CSSS508, Week 3

Manipulating and Summarizing Data

Chuck Lanfear

Oct 8, 2019

Updated: Oct 9, 2019

UW CS&SS

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*: `x %>% f(y) = f(x, y)`. Read out loud: "and then..."

```r
library(dplyr)
library(gapminder)
gapminder %>% filter(country == "Canada") %>% head(2)
```

```
## # A tibble: 2 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.
```

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.

```
yugoslavia %>% 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]

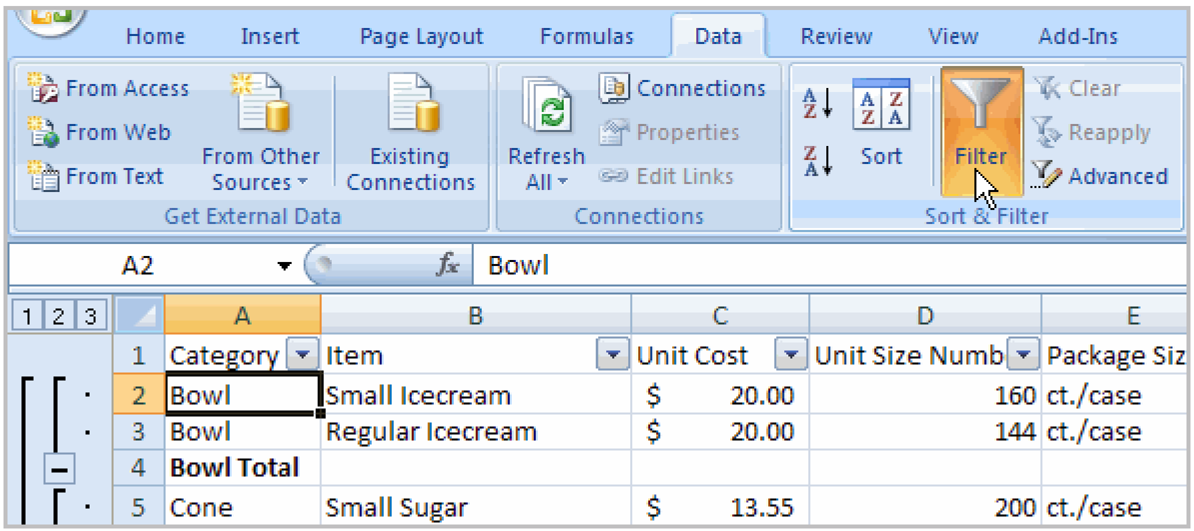
[1] Note this is just a stylistic convention: If you prefer, you *can* do assignment at the end of the chain.

Filtering Rows (subsetting)

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

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

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",
                       "Macedonia", "Montenegro", "Serbia", "Slovenia")
yugoslavia <- gapminder %>% filter(country %in% former_yugoslavia)
tail(yugoslavia, 2)
```

```
## # A tibble: 2 x 6
##   country  continent  year lifeExp     pop gdpPercap
##   <fct>    <fct>     <int>   <dbl>   <int>     <dbl>
## 1 Slovenia Europe     2002    76.7 2011497    20660.
## 2 Slovenia Europe     2007    77.9 2009245    25768.
```

[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(413) # 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 Bosnia and Herzegovina Europe     1987    71.1 4338977     4314.
## 2 Bosnia and Herzegovina Europe     1967    64.8 3585000     2172.
## 3 Montenegro             Europe     2002    74.0  720230     6557.
## 4 Montenegro             Europe     1987    74.9  569473    11733.
## 5 Slovenia               Europe     1952    65.6 1489518     4215.
## 6 Serbia                 Europe     1982    70.2 9032824    15181.
```

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 continguous 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>,
```

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

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)
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(short_country, year, pop) %>%
    arrange(year, short_country) %>%
    head(3)
```

```
## # A tibble: 3 x 3
##   short_country  year     pop
##   <chr>         <int>   <int>
## 1 B and H        1952 2791000
## 2 Croatia        1952 3882229
## 3 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!

`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()` 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()`).

`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_at()`

Maybe you need to calculate the mean and standard deviation of a bunch of columns. With `summarize_at()`, put the variables to compute over first in `vars()` (like `select()` syntax) and put the functions to use in a `list()` after.

```
yugoslavia %>%
    filter(year == 1982) %>%
    summarize_at(vars(lifeExp, pop), list(mean = mean, sd = sd))
```

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

You can also use `purrr` syntax (e.g. `~ mean(.)`) and it will automatically name the outputs.

Avoiding Repetition

Other functions:

There are additional `dplyr` functions similar to `summarize_at()`:

- `summarize_all()` and `mutate_all()` summarize / mutate *all* variables sent to them in the same way. For instance, getting the mean and standard deviation of an entire dataframe (using `purrr` style functions):

```
dataframe %>% summarize_all(list(~mean(.), ~sd(.)))
```

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

```
dataframe %>% summarize_if(is.numeric, list(~mean(.), ~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

Category	(All)							
Sum of Amount	**Column**							
Row Labels	**Apple**	**Banana**	**Beans**	**Broccoli**	**Carrots**	**Mango**	**Orange**	**Grand Total**
Australia	20634	52721	14433	17953	8106	9186	8680	131713
Canada	24867	33775		12407		3767	19929	94745
France	80193	36094	680	5341	9104	7388	2256	141056
Germany	9082	39686	29905	37197	21636	8775	8887	155168
New Zealand	10332	40050		4390			12010	66782
United Kingdom	17534	42908	5100	38436	41815	5600	21744	173137
United States	28615	95061	7163	26715	56284	22363	30932	267133
Grand Total	**191257**	**340295**	**57281**	**142439**	**136945**	**57079**	**104438**	**1029734**

`group_by()` example

```r
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`*!

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. UW registrar data with police stop records.
  - Often large surveys are broken into different data sets for each level (e.g. household, individual, neighborhood)

Joining in Concept

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.

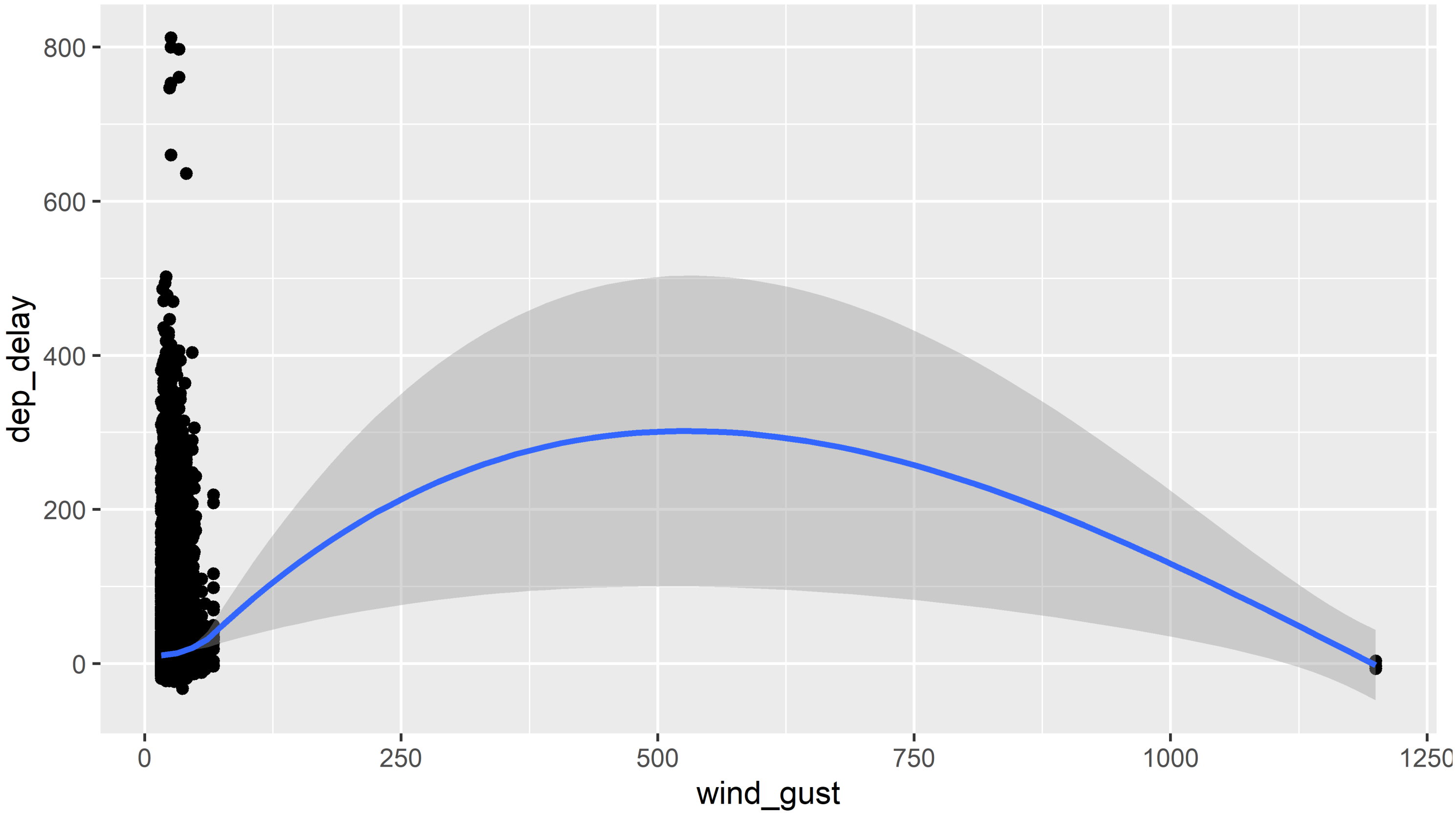
Join Example #3

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]

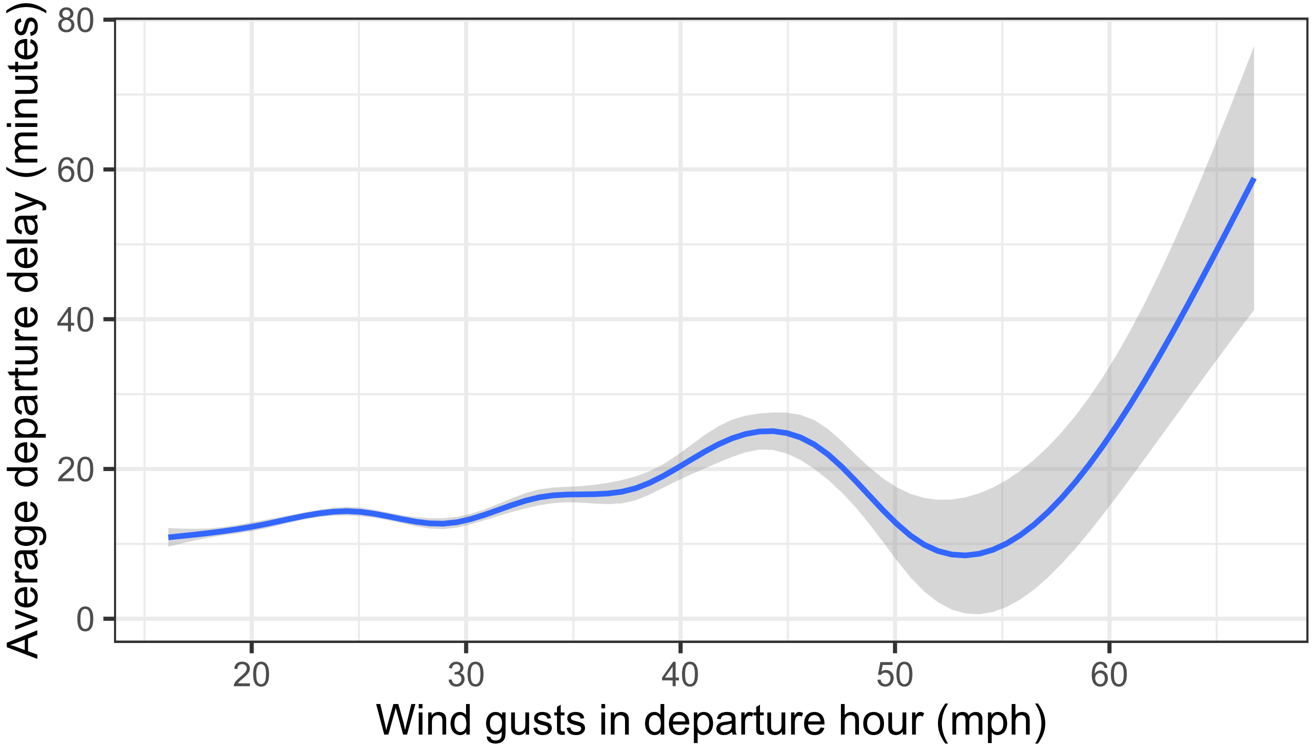
[1] These observations appear to have been fixed in the current data.

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?
- Use the time zone data in `airports` to convert flight arrival times to NYC local time.
    - What is the distribution of arrival times for flights leaving NYC over a 24 hour period?
    - Are especially late or early arrivals particular to some regions or 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)`).

DUE: 11:59 PM, October 15th