Manipulating Data in R

Recap of Data Cleaning

- `is.na()`,`any(is.na())`, `count()`, and functions from `naniar` like `gg_miss_var()` can help determine if we have `NA` values
- `filter()` automatically removes `NA` values - can't confirm or deny if condition is met (need `| is.na()` to keep them)
- `drop_na()` can help you remove `NA` values from a variable or an entire data frame
- `NA` values can change your calculation results
- think about what `NA` values represent

Recap of Data Cleaning

- `case_when()` can recode **entire values** based on conditions
  - remember `case_when()` needs `TRUE ~ varaible` 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

Cheatsheet

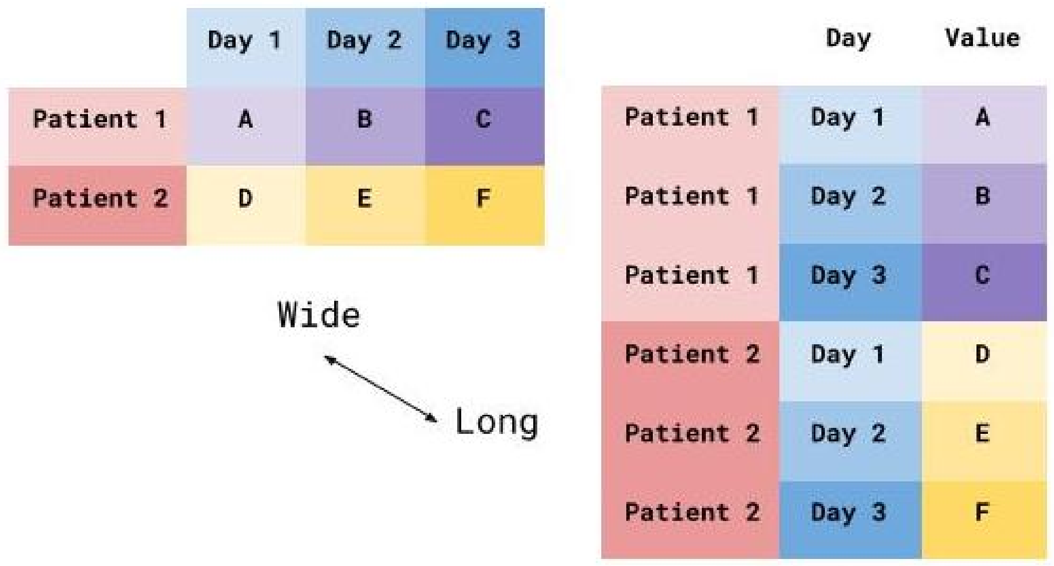
Manipulating Data

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.



	Day 1	Day 2	Day 3
Patient 1	A	B	C
Patient 2	D	E	F

	Day	Value
Patient 1	Day 1	A
Patient 1	Day 2	B
Patient 1	Day 3	C
Patient 2	Day 1	D
Patient 2	Day 2	E
Patient 2	Day 3	F

CC-BY jhudatascience.org

What is wide/long data?

Data is stored *differently* in the tibble.

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

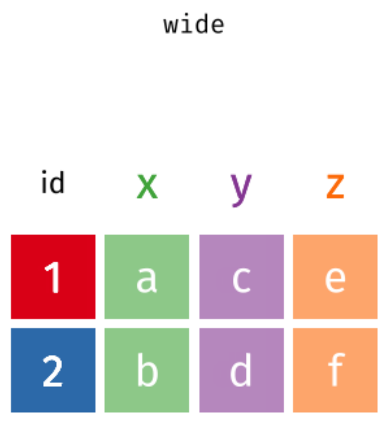
```
# A tibble: 2 × 4
  State   June_vacc_rate May_vacc_rate April_vacc_rate
  <chr>            <dbl>         <dbl>           <dbl>
1 Alabama          0.516         0.514           0.511
2 Alaska           0.627         0.626           0.623
```

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


wide

id	x	y	z
1	a	c	e
2	b	d	f

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

`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)
- `separate` - string into multiple columns (review)

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

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

- First describe which columns we want to “pivot_longer”

```
{long_data} <- {wide_data} %>% pivot_longer(cols = {columns to pivot})
```

Reshaping data from wide to long

```
wide_vacc <- read_csv(
  file = "https://jhudatascience.org/intro_to_r/data/wide_vacc.csv")

wide_vacc
```

```
# A tibble: 1 × 3
  June_vacc_rate May_vacc_rate April_vacc_rate
           <dbl>         <dbl>           <dbl>
1          0.516         0.514           0.511
```

```
long_vacc <- wide_vacc %>% pivot_longer(cols = everything())
long_vacc
```

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

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 data from wide to long

```
wide_vacc
```

```
# A tibble: 1 × 3
  June_vacc_rate May_vacc_rate April_vacc_rate
           <dbl>         <dbl>           <dbl>
1          0.516         0.514           0.511
```

```
long_vacc <- wide_vacc %>% pivot_longer(cols = everything(),
                                        names_to = "Month",
                                        values_to = "Rate")
long_vacc
```

```
# A tibble: 3 × 2
  Month            Rate
  <chr>           <dbl>
1 June_vacc_rate  0.516
2 May_vacc_rate   0.514
3 April_vacc_rate 0.511
```

Newly created column names are enclosed in quotation marks.

Data used: Charm City Circulator

http://jhudatascience.org/intro_to_r/data/Charm_City_Circulator_Ridership.csv

```
library(jhur)
circ <- read_circulator()
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
# ℹ 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
```

Reshaping data from **wide to long**

Un-pivoted columns (`day`, `date`, `daily`) are similar

```
circ %>% select(day, date, daily) %>% head()
```

```
# A tibble: 6 × 3
  day       date       daily
  <chr>     <chr>      <dbl>
1 Monday    01/11/2010  952
2 Tuesday   01/12/2010  796
3 Wednesday 01/13/2010 1212.
4 Thursday  01/14/2010 1214.
5 Friday    01/15/2010 1644
6 Saturday  01/16/2010 1490.
```

```
long %>% select(day, date, daily) %>% head()
```

```
# A tibble: 6 × 3
  day    date       daily
  <chr>  <chr>      <dbl>
1 Monday 01/11/2010   952
2 Monday 01/11/2010   952
3 Monday 01/11/2010   952
4 Monday 01/11/2010   952
5 Monday 01/11/2010   952
6 Monday 01/11/2010   952
```

Cleaning up long data

We will use `str_replace` from the `stringr` package to put _ in the names

```
long <- long %>% mutate(
  name = str_replace(string = name, pattern = "B", replacement = "_B"),
  name = str_replace(string = name, pattern = "A", replacement = "_A")
)
long
```

```
# A tibble: 13,752 × 5
   day    date       daily name              value
   <chr>  <chr>      <dbl> <chr>             <dbl>
 1 Monday 01/11/2010   952 orange_Boardings    877
 2 Monday 01/11/2010   952 orange_Alightings  1027
 3 Monday 01/11/2010   952 orange_Average      952
 4 Monday 01/11/2010   952 purple_Boardings     NA
 5 Monday 01/11/2010   952 purple_Alightings    NA
 6 Monday 01/11/2010   952 purple_Average       NA
 7 Monday 01/11/2010   952 green_Boardings      NA
 8 Monday 01/11/2010   952 green_Alightings     NA
 9 Monday 01/11/2010   952 green_Average        NA
10 Monday 01/11/2010   952 banner_Boardings     NA
# … 13,742 more rows
```

Cleaning up long data with `separate()`

- first argument - which column should be split up?
- "`into =`" gives names to the new columns
- "`sep =`" to show where the separation should happen.

```
long <- long %>%
  separate(name, into = c("line", "type"), sep = "_")
long
```

```
# A tibble: 13,752 × 6
   day    date       daily line   type       value
   <chr>  <chr>      <dbl> <chr>  <chr>      <dbl>
 1 Monday 01/11/2010   952 orange Boardings    877
 2 Monday 01/11/2010   952 orange Alightings  1027
 3 Monday 01/11/2010   952 orange Average      952
 4 Monday 01/11/2010   952 purple Boardings     NA
 5 Monday 01/11/2010   952 purple Alightings    NA
 6 Monday 01/11/2010   952 purple Average       NA
 7 Monday 01/11/2010   952 green  Boardings     NA
 8 Monday 01/11/2010   952 green  Alightings    NA
 9 Monday 01/11/2010   952 green  Average       NA
10 Monday 01/11/2010   952 banner Boardings     NA
# ℹ 13,742 more rows
```

Mission: Taking the average boardings by line

Filter by Boardings only..

```
long <- long %>%
  filter(type == "Boardings")
long
```

```
# A tibble: 4,584 × 6
   day       date       daily line   type       value
   <chr>     <chr>      <dbl> <chr>  <chr>      <dbl>
 1 Monday    01/11/2010  952  orange Boardings    877
 2 Monday    01/11/2010  952  purple Boardings     NA
 3 Monday    01/11/2010  952  green  Boardings     NA
 4 Monday    01/11/2010  952  banner Boardings     NA
 5 Tuesday   01/12/2010  796  orange Boardings    777
 6 Tuesday   01/12/2010  796  purple Boardings     NA
 7 Tuesday   01/12/2010  796  green  Boardings     NA
 8 Tuesday   01/12/2010  796  banner Boardings     NA
 9 Wednesday 01/13/2010 1212. orange Boardings   1203
10 Wednesday 01/13/2010 1212. purple Boardings     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(line) %>%
  summarize("avg_boardings" = mean(value, na.rm = TRUE))
```

```
# A tibble: 4 × 2
  line   avg_boardings
  <chr>          <dbl>
1 banner          830.
2 green          1929.
3 orange         3031.
4 purple         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

```
long_vacc

# A tibble: 3 × 2
  Month              Rate
  <chr>             <dbl>
1 June_vacc_rate  0.516
2 May_vacc_rate   0.514
3 April_vacc_rate 0.511

wide_vacc <- long_vacc %>% pivot_wider(names_from = "Month",
                                       values_from = "Rate")
wide_vacc

# A tibble: 1 × 3
  June_vacc_rate May_vacc_rate April_vacc_rate
           <dbl>         <dbl>           <dbl>
1          0.516         0.514           0.511
```

Reshaping Charm City Circulator

```
long
```

```
# A tibble: 4,584 × 6
   day       date       daily line   type       value
   <chr>     <chr>      <dbl> <chr>  <chr>      <dbl>
 1 Monday    01/11/2010  952  orange Boardings   877
 2 Monday    01/11/2010  952  purple Boardings    NA
 3 Monday    01/11/2010  952  green  Boardings    NA
 4 Monday    01/11/2010  952  banner Boardings    NA
 5 Tuesday   01/12/2010  796  orange Boardings   777
 6 Tuesday   01/12/2010  796  purple Boardings    NA
 7 Tuesday   01/12/2010  796  green  Boardings    NA
 8 Tuesday   01/12/2010  796  banner Boardings    NA
 9 Wednesday 01/13/2010 1212. orange Boardings  1203
10 Wednesday 01/13/2010 1212. purple Boardings    NA
# ℹ 4,574 more rows
```

Reshaping Charm City Circulator

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

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

Summary

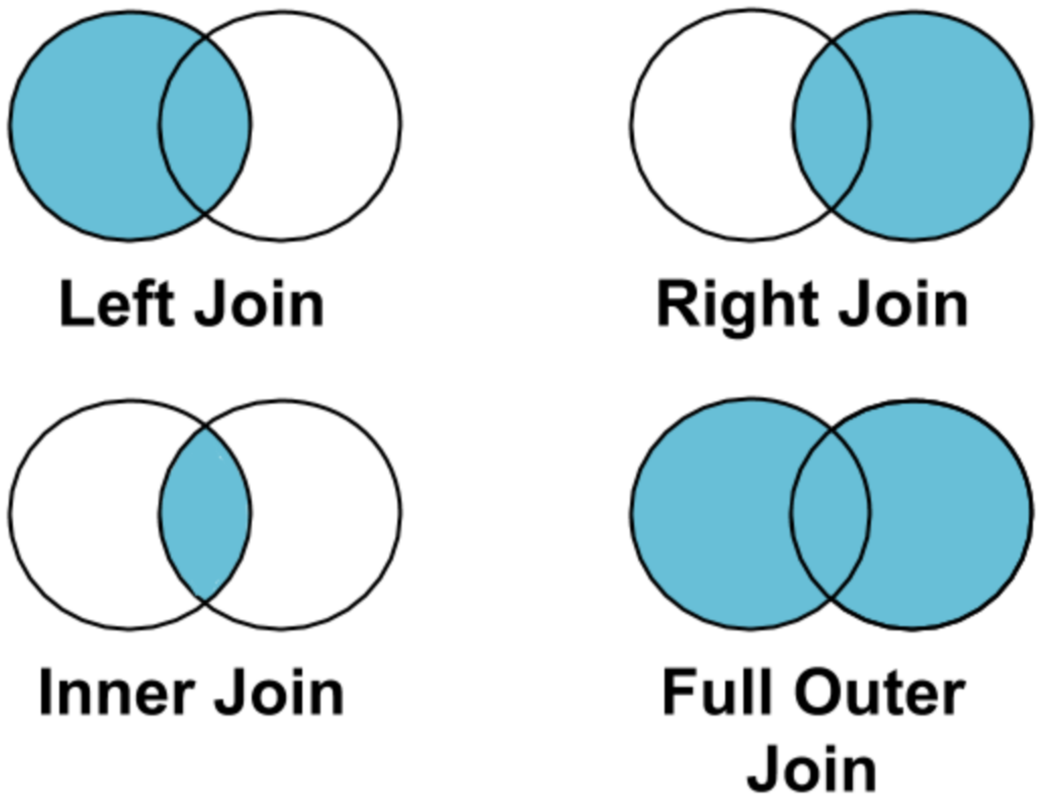
- `tidyr` package helps us convert between wide and long data
- `pivot_longer()` goes from wide -> long
    - Specify columns you want to pivot
    - Specify `names_to =` and `values_to =` for custom naming
- `pivot_wider()` goes from long -> wide
    - Specify `names_from =` and `values_from =`

Lab Part 1

- Class Website
- Lab

Joining

“Combining datasets”



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
```

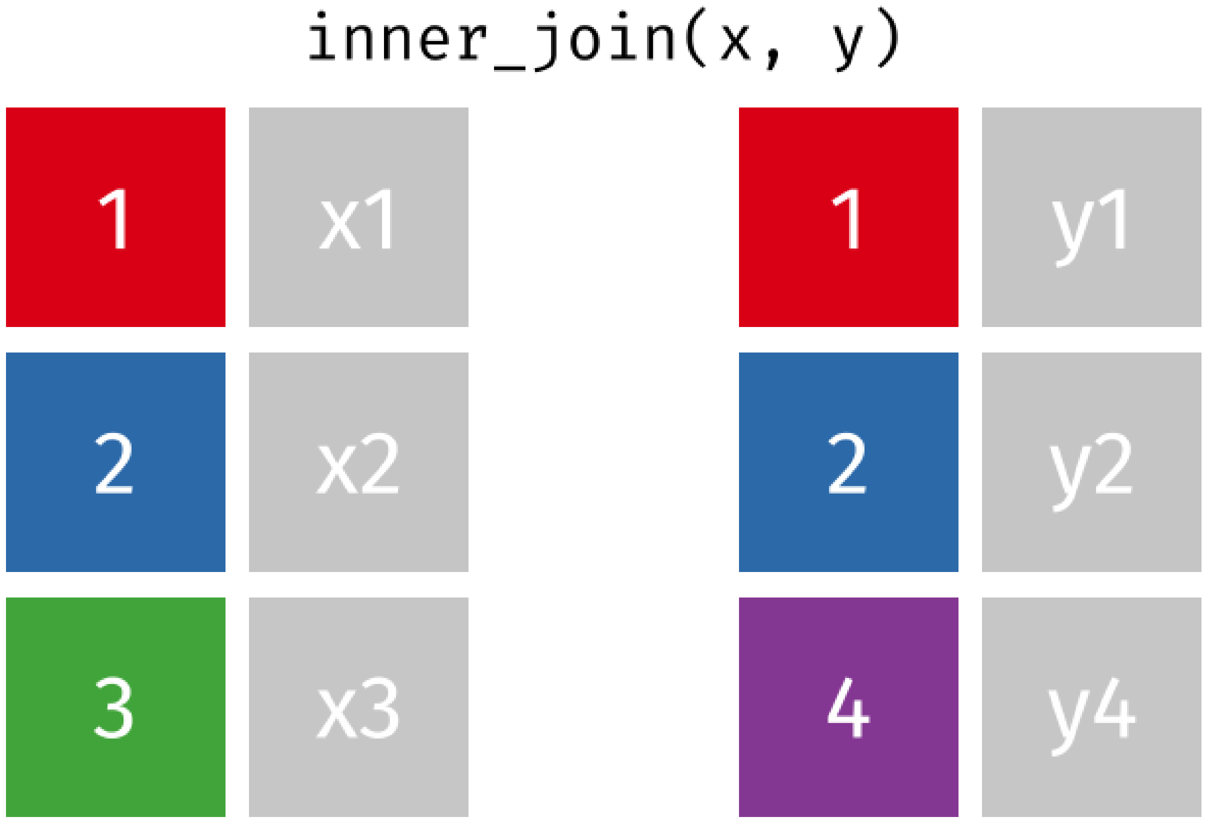
```
# A tibble: 2 × 3
  State   June_vacc_rate May_vacc_rate
  <chr>            <dbl>         <dbl>
1 Alabama          0.516         0.514
2 Alaska           0.627         0.626
```

```
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



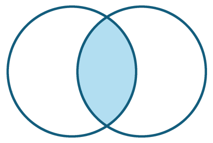
Inner Join

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

```
Joining with `by = join_by(State)`
```

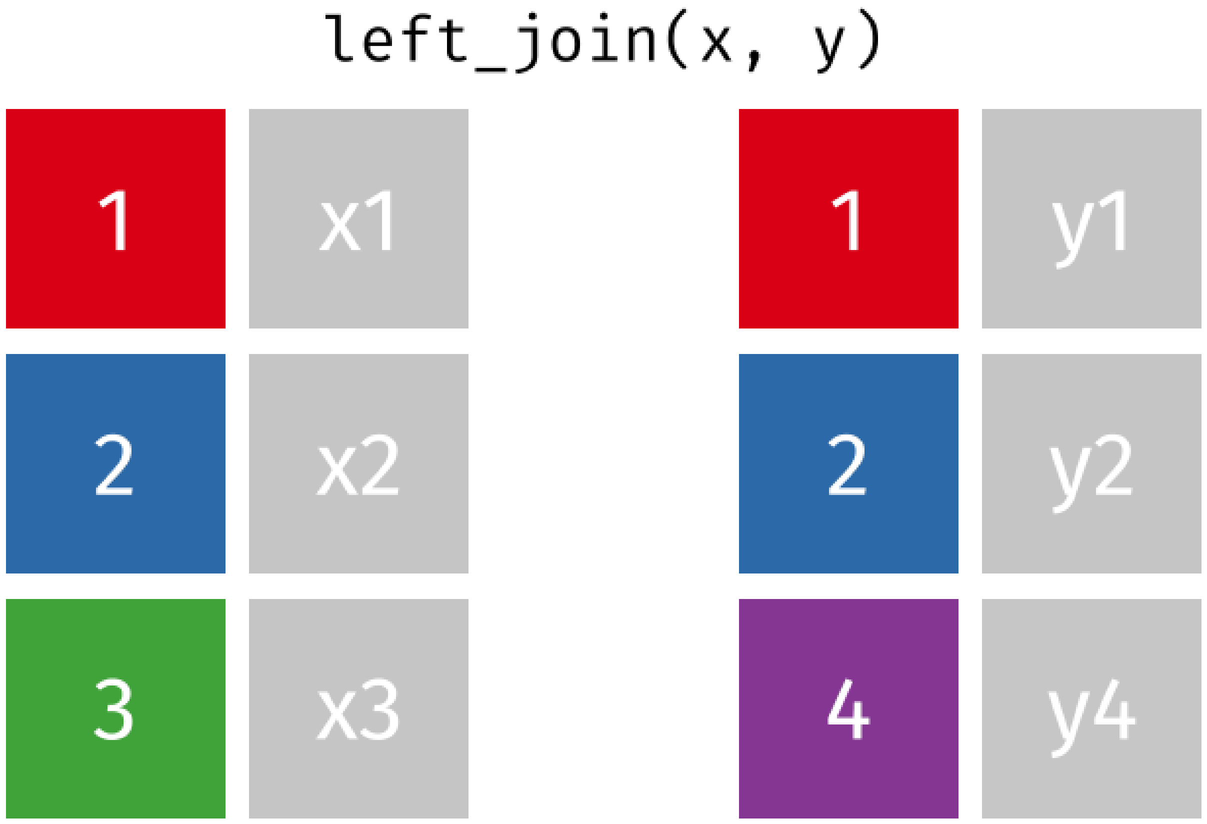
```
ij
```

```
# 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

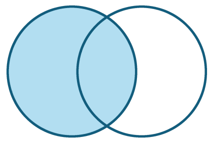
“Everything to the left of the comma”

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

```
Joining with `by = join_by(State)`
```

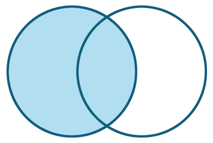
```
lj
```

```
# 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
```



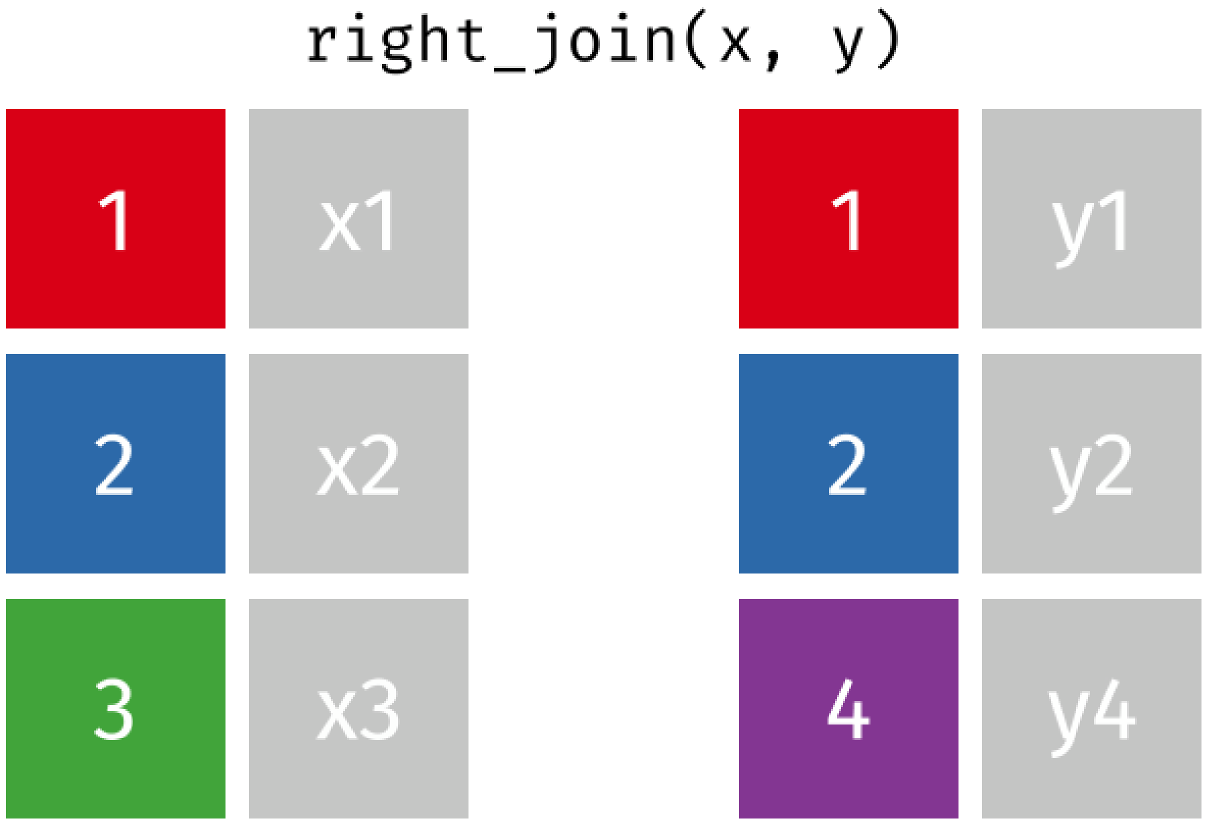
Install **tidylog** package to log outputs

```
# 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 x 1
> rows only in y (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

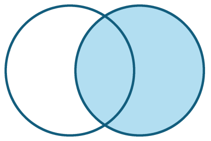
“Everything to the right of the comma”

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

```
Joining with `by = join_by(State)`
right_join: added one column (April_vacc_rate)
> rows only in x (1)
> rows only in y 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
```



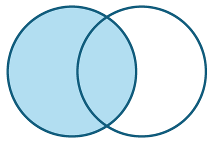
Left Join: Switching arguments

```
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 x 1
> rows only in y (1)
> matched rows 1
> ===
> rows total 2
```

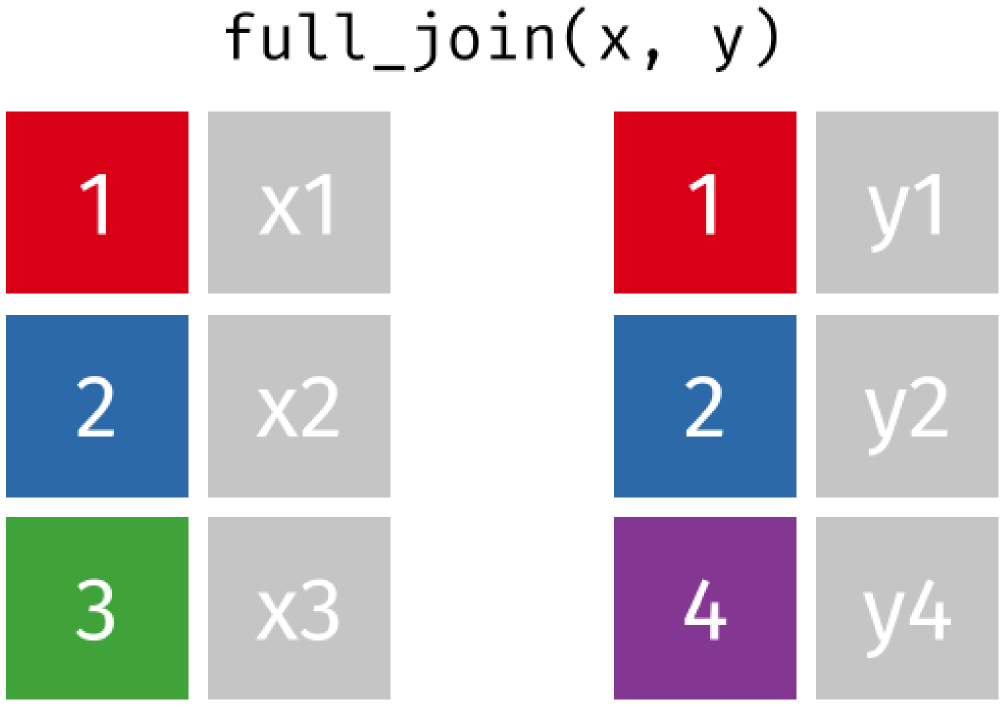
```
lj2
```

```
# 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



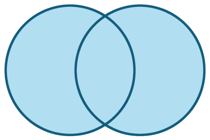
Full Join

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

```
Joining with `by = join_by(State)`
full_join: added one column (April_vacc_rate)
> rows only in x 1
> rows only in y 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
```



Watch out for "`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
```

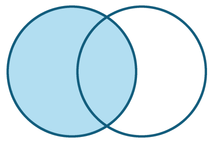
```
data_cold
```

```
# 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
```

Watch out for “`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 x 1
> rows only in y (1)
> matched rows 2 (includes duplicates)
> ===
> rows total 3
```



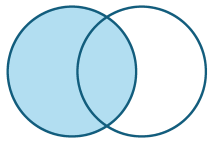
Watch out for “`includes duplicates`”

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

```
lj
```

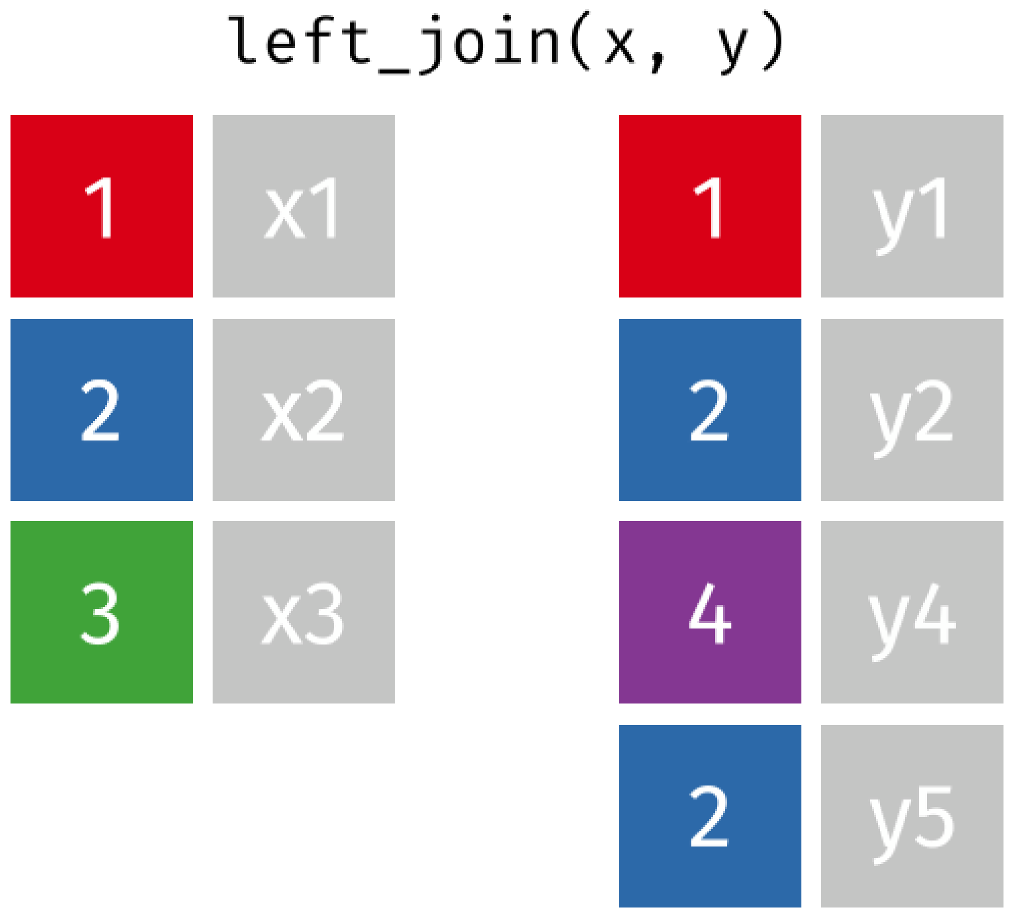
```
# A tibble: 3 × 4
  State   state_bird       vacc_rate month
  <chr>   <chr>                <dbl> <chr>
1 Alabama wild turkey         NA     <NA>
2 Alaska  willow ptarmigan     0.623 April
3 Alaska  willow ptarmigan     0.626 May
```

Note that “Alaska willow ptarmigan” appears twice.



Watch out for “**`includes duplicates`**”

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



Stop **`tidylog`**

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

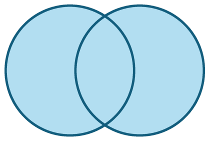
```r
unloadNamespace("tidylog")
```

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`

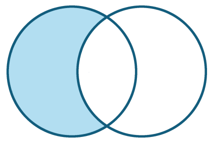
```
anti_join(data_As, data_cold, by = "State")
```

```
# 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
```



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
- `antijoin(x, y)` shows what is only in `x` (missing from `y`)

Lab Part 2

- Class Website
- Lab

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

Inconsistencies in non-pivoted columns?

Notice “daily” column has different values

```
long2
```

```
# A tibble: 4,584 × 6
   day       date       daily line   type       value
   <chr>     <chr>      <dbl> <chr>  <chr>      <dbl>
 1 Monday    01/11/2010  952  orange Boardings    877
 2 MONDAY    01/11/2010  952  purple Boardings     NA
 3 Monday    01/11/2010  952  green  Boardings     NA
 4 Monday    01/11/2010  952  banner Boardings     NA
 5 Tuesday   01/12/2010  796  orange Boardings    777
 6 Tuesday   01/12/2010  796  purple Boardings     NA
 7 Tuesday   01/12/2010  796  green  Boardings     NA
 8 Tuesday   01/12/2010  796  banner Boardings     NA
 9 Wednesday 01/13/2010 1212. orange Boardings   1203
10 Wednesday 01/13/2010 1212. purple Boardings     NA
# ℹ 4,574 more rows
```

Inconsistencies in non-pivoted columns?

R won’t drop data while pivoting.

```
wide2 <- long2 %>% pivot_wider(names_from = "type",
                             values_from = "value")
wide2
```

```
# A tibble: 4,584 × 5
   day       date       daily line   Boardings
   <chr>     <chr>      <dbl> <chr>      <dbl>
 1 Monday    01/11/2010  952  orange       877
 2 MONDAY    01/11/2010  952  purple        NA
 3 Monday    01/11/2010  952  green         NA
 4 Monday    01/11/2010  952  banner        NA
 5 Tuesday   01/12/2010  796  orange       777
 6 Tuesday   01/12/2010  796  purple        NA
 7 Tuesday   01/12/2010  796  green         NA
 8 Tuesday   01/12/2010  796  banner        NA
 9 Wednesday 01/13/2010 1212. orange      1203
10 Wednesday 01/13/2010 1212. purple        NA
# ℹ 4,574 more rows
```

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.