

# Intro to R

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 ~ 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

[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.

Wide

Long

	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

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## 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](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	
2	Tuesday	01/1...	777	815	796	
3	Wednesday	01/1...	1203	1220	1212.	
4	Thursday	01/1...	1194	1233	1214.	
5	Friday	01/1...	1645	1643	1644	

```
#   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  
#   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 <chr>	date <chr>	daily <dbl>	name <chr>	value <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  
#   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 <chr>	date <chr>	daily <dbl>	line <chr>	type <chr>	value <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

```
#   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](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  
#   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 <chr>	date <chr>	daily <dbl>	line <chr>	type <chr>	value <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

```
#   4,574 more rows
```

# Reshaping Charm City Circulator

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

```
# 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  
#   4,574 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 =`

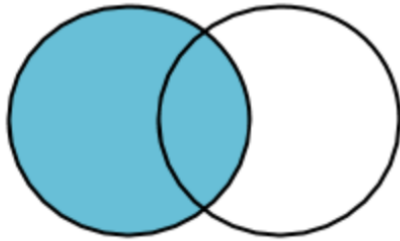
# Lab Part 1

[Class Website](#)

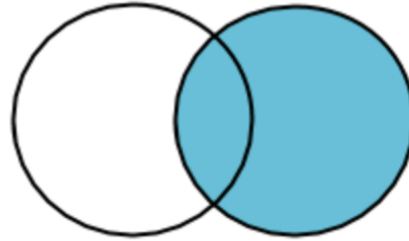
[Lab](#)

# Joining

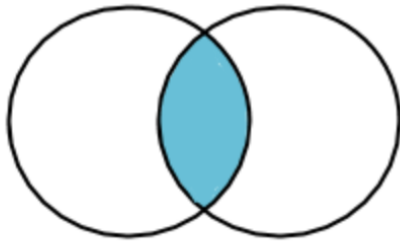
“Combining datasets”



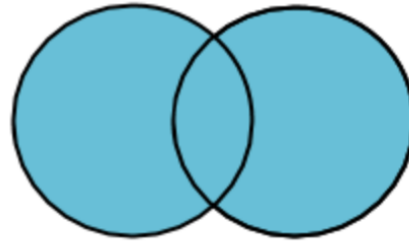
**Left Join**



**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(x, y)`



# 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(x, y)`



# 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(x, y)`





## 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(x, y)`



# FullJoin

```
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
```

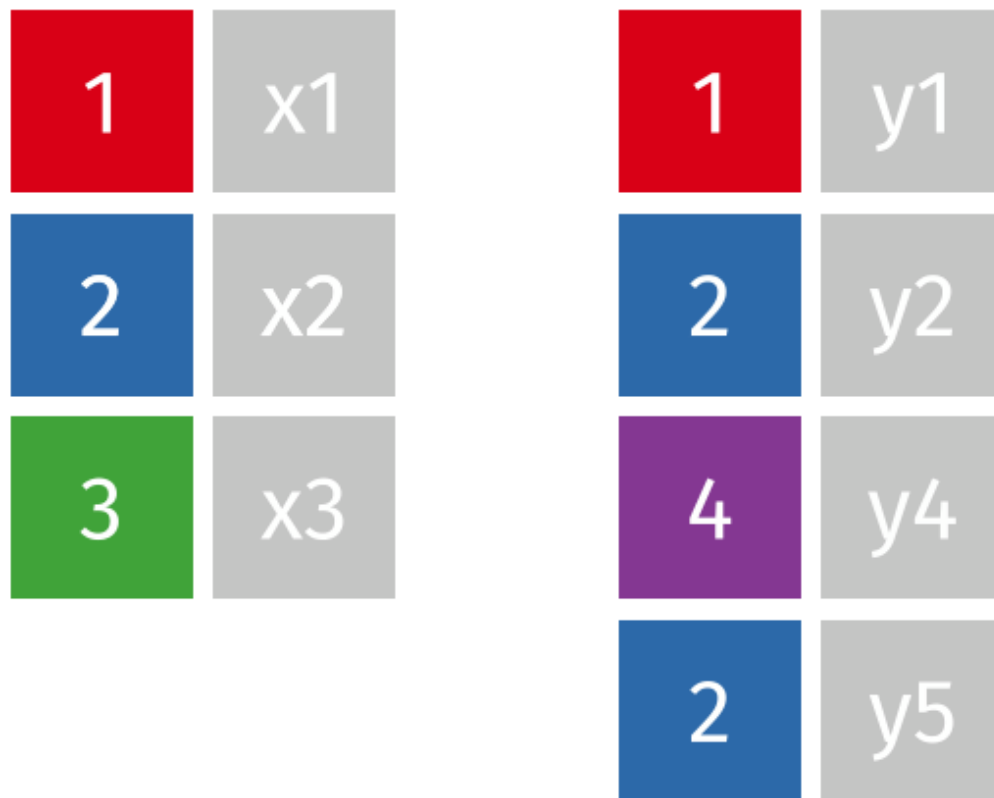
```
# A tibble: 3 × 4
  State    state_bird      vacc_rate month
  <chr>    <chr>          <dbl> <chr>
1 Alabama wild turkey      NA    <NA>
2 Alaska  willow ptarmigan  0.623 April
3 Alaska  willow ptarmigan  0.626 May
```

Note that “Alaska willow ptarmigan” appears twice.

## Watch out for “includes duplicates”

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

`left_join(x, y)`





## 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"))
```

## 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>

## 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
- `setdiff(x, y)` shows what in x is missing from y

## Lab Part 2

[Class Website](#)

[Lab](#)



Image by [Gerd Altmann](#) from [Pixabay](#)



**Additional Slides**

## 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
#   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 <chr>	date <chr>	daily <dbl>	line <chr>	Boardings <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

```
#   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.