Manipulating Data in R

Recap of Data Cleaning

- `is.na()`,`any(is.na())`, `all(is.na())`,`count()`, and functions from `naniar` like `gg_miss_var()` and `miss_var_summary` can help determine if we have `NA` values
- `miss_var_which()` can help you drop columns that have any missing values.
- `filter()` automatically removes `NA` values
- `drop_na()` can help you remove `NA` values
- `NA` values can change your calculation results
- think about what `NA` values represent - don't drop them if you shouldn't
- `replace_na()` will replace `NA values with a particular value

Recap of Data Cleaning

- `case_when()` can recode **entire values** based on conditions
  - remember `case_when()` needs `TRUE ~ variable` to keep values that aren't specified by conditions, otherwise will be `NA`
- `stringr` package has great functions for looking for specific **parts of values** especially `filter()` and `str_detect()` combined
  - also has other useful string manipulation functions like `str_replace()` and more!
  - `separate()` can split columns into additional columns
  - `unite()` can combine columns

 Day 5 Cheatsheet

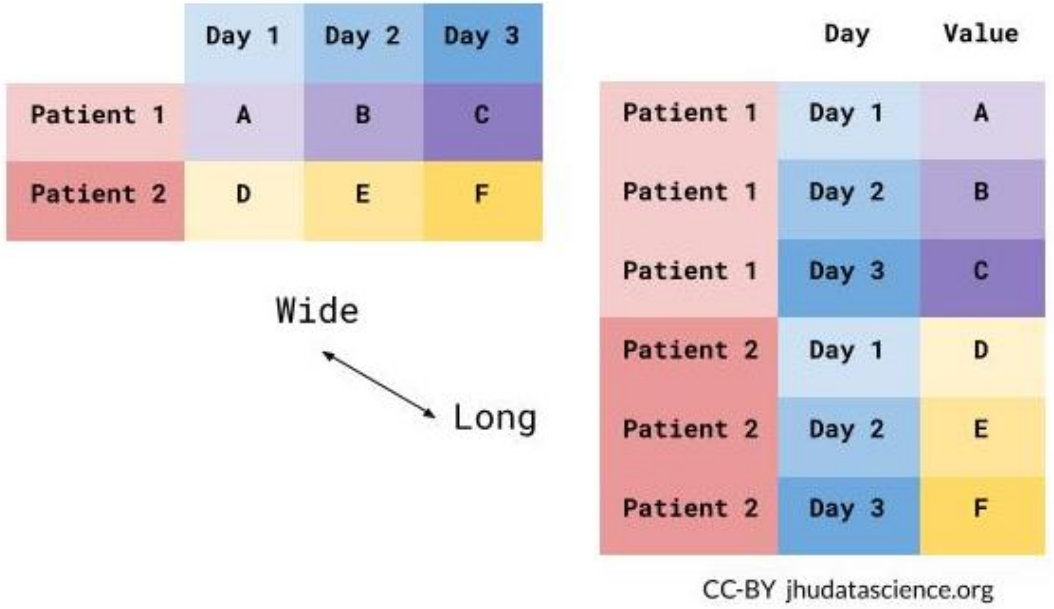
Manipulating Data

In this module, we will show you how to:

1. Reshape data from wide to long
2. Reshape data from long to wide
3. Merge Data/Joins

What is wide/long data?

Data is wide or long **with respect** to certain variables.



What is wide/long data?

Data is stored *differently* in the tibble.

Here's a small dataset looking at vaccination rates over three months in Alabama.

Wide: has many columns

```
# A tibble: 1 × 4
  State   June_vacc_rate May_vacc_rate April_vacc_rate
  <chr>            <dbl>         <dbl>           <dbl>
1 Alabama          0.516         0.514           0.511
```

Long: column names become data

```
# A tibble: 3 × 3
  State   name            value
  <chr>   <chr>           <dbl>
1 Alabama June_vacc_rate  0.516
2 Alabama May_vacc_rate   0.514
3 Alabama April_vacc_rate 0.511
```

What is wide/long data?

Wide: multiple columns per individual, values spread across multiple columns

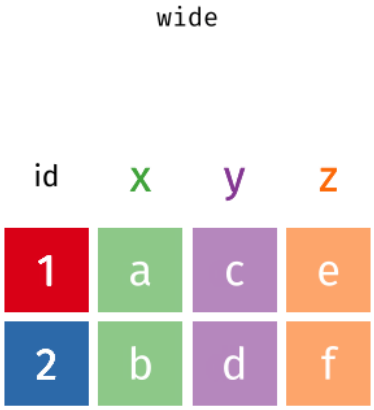
```
# A tibble: 2 × 4
  State   June_vacc_rate May_vacc_rate April_vacc_rate
  <chr>            <dbl>         <dbl>           <dbl>
1 Alabama          0.516         0.514           0.511
2 Alaska           0.627         0.626           0.623
```

Long: multiple rows per observation, a single column contains the values

```
# A tibble: 6 × 3
  State   name             value
  <chr>   <chr>            <dbl>
1 Alabama June_vacc_rate  0.516
2 Alabama May_vacc_rate   0.514
3 Alabama April_vacc_rate 0.511
4 Alaska  June_vacc_rate  0.627
5 Alaska  May_vacc_rate   0.626
6 Alaska  April_vacc_rate 0.623
```

What is wide/long data?

https://github.com/gadenbuie/tidyexplain/blob/main/images/tidyr-pivoting.gif



Why do we need to switch between wide/long data?

Wide: **Easier for humans to read**

```
# A tibble: 2 × 4
  State   June_vacc_rate May_vacc_rate April_vacc_rate
  <chr>            <dbl>         <dbl>           <dbl>
1 Alabama          0.516         0.514           0.511
2 Alaska           0.627         0.626           0.623
```

Long: **Easier for R to make plots & do analysis**

```
# A tibble: 6 × 3
  State   name            value
  <chr>   <chr>           <dbl>
1 Alabama June_vacc_rate  0.516
2 Alabama May_vacc_rate   0.514
3 Alabama April_vacc_rate 0.511
4 Alaska  June_vacc_rate  0.627
5 Alaska  May_vacc_rate   0.626
6 Alaska  April_vacc_rate 0.623
```

Pivoting using `tidyr` package (part of `tidyverse`)

`tidyr` allows you to "tidy" your data. We will be talking about:

- `pivot_longer` - make multiple columns into variables, (wide to long)
- `pivot_wider` - make a variable into multiple columns, (long to wide)

The `reshape` command exists. Its arguments are considered more confusing, so we don't recommend it.

You might see old functions `gather` and `spread` when googling. These are older iterations of `pivot_longer` and `pivot_wider`, respectively.

`pivot_longer`...

Reshaping data from wide to long

```
ex_wide
```

```
# A tibble: 2 × 4
  State   June_vacc_rate May_vacc_rate April_vacc_rate
  <chr>            <dbl>         <dbl>           <dbl>
1 Alabama          0.516         0.514           0.511
2 Alaska           0.627         0.626           0.623
```

```
ex_long <- ex_wide %>% pivot_longer(cols = ends_with("rate"))
ex_long
```

```
# A tibble: 6 × 3
  State   name             value
  <chr>   <chr>            <dbl>
1 Alabama June_vacc_rate  0.516
2 Alabama May_vacc_rate   0.514
3 Alabama April_vacc_rate 0.511
4 Alaska  June_vacc_rate  0.627
5 Alaska  May_vacc_rate   0.626
6 Alaska  April_vacc_rate 0.623
```

GUT CHECK!

What does `pivot_longer()` do?

A. Summarize data

B. Import data

C. Reshape data

Reshaping wide to long: Better column names

`pivot_longer()` - puts column data into rows (`tidyr` package)

- First describe which columns we want to “pivot_longer”
- `names_to =` new name for old columns
- `values_to =` new name for old cell values

```
{long_data} <- {wide_data} %>% pivot_longer(cols = {columns to pivot},
                                            names_to = {name for old columns},
                                            values_to = {name for cell values})
```

Reshaping wide to long: Better column names

Newly created column names (“Month” and “Rate”) are enclosed in quotation marks. It helps us be more specific than “name” and “value”.

```
ex_long <- ex_wide %>% pivot_longer(cols = ends_with("rate"),
                                    names_to = "Month",
                                    values_to = "Rate")
ex_long
```

```
# A tibble: 6 × 3
  State   Month            Rate
  <chr>   <chr>           <dbl>
1 Alabama June_vacc_rate  0.516
2 Alabama May_vacc_rate   0.514
3 Alabama April_vacc_rate 0.511
4 Alaska  June_vacc_rate  0.627
5 Alaska  May_vacc_rate   0.626
6 Alaska  April_vacc_rate 0.623
```

Data used: Charm City Circulator

```
circ <-
  read_csv("http://jhudatascience.org/intro_to_r/data/Charm_City_Circulator_Ridership.csv")
head(circ, 5)
```

```
# A tibble: 5 × 15
  day       date  orangeBoardings orangeAlightings orangeAverage purpleBoardings
  <chr>     <chr>           <dbl>            <dbl>         <dbl>           <dbl>
1 Monday    01/1…             877             1027           952              NA
2 Tuesday   01/1…             777              815           796              NA
3 Wednesday 01/1…            1203             1220          1212.             NA
4 Thursday  01/1…            1194             1233          1214.             NA
5 Friday    01/1…            1645             1643          1644              NA
# … 9 more variables: purpleAlightings <dbl>, purpleAverage <dbl>,
#   greenBoardings <dbl>, greenAlightings <dbl>, greenAverage <dbl>,
#   bannerBoardings <dbl>, bannerAlightings <dbl>, bannerAverage <dbl>,
#   daily <dbl>
```

Mission: Taking the average boardings by line

Let's imagine we want to create a table of average boardings by route/line. Results should look something like:

```
# A tibble: 4 × 2
  line   avg_boardings
  <chr>  <chr>
1 orange 600(?)
2 purple 700(?)
3 green  500(?)
4 banner 400(?)
```

Reshaping data from wide to long

```
long <- circ %>%
  pivot_longer(starts_with(c("orange","purple","green","banner")))
long
```

```
# A tibble: 13,752 × 5
   day    date       daily name              value
   <chr>  <chr>      <dbl> <chr>             <dbl>
 1 Monday 01/11/2010   952 orangeBoardings     877
 2 Monday 01/11/2010   952 orangeAlightings   1027
 3 Monday 01/11/2010   952 orangeAverage       952
 4 Monday 01/11/2010   952 purpleBoardings      NA
 5 Monday 01/11/2010   952 purpleAlightings     NA
 6 Monday 01/11/2010   952 purpleAverage        NA
 7 Monday 01/11/2010   952 greenBoardings       NA
 8 Monday 01/11/2010   952 greenAlightings      NA
 9 Monday 01/11/2010   952 greenAverage         NA
10 Monday 01/11/2010   952 bannerBoardings      NA
# ℹ 13,742 more rows
```

Just keep "boardings"

Filter by Boardings only..

```
long <- long %>% filter(str_detect(name, "Boardings"))
long
```

```
# A tibble: 4,584 × 5
   day       date       daily name              value
   <chr>     <chr>      <dbl> <chr>             <dbl>
 1 Monday    01/11/2010  952  orangeBoardings   877
 2 Monday    01/11/2010  952  purpleBoardings    NA
 3 Monday    01/11/2010  952  greenBoardings     NA
 4 Monday    01/11/2010  952  bannerBoardings    NA
 5 Tuesday   01/12/2010  796  orangeBoardings   777
 6 Tuesday   01/12/2010  796  purpleBoardings    NA
 7 Tuesday   01/12/2010  796  greenBoardings     NA
 8 Tuesday   01/12/2010  796  bannerBoardings    NA
 9 Wednesday 01/13/2010 1212. orangeBoardings  1203
10 Wednesday 01/13/2010 1212. purpleBoardings    NA
# ℹ 4,574 more rows
```

Mission: Taking the average boardings by line

Now our data is more tidy, and we can take the averages easily!

```
long %>%
  group_by(name) %>%
  summarize("avg_boardings" = mean(value, na.rm = TRUE))
```

```
# A tibble: 4 × 2
  name            avg_boardings
  <chr>                   <dbl>
1 bannerBoardings          830.
2 greenBoardings          1929.
3 orangeBoardings         3031.
4 purpleBoardings         4127.
```

Reshaping data from **wide to long**

There are many ways to **select** the columns we want. Check out https://dplyr.tidyverse.org/reference/dplyr_tidy_select.html to look at more column selection options.

```
circ %>%
  pivot_longer( !c(day, date, daily))
```

```
# A tibble: 13,752 × 5
   day    date       daily name              value
   <chr>  <chr>      <dbl> <chr>             <dbl>
 1 Monday 01/11/2010   952 orangeBoardings     877
 2 Monday 01/11/2010   952 orangeAlightings   1027
 3 Monday 01/11/2010   952 orangeAverage       952
 4 Monday 01/11/2010   952 purpleBoardings      NA
 5 Monday 01/11/2010   952 purpleAlightings     NA
 6 Monday 01/11/2010   952 purpleAverage        NA
 7 Monday 01/11/2010   952 greenBoardings       NA
 8 Monday 01/11/2010   952 greenAlightings      NA
 9 Monday 01/11/2010   952 greenAverage         NA
10 Monday 01/11/2010   952 bannerBoardings      NA
# ℹ 13,742 more rows
```

`pivot_wider`...

Reshaping data from **long to wide**

`pivot_wider()` - spreads row data into columns (`tidyr` package)

- `names_from =` the old column whose contents will be spread into multiple new column names.
- `values_from =` the old column whose contents will fill in the values of those new columns.

```
{wide_data} <- {long_data} %>%
  pivot_wider(names_from = {Old column name: contains new column names},
              values_from = {Old column name: contains new cell values})
```

Reshaping data from long to wide

We can use `pivot_wider` to convert long data to wide format. Let's try it with the vaccine data from earlier.

```
ex_long
```

```
# A tibble: 6 × 3
  State   Month            Rate
  <chr>   <chr>           <dbl>
1 Alabama June_vacc_rate  0.516
2 Alabama May_vacc_rate   0.514
3 Alabama April_vacc_rate 0.511
4 Alaska  June_vacc_rate  0.627
5 Alaska  May_vacc_rate   0.626
6 Alaska  April_vacc_rate 0.623
```

Reshaping data from long to wide

We can use `pivot_wider` to convert long data to wide format. Let's try it with the vaccine data from earlier.

```
ex_wide2 <- ex_long %>% pivot_wider(names_from = "Month",
                                    values_from = "Rate")
ex_wide2
```

```
# A tibble: 2 × 4
  State   June_vacc_rate May_vacc_rate April_vacc_rate
  <chr>            <dbl>         <dbl>           <dbl>
1 Alabama          0.516         0.514           0.511
2 Alaska           0.627         0.626           0.623
```

Reshaping Charm City Circulator

```
wide <- long %>% pivot_wider(names_from = "name",
                             values_from = "value")
wide
```

```
# A tibble: 1,146 × 7
   day       date       daily orangeBoardings purpleBoardings greenBoardings
   <chr>     <chr>      <dbl>            <dbl>            <dbl>           <dbl>
 1 Monday    01/11/2010  952              877               NA              NA
 2 Tuesday   01/12/2010  796              777               NA              NA
 3 Wednesday 01/13/2010 1212.            1203               NA              NA
 4 Thursday  01/14/2010 1214.            1194               NA              NA
 5 Friday    01/15/2010 1644             1645               NA              NA
 6 Saturday  01/16/2010 1490.            1457               NA              NA
 7 Sunday    01/17/2010  888.             839               NA              NA
 8 Monday    01/18/2010 1000.             999               NA              NA
 9 Tuesday   01/19/2010 1035             1023               NA              NA
10 Wednesday 01/20/2010 1396.            1375               NA              NA
# … 1,136 more rows
# … 1 more variable: bannerBoardings <dbl>
```

Summary

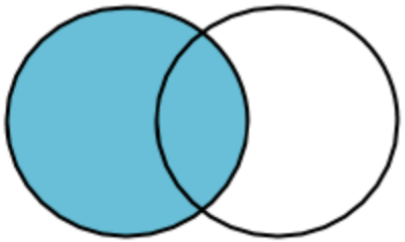
- `tidyr` package (part of `tidyverse`) helps us convert between wide and long data
- `pivot_longer()` goes from wide -> long
  - Specify columns you want to pivot
  - Specify `names_to =` and `values_to =` for custom naming
- `pivot_wider()` goes from long -> wide
  - Specify `names_from =` and `values_from =`

Lab Part 1

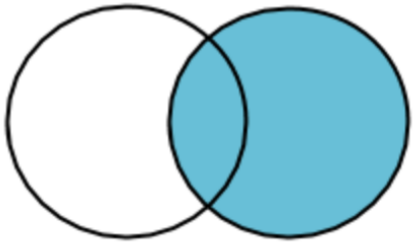
- Class Website
- Lab

Joining

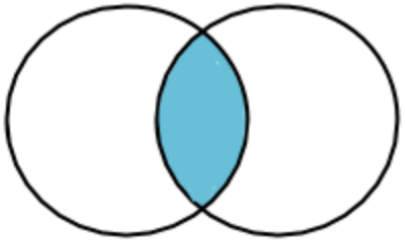
"Combining datasets"



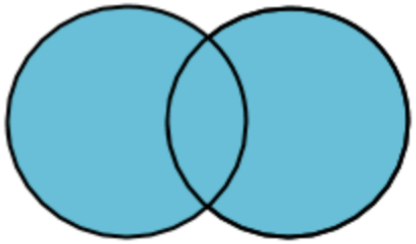
Left Join



Right Join



Inner Join



Full Outer Join

Joining in `dplyr`

- Merging/joining data sets together - usually on key variables, usually "id"
- `?join` - see different types of joining for `dplyr`
- `inner_join(x, y)` - only rows that match for `x` and `y` are kept
- `full_join(x, y)` - all rows of `x` and `y` are kept
- `left_join(x, y)` - all rows of `x` are kept even if not merged with `y`
- `right_join(x, y)` - all rows of `y` are kept even if not merged with `x`
- `anti_join(x, y)` - all rows from `x` not in `y` keeping just columns from `x`.

Merging: Simple Data

```
data_As <- read_csv(
  file = "https://jhudatascience.org/intro_to_r/data/data_As_1.csv")
data_cold <- read_csv(
  file = "https://jhudatascience.org/intro_to_r/data/data_cold_1.csv")
```

```
data_As
```

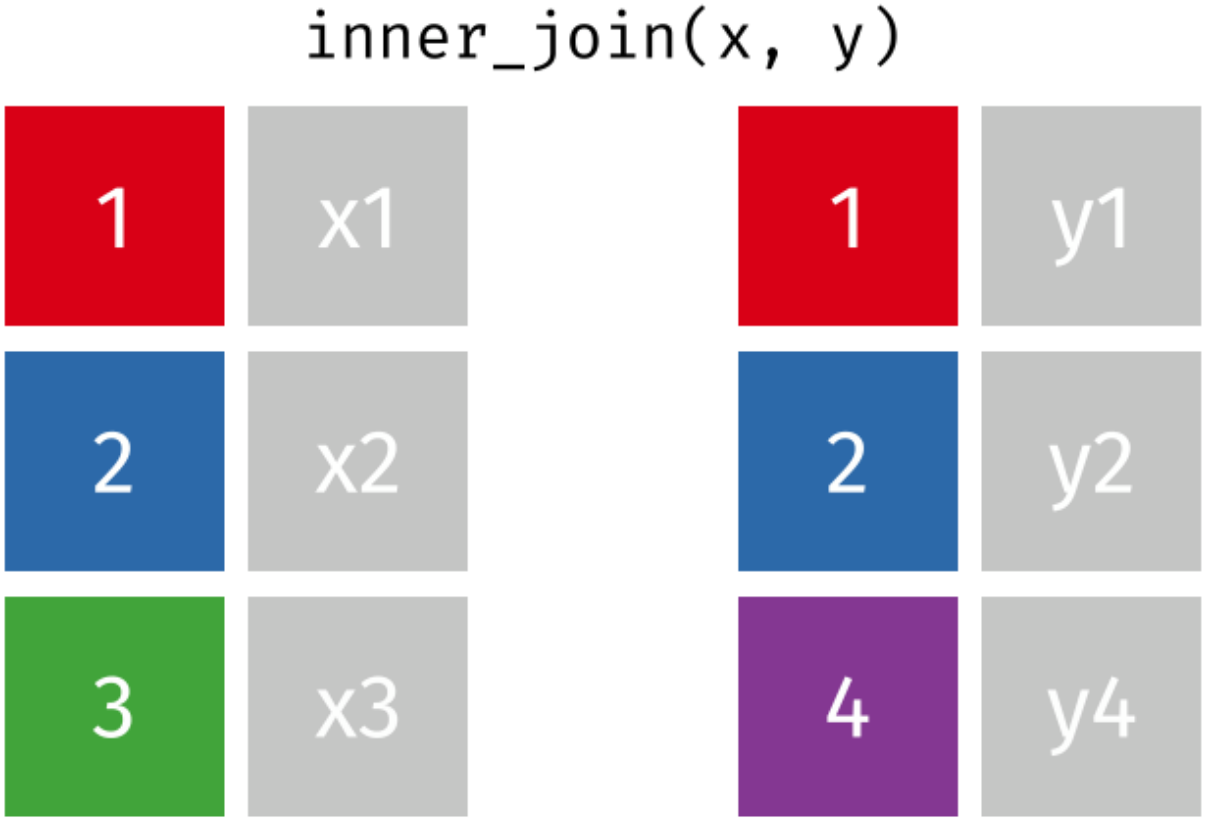
```
# A tibble: 2 × 3
  State   June_vacc_rate May_vacc_rate
  <chr>            <dbl>         <dbl>
1 Alabama          0.516         0.514
2 Alaska           0.627         0.626
```

```
data_cold
```

```
# A tibble: 2 × 2
  State  April_vacc_rate
  <chr>            <dbl>
1 Maine            0.795
2 Alaska           0.623
```

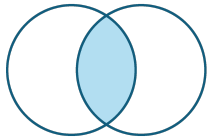
Inner Join

https://github.com/gadenbuie/tidyexplain/blob/main/images/inner-join.gif



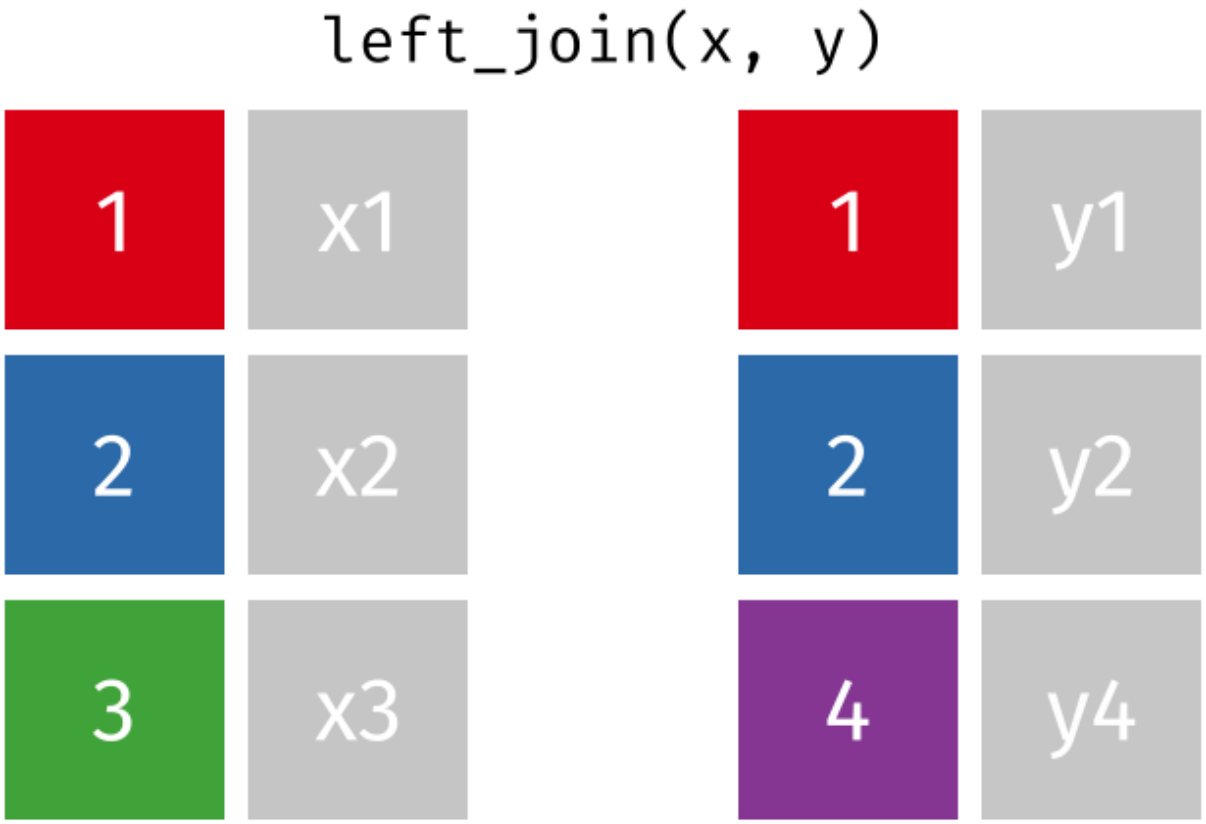
Inner Join

```
ij <- inner_join(data_As, data_cold)

Joining with `by = join_by(State)`

ij

# A tibble: 1 × 4
  State  June_vacc_rate May_vacc_rate April_vacc_rate
  <chr>           <dbl>         <dbl>           <dbl>
1 Alaska          0.627         0.626           0.623
```



Left Join

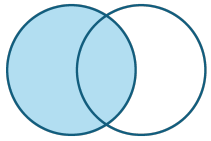
https://raw.githubusercontent.com/gadenbuie/tidyexplain/main/images/left-join.gif



Left Join

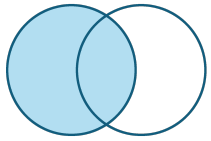
"Everything to the left of the comma"

```
lj <- left_join(data_As, data_cold)

Joining with `by = join_by(State)`

lj

# A tibble: 2 × 4
  State   June_vacc_rate May_vacc_rate April_vacc_rate
  <chr>            <dbl>         <dbl>           <dbl>
1 Alabama          0.516         0.514          NA
2 Alaska           0.627         0.626           0.623
```



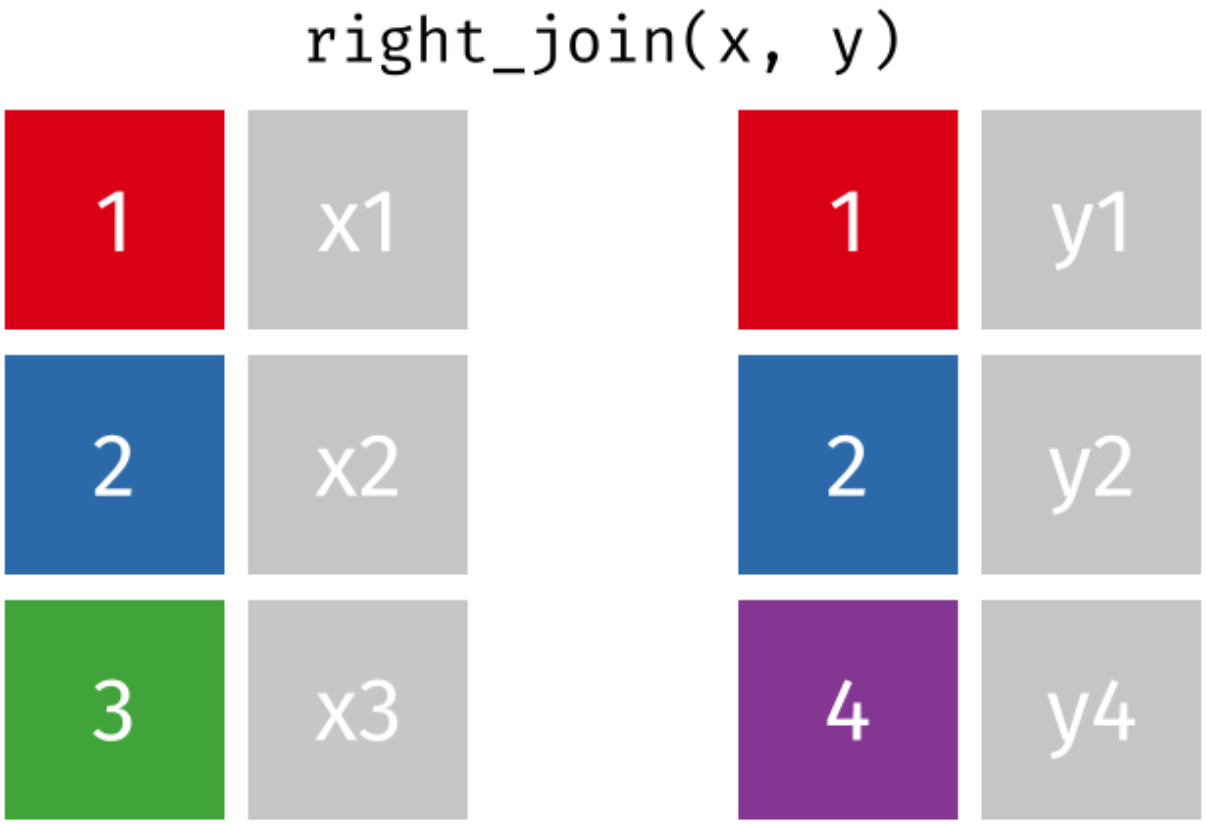
Install **tidylog** package to log outputs

```
# install.packages("tidylog")
library(tidylog)
left_join(data_As, data_cold)

Joining with `by = join_by(State)`
left_join: added one column (April_vacc_rate)
> rows only in data_As 1
> rows only in data_cold (1)
> matched rows 1
> ===
> rows total 2

# A tibble: 2 × 4
  State   June_vacc_rate May_vacc_rate April_vacc_rate
  <chr>            <dbl>         <dbl>           <dbl>
1 Alabama          0.516         0.514          NA
2 Alaska           0.627         0.626           0.623
```



Right Join

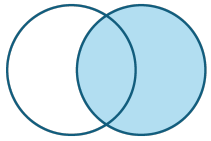
https://raw.githubusercontent.com/gadenbuie/tidyexplain/main/images/right-join.gif



Right Join

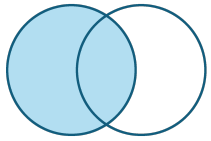
"Everything to the right of the comma"

```
rj <- right_join(data_As, data_cold)

Joining with `by = join_by(State)`
right_join: added one column (April_vacc_rate)
> rows only in data_As (1)
> rows only in data_cold 1
> matched rows 1
> ===
> rows total 2

rj

# A tibble: 2 × 4
  State  June_vacc_rate May_vacc_rate April_vacc_rate
  <chr>           <dbl>         <dbl>           <dbl>
1 Alaska          0.627         0.626           0.623
2 Maine          NA            NA               0.795
```



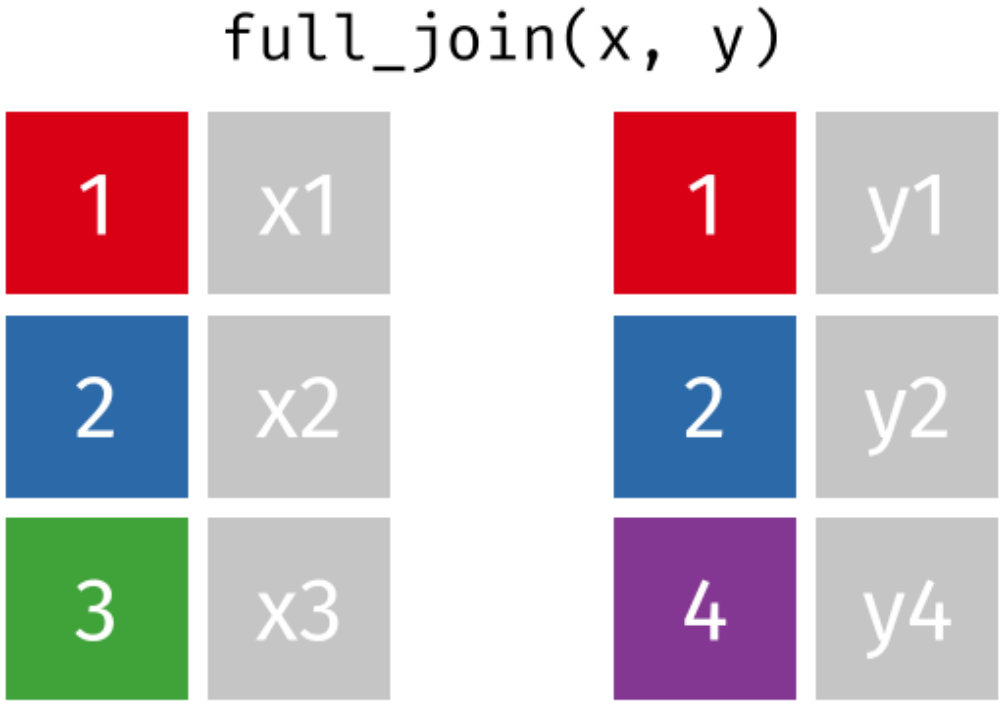
Left Join: Switching arguments

```
lj2 <- left_join(data_cold, data_As)

Joining with `by = join_by(State)`
left_join: added 2 columns (June_vacc_rate, May_vacc_rate)
> rows only in data_cold 1
> rows only in data_As (1)
> matched rows 1
> ===
> rows total 2

lj2

# A tibble: 2 × 4
  State  April_vacc_rate June_vacc_rate May_vacc_rate
  <chr>            <dbl>          <dbl>         <dbl>
1 Maine            0.795         NA            NA
2 Alaska           0.623          0.627         0.626
```



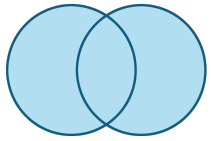
Full Join

https://raw.githubusercontent.com/gadenbuie/tidyexplain/main/images/full-join.gif



Full Join

```
fj <- full_join(data_As, data_cold)

Joining with `by = join_by(State)`
full_join: added one column (April_vacc_rate)
> rows only in data_As 1
> rows only in data_cold 1
> matched rows 1
> ===
> rows total 3

fj

# A tibble: 3 × 4
  State   June_vacc_rate May_vacc_rate April_vacc_rate
  <chr>            <dbl>         <dbl>           <dbl>
1 Alabama          0.516         0.514          NA
2 Alaska           0.627         0.626           0.623
3 Maine           NA            NA               0.795
```



“includes duplicates”

```
data_As <- read_csv(
  file = "https://jhudatascience.org/intro_to_r/data/data_As_2.csv")
data_cold <- read_csv(
  file = "https://jhudatascience.org/intro_to_r/data/data_cold_2.csv")
```

```
data_As
```

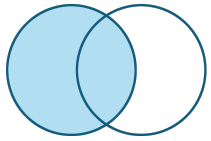
```
# A tibble: 2 × 2
  State   state_bird
  <chr>   <chr>
1 Alabama wild turkey
2 Alaska  willow ptarmigan
```

```
data_cold
```

```
# A tibble: 3 × 3
  State  vacc_rate month
  <chr>      <dbl> <chr>
1 Maine      0.795 April
2 Alaska     0.623 April
3 Alaska     0.626 May
```

“includes duplicates”

```
lj <- left_join(data_As, data_cold)

Joining with `by = join_by(State)`
left_join: added 2 columns (vacc_rate, month)
> rows only in data_As 1
> rows only in data_cold (1)
> matched rows 2 (includes duplicates)
> ===
> rows total 3
```



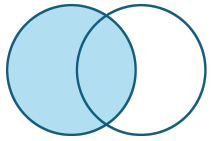
“includes duplicates”

Data including the joining column (“State”) has been duplicated.

```
lj
```

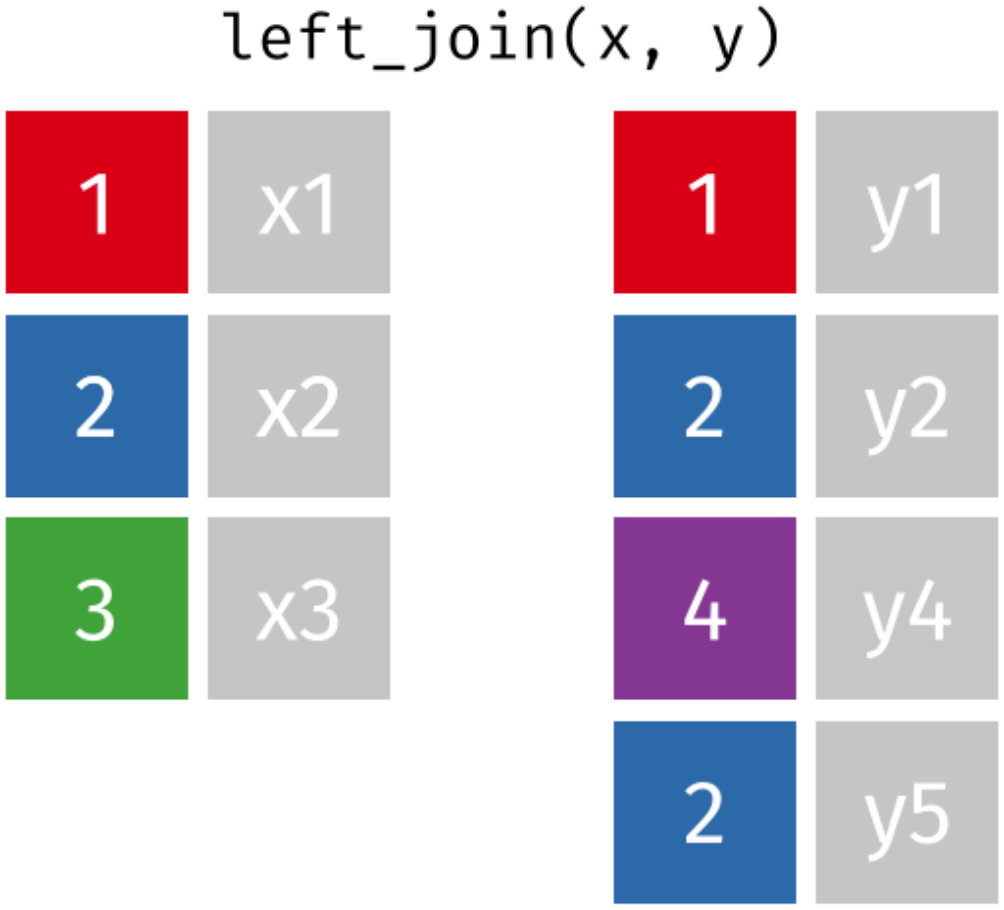
```
# A tibble: 3 × 4
  State   state_bird       vacc_rate month
  <chr>   <chr>                <dbl> <chr>
1 Alabama wild turkey         NA     <NA>
2 Alaska  willow ptarmigan     0.623 April
3 Alaska  willow ptarmigan     0.626 May
```

Note that “Alaska willow ptarmigan” appears twice.



"includes duplicates"

https://github.com/gadenbuie/tidyexplain/blob/main/images/left-join-extra.gif



Stop `tidylog`

`unloadNamespace()` does the opposite of `library()`.

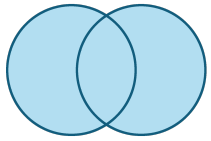
```
unloadNamespace("tidylog")
```

Using the **by** argument

By default joins use the intersection of column names. If `by` is specified, it uses that.

```
full_join(data_As, data_cold, by = "State")
```

```
# A tibble: 4 × 4
  State   state_bird       vacc_rate month
  <chr>   <chr>                <dbl> <chr>
1 Alabama wild turkey             NA <NA>
2 Alaska  willow ptarmigan      0.623 April
3 Alaska  willow ptarmigan      0.626 May
4 Maine   <NA>                  0.795 April
```

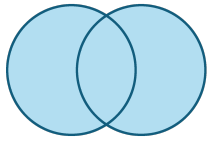


Using the **by** argument

You can join based on multiple columns by using something like `by = c(col1, col2)`.

If the datasets have two different names for the same data, use:

```
full_join(x, y, by = c("a" = "b"))
```



`anti_join` : what's missing

Entries in `data_As` but not in `data_cold`

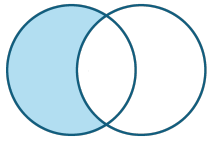
```
anti_join(data_As, data_cold, by = "State")
```

```
# A tibble: 1 × 2
  State   state_bird
  <chr>   <chr>
1 Alabama wild turkey
```

Entries in `data_cold` but not in `data_As`

```
anti_join(data_cold, data_As, by = "State") # order switched
```

```
# A tibble: 1 × 3
  State vacc_rate month
  <chr>     <dbl> <chr>
1 Maine     0.795 April
```



GUT CHECK!

Why use `join` functions?

A. Combine different data sources

B. Connect Rmd to other files

C. Using one data source is too easy and we want our analysis ~ fancy ~

Summary

- Merging/joining data sets together - assumes all column names that overlap
  - use the `by = c("a" = "b")` if they differ
- `inner_join(x, y)` - only rows that match for `x` and `y` are kept
- `full_join(x, y)` - all rows of `x` and `y` are kept
- `left_join(x, y)` - all rows of `x` are kept even if not merged with `y`
- `right_join(x, y)` - all rows of `y` are kept even if not merged with `x`
- Use the `tidylog` package for a detailed summary
- `anti_join(x, y)` shows what is only in `x` (missing from `y`)

Lab Part 2

- Class Website
- Lab

~

- Day 6 Cheatsheet
- Posit's `tidyr` Cheatsheet
- Posit's `dplyr` Cheatsheet
- Joining Open Case Study

Image by Gerd Altmann from Pixabay

Additional Slides

Getting the set difference with `setdiff`

We might want to determine what indexes ARE in the first dataset that AREN'T in the second.

For this to work, the datasets need the same columns.

We'll just select the index using `select()`.

```
A_states <- data_As %>% select(State)
cold_states <- data_cold %>% select(State)
```

Getting the set difference with `setdiff`

States in `A_states` but not in `cold_states`

```
dplyr::setdiff(A_states, cold_states)
```

```
# A tibble: 1 × 1
  State
  <chr>
1 Alabama
```

States in `cold_states` but not in `A_states`

```
dplyr::setdiff(cold_states, A_states)
```

```
# A tibble: 1 × 1
  State
  <chr>
1 Maine
```

Getting the set difference with `setdiff`

Why did we use `dplyr::setdiff`?

There is a base R function, also called `setdiff` that requires vectors.

In other words, we use `dplyr::` to be specific about the package we want to use.

More set operations can be found here:
https://dplyr.tidyverse.org/reference/setops.html

Fast manipulation using **collapse** package

https://sebkrantz.github.io/collapse/

Might be helpful if your data is very large. However, `dplyr` and `tidyr` functions are great for most applications.