Relational Data

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Introduction to Relational Data

What is **relational data**?

Often data analysis involve multiple tables of related data.

The data analysis steps we need to do typically depend on the *relationships* between the different tables of data.

Each relationship is defined on a *pair* of tables.

We need data manipulation verbs that work on pairs of tables.

Introduction to Relational Data

`dplyr` provides three families of verbs for working with relational data:

- **Mutating joins** add new variables from one data frame to matching observations in another
- **Filtering joins** filter observations from one data frame based on matching observations in another
- **Set operations** treat observations (rows) as elements of a set

Most relational data live in *relational database management systems* (RDBMS) such as MySQL, SQLite, PostgreSQL, etc. and are accessed via Structured Query Language (SQL).

We will see that the names of `dplyr` verbs for relational data are heavily influenced by their SQL equivalents.

Relational Data in R

```r
library(nycflights13)
```

The `nycflights13` package we have been using for examples and homework actually includes five related tables:

- `airlines` gives airline names based on their abbreviated code
- `airports` gives information about airports, identified by `faa` code
- `flights` gives the data on individual flights out of NYC airports
- `planes` gives information about each plane, identified by `tailnum`
- `weather` gives weather information for each NYC airport by hour

nycflights13 - airlines

```
airlines
```

```
## # A tibble: 16 x 2
##    carrier                         name
##      <chr>                        <chr>
## 1       9E        Endeavor Air Inc.
## 2       AA   American Airlines Inc.
## 3       AS     Alaska Airlines Inc.
## 4       B6          JetBlue Airways
## 5       DL     Delta Air Lines Inc.
## 6       EV ExpressJet Airlines Inc.
## 7       F9   Frontier Airlines Inc.
## 8       FL AirTran Airways Corporation
## 9       HA   Hawaiian Airlines Inc.
## 10      MQ                Envoy Air
## 11      OO    SkyWest Airlines Inc.
## 12      UA    United Air Lines Inc.
## 13      US          US Airways Inc.
## 14      VX           Virgin America
## 15      WN   Southwest Airlines Co.
## 16      YV       Mesa Airlines Inc.
```

nycflights13 - airports

```
airports
```

```
## # A tibble: 1,458 x 8
##      faa                           name      lat        lon
##    <chr>                          <chr>    <dbl>      <dbl> <
##  1   04G              Lansdowne Airport 41.13047  -80.61958
##  2   06A  Moton Field Municipal Airport 32.46057  -85.68003
##  3   06C            Schaumburg Regional 41.98934  -88.10124
##  4   06N                Randall Airport 41.43191  -74.39156
##  5   09J          Jekyll Island Airport 31.07447  -81.42778
##  6   0A9 Elizabethton Municipal Airport 36.37122  -82.17342
##  7   0G6        Williams County Airport 41.46731  -84.50678
##  8   0G7  Finger Lakes Regional Airport 42.88356  -76.78123
##  9   0P2   Shoestring Aviation Airfield 39.79482  -76.64719
## 10   0S9          Jefferson County Intl 48.05381 -122.81064
## # ... with 1,448 more rows, and 2 more variables: dst <chr>,
```

nycflights13 - flights

```
flights
```

```
## # A tibble: 336,776 x 19
##     year month   day dep_time sched_dep_time dep_delay arr_ti
##    <int> <int> <int>    <int>          <int>     <dbl>    <in
##  1  2013     1     1      517            515         2       8
##  2  2013     1     1      533            529         4       8
##  3  2013     1     1      542            540         2       9
##  4  2013     1     1      544            545        -1      10
##  5  2013     1     1      554            600        -6       8
##  6  2013     1     1      554            558        -4       7
##  7  2013     1     1      555            600        -5       9
##  8  2013     1     1      557            600        -3       7
##  9  2013     1     1      557            600        -3       8
## 10  2013     1     1      558            600        -2       7
## # ... with 336,766 more rows, and 12 more variables: sched_ar
## #   arr_delay <dbl>, carrier <chr>, flight <int>, tailnum <ch
## #   origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>,
## #   minute <dbl>, time_hour <dttm>
```

nycflights13 - planes

```
planes
```

```
## # A tibble: 3,322 x 9
##    tailnum  year                    type     manufacturer
##      <chr> <int>                   <chr>            <chr>
##  1  N10156  2004 Fixed wing multi engine         EMBRAER EMB
##  2  N102UW  1998 Fixed wing multi engine AIRBUS INDUSTRIE  A3
##  3  N103US  1999 Fixed wing multi engine AIRBUS INDUSTRIE  A3
##  4  N104UW  1999 Fixed wing multi engine AIRBUS INDUSTRIE  A3
##  5  N10575  2002 Fixed wing multi engine         EMBRAER EMB
##  6  N105UW  1999 Fixed wing multi engine AIRBUS INDUSTRIE  A3
##  7  N107US  1999 Fixed wing multi engine AIRBUS INDUSTRIE  A3
##  8  N108UW  1999 Fixed wing multi engine AIRBUS INDUSTRIE  A3
##  9  N109UW  1999 Fixed wing multi engine AIRBUS INDUSTRIE  A3
## 10  N110UW  1999 Fixed wing multi engine AIRBUS INDUSTRIE  A3
## # ... with 3,312 more rows, and 4 more variables: engines <in
## #   seats <int>, speed <int>, engine <chr>
```

nycflights13 - weather

```
weather
```

```
## # A tibble: 26,130 x 15
##    origin  year month   day  hour  temp  dewp humid wind_dir
##     <chr> <dbl> <dbl> <int> <int> <dbl> <dbl> <dbl>    <dbl>
##  1    EWR  2013     1     1     0 37.04 21.92 53.97      230
##  2    EWR  2013     1     1     1 37.04 21.92 53.97      230
##  3    EWR  2013     1     1     2 37.94 21.92 52.09      230
##  4    EWR  2013     1     1     3 37.94 23.00 54.51      230
##  5    EWR  2013     1     1     4 37.94 24.08 57.04      240
##  6    EWR  2013     1     1     6 39.02 26.06 59.37      270
##  7    EWR  2013     1     1     7 39.02 26.96 61.63      250
##  8    EWR  2013     1     1     8 39.02 28.04 64.43      240
##  9    EWR  2013     1     1     9 39.92 28.04 62.21      250
## 10    EWR  2013     1     1    10 39.02 28.04 64.43      260
## # ... with 26,120 more rows, and 5 more variables: wind_gust
## #   precip <dbl>, pressure <dbl>, visib <dbl>, time_hour <dtt
```

Relations in `nycflights13`

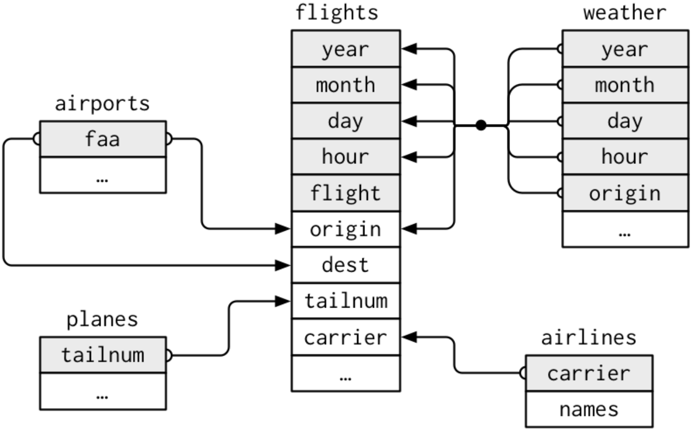


Figure 1: nycflights13

Keys

Variables used to connect tables are called **keys**.

A key may be a single variable, or multiple variables.

- A **primary key** uniquely identifies an observation in its own table
  - `planes` has a primary key of `tailnum`
  - `airports` has a primary key of `faa`
  - `weather` has a primary key of `(year, month, day, hour, origin)`
- A **foreign key** uniquely identifies an observation in another table
  - `flights` has a foreign key of `tailnum` for `planes`
  - `flights` has a foreign key of `carrier` for `airlines`
  - `flights` has a foreign key of `(year, month, day, hour, origin)` for `weather`

Checking primary keys

```
planes %>%
  count(tailnum) %>%
  filter(n > 1)
```

```
## # A tibble: 0 x 2
## # ... with 2 variables: tailnum <chr>, n <int>
```

Checking primary keys

```r
weather %>%
  count(year, month, day, hour, origin) %>%
  filter(n > 1)
```

```
## # A tibble: 0 x 6
## # ... with 6 variables: year <dbl>, month <dbl>, day <int>, h
## #   origin <chr>, n <int>
```

What is the primary key of `flights`?

```
flights %>%
  count(year, month, day, flight) %>%
  filter(n > 1)
```

```
## # A tibble: 29,768 x 5
##     year month   day flight     n
##    <int> <int> <int>  <int> <int>
##  1  2013     1     1      1     2
##  2  2013     1     1      3     2
##  3  2013     1     1      4     2
##  4  2013     1     1     11     3
##  5  2013     1     1     15     2
##  6  2013     1     1     21     2
##  7  2013     1     1     27     4
##  8  2013     1     1     31     2
##  9  2013     1     1     32     2
## 10  2013     1     1     35     2
## # ... with 29,758 more rows
```

Add a primary key to flights

Called a **surrogate key**.

```
flights %>%
  mutate(row_id=row_number()) %>%
  select(row_id, year:dep_delay)
```

```
## # A tibble: 336,776 x 7
##    row_id  year month   day dep_time sched_dep_time dep_delay
##     <int> <int> <int> <int>    <int>          <int>     <dbl>
##  1      1  2013     1     1      517            515         2
##  2      2  2013     1     1      533            529         4
##  3      3  2013     1     1      542            540         2
##  4      4  2013     1     1      544            545        -1
##  5      5  2013     1     1      554            600        -6
##  6      6  2013     1     1      554            558        -4
##  7      7  2013     1     1      555            600        -5
##  8      8  2013     1     1      557            600        -3
##  9      9  2013     1     1      557            600        -3
## 10     10  2013     1     1      558            600        -2
## # ... with 336,766 more rows
```

Why are keys important?

- A primary key and a foreign key in another table form a **relation**
- These relations are typically "one-to-many"
  - `tailnum` in `planes` connecting to many flights in `flights`
  - `carrier` in `airlines` connecting to many flights in `flights`
- We typically use these relations to describe how we **join** tables
- But as we will see soon, we can explicitly specify which variables are used to join tables, so why else might keys be important?

How is relational data stored?

- Why don't we always keep all tables in memory like `nycflights13`?
- How do RDBMS's store the data in their tables?
- Are RDBMS's only good for accessing large data on disk?
- Why does data in a RDBMS sometimes occupy more storage space than the actual data?
- Why (as seen in the homework) are keys explicitly specified when creating tables in SQL?

How does a RDBMS actually manage relational data?

- RBDMS's use **indexing** to look up data faster
- Indexes store where (in storage) to find particular rows in a table
- Indexes require additional storage space but allow faster queries
- Indexes are often a different type of data structure
  - B-trees (sorted data)
  - Hash tables (unsorted data)
- Primary and foreign keys are often indexed
- When working with data in memory, this often isn't important, but indexing can be very important when accessing data stored on disk

Visualizing joins

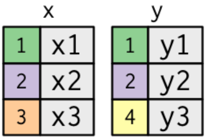


Figure 2: Two tables

Visualizing joins

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

Mutating joins

Similar to `mutate()`, **mutating joins** *add new variables* from one table (`x`) to matching observations in another (`y`)

- **Inner joins** keep only observations the appear in both `x` and `y`
- **Outer joins** keep observations that appear in at least one of `x` or `y`
  - A **left join** keeps all observations in `x`
  - A **right join** keeps all observations in `y`
  - A **full join** keeps all observations from both `x` and `y`

Mutating joins

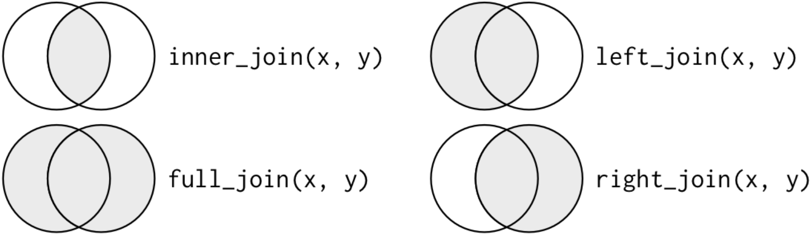


Figure 3: Types of joins as Venn diagrams

Visualizing joins

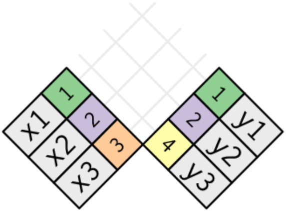


Figure 4: Two tables with possible matches

Inner joins

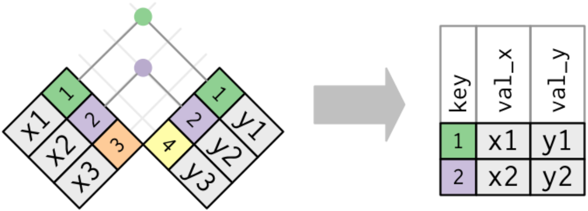


Figure 5: Keep observations that appear in both

Inner joins

```r
inner_join(x, y)
```

```
## Joining, by = "key"
```

```
## # A tibble: 2 x 3
##     key val_x val_y
##   <dbl> <chr> <chr>
## 1     1    x1    y1
## 2     2    x2    y2
```

Inner joins

We can specify the variables used to join `x` and `y` explicitly.

```
inner_join(x, y, by = "key")
```

```
## # A tibble: 2 x 3
##     key val_x val_y
##   <dbl> <chr> <chr>
## 1     1    x1    y1
## 2     2    x2    y2
```

Joining by all variables that appear in both (default) is a **natural join**.

Inner joins

`dplyr`:

```
inner_join(x, y, by = "z")
```

base R:

```
merge(x, y, by = "z")
```

SQL:

```
SELECT * FROM x INNER JOIN y USING (z)
```

Inner joins can silently drop observations, so are rarely used for data analysis.

Outer joins

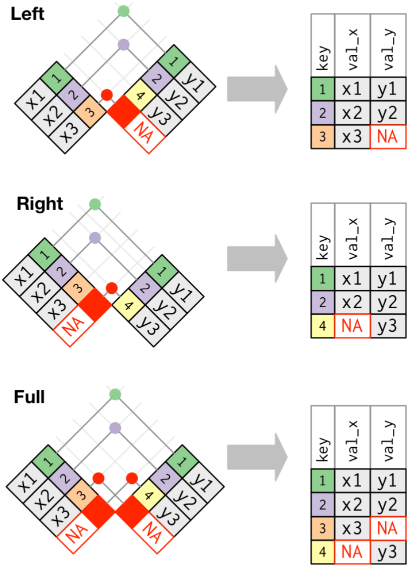


Figure 6: Keep observations that appear in at least one

Left join

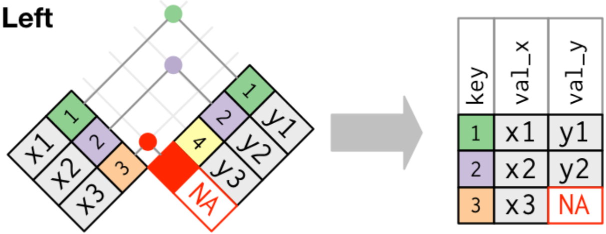


Figure 7: Keep observations that appear in `x`

Left join

```r
left_join(x, y)
```

```
## Joining, by = "key"
```

```
## # A tibble: 3 x 3
##     key val_x val_y
##   <dbl> <chr> <chr>
## 1     1    x1    y1
## 2     2    x2    y2
## 3     3    x3  <NA>
```

Left join

`dplyr`:

```r
left_join(x, y, by = "z")
```

`base` R:

```r
merge(x, y, all.x = TRUE, by = "z")
```

SQL:

```sql
SELECT * FROM x LEFT OUTER JOIN y USING (z)
```

Left joins are the most common type of join.

Right join

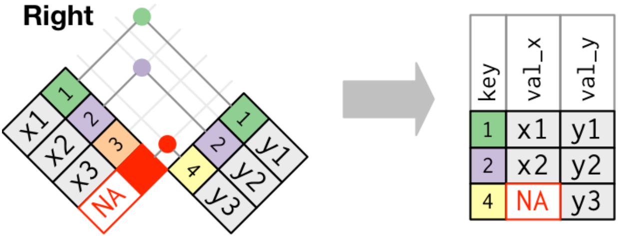


Figure 8: Keep observations that appear in y

Right join

```
right_join(x, y)
```

```
## Joining, 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
```

Right join

`dplyr`:

```r
right_join(x, y, by = "z")
```

`base` R:

```r
merge(x, y, all.y = TRUE, by = "z")
```

SQL:

```sql
SELECT * FROM x RIGHT OUTER JOIN y USING (z)
```

Left versus right joins

What is the difference between the following calls?

```
left_join(x, y)
```

```
right_join(y, x)
```

```r
left_join(x, y)
```

```
## Joining, by = "key"

## # A tibble: 3 x 3
##     key val_x val_y
##   <dbl> <chr> <chr>
## 1     1    x1    y1
## 2     2    x2    y2
## 3     3    x3  <NA>
```

```r
right_join(y, x)
```

```
## Joining, by = "key"

## # A tibble: 3 x 3
##     key val_y val_x
##   <dbl> <chr> <chr>
## 1     1    y1    x1
## 2     2    y2    x2
## 3     3  <NA>    x3
```

`left_join(x, y)` vs `right_join(y, x)`

- The only difference is the order of the returned columns
- Explicit right joins exist primarily for expressiveness
- Some RDBMS's do not even implement right joins (e.g., SQLite)

Full join

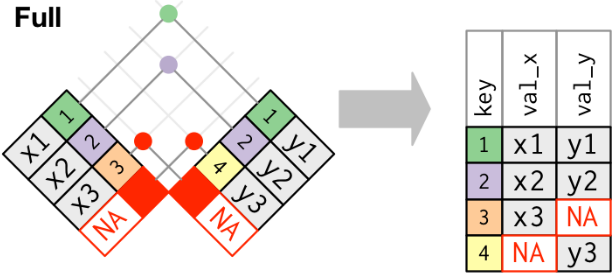


Figure 9: Keep observations that appear in either

Full join

```r
full_join(x, y)
```

```
## Joining, by = "key"
```

```
## # A tibble: 4 x 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
```

Full join

`dplyr`:

```r
full_join(x, y, by = "z")
```

`base` R:

```r
merge(x, y, all.x = TRUE, all.y = TRUE, by = "z")
```

SQL:

```sql
SELECT * FROM x FULL OUTER JOIN y USING (z)
```

Duplicate keys

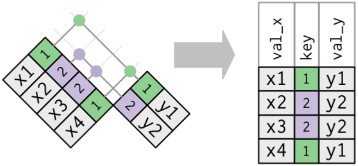
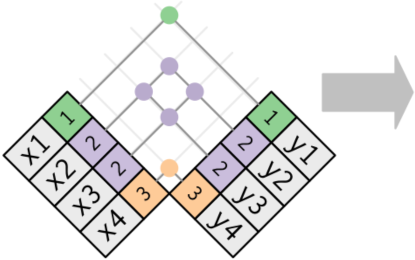


Figure 10: “One-to-many”

Duplicate keys



key	val_x	val_y
1	x1	y1
2	x2	y2
2	x2	y3
2	x3	y2
2	x3	y3
3	x4	y4

Figure 11: “Many-to-many”

Differently-named keys

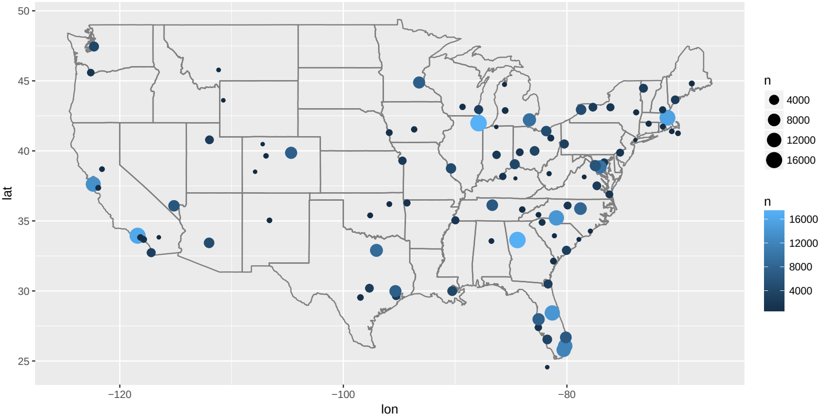
```r
x2 <- x %>% rename(a = key)
y2 <- y %>% rename(b = key)
left_join(x2, y2, by = c("a" = "b"))
```

```
## # A tibble: 3 x 3
##         a val_x val_y
##     <dbl> <chr> <chr>
## 1       1    x1    y1
## 2       2    x2    y2
## 3       3    x3  <NA>
```

Plot most popular flight destinations

```
flights %>%
  filter(dest != "HNL", dest != "ANC") %>%
  count(dest) %>%
  left_join(airports, by = c("dest" = "faa")) %>%
  ggplot(aes(lon, lat, size=n, color=n)) +
  borders("state") +
  geom_point() +
  coord_quickmap()
```

```
## Warning: Removed 4 rows containing missing values (geom_point
```



Get total number of flights flown by each type of plane

```r
flights %>%
  left_join(planes, by = "tailnum") %>%
  count(type)
```

```
## # A tibble: 4 x 2
##                        type      n
##                       <chr>  <int>
## 1  Fixed wing multi engine 282074
## 2 Fixed wing single engine   1686
## 3               Rotorcraft    410
## 4                     <NA>  52606
```

Filtering joins

Similar to `filter()`, **filtering joins** do not add new variables, but instead *subset the observations* from one table (`x`) based on observations in another (`y`)

- **Semi joins** *keep* all observations in `x` that have a match in `y`
- **Anti joins** *drop* all observations in `x` that have a match in `y`

Semi joins

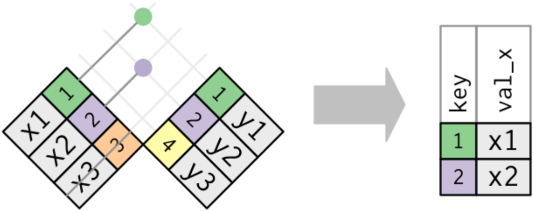


Figure 12: Keeps all observations that match

Semi joins

```r
semi_join(x, y)
```

```
## Joining, by = "key"
```

```
## # A tibble: 2 x 2
##     key val_x
##   <dbl> <chr>
## 1     1    x1
## 2     2    x2
```

Semi joins with duplicate keys

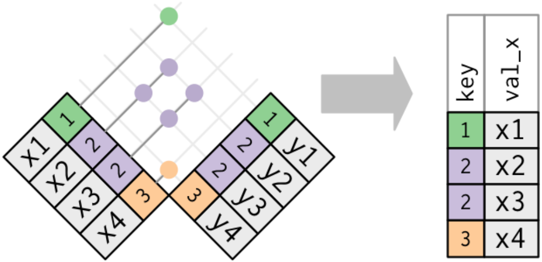


Figure 13: Keeps all observations that match

Semi joins never duplicate rows (unlike mutating joins).

Keep only flights from most popular destinations

```
top_dest <- flights %>%
  count(dest) %>%
  filter(n > 10000)

semi_join(flights, top_dest)
```

```
## Joining, by = "dest"

## # A tibble: 131,440 x 19
##     year month   day dep_time sched_dep_time dep_delay arr_time
##    <int> <int> <int>    <int>          <int>     <dbl>    <int>
##  1  2013     1     1      542            540         2      923
##  2  2013     1     1      554            600        -6      812
##  3  2013     1     1      554            558        -4      740
##  4  2013     1     1      555            600        -5      913
##  5  2013     1     1      557            600        -3      838
##  6  2013     1     1      558            600        -2      753
##  7  2013     1     1      558            600        -2      924
##  8  2013     1     1      558            600        -2      923
##  9  2013     1     1      559            559         0      702
## 10  2013     1     1      600            600         0      851
## # ... with 131,430 more rows, and 12 more variables: sched_arr_time
```

Anti joins

Figure 14:

Anti joins

```r
anti_join(x, y)
```

```
## Joining, by = "key"
```

```
## # A tibble: 1 x 2
##     key val_x
##   <dbl> <chr>
## 1     3    x3
```

Why did we have missing values when plotting destination airports?

```r
flights %>%
  anti_join(airports, by = c("dest" = "faa")) %>%
  count(dest)
```

```
## # A tibble: 4 x 2
##    dest     n
##   <chr> <int>
## 1   BQN   896
## 2   PSE   365
## 3   SJU  5819
## 4   STT   522
```

Set operations

Set operations take two tables with the same variables and compare whole rows (i.e., every variable in each row), to treat observations like members of sets.

- `intersect(x, y)` returns observations in both `x` and `y`
- `union(x, y)` returns all unique observations in `x` and `y`
- `setdiff(x, y)` returns the observations in `x` that aren't in `y`

These are less commonly used for data analysis than the joins.

Set operations

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

Intersection

```r
intersect(df1, df2)
```

```
## # A tibble: 1 x 2
##       x     y
##   <dbl> <dbl>
## 1     1     1
```

Union

```r
union(df1, df2)
```

```
## # A tibble: 3 x 2
##       x     y
##   <dbl> <dbl>
## 1     1     2
## 2     2     1
## 3     1     1
```

Difference

```r
setdiff(df1, df2)
```

```
## # A tibble: 1 x 2
##       x     y
##   <dbl> <dbl>
## 1     2     1
```

R and databases

Often, relational data is stored in a database managed by an RDBMS, so we need to know how to work with data in a database.

A database can also be a good solution for data which you do not want to load all into memory at once.

R and `dplyr` can interface with databases through the `DBI` package and a suitable backend:

- `RSQLite` works with SQLite databases
- `RMySQL` works with MySQL databases
- `RPostgreSQL` works with PostgreSQL databases

etc.

We can work with these with `dplyr` using the `dbplyr` package.

R and databases with dbplyr

Suppose we wish to work with an SQLite database.

First we need to install the necessary packages.

```r
install.packages(c("DBI", "RSQLite", "dbplyr"))
```

```r
library(dbplyr)
```

```
##
## Attaching package: 'dbplyr'

## The following objects are masked from 'package:dplyr':
##
##     ident, sql
```

```r
library(RSQLite)
```

Connecting to a database in R

The DBLP is a database containing bibliographic data on major computer science journals and proceedings. A subset of it has been loaded into the SQLite database file "dblp.db".

First, we need to open a *connection* to the database using `dbConnect()`.

The first argument of `dbConnect()` is the backend to use (provided by the `RSQLite` package in this case), and the second is the filepath to the database.

```
dbpath <- paste0("~/Documents/Northeastern/",
                 "Courses/DS5110-Spring2018/data/",
                 "DBLP-CSR-sqlite/dblp.db")
con <- dbConnect(SQLite(), dbname=dbpath)
```

Creating a `tbl` of the connected database

A `tbl` is the tidyverse's generalized notion of tabular data.

A tibble is a type of `tbl`. We can also create a `tbl` from a database.

```
dblp <- tbl(con, "general")
```

The first argument is the data source (our database connection).

The second argument is the name of the table within the database.

Our SQLite database contains the table "general", which has information about papers published in computer science journals and proceedings.

```
dblp
```

```
## # Source:   table<general> [?? x 10]
## # Database: sqlite 3.19.3
## #   [/Users/kuwisdelu/Dropbox/Northeastern/Courses/DS5110-Spr
##                          k  year  conf        crossref    cs
##                      <chr> <int> <chr>           <chr> <int> <in
##  1     conf/aaai/0001M13  2013  AAAI conf/aaai/2013     1
##  2     conf/aaai/0001T15  2015  AAAI conf/aaai/2015     1
##  3  conf/aaai/0001TZLL14  2014  AAAI conf/aaai/2014     1
##  4    conf/aaai/0001VD15  2015  AAAI conf/aaai/2015     1
##  5    conf/aaai/0001YT15  2015  AAAI conf/aaai/2015     1
##  6 conf/aaai/0002GYSZL14  2014  AAAI conf/aaai/2014     1
##  7     conf/aaai/0002Z15  2015  AAAI conf/aaai/2015     1
##  8    conf/aaai/0002ZL15  2015  AAAI conf/aaai/2015     1
##  9   conf/aaai/0003MGF14  2014  AAAI conf/aaai/2014     1
## 10   conf/aaai/0005YJZ15  2015  AAAI conf/aaai/2015     1
## # ... with more rows, and 3 more variables: th <int>, publish
## #   link <chr>
```

We can perform dplyr operations on the database using dplyr verbs.

```
dblp %>% summarise(cs_papers=sum(cs))
```

```
## # Source:   lazy query [?? x 1]
## # Database: sqlite 3.19.3
## #   [/Users/kuwisdelu/Dropbox/Northeastern/Courses/DS5110-Spr
##   cs_papers
##       <int>
## 1     96823
```

```r
dblp %>%
  filter(year > 2010) %>%
  group_by(year) %>%
  summarise(cs_papers=sum(cs))
```

```
## # Source:   lazy query [?? x 2]
## # Database: sqlite 3.19.3
## #   [/Users/kuwisdelu/Dropbox/Northeastern/Courses/DS5110-Spr
##    year cs_papers
##   <int>     <int>
## 1  2011      6060
## 2  2012      5772
## 3  2013      7391
## 4  2014      6538
## 5  2015      5910
```

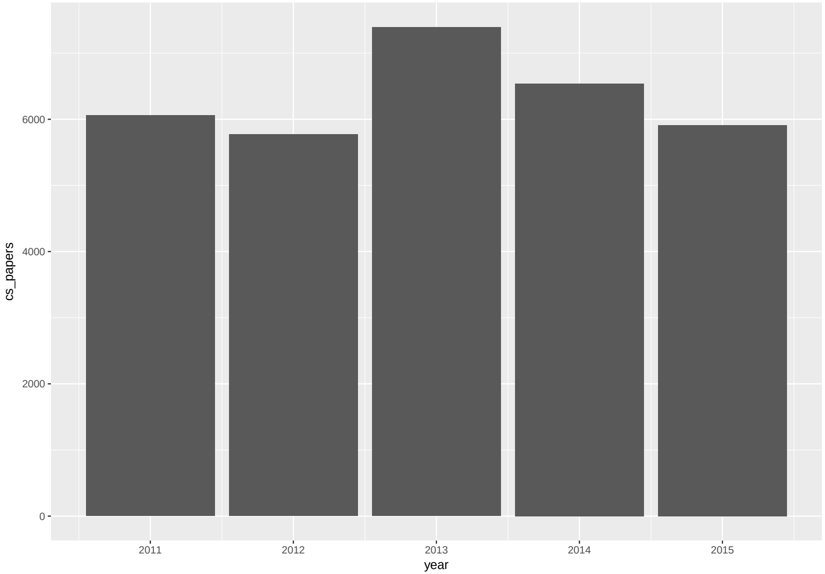
Note that the result isn't actually pulled into memory automatically.

```
dblp %>%
  filter(year > 2010) %>%
  group_by(year) %>%
  summarise(cs_papers=sum(cs)) %>%
  ggplot() +
  geom_col(aes(x=year, y=cs_papers))
```

```
## Error: ggplot2 doesn't know how to deal with data of class tb
```

To force `dplyr` to execute the operations and pull the result into memory, we need to use `collect()`.

```
dblp %>%
  filter(year > 2010) %>%
  group_by(year) %>%
  summarise(cs_papers=sum(cs)) %>%
  collect() %>%
  ggplot() +
  geom_col(aes(x=year, y=cs_papers))
```



cs_papers
6000
4000
2000
0
2011
2012
2013
2014
2015
year

When working with databases, `dbplyr` tries to offload as much work as possible to the database itself, and delay execution until we need the result.

We can see the actual SQL commands generated using `show_query()`

```
query <- dblp %>%
  filter(year > 2010) %>%
  group_by(year) %>%
  summarise(cs_papers=sum(cs))
show_query(query)
```

```
## <SQL>
## SELECT `year`, SUM(`cs`) AS `cs_papers`
## FROM `general`
## WHERE (`year` > 2010.0)
## GROUP BY `year`
```

Pulling database data into R

Not all databases support all `dplyr` data manipulation verbs, so if necessary (and the data is small enough), we can always pull the data into R as a tibble and work that way.

```
dblp %>% collect()
```

```
## # A tibble: 148,521 x 10
##                           k  year  conf        crossref    cs
##                       <chr> <int> <chr>           <chr> <int> <in
##  1      conf/aaai/0001M13  2013  AAAI conf/aaai/2013     1
##  2      conf/aaai/0001T15  2015  AAAI conf/aaai/2015     1
##  3   conf/aaai/0001TZLL14  2014  AAAI conf/aaai/2014     1
##  4     conf/aaai/0001VD15  2015  AAAI conf/aaai/2015     1
##  5     conf/aaai/0001YT15  2015  AAAI conf/aaai/2015     1
##  6 conf/aaai/0002GYSZL14  2014  AAAI conf/aaai/2014     1
##  7      conf/aaai/0002Z15  2015  AAAI conf/aaai/2015     1
##  8     conf/aaai/0002ZL15  2015  AAAI conf/aaai/2015     1
##  9    conf/aaai/0003MGF14  2014  AAAI conf/aaai/2014     1
## 10    conf/aaai/0005YJZ15  2015  AAAI conf/aaai/2015     1
## # ... with 148,511 more rows, and 3 more variables: th <int>,
## #   publisher <chr>, link <chr>
```