962             5  17099107             5257.
## 4  1967             5  17878535             6656.
## 5  1972             5  18579786             8730.
```

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

Each value of year is its own **group**!

Window Functions

Grouping can also be used with `mutate()` or `filter()` to give rank orders within a group, lagged values, and cumulative sums. You can read more about window functions in this vignette.

```
yugoslavia %>%
  select(country, year, pop) %>%
  filter(year >= 2002) %>%
  group_by(country) %>%
  mutate(lag_pop = lag(pop, order_by = year),
         pop_chg = pop - lag_pop) %>%
  head(4)
```

```
## # A tibble: 4 x 5
## # Groups:   country [2]
##   country                 year     pop lag_pop pop_chg
##   <fct>                  <int>   <int>   <int>   <int>
## 1 Bosnia and Herzegovina  2002 4165416      NA      NA
## 2 Bosnia and Herzegovina  2007 4552198 4165416  386782
## 3 Croatia                 2002 4481020      NA      NA
## 4 Croatia                 2007 4493312 4481020   12292
```

Joining (Merging) Data Frames

When Do We Need to Join Tables?

- Want to make columns using criteria too complicated for `ifelse()` or `case_when()`
    - We can work with small sets of variables then combine them back together.
- Combine data stored in separate data sets: e.g. Local lockdown measures and stationary bike sales.
    - Often large surveys are broken into different data sets for each level (e.g. household, individual, neighborhood)

Concept: Joins

We need to think about the following when we want to merge data frames `A` and `B`:

- Which *rows* are we keeping from each data frame?
- Which *columns* are we keeping from each data frame?
- Which variables determine whether rows *match*?

Join Types: Rows and columns kept

There are many types of joins[1]...

- `A %>% left_join(B)`: keep all rows from `A`, matched with `B` wherever possible (`NA` when not), keep columns from both `A` and `B`
- `A %>% right_join(B)`: keep all rows from `B`, matched with `A` wherever possible (`NA` when not), keep columns from both `A` and `B`
- `A %>% inner_join(B)`: keep only rows from `A` and `B` that match, keep columns from both `A` and `B`
- `A %>% full_join(B)`: keep all rows from both `A` and `B`, matched wherever possible (`NA` when not), keep columns from both `A` and `B`
- `A %>% semi_join(B)`: keep rows from `A` that match rows in `B`, keep columns from only `A`
- `A %>% anti_join(B)`: keep rows from `A` that *don't* match a row in `B`, keep columns from only `A`

[1] Usually `left_join()` does the job.

Matching Criteria

We say rows should *match* because they have some columns containing the same value. We list these in a `by =` argument to the join.

Matching Behavior:

- No `by`: Match using all variables in `A` and `B` that have identical names
- `by = c("var1", "var2", "var3")`: Match on identical values of `var1`, `var2`, and `var3` in both `A` and `B`
- `by = c("Avar1" = "Bvar1", "Avar2" = "Bvar2")`: Match identical values of `Avar1` variable in `A` to `Bvar1` variable in `B`, and `Avar2` variable in `A` to `Bvar2` variable in `B`

Note: If there are multiple matches, you'll get *one row for each possible combination* (except with `semi_join()` and `anti_join()`).

Need to get more complicated? Break it into multiple operations.

`nycflights13` Data

We'll use data in the [`nycflights13` package](). Install and load it:

```
# install.packages("nycflights13") # Uncomment to run
library(nycflights13)
```

It includes five dataframes, 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

Note these are *separate data frames*, each needing to be *loaded separately*:

```
data(flights)
data(airlines)
data(airports)
# and so on...
```

Join Example #1

Who manufactures the planes that flew to Seattle?

```
flights %>% filter(dest == "SEA") %>% select(tailnum) %>%
    left_join(planes %>% select(tailnum, manufacturer),
              by = "tailnum") %>%
    count(manufacturer) %>% # Count observations by manufacturer
    arrange(desc(n)) # Arrange data descending by count
```

```
## # A tibble: 6 x 2
##   manufacturer           n
##   <chr>              <int>
## 1 BOEING              2659
## 2 AIRBUS               475
## 3 AIRBUS INDUSTRIE     394
## 4 <NA>                 391
## 5 BARKER JACK L          2
## 6 CIRRUS DESIGN CORP     2
```

Note you can perform operations on the data inside functions such as `left_join()` and the *output* will be used by the function.

Join Example #2

Which airlines had the most flights to Seattle from NYC?

```
flights %>% filter(dest == "SEA") %>%
    select(carrier) %>%
    left_join(airlines, by = "carrier") %>%
    group_by(name) %>%
    tally() %>%
    arrange(desc(n))
```

```
## # A tibble: 5 x 2
##   name                        n
##   <chr>                   <int>
## 1 Delta Air Lines Inc.     1213
## 2 United Air Lines Inc.    1117
## 3 Alaska Airlines Inc.      714
## 4 JetBlue Airways           514
## 5 American Airlines Inc.    365
```

`tally()` is a shortcut for `summarize(n(.))`: It creates a variable `n` equal to the number of rows in each group.

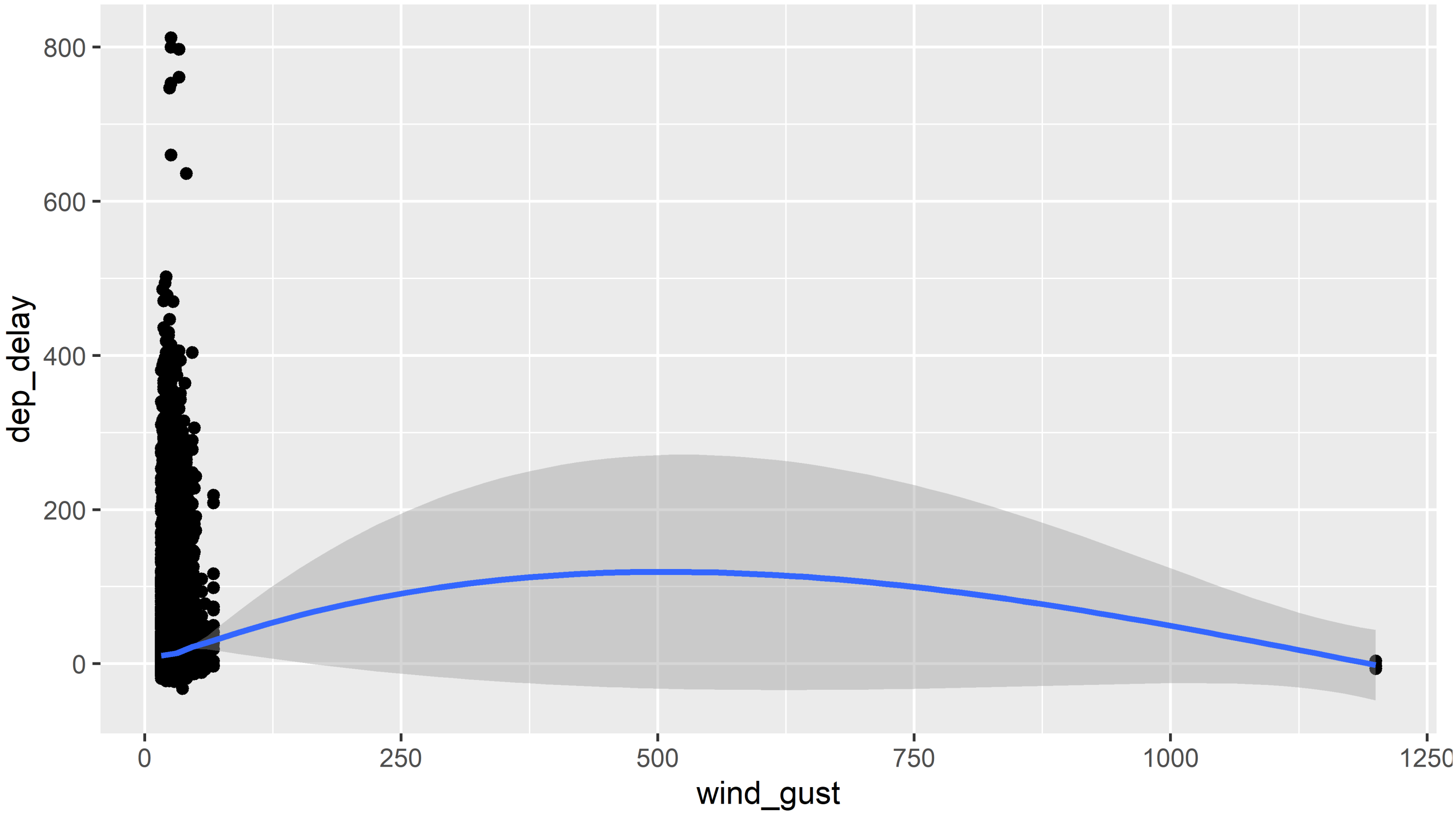
Join Example #3

Is there a relationship between departure delays and wind gusts?

```
library(ggplot2)
flights %>%
    select(origin, year, month, day, hour, dep_delay) %>%
    inner_join(weather,
           by = c("origin", "year", "month", "day", "hour")) %>%
    select(dep_delay, wind_gust) %>%
    # removing rows with missing values
    filter(!is.na(dep_delay) & !is.na(wind_gust)) %>%
    ggplot(aes(x = wind_gust, y = dep_delay)) +
      geom_point() +
      geom_smooth()
```

Because the data are the first argument for `ggplot()`, we can pipe them straight into a plot.

Wind Gusts and Delays



Check out those 1200 mph winds![1]

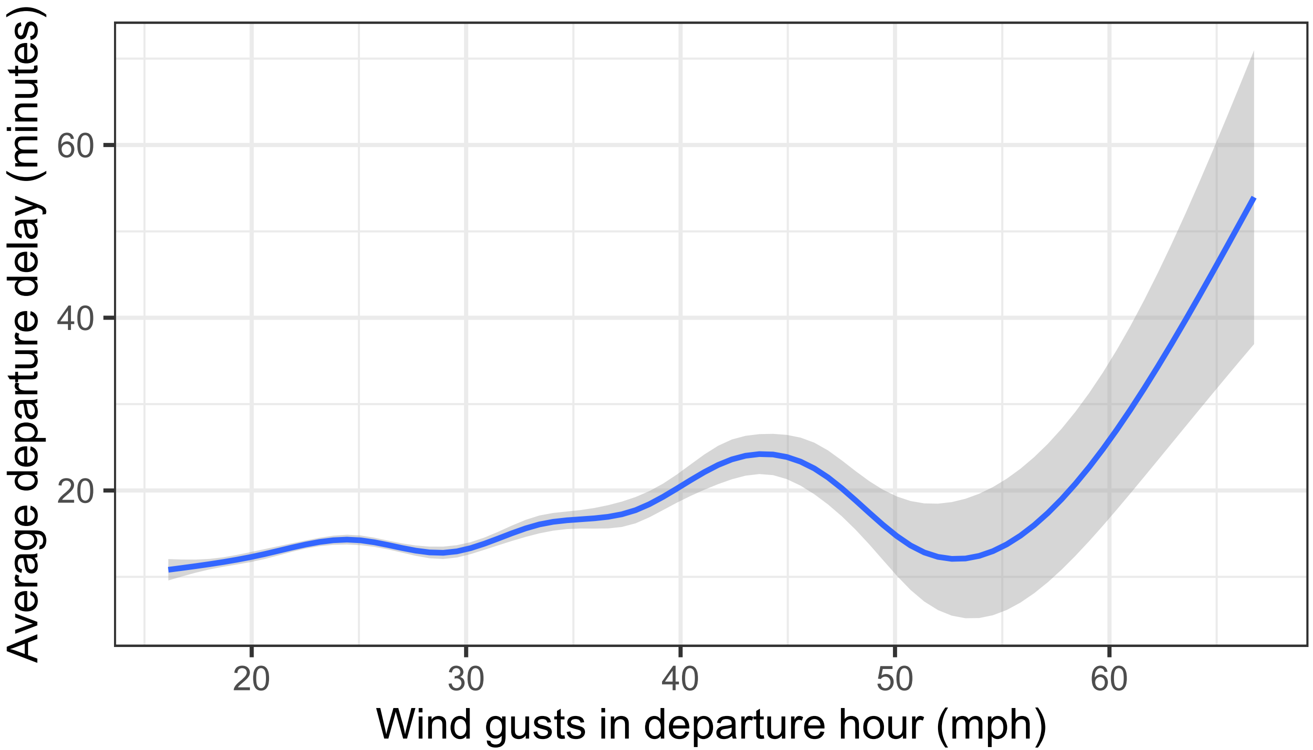
[1] These observations appear to have been fixed in the current data.

Redo After Removing Extreme Outliers, Just Trend

```
flights %>%
    select(origin, year, month, day, hour, dep_delay) %>%
    inner_join(weather, by = c("origin", "year", "month", "day", "hour")) %>%
    select(dep_delay, wind_gust) %>%
    filter(!is.na(dep_delay) & !is.na(wind_gust) & wind_gust < 250) %>%
    ggplot(aes(x = wind_gust, y = dep_delay)) +
      geom_smooth() +
      theme_bw(base_size = 16) +
      xlab("Wind gusts in departure hour (mph)") +
      ylab("Average departure delay (minutes)")
```

I removed `geom_point()` to focus on the mean trend produced by `geom_smooth()`.

Wind Gusts and Delays: Mean Trend



Tinkering Suggestions

Some possible questions to investigate:

- What are the names of the most common destination airports?
- Which airlines fly from NYC to your home city?
- Is there a relationship between departure delays and precipitation?
- What is the distribution of departure times for flights leaving NYC over a 24 hour period?
  - Are especially late or early arrivals departures to some regions or for some airlines?

Warning: `flights` has 336776 rows, so if you do a sloppy join, you can end up with **many** matches per observation and have the data *explode* in size.

Homework 3

Pick something to look at in the `nycflights13` data and write up a .Rmd file showing your investigation. Upload both the .Rmd file and the .html file to Canvas. You must use at least once: `mutate()`, `summarize()`, `group_by()`, and any join. *Include at least one nicely formatted plot (`ggplot2`) and one table (`pander`)*. In plots and tables, use "nice" variable names (try out spaces!) and rounded values (<= 3 digits).

This time, *include all your code in your output document* (`echo=TRUE`), using comments and line breaks separating commands so that it is clear to a peer what you are doing (or trying to do!). You must write up your observations briefly in words as well.

Note: If you want to see the `nycflights13` dataframes in the environment, you will need to load *each one*: `airlines`, `airports`, `flights`, `planes`, and `weather` (e.g. `data(flights)`).