Gov 50: 11. Tidying and Joining Data

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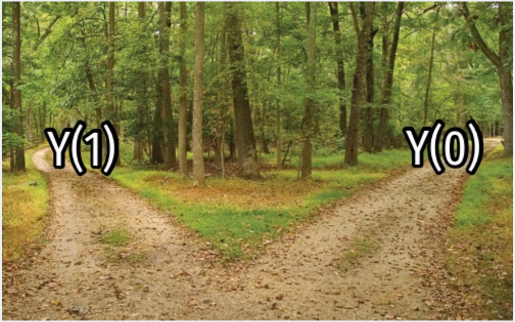
Roadmap

1. Causality review
2. Pivoting data longer
3. Joining data sets

1/ Causality review

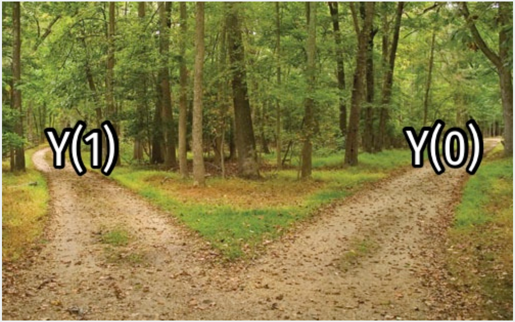
Potential outcomes



Potential outcomes:

- $Y_i(1)$ is the value that the outcome would take if gave unit i **treatment** and changed nothing else about them.

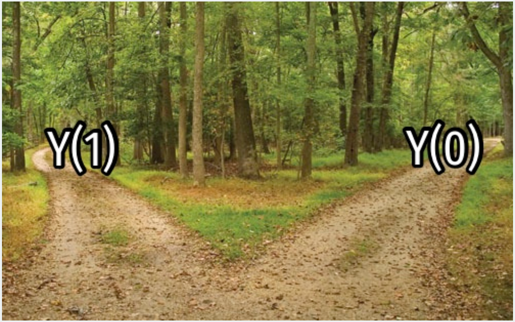
Potential outcomes



Potential outcomes:

- $Y_i(1)$ is the value that the outcome would take if gave unit i **treatment** and changed nothing else about them.
- $Y_i(0)$ is the value that the outcome would take if gave unit i **no treatment** and changed nothing else about them.

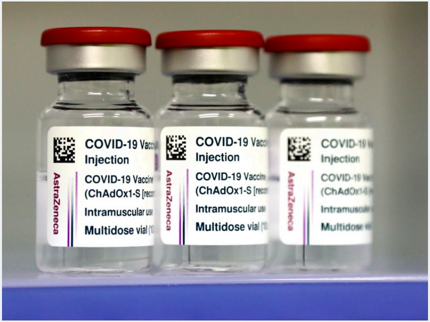
Potential outcomes



Potential outcomes:

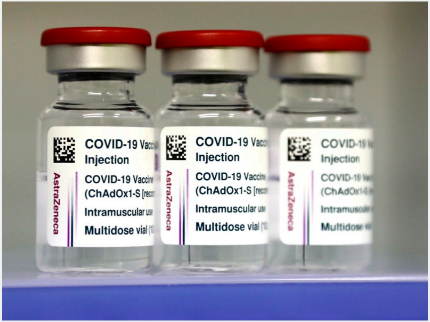
- $Y_i(1)$ is the value that the outcome would take if gave unit i **treatment** and changed nothing else about them.
- $Y_i(0)$ is the value that the outcome would take if gave unit i **no treatment** and changed nothing else about them.
- Not the **possible values** of the outcome

COVID-19 vaccine trials



Treatment: $T_i = 1$ if vaccinated, $T_i = 0$ if not

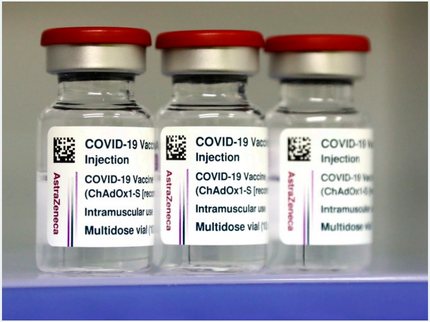
COVID-19 vaccine trials



Treatment: $T_i = 1$ if vaccinated, $T_i = 0$ if not

Outcome: $Y_i = 1$ if acquired COVID after 12 weeks, $Y_i = 0$ if not

COVID-19 vaccine trials

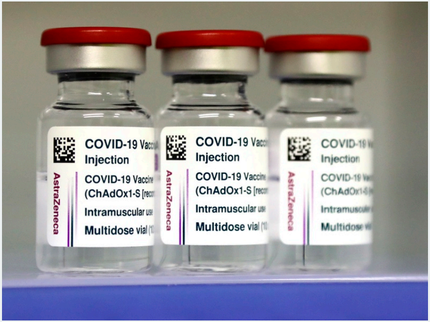


Treatment: $T_i = 1$ if vaccinated, $T_i = 0$ if not

Outcome: $Y_i = 1$ if acquired COVID after 12 weeks, $Y_i = 0$ if not

1. What are the potential outcomes $Y_i(1)$ and $Y_i(0)$?

COVID-19 vaccine trials



Treatment: $T_i = 1$ if vaccinated, $T_i = 0$ if not

Outcome: $Y_i = 1$ if acquired COVID after 12 weeks, $Y_i = 0$ if not

1. What are the potential outcomes $Y_i(1)$ and $Y_i(0)$?
2. Why not compare early volunteers for the vaccine to the overall population?

2/ Pivoting data longer

Mortality data

```r
library(tidyverse)
library(gov50data)
mortality
```

```
## # A tibble: 217 x 52
##    country        country_code indicator `1972` `1973` `1974`
##    <chr>          <chr>        <chr>      <dbl>  <dbl>  <dbl>
##  1 Aruba          ABW          Mortalit~   NA     NA     NA
##  2 Afghanistan    AFG          Mortalit~  291    285.   280.
##  3 Angola         AGO          Mortalit~   NA     NA     NA
##  4 Albania        ALB          Mortalit~   NA     NA     NA
##  5 Andorra        AND          Mortalit~   NA     NA     NA
##  6 United Arab ~  ARE          Mortalit~   80.1   72.6   65.7
##  7 Argentina      ARG          Mortalit~   69.7   68.2   66.1
##  8 Armenia        ARM          Mortalit~   NA     NA     NA
##  9 American Sam~  ASM          Mortalit~   NA     NA     NA
## 10 Antigua and ~  ATG          Mortalit~   26.9   25.1   23.5
## # i 207 more rows
## # i 46 more variables: `1975` <dbl>, `1976` <dbl>,
## #   `1977` <dbl>, `1978` <dbl>, `1979` <dbl>, `1980` <dbl>,
## #   `1981` <dbl>, `1982` <dbl>, `1983` <dbl>, `1984` <dbl>,
## #   `1985` <dbl>, `1986` <dbl>, `1987` <dbl>, `1988` <dbl>,
```

Pivoting longer

Mortality data in a “wide” format (years in columns).

We can convert this to country-year rows with `pivot_longer()`.

```
mydata |>
  pivot_longer(
    cols = <<variables to pivot>>,
    names_to = <<new variable to put column names>>,
    values_to = <<new variable to put column values>>
  )
```

Pivoting the mortality data

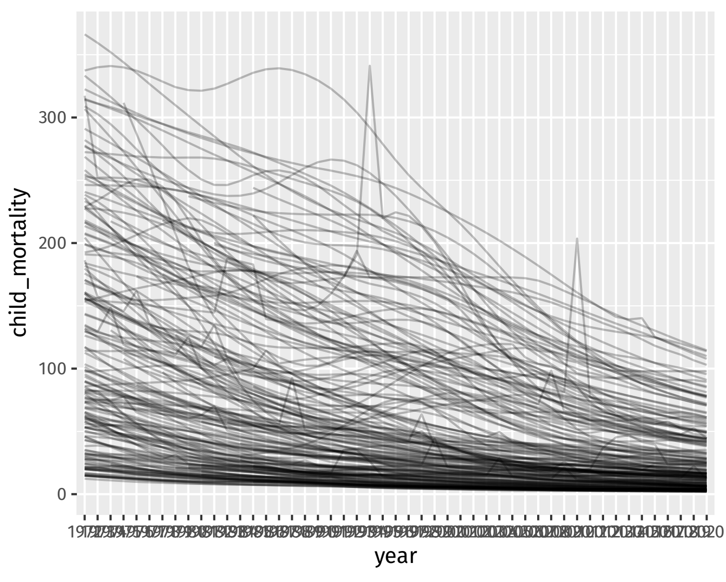
```r
mortality |>
  select(-indicator) |>
  pivot_longer(
    cols = `1972`:`2020`,
    names_to = "year",
    values_to = "child_mortality"
  )
```

```
## # A tibble: 10,633 x 4
##    country country_code year  child_mortality
##    <chr>   <chr>        <chr>           <dbl>
##  1 Aruba   ABW          1972               NA
##  2 Aruba   ABW          1973               NA
##  3 Aruba   ABW          1974               NA
##  4 Aruba   ABW          1975               NA
##  5 Aruba   ABW          1976               NA
##  6 Aruba   ABW          1977               NA
##  7 Aruba   ABW          1978               NA
##  8 Aruba   ABW          1979               NA
##  9 Aruba   ABW          1980               NA
## 10 Aruba   ABW          1981               NA
## # i 10,623 more rows
```

Let's do line plots!

```
mortality |>
  select(-indicator) |>
  pivot_longer(
    cols = `1972`:`2020`,
    names_to = "year",
    values_to = "child_mortality"
  ) |>
  ggplot(mapping = aes(x = year, y = child_mortality, group = country)) +
  geom_line(alpha = 0.25)
```

Hmm, what's going on?



Making sure year is numeric

By default, pivoted column names are characters, but we can transform them:

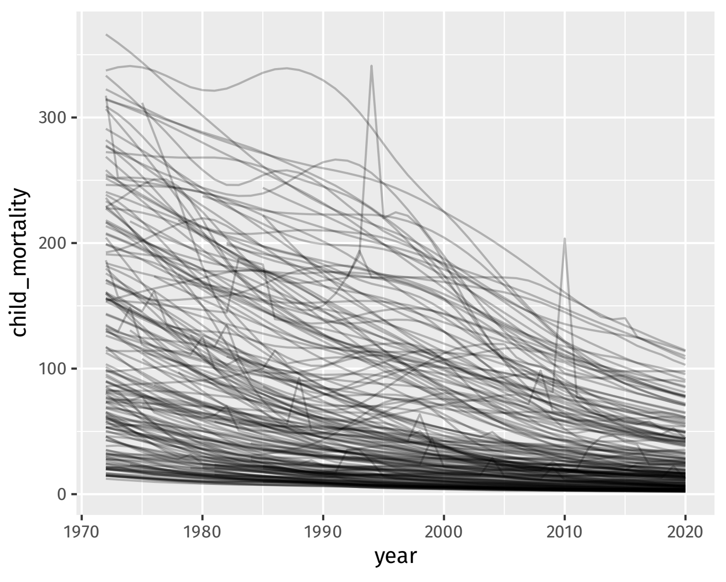
```r
mortality_long <- mortality |>
  select(-indicator) |>
  pivot_longer(
    cols = `1972`:`2020`,
    names_to = "year",
    values_to = "child_mortality"
  ) |>
  mutate(year = as.integer(year))
mortality_long
```

```
## # A tibble: 10,633 x 4
##    country country_code  year child_mortality
##    <chr>   <chr>        <int>           <dbl>
##  1 Aruba   ABW           1972              NA
##  2 Aruba   ABW           1973              NA
##  3 Aruba   ABW           1974              NA
##  4 Aruba   ABW           1975              NA
##  5 Aruba   ABW           1976              NA
##  6 Aruba   ABW           1977              NA
```

Let's (re)do line plots!

```
mortality_long |>
  ggplot(mapping = aes(x = year, y = child_mortality, group = country)) +
  geom_line(alpha = 0.25)
```

There we go


child_mortality
300
200
100
0
1970
1980
1990
2000
2010
2020
year

Spotify data

```
spotify
```

```
## # A tibble: 490 x 54
##    `Track Name`    Artist week1 week2 week3 week4 week5 week6
##    <chr>           <chr>  <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
##  1 The Box         Roddy~     1     1     1     1     1     1
##  2 ROXANNE         Arizo~     2     4     5     4     4     4
##  3 Yummy           Justi~     3     6    17    17    17    24
##  4 Circles         Post ~     4     7     9    10     7    10
##  5 BOP             DaBaby     5     5     7     5    11    12
##  6 Falling         Trevo~     6     8    10     7     6     8
##  7 Dance Monkey    Tones~     7    13    13    12    12    13
##  8 Bandit (with ~ Juice~     8    11    14    14    15    20
##  9 Futsal Shuffl~ Lil U~     9     9    19    21    24    32
## 10 everything i ~ Billi~    10    17    28     9     8    11
## # i 480 more rows
## # i 46 more variables: week7 <dbl>, week8 <dbl>,
## #   week9 <dbl>, week10 <dbl>, week11 <dbl>, week12 <dbl>,
## #   week13 <dbl>, week14 <dbl>, week15 <dbl>, week16 <dbl>,
## #   week17 <dbl>, week18 <dbl>, week19 <dbl>, week20 <dbl>,
## #   week21 <dbl>, week22 <dbl>, week23 <dbl>, week24 <dbl>,
## #   week25 <dbl>, week26 <dbl>, week27 <dbl>, ...
```

Pivoting not ideal

Last approach isn't ideal because of the week prefix:

```r
spotify |>
  pivot_longer(
    cols = c(-`Track Name`, -Artist),
    names_to = "week_of_year",
    values_to = "rank"
  )
```

```
## # A tibble: 25,480 x 4
##    `Track Name` Artist      week_of_year  rank
##    <chr>        <chr>       <chr>        <dbl>
##  1 The Box      Roddy Ricch week1            1
##  2 The Box      Roddy Ricch week2            1
##  3 The Box      Roddy Ricch week3            1
##  4 The Box      Roddy Ricch week4            1
##  5 The Box      Roddy Ricch week5            1
##  6 The Box      Roddy Ricch week6            1
##  7 The Box      Roddy Ricch week7            1
##  8 The Box      Roddy Ricch week8            1
##  9 The Box      Roddy Ricch week9            1
## 10 The Box      Roddy Ricch week10           1
## # i 25,470 more rows
```

Removing a column name prefix

When the data in the column name has a fixed prefix, we can use the `names_prefix` to remove it when moving the data to rows

```
spotify |>
  pivot_longer(
    cols = c(-`Track Name`, -Artist),
    names_to = "week_of_year",
    values_to = "rank",
    names_prefix = "week"
  ) |>
  mutate(
    week_of_year = as.integer(week_of_year)
  )
```

Removing a column name prefix

```
## # A tibble: 25,480 x 4
##    `Track Name` Artist      week_of_year  rank
##    <chr>        <chr>              <int> <dbl>
##  1 The Box      Roddy Ricch            1     1
##  2 The Box      Roddy Ricch            2     1
##  3 The Box      Roddy Ricch            3     1
##  4 The Box      Roddy Ricch            4     1
##  5 The Box      Roddy Ricch            5     1
##  6 The Box      Roddy Ricch            6     1
##  7 The Box      Roddy Ricch            7     1
##  8 The Box      Roddy Ricch            8     1
##  9 The Box      Roddy Ricch            9     1
## 10 The Box      Roddy Ricch           10     1
## # i 25,470 more rows
```

3/ Joining data sets

Gapminder data

```r
library(gapminder)
gapminder
```

```
## # A tibble: 1,704 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.
## # i 1,694 more rows
```

Joining data sets

What if we want to add the `child_mortality` variable to the `gampinder` data?

Joining data sets

What if we want to add the `child_mortality` variable to the `gampinder` data?

Just add the columns? Rows are not aligned properly!

```
gapminder |>
  select(country, year) |>
  head()
```

```
## # A tibble: 6 x 2
##   country      year
##   <fct>       <int>
## 1 Afghanistan  1952
## 2 Afghanistan  1957
## 3 Afghanistan  1962
## 4 Afghanistan  1967
## 5 Afghanistan  1972
## 6 Afghanistan  1977
```

```
mortality_long |>
  select(country, year) |>
  head()
```

```
## # A tibble: 6 x 2
##   country  year
##   <chr>   <int>
## 1 Aruba    1972
## 2 Aruba    1973
## 3 Aruba    1974
## 4 Aruba    1975
## 5 Aruba    1976
## 6 Aruba    1977
```

Key variables

A **primary key** is a variable or set of variables that uniquely identifies rows in the data.

- `{country, year}` in the `gapminder` data

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- `{country, year}` in the `gapminder` data

A **foreign key** is the corresponding variable(s) in another table.

- `{country, year}` in the `mortality_long` data

Key variables

A **primary key** is a variable or set of variables that uniquely identifies rows in the data.

- `{country, year}` in the `gapminder` data

A **foreign key** is the corresponding variable(s) in another table.

- `{country, year}` in the `mortality_long` data

If we align the two tables based on these variables, we can add variables from one to the other.

Checking that the keys are unique

Things get weird if these keys are not unique. Let's check.

Checking primary key is unique:

```
gapminder |>
  count(country, year) |>
  filter(n > 1)
```

```
## # A tibble: 0 x 3
```

Checking foreign key:

```
mortality_long |>
  count(country, year) |>
  filter(n > 1)
```

```
## # A tibble: 0 x 3
```

`left_join()`: add variables to primary table

`left_join()` keeps all rows from the first argument/piped data:

```
gapminder |>
  left_join(mortality_long) |>
  select(country, year, lifeExp, pop, gdpPercap, child_mortality) |>
  head(n = 6)
```

```
## Joining with `by = join_by(country, year)`
```

```
## # A tibble: 6 x 6
##   country      year lifeExp     pop gdpPercap child_mortality
##   <chr>       <int>   <dbl>   <int>     <dbl>           <dbl>
## 1 Afghanistan  1952    28.8 8.43e6      779.              NA
## 2 Afghanistan  1957    30.3 9.24e6      821.              NA
## 3 Afghanistan  1962    32.0 1.03e7      853.              NA
## 4 Afghanistan  1967    34.0 1.15e7      836.              NA
## 5 Afghanistan  1972    36.1 1.31e7      740.             291
## 6 Afghanistan  1977    38.4 1.49e7      786.             262.
```

Rows in primary table not in foreign table: new values are NA.

inner_join(): add and filter

inner_join() adds the variables from the foreign table and filters to rows in both tables:

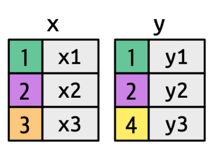
```
gapminder |>
  inner_join(mortality_long) |>
  select(country, year, lifeExp, pop, gdpPercap, child_mortality) |>
  head(n = 6)
```

```
## Joining with `by = join_by(country, year)`
```

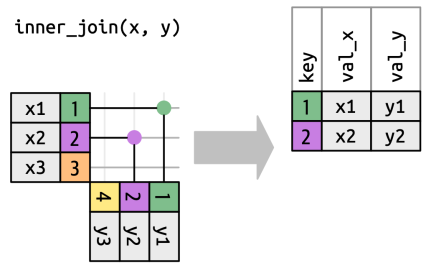
```
## # A tibble: 6 x 6
##   country      year lifeExp    pop gdpPercap child_mortality
##   <chr>       <int>   <dbl>  <int>     <dbl>           <dbl>
## 1 Afghanistan  1972    36.1 1.31e7      740.             291
## 2 Afghanistan  1977    38.4 1.49e7      786.             262.
## 3 Afghanistan  1982    39.9 1.29e7      978.             231.
## 4 Afghanistan  1987    40.8 1.39e7      852.             198.
## 5 Afghanistan  1992    41.7 1.63e7      649.             166.
## 6 Afghanistan  1997    41.8 2.22e7      635.             142.
```

How inner joins work

Two data sets:

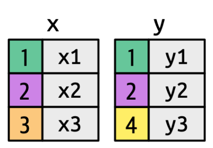


Find matching keys:

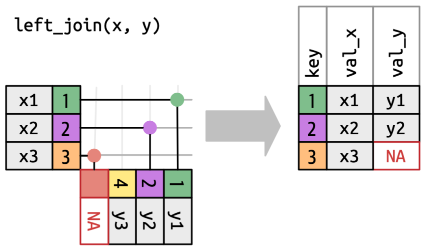


How left joins work

Two data sets:



Keep all x keys:



Credit: R for Data Science

More complicated example

```r
library(nycflights13)
flights2 <- flights |>
  select(year, time_hour, origin, dest, tailnum, carrier)
flights2
```

```
## # A tibble: 336,776 x 6
##     year time_hour           origin dest  tailnum carrier
##    <int> <dttm>              <chr>  <chr> <chr>   <chr>
##  1  2013 2013-01-01 05:00:00 EWR    IAH   N14228  UA
##  2  2013 2013-01-01 05:00:00 LGA    IAH   N24211  UA
##  3  2013 2013-01-01 05:00:00 JFK    MIA   N619AA  AA
##  4  2013 2013-01-01 05:00:00 JFK    BQN   N804JB  B6
##  5  2013 2013-01-01 06:00:00 LGA    ATL   N668DN  DL
##  6  2013 2013-01-01 05:00:00 EWR    ORD   N39463  UA
##  7  2013 2013-01-01 06:00:00 EWR    FLL   N516JB  B6
##  8  2013 2013-01-01 06:00:00 LGA    IAD   N829AS  EV
##  9  2013 2013-01-01 06:00:00 JFK    MCO   N593JB  B6
## 10  2013 2013-01-01 06:00:00 LGA    ORD   N3ALAA  AA
## # i 336,766 more rows
```

Planes data

```
planes2 <- planes |>
  select(tailnum, year, type, engine, seats)
planes2
```

```
## # A tibble: 3,322 x 5
##    tailnum  year type                          engine    seats
##    <chr>   <int> <chr>                         <chr>     <int>
##  1 N10156   2004 Fixed wing multi engine Turbo-fan    55
##  2 N102UW   1998 Fixed wing multi engine Turbo-fan   182
##  3 N103US   1999 Fixed wing multi engine Turbo-fan   182
##  4 N104UW   1999 Fixed wing multi engine Turbo-fan   182
##  5 N10575   2002 Fixed wing multi engine Turbo-fan    55
##  6 N105UW   1999 Fixed wing multi engine Turbo-fan   182
##  7 N107US   1999 Fixed wing multi engine Turbo-fan   182
##  8 N108UW   1999 Fixed wing multi engine Turbo-fan   182
##  9 N109UW   1999 Fixed wing multi engine Turbo-fan   182
## 10 N110UW   1999 Fixed wing multi engine Turbo-fan   182
## # i 3,312 more rows
```

year here is manufacture year.

What happens with naive join?

```
flights2 |>
  left_join(planes2)
```

```
## Joining with `by = join_by(year, tailnum)`
```

```
## # A tibble: 336,776 x 9
##     year time_hour           origin dest  tailnum carrier type  engine
##    <int> <dttm>              <chr>  <chr> <chr>   <chr>   <chr> <chr>
##  1  2013 2013-01-01 05:00:00 EWR    IAH   N14228  UA      <NA>  <NA>
##  2  2013 2013-01-01 05:00:00 LGA    IAH   N24211  UA      <NA>  <NA>
##  3  2013 2013-01-01 05:00:00 JFK    MIA   N619AA  AA      <NA>  <NA>
##  4  2013 2013-01-01 05:00:00 JFK    BQN   N804JB  B6      <NA>  <NA>
##  5  2013 2013-01-01 06:00:00 LGA    ATL   N668DN  DL      <NA>  <NA>
##  6  2013 2013-01-01 05:00:00 EWR    ORD   N39463  UA      <NA>  <NA>
##  7  2013 2013-01-01 06:00:00 EWR    FLL   N516JB  B6      <NA>  <NA>
##  8  2013 2013-01-01 06:00:00 LGA    IAD   N829AS  EV      <NA>  <NA>
##  9  2013 2013-01-01 06:00:00 JFK    MCO   N593JB  B6      <NA>  <NA>
## 10  2013 2013-01-01 06:00:00 LGA    ORD   N3ALAA  AA      <NA>  <NA>
## # i 336,766 more rows
## # i 1 more variable: seats <int>
```

Specify the joining variables

```r
flights2 |>
  left_join(planes2, by = "tailnum")
```

```
## # A tibble: 336,776 x 10
##    year.x time_hour           origin dest  tailnum carrier year.y
##     <int> <dttm>              <chr>  <chr> <chr>   <chr>    <int>
##  1   2013 2013-01-01 05:00:00 EWR    IAH   N14228  UA        1999
##  2   2013 2013-01-01 05:00:00 LGA    IAH   N24211  UA        1998
##  3   2013 2013-01-01 05:00:00 JFK    MIA   N619AA  AA        1990
##  4   2013 2013-01-01 05:00:00 JFK    BQN   N804JB  B6        2012
##  5   2013 2013-01-01 06:00:00 LGA    ATL   N668DN  DL        1991
##  6   2013 2013-01-01 05:00:00 EWR    ORD   N39463  UA        2012
##  7   2013 2013-01-01 06:00:00 EWR    FLL   N516JB  B6        2000
##  8   2013 2013-01-01 06:00:00 LGA    IAD   N829AS  EV        1998
##  9   2013 2013-01-01 06:00:00 JFK    MCO   N593JB  B6        2004
## 10   2013 2013-01-01 06:00:00 LGA    ORD   N3ALAA  AA          NA
## # i 336,766 more rows
## # i 3 more variables: type <chr>, engine <chr>, seats <int>
```

Change variables names

```
flights2 |>
  left_join(planes2 |> rename(manufacture_year = year))
```

```
## Joining with `by = join_by(tailnum)`
```

```
## # A tibble: 336,776 x 10
##     year time_hour           origin dest  tailnum carrier
##    <int> <dttm>              <chr>  <chr> <chr>   <chr>
##  1  2013 2013-01-01 05:00:00 EWR    IAH   N14228  UA
##  2  2013 2013-01-01 05:00:00 LGA    IAH   N24211  UA
##  3  2013 2013-01-01 05:00:00 JFK    MIA   N619AA  AA
##  4  2013 2013-01-01 05:00:00 JFK    BQN   N804JB  B6
##  5  2013 2013-01-01 06:00:00 LGA    ATL   N668DN  DL
##  6  2013 2013-01-01 05:00:00 EWR    ORD   N39463  UA
##  7  2013 2013-01-01 06:00:00 EWR    FLL   N516JB  B6
##  8  2013 2013-01-01 06:00:00 LGA    IAD   N829AS  EV
##  9  2013 2013-01-01 06:00:00 JFK    MCO   N593JB  B6
## 10  2013 2013-01-01 06:00:00 LGA    ORD   N3ALAA  AA
## # i 336,766 more rows
## # i 4 more variables: manufacture_year <int>, type <chr>,
## #   engine <chr>, seats <int>
```