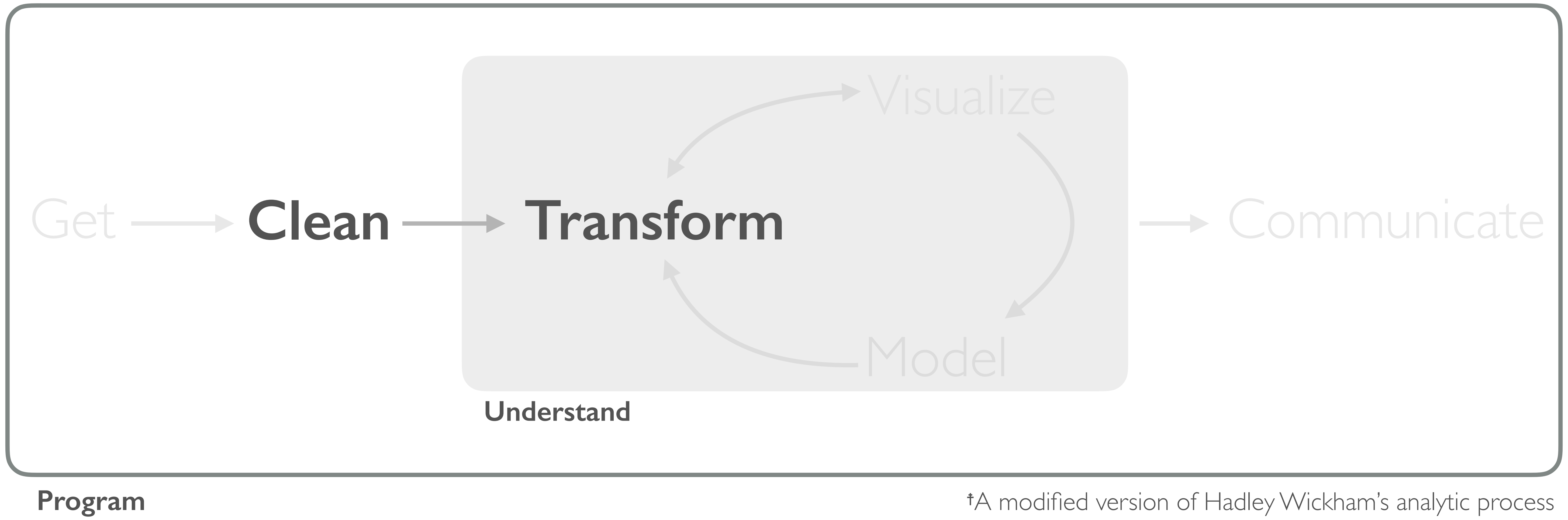
RELATIONAL DATA

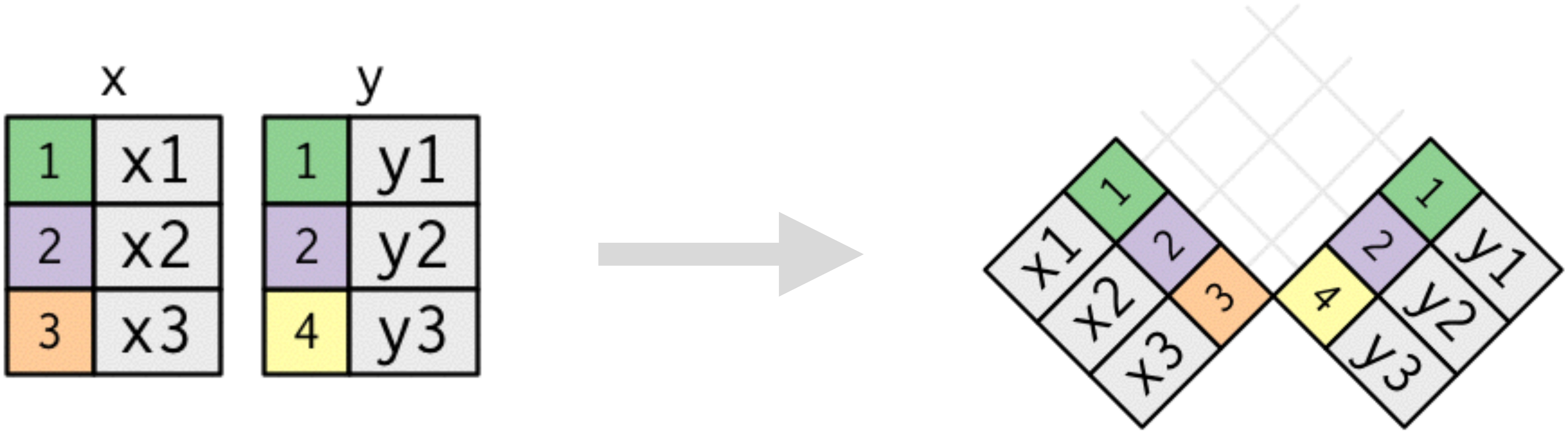


†A modified version of Hadley Wickham's analytic process

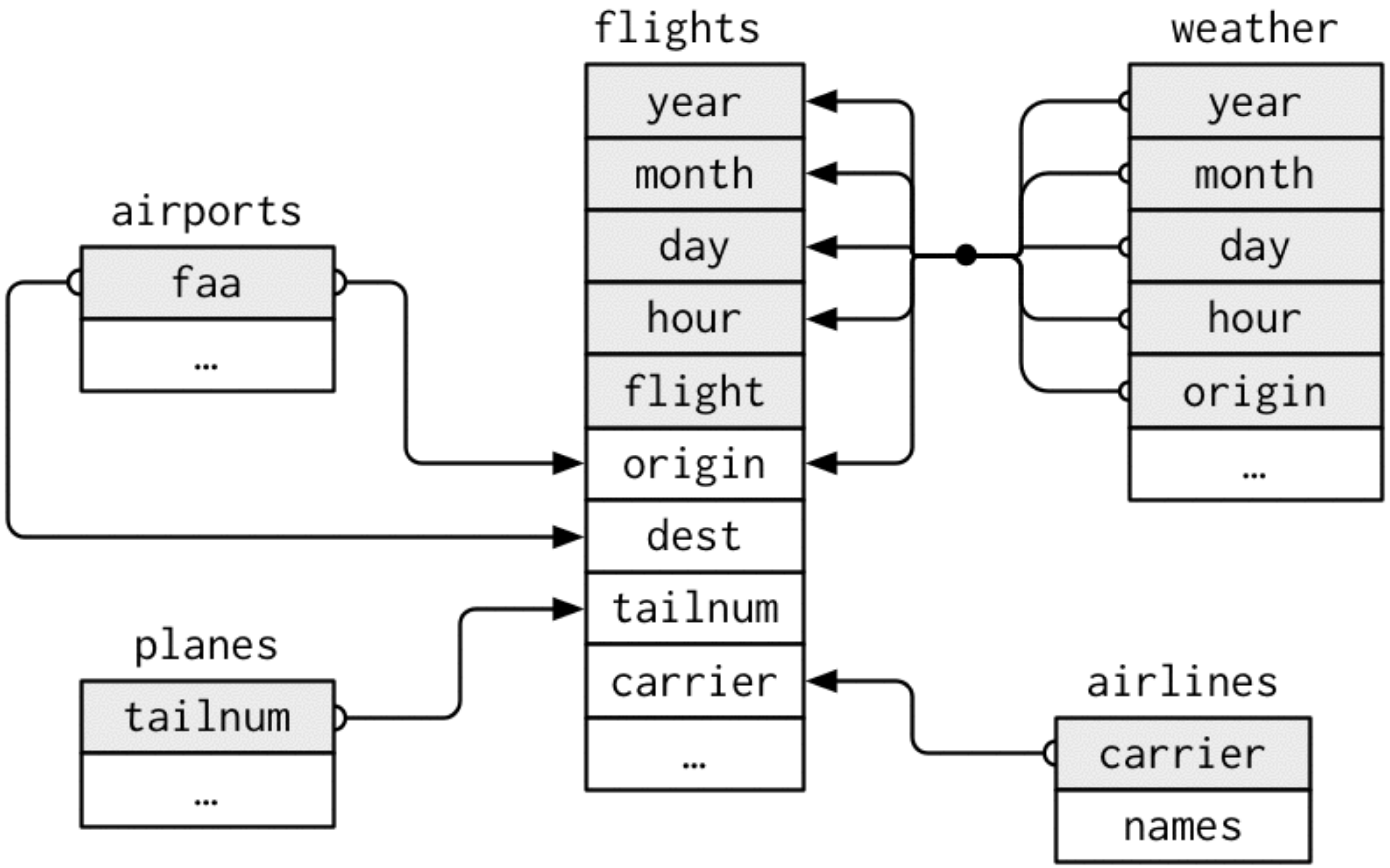
“It’s rare that a data analysis involves only a single table of data. Typically you have many tables of data, and you must combine them to answer the questions that you’re interested in.”

- Garrett Grolemund & Hadley Wickham

WHAT IS RELATIONAL DATA?



WHAT IS RELATIONAL DATA?



VERBS

To work with relational data you need verbs that work with pairs of tables. There are three families of verbs designed to work with relational data:

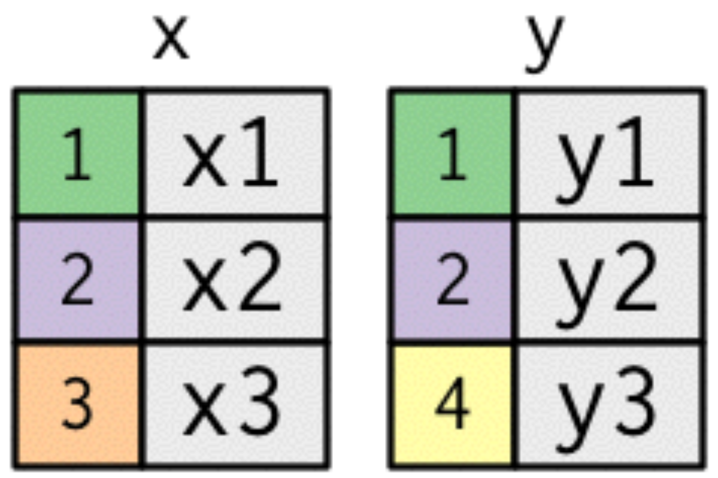
- **Mutating joins :** add new variables to one data frame by matching observations in another.
- **Filter joins :** filter observations from one data frame based on whether or not they match an observation in the other table.
- **Set operations :** treat observations as if they were set elements

PREREQUISITES

PACKAGE PREREQUISITE

```
library(nycflights13)
library(tidyverse)
#> Loading tidyverse: ggplot2
#> Loading tidyverse: tibble
#> Loading tidyverse: tidyr
#> Loading tidyverse: readr
#> Loading tidyverse: purrr
#> Loading tidyverse: dplyr
#> Conflicts with tidy packages ----------------------------------------------
#> filter(): dplyr, stats
#> lag():    dplyr, stats
```

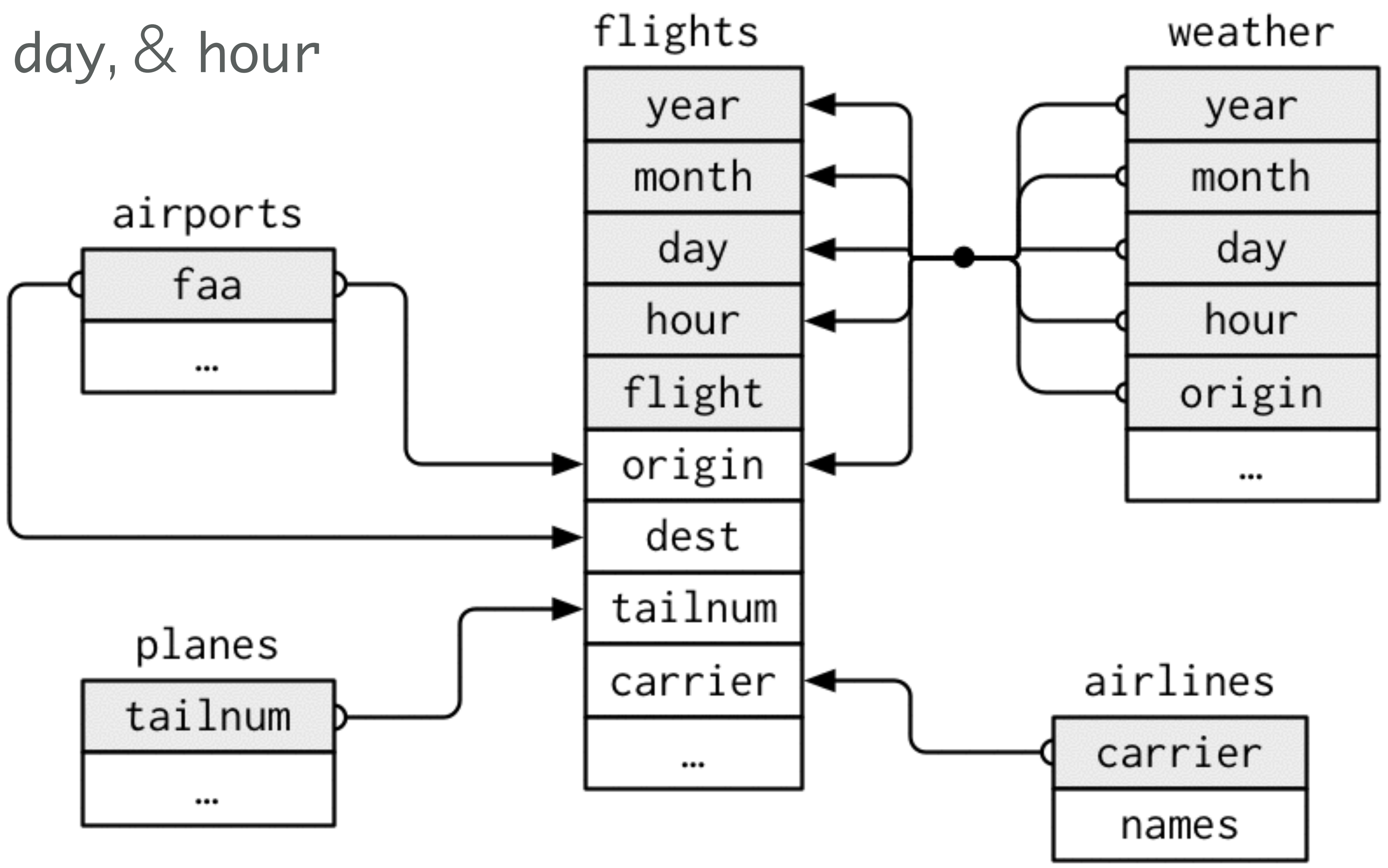
EXAMPLE DATA PREREQUISITE




```
x <- tribble(
  ~key, ~val_x,
     1, "x1",
     2, "x2",
     3, "x3"
)
y <- tribble(
  ~key, ~val_y,
     1, "y1",
     2, "y2",
     4, "y3"
)
```

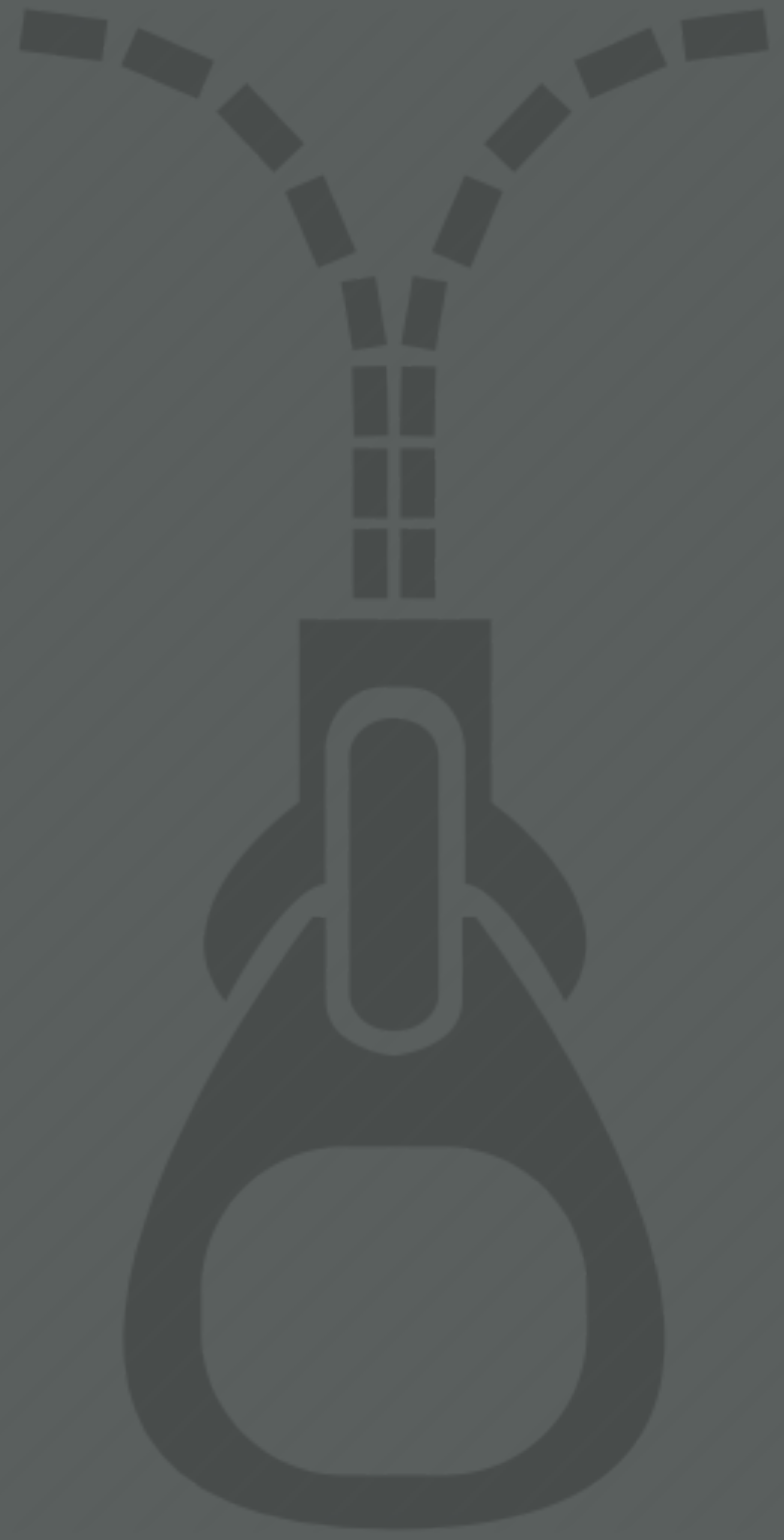
EXERCISE DATA PREREQUISITE

- For `nycflights13`:
  - `flights` connects to planes via `tailnum`
  - `flights` connects to airlines via `carrier`
  - `flights` connects to airports via `origin` & `dest`
  - `flights` connects to weather via `origin, year, month, day`, & `hour`



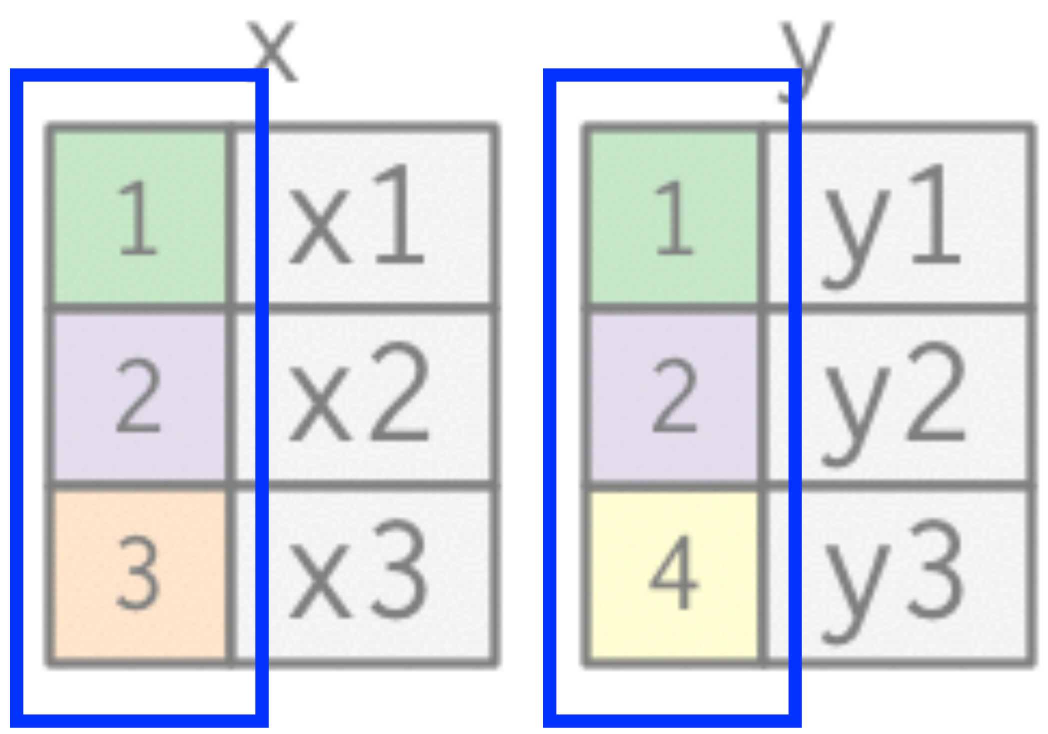
MUTATING JOINS

Adding variables



INNER JOIN

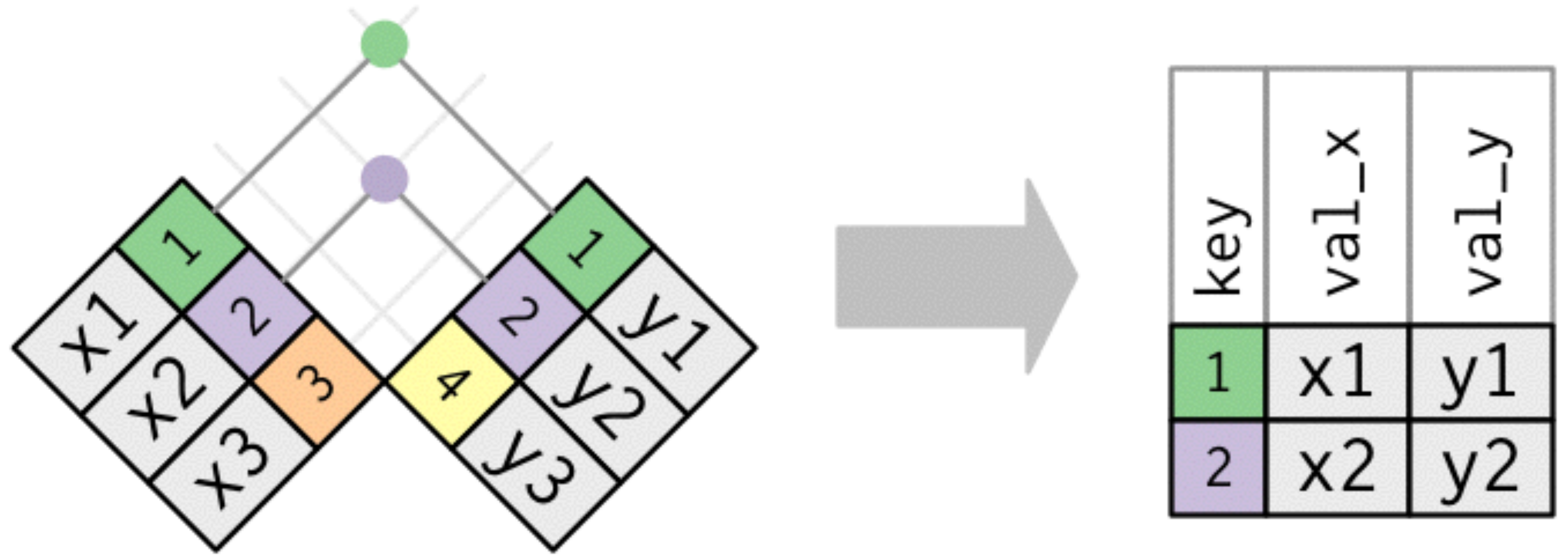
- Simplest type of join
- matches pairs of observations whenever their **keys** are equal
- **keys** are variables that connect pairs of tables



INNER JOIN

- use by to tell dplyr which variable is the key
- unmatched rows are not included in the result

```
x %>% inner_join(y, by = "key")
# A tibble: 2 × 3
    key val_x val_y
  <dbl> <chr> <chr>
1     1    x1    y1
2     2    x2    y2
```

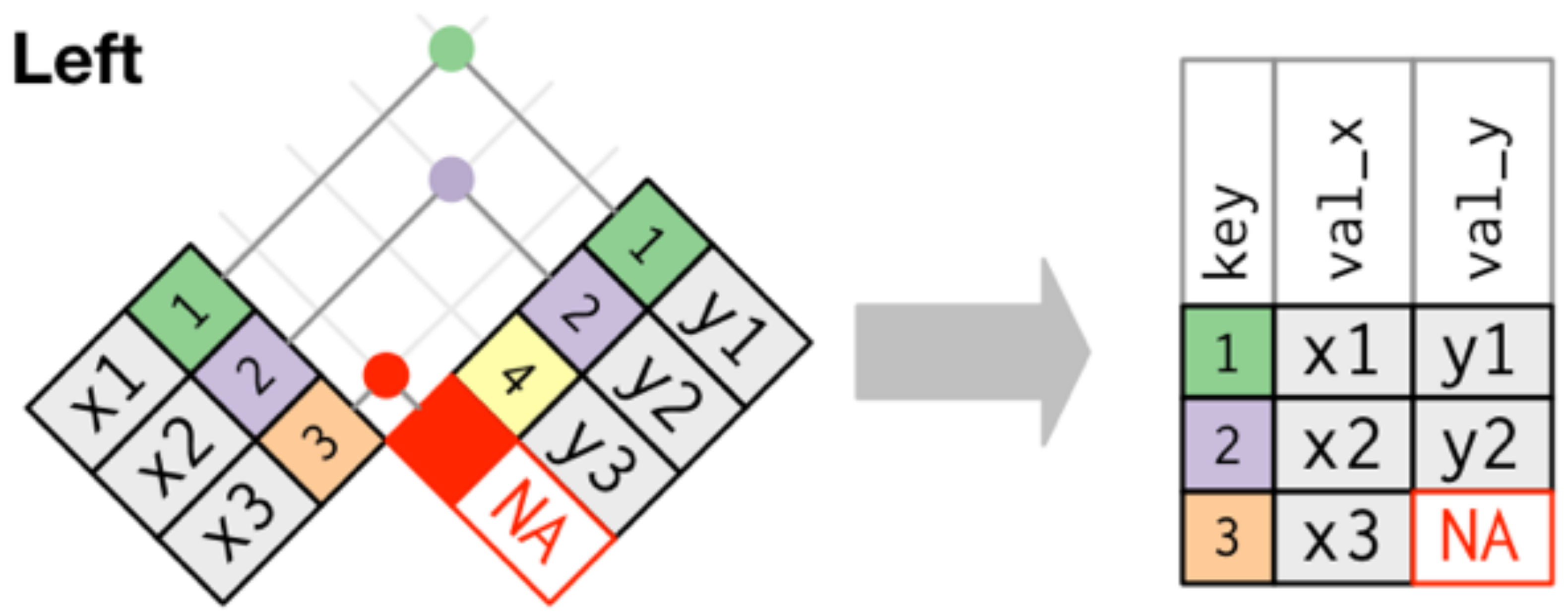


OUTER JOINS

- Outer joins keep observations that appear in at least one of the tables
- There are 3 types of outer joins:

OUTER JOINS

- Outer joins keep observations that appear in at least one of the tables
- There are 3 types of outer joins:
  - **left join**: keeps all observations in x

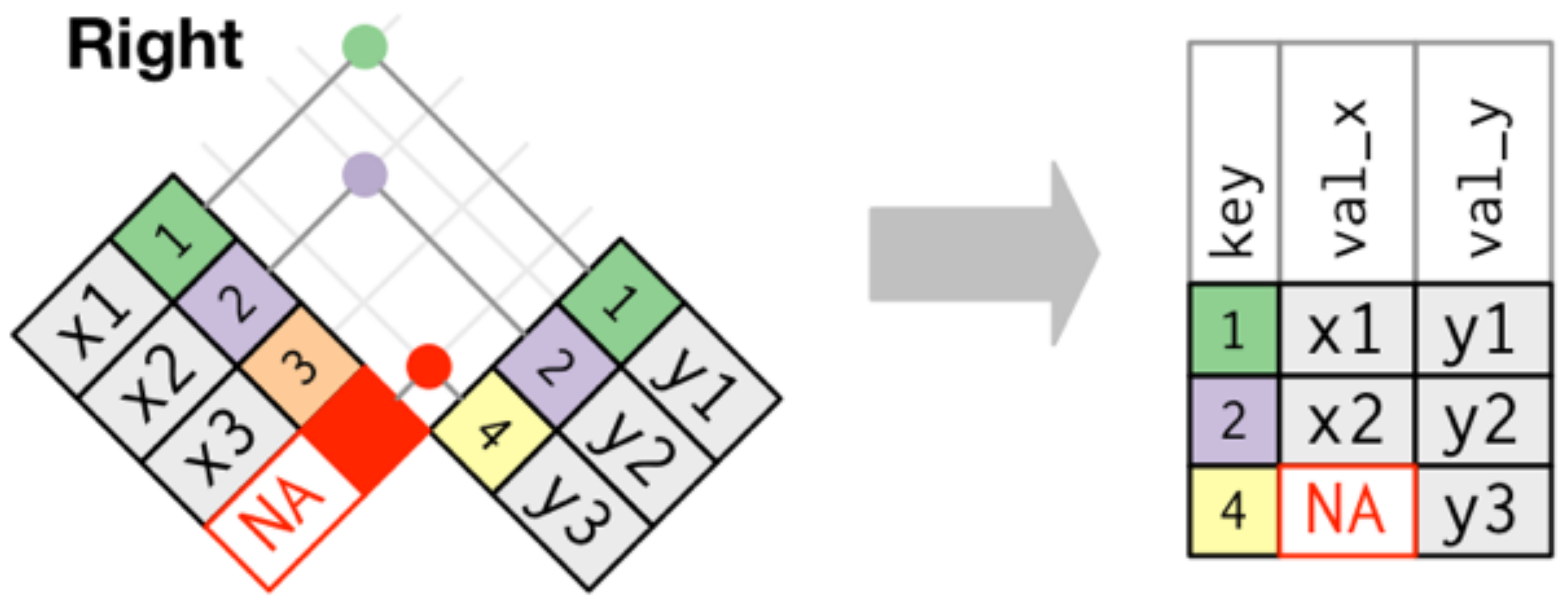



```
x %>% left_join(y, by = "key")
# A tibble: 3 × 3
    key val_x val_y
  <dbl> <chr> <chr>
1     1    x1    y1
2     2    x2    y2
3     3    x3  <NA>
```

Note how missing values get filled in with NA

OUTER JOINS

- Outer joins keep observations that appear in at least one of the tables
- There are 3 types of outer joins:
  - left join: keeps all observations in x
  - **right join**: keeps all observations in y

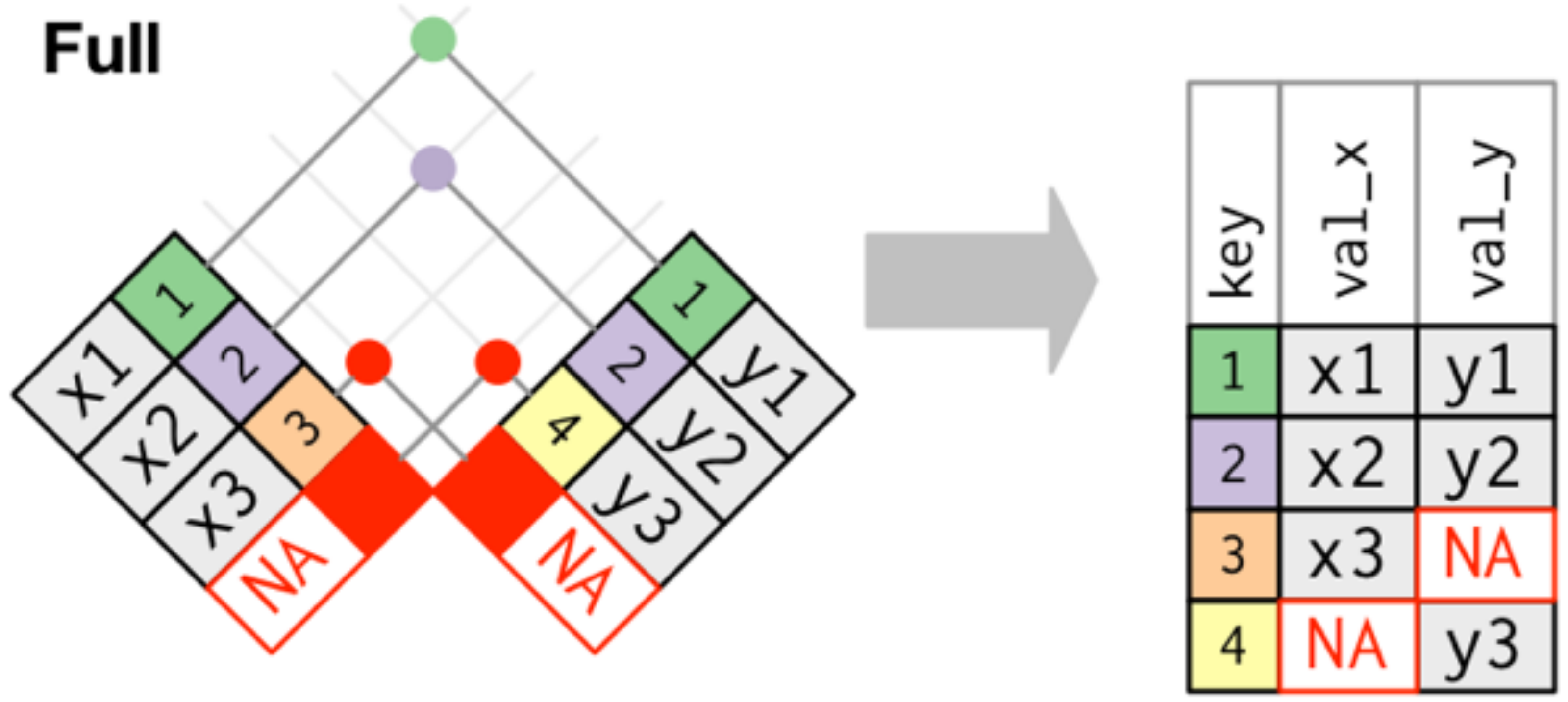



```
x %>% right_join(y, by = "key")
# A tibble: 3 x 3
    key val_x val_y
  <dbl> <chr> <chr>
1     1    x1    y1
2     2    x2    y2
3     4  <NA>    y3
```

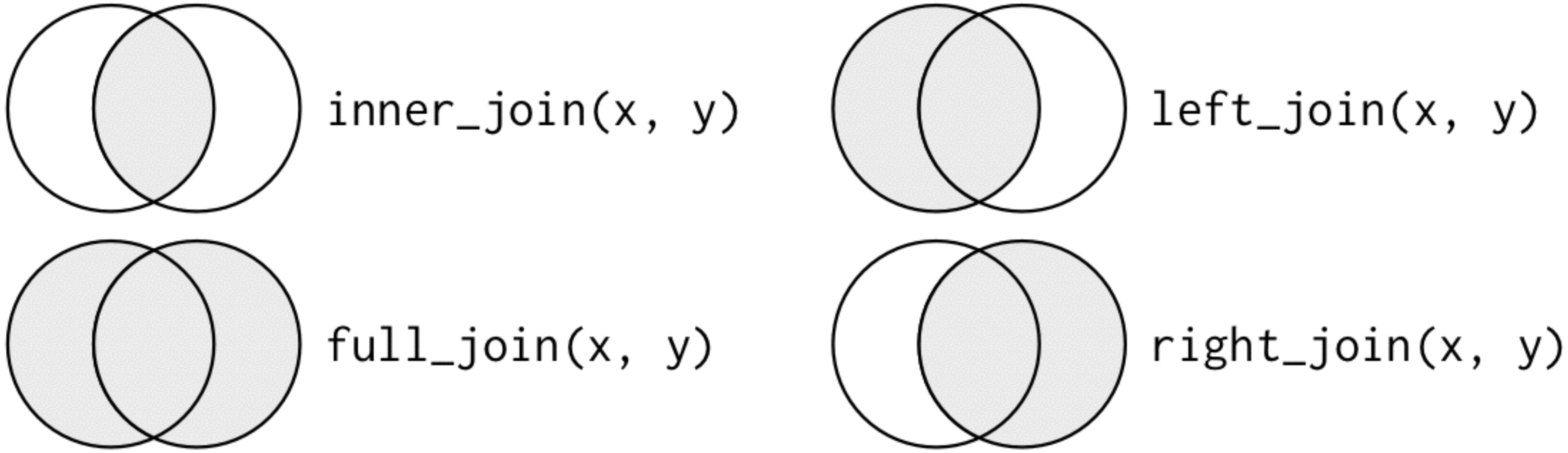
OUTER JOINS

- Outer joins keep observations that appear in at least one of the tables
- There are 3 types of outer joins:
  - left join: keeps all observations in x
  - right join: keeps all observations in y
  - **full join**: keeps all observations in x and y

```
x %>% full_join(y, by = "key")
# A tibble: 4 × 3
    key val_x val_y
  <dbl> <chr> <chr>
1     1    x1    y1
2     2    x2    y2
3     3    x3  <NA>
4     4  <NA>    y3
```



COMPARING JOINS



DEFINING KEYS

- What if our **key names** don't match?

```
x <- tribble(
  ~key1, ~val_x,
     1, "x1",
     2, "x2",
     3, "x3"
)
y <- tribble(
  ~key2, ~val_y,
     1, "y1",
     2, "y2",
     4, "y3"
)
```

DEFINING KEYS

- What if our **keys** don't match?

```
x %>% inner_join(y, by = c("key1" = “key2”))
# A tibble: 2 x 3
   key1 val_x val_y
  <dbl> <chr> <chr>
1     1    x1    y1
2     2    x2    y2
```

YOUR TURN!

1. *take the flights data and then*
   1. *left join airlines data*
   2. *filter for "Virgin America"*
   3. *group by time_hour*
   4. *summarise data by computing the mean dep_delay*
   5. *create ggplot with x = time_hour, y = average dep_delay, and create a line plot with geom_line*

2. *Can you figure out how to add the location of the origin <u>and</u> destination (i.e. the* **`lat`** *and* **`lon`***) from* **`airports`** *to* **`flights`** data? Hint: use two consecutive left_joins.

SOLUTION

```
# problem 1
flights %>%
  left_join(airlines) %>%
  filter(name == "Virgin America") %>%
  group_by(time_hour) %>%
  summarise(delay = mean(dep_delay, na.rm = TRUE)) %>%
  ggplot(aes(time_hour, delay)) +
    geom_line()

# problem 2
flights %>%
  left_join(airports, by = c("origin" = "faa")) %>%
  left_join(airports, by = c("dest" = "faa")) %>%
  select(dest, origin, origin_lat = lat.x, origin_lon = lon.x,
         dest_lat = lat.y, dest_lon = lon.y, arr_delay)
```

FILTERING JOINS

Filtering variables based on another data set

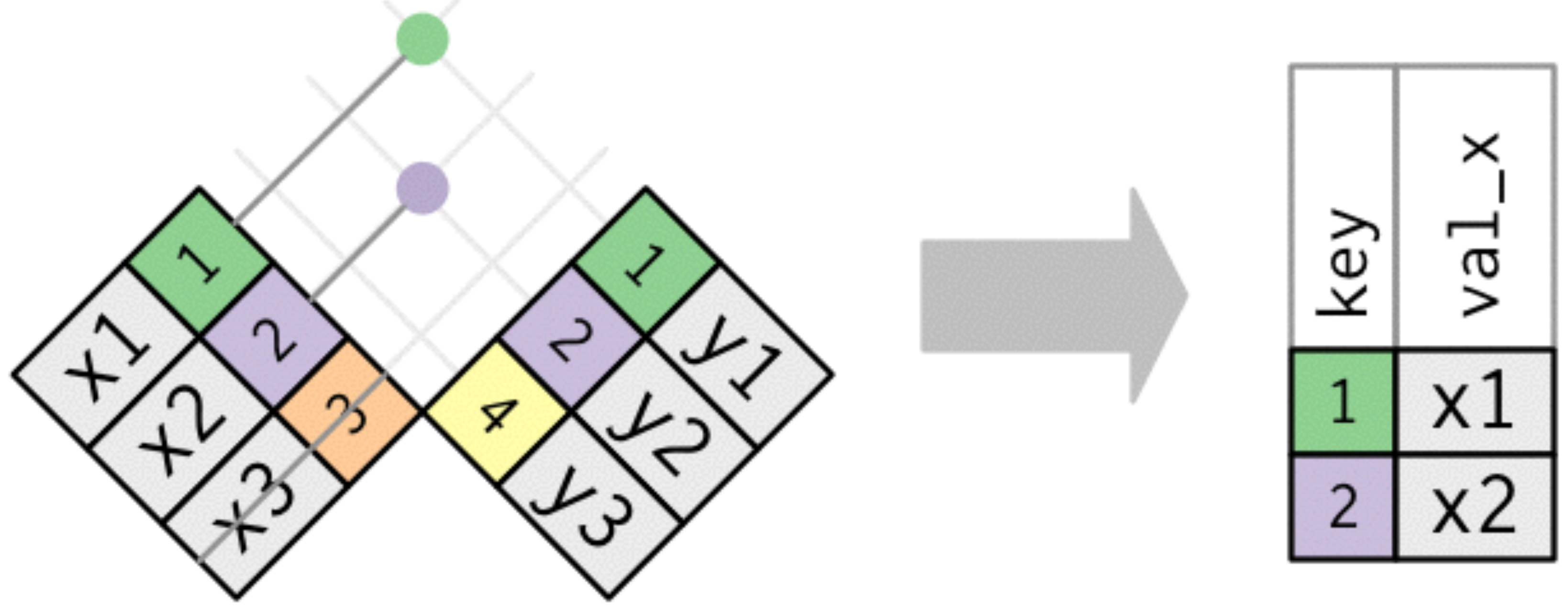
FILTERING JOINS

- Filtering joins affect the observations rather than adding variables
- There are 2 types of filtering joins:

FILTERING JOINS

- Filtering joins affect the observations rather than adding variables
- There are 2 types of filtering joins:
  - **semi join**: keeps all observations in x that have a match in y

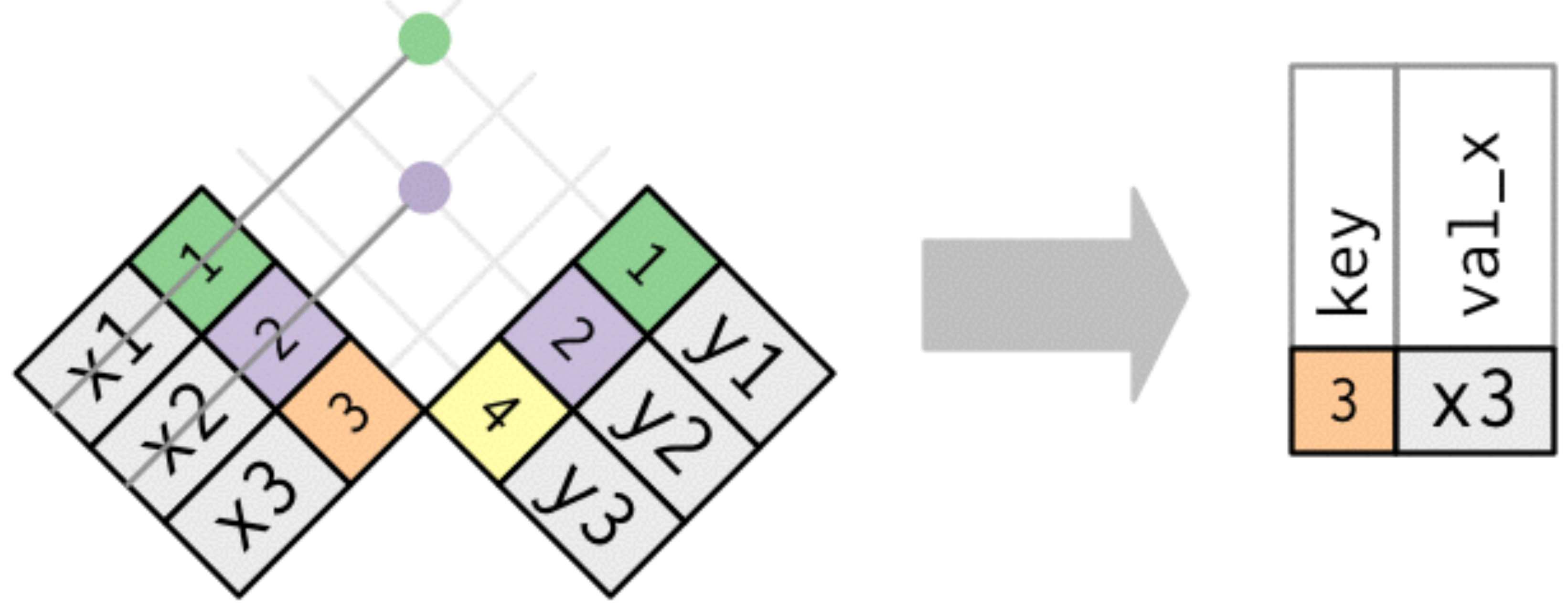
```
x %>% semi_join(y, by = "key")
# A tibble: 2 × 2
    key val_x
  <dbl> <chr>
1     1    x1
2     2    x2
```



FILTERING JOINS

- Filtering joins affect the observations rather than adding variables
- There are 2 types of filtering joins:
  - semi join: keeps all observations in x that have a match in y
  - **anti join**: drops all observations in x that have a match in y

```
x %>% anti_join(y, by = "key")
# A tibble: 1 × 2
    key val_x
  <dbl> <chr>
1     3    x3
```



YOUR TURN!

1. *How many flights in the* **`flights`** *data have matching* **`plane`** *metadata (***`tailnum`*** is your key)? How many do not? Hint: use* **`tally()`** *after your joining functions.*

2. *Filter the* **`airports`** *data for those airports that do not have matching <u>destination values</u> in the* **`flights`** *data (***`faa`*** and* **`dest`** *are your keys). How many <u>unique</u> airports do you find? Hint: use the* **`distinct()`** *and* **`tally()`** *functions after your joining function.*

SOLUTION

```r
# problem 1a --> 284,170
flights %>%
  semi_join(planes, by = "tailnum") %>%
  tally()

# problem 1b --> 52,606
flights %>%
  anti_join(planes, by = "tailnum") %>%
  tally()

# problem 2 --> 1,279
airports %>%
  anti_join(flights, by = c("faa" = "dest")) %>%
  distinct(name) %>%
  tally()
```

SET OPERATIONS

Treat observations as set elements

SET OPERATIONS

- I use these least frequently
- Compares **entire row** in each data set

SET OPERATIONS

- I use these least frequently
- Compares **entire row** in each data set
- `intersect(x, y)`: return only observations in both `x` and `y`.
- `union(x, y)`: return unique observations in `x` and `y`.
- `setdiff(x, y)`: return observations in `x`, but not in `y`

Illustrate with these two data sets

```
df1 <- tribble(
  ~x, ~y,
   1,  1,
   2,  1
)
df2 <- tribble(
  ~x, ~y,
   1,  1,
   1,  2
)
```

SET OPERATIONS

- I use these least frequently
- Compares **entire row** in each data set
- `intersect(x, y)`: return only observations in both x and y.
- `union(x, y)`: return unique observations in x and y.
- `setdiff(x, y)`: return observations in x, but not in y

```
intersect(df1, df2)
# A tibble: 1 × 2
      x     y
  <dbl> <dbl>
1     1     1
```

Illustrate with these two data sets

```
df1 <- tribble(
  ~x, ~y,
   1,  1,
   2,  1
)
df2 <- tribble(
  ~x, ~y,
   1,  1,
   1,  2
)
```

SET OPERATIONS

- I use these least frequently
- Compares **entire row** in each data set
- `intersect(x, y)`: return only observations in both x and y.
- `union(x, y)`: return unique observations in x and y.
- `setdiff(x, y)`: return observations in x, but not in y

```
union(df1, df2)
# A tibble: 3 × 2
      x     y
  <dbl> <dbl>
1     1     2
2     2     1
3     1     1
```

Illustrate with these two data sets

```
df1 <- tribble(
  ~x, ~y,
   1,  1,
   2,  1
)
df2 <- tribble(
  ~x, ~y,
   1,  1,
   1,  2
)
```

SET OPERATIONS

- I use these least frequently
- Compares **entire row** in each data set
- `intersect(x, y)`: return only observations in both x and y.
- `union(x, y)`: return unique observations in x and y.
- `setdiff(x, y)`: return observations in x, but not in y

```
setdiff(df1, df2)
# A tibble: 1 × 2
      x     y
  <dbl> <dbl>
1     2     1
```

Illustrate with these two data sets

```
df1 <- tribble(
  ~x, ~y,
   1,  1,
   2,  1
)
df2 <- tribble(
  ~x, ~y,
   1,  1,
   1,  2
)
```

CHALLENGE

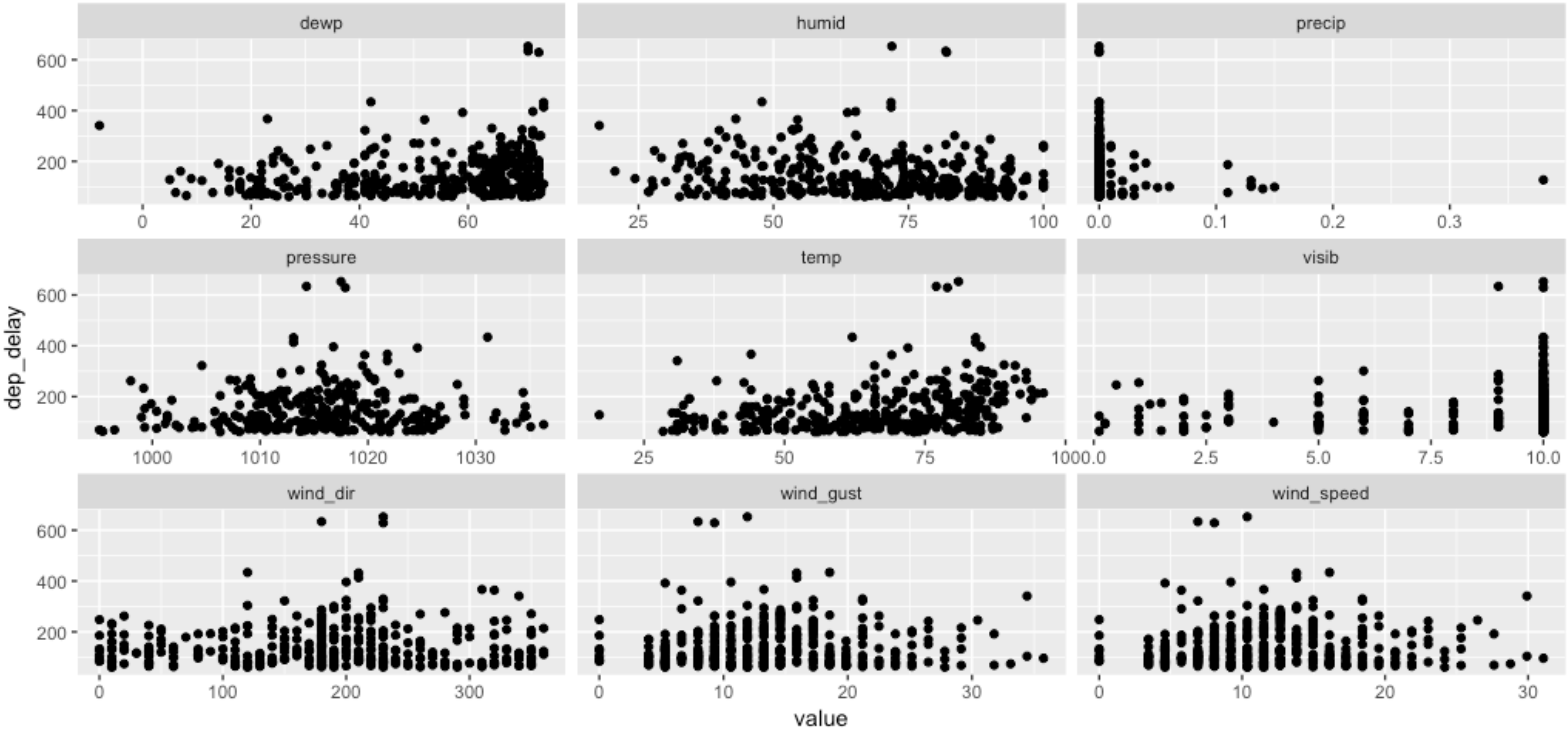
DOES WEATHER INFLUENCE DELAYS?

1. *Using the %>% operator, take the flights data and then*
   i. *left join airlines data using carrier as the key*
   ii. *Filter for only Virgin America flights with a departure delay greater than one hour*
   iii. *inner join weather data with the keys:* `by = c("year", "month", "day", "origin", “hour")`
   iv. *select* **`dep_delay`** *and* **`temp:visib`**
   v. *gather the* **`temp:visib`** *variables into one variable*
   vi. *Plot the relationships between departure delay and each of the weather variables (dewpoint, humidity, precipitation, pressure, temp, visibility, wind direction, wind gust, and wind speed).*
   vii. *Can you use faceting to compare all these relationships at once?*

SOLUTION

```
flights %>%
  left_join(airlines, by = "carrier") %>%
  filter(name == "Virgin America",
         dep_delay > 60) %>%
  inner_join(weather, by = c("year", "month", "day", "origin", "hour")) %>%
  select(dep_delay, temp:visib) %>%
  gather(variable, value, -dep_delay) %>%
  ggplot(aes(value, dep_delay)) +
    geom_point() +
    facet_wrap(~ variable, scales = "free_x")
```

SOLUTION



dewp
humid
precip
pressure
temp
visib
wind_dir
wind_gust
wind_speed
dep_delay
value
600
400
200
0
20
40
60
25
50
75
100
0.0
0.1
0.2
0.3
1000
1010
1020
1030
2.5
5.0
7.5
10.0
300
10
30

WHAT TO REMEMBER

FUNCTIONS TO REMEMBER

Operator/Function	Description
`inner_join, left_join, right_join, full_join`	mutating join: add new variables to one data frame by matching observations in another.
`semi_join, anti_join`	filtering joins: filter observations from one data frame based on whether or not they match an observation in the other table
`intersect, union, setdiff`	set operations: treat observations as if they were set elements