Tidy R programming with databases: applications with the OMOP common data model

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Preface

Is this book for me?

We've written this book for anyone interested in a working with databases using a tidyverse style approach. That is, human centered, consistent, composable, and inclusive (see https://design.tidyverse.org/unifying.html for more details on these principles).

New to R? We recommend you compliment the book with R for data science

New to databases? We recommend you take a look at some web tutorials on SQL, such as SQLBolt or SQLZoo

New to the OMOP CDM? We'd recommend you pare this book with The Book of OHDSI

How is the book organised?

The book is divided into two parts. The first half of the book is focused on the general principles for working with databases from R. In these chapters you will see how you can use familiar tidyverse-style code to build up analytic pipelines that start with data held in a database and end with your analytic results. The second half of the book is focused on working with data in the OMOP Common Data Model (CDM) format, a widely used data format for health care data. In these chapters you will see how to work with this data format using the general principles from the first half of the book along with a set of R packages that have been built for the OMOP CDM.

Citation

TO ADD

Packages	Version	Link
bit64	4.6.0-1	
CDMConnector	2.0.0	
cli	3.6.4	
clock	0.7.2	
CodelistGenerator	3.4.1	
CohortCharacteristics	0.5.1	
CohortConstructor	0.3.5	
DBI	1.2.3	
dbplyr	2.5.0	
dm	1.0.11	
dplyr	1.1.4	
duckdb	1.2.1	
ggplot2	3.5.1	
here	1.0.1	
Lahman	12.0-0	
omock	0.3.2	
omopgenerics	1.1.1	
palmerpenguins	0.1.1	
PatientProfiles	1.3.1	
purrr	1.0.4	
sloop	1.0.1	
stringr	1.5.1	
tidyr	1.3.1	

License

Code

The source code for the book can be found at this Github repository

renv

This book is rendered using the following version of packages:

Note here only the packages called explicitly are mentioned for the full list of packages and versions used see the book renv file in github.

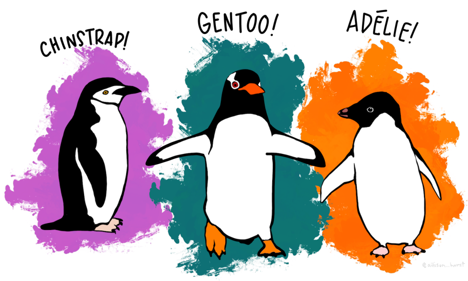
Part I

Getting started with working databases from R

In this first half of the book we will see how we can work with databases from R. In the following chapters we'll see that when working with data held in a relational database we can leverage various open-source R packages to help us perform tidyverse-style data analyses.

- In Chapter 1 we will perform a simple data analysis from start to finish using a table in a database.
- In Chapter 2 we will see in more detail how familiar dplyr functions can be used to combine data spread across different tables in a database into an analytic dataset which we can then bring into R for further analysis.
- In Chapter 3 we will see how we can perform more complex data manipulation via translation of R code into SQL specific to the database management system being used.
- In Chapter 4 we will see how we can build data pipelines by creating a data model in R to represent the relational database we're working with and creating functions and methods to work with it.

1 A first analysis using data in a database



Artwork by @allison_horst

Before we start thinking about working with healthcare data spread across a database using the OMOP common data model, let's first do a simpler analysis. In this case we will do a quick data analysis with R using a simpler dataset held in a database to understand the general approach. For this we'll use data from palmerpenguins package, which contains data on penguins collected from the Palmer Station in Antarctica.

1.1 Getting set up

Assuming that you have R and RStudio already set up[1], first we need to install a few packages not included in base R if we don't already have them.

```
install.packages("dplyr")
install.packages("dbplyr")
install.packages("ggplot2")
install.packages("DBI")
install.packages("duckdb")
install.packages("palmerpenguins")
```

Once installed, we can load them like so.

```r
library(dplyr)
library(dbplyr)
library(ggplot2)
library(DBI)
library(duckdb)
library(palmerpenguins)
```

1.2 Taking a peek at the data

The package `palmerpenguins` contains two datasets, one of them called `penguins`, which we will use in this chapter. We can get an overview of the data using the `glimpse()` command.

```r
glimpse(penguins)
```

```
Rows: 344
Columns: 8
$ species           <fct> Adelie, Adelie, Adelie, Adelie, Adelie, Adelie, Adel~
$ island            <fct> Torgersen, Torgersen, Torgersen, Torgersen, Torgerse~
$ bill_length_mm    <dbl> 39.1, 39.5, 40.3, NA, 36.7, 39.3, 38.9, 39.2, 34.1, ~
$ bill_depth_mm     <dbl> 18.7, 17.4, 18.0, NA, 19.3, 20.6, 17.8, 19.6, 18.1, ~
$ flipper_length_mm <int> 181, 186, 195, NA, 193, 190, 181, 195, 193, 190, 186~
$ body_mass_g       <int> 3750, 3800, 3250, NA, 3450, 3650, 3625, 4675, 3475, ~
$ sex               <fct> male, female, female, NA, female, male, female, male~
$ year              <int> 2007, 2007, 2007, 2007, 2007, 2007, 2007, 2007, 2007~
```

Or we could take a look at the first rows of the data using `head()` :

```r
head(penguins, 5)
```

```
# A tibble: 5 x 8
  species island    bill_length_mm bill_depth_mm flipper_length_mm body_mass_g
  <fct>   <fct>              <dbl>         <dbl>             <int>       <int>
1 Adelie  Torgersen           39.1          18.7               181        3750
2 Adelie  Torgersen           39.5          17.4               186        3800
3 Adelie  Torgersen           40.3          18                 195        3250
4 Adelie  Torgersen           NA            NA                  NA          NA
5 Adelie  Torgersen           36.7          19.3               193        3450
# i 2 more variables: sex <fct>, year <int>
```

1.3 Inserting data into a database

Let's put our penguins data into a duckdb database. We need to first create the database and then add the penguins data to it.

```
db <- dbConnect(drv = duckdb())
dbWriteTable(db, "penguins", penguins)
```

We can see that our database now has one table:

```
dbListTables(db)
```

```
[1] "penguins"
```

And now that the data is in a database we could use SQL to get the first rows that we saw before.

```
dbGetQuery(db, "SELECT * FROM penguins LIMIT 5")
```

```
  species    island bill_length_mm bill_depth_mm flipper_length_mm body_mass_g
1  Adelie Torgersen           39.1          18.7               181        3750
2  Adelie Torgersen           39.5          17.4               186        3800
3  Adelie Torgersen           40.3          18.0               195        3250
4  Adelie Torgersen             NA            NA                NA          NA
5  Adelie Torgersen           36.7          19.3               193        3450
     sex year
1   male 2007
2 female 2007
3 female 2007
4   <NA> 2007
5 female 2007
```

Connecting to databases from R

Database connections from R can be made using the DBI package. The back-end for DBI is facilitated by database specific driver packages. In the code snipets above we created a new, empty, in-process duckdb database to which we then added our dataset. But we could have instead connected to an existing duckdb database. This could, for example, look like

```r
db <- dbConnect(drv = duckdb(),
                dbdir = here("my_duckdb_database.ducdkb"))
```

In this book for simplicity we will mostly be working with in-process duckdb databases with synthetic data. However, when analysing real patient data we will be more often working with client-server databases, where we are connecting from our computer to a central server with the database or working with data held in the cloud. The approaches shown throughout this book will work in the same way for these other types of database management systems, but the way to connect to the database will be different (although still using DBI). In general, creating connections is supported by associated back-end packages. For example a connection to a Postgres database would use the RPostgres R package and look something like:

```r
db <- dbConnect(Postgres(),
                dbname = Sys.getenv("CDM5_POSTGRESQL_DBNAME"),
                host = Sys.getenv("CDM5_POSTGRESQL_HOST"),
                user = Sys.getenv("CDM5_POSTGRESQL_USER"),
                password = Sys.getenv("CDM5_POSTGRESQL_PASSWORD"))
```

1.4 Translation from R to SQL

Instead of using SQL to query our database, we might instead want to use the same R code as before. However, instead of working with the local dataset, now we will need it to query the data held in the database. To do this, first we can create a reference to the table in the database as such:

```r
penguins_db <- tbl(db, "penguins")
penguins_db
```

```
# Source:   table<penguins> [?? x 8]
# Database: DuckDB v1.2.1 [unknown@Linux 6.11.0-1012-azure:R 4.5.0/:memory:]
   species island    bill_length_mm bill_depth_mm flipper_length_mm body_mass_g
   <fct>   <fct>              <dbl>         <dbl>             <int>       <int>
 1 Adelie  Torgersen           39.1          18.7               181        3750
 2 Adelie  Torgersen           39.5          17.4               186        3800
 3 Adelie  Torgersen           40.3          18                 195        3250
 4 Adelie  Torgersen           NA            NA                  NA          NA
 5 Adelie  Torgersen           36.7          19.3               193        3450
 6 Adelie  Torgersen           39.3          20.6               190        3650
```

```
 7 Adelie  Torgersen           38.9          17.8                181         3625
 8 Adelie  Torgersen           39.2          19.6                195         4675
 9 Adelie  Torgersen           34.1          18.1                193         3475
10 Adelie  Torgersen           42            20.2                190         4250
# i more rows
# i 2 more variables: sex <fct>, year <int>
```

Once we have this reference, we can then use it with familiar looking R code.

```r
head(penguins_db, 5)
```

```
# Source:   SQL [?? x 8]
# Database: DuckDB v1.2.1 [unknown@Linux 6.11.0-1012-azure:R 4.5.0/:memory:]
  species island    bill_length_mm bill_depth_mm flipper_length_mm body_mass_g
  <fct>   <fct>              <dbl>         <dbl>             <int>       <int>
1 Adelie  Torgersen           39.1          18.7               181        3750
2 Adelie  Torgersen           39.5          17.4               186        3800
3 Adelie  Torgersen           40.3          18                 195        3250
4 Adelie  Torgersen           NA            NA                  NA          NA
5 Adelie  Torgersen           36.7          19.3               193        3450
# i 2 more variables: sex <fct>, year <int>
```

The magic here is provided by the `dbplyr` package, which takes the R code and converts it into SQL. In this case the query looks like the SQL we wrote directly before.

```r
head(penguins_db, 5) |>
  show_query()
```

```
<SQL>
SELECT penguins.*
FROM penguins
LIMIT 5
```

1.5 Example analysis

More complicated SQL can also be generated by using familiar `dplyr` code. For example, we could get a summary of bill length by species like so:

```r
penguins_db |>
  group_by(species) |>
  summarise(
    n = n(),
    min_bill_length_mm = min(bill_length_mm),
    mean_bill_length_mm = mean(bill_length_mm),
    max_bill_length_mm = max(bill_length_mm)
  ) |>
  mutate(min_max_bill_length_mm = paste0(
    min_bill_length_mm,
    " to ",
    max_bill_length_mm
  )) |>
  select(
    "species",
    "mean_bill_length_mm",
    "min_max_bill_length_mm"
  )
```

```
# Source:   SQL [?? x 3]
# Database: DuckDB v1.2.1 [unknown@Linux 6.11.0-1012-azure:R 4.5.0/:memory:]
  species   mean_bill_length_mm min_max_bill_length_mm
  <fct>                   <dbl> <chr>
1 Adelie                   38.8 32.1 to 46.0
2 Chinstrap                48.8 40.9 to 58.0
3 Gentoo                   47.5 40.9 to 59.6
```

The benefit of using `dbplyr` now becomes quite clear if we take a look at the corresponding SQL that is generated for us:

```r
penguins_db |>
  group_by(species) |>
  summarise(
    n = n(),
    min_bill_length_mm = min(bill_length_mm),
    mean_bill_length_mm = mean(bill_length_mm),
    max_bill_length_mm = max(bill_length_mm)
  ) |>
  mutate(min_max_bill_length_mm = paste0(min, " to ", max)) |>
  select(
    "species",
```

```
    "mean_bill_length_mm",
    "min_max_bill_length_mm"
  ) |>
  show_query()
```

```
<SQL>
SELECT
  species,
  mean_bill_length_mm,
  CONCAT_WS('', .Primitive("min"), ' to ', .Primitive("max")) AS min_max_bill_length_mm
FROM (
  SELECT
    species,
    COUNT(*) AS n,
    MIN(bill_length_mm) AS min_bill_length_mm,
    AVG(bill_length_mm) AS mean_bill_length_mm,
    MAX(bill_length_mm) AS max_bill_length_mm
  FROM penguins
  GROUP BY species
) q01
```

Instead of having to write this somewhat complex SQL specific to `duckdb` we can use the friendlier `dplyr` syntax that may well be more familiar if coming from an R programming background.

Not having to worry about the SQL translation behind our queries allows us to interrogate the database in a simple way even for more complex questions. For instance, suppose now that we are particularly interested in the body mass variable. We can first notice that there are a couple of missing records for this.

```
penguins_db |>
  mutate(missing_body_mass_g = if_else(
    is.na(body_mass_g), 1, 0
  )) |>
  group_by(species, missing_body_mass_g) |>
  tally()
```

```
# Source:   SQL [?? x 3]
# Database: DuckDB v1.2.1 [unknown@Linux 6.11.0-1012-azure:R 4.5.0/:memory:]
  species   missing_body_mass_g     n
  <fct>                   <dbl> <dbl>
```

```
1 Adelie                         0   151
2 Gentoo                         0   123
3 Adelie                         1     1
4 Gentoo                         1     1
5 Chinstrap                      0    68
```

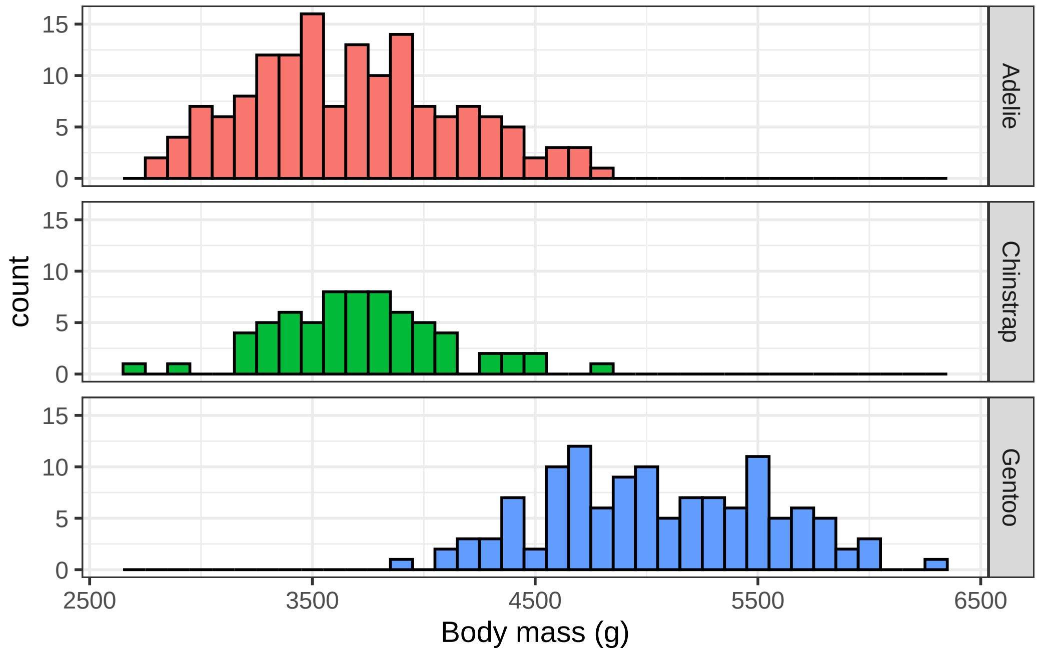
We can get the mean for each of the species (dropping those two missing records).

```
penguins_db |>
  group_by(species) |>
  summarise(mean_body_mass_g = round(mean(body_mass_g, na.rm = TRUE)))
```

```
# Source:   SQL [?? x 2]
# Database: DuckDB v1.2.1 [unknown@Linux 6.11.0-1012-azure:R 4.5.0/:memory:]
  species   mean_body_mass_g
  <fct>                <dbl>
1 Adelie                3701
2 Chinstrap             3733
3 Gentoo                5076
```

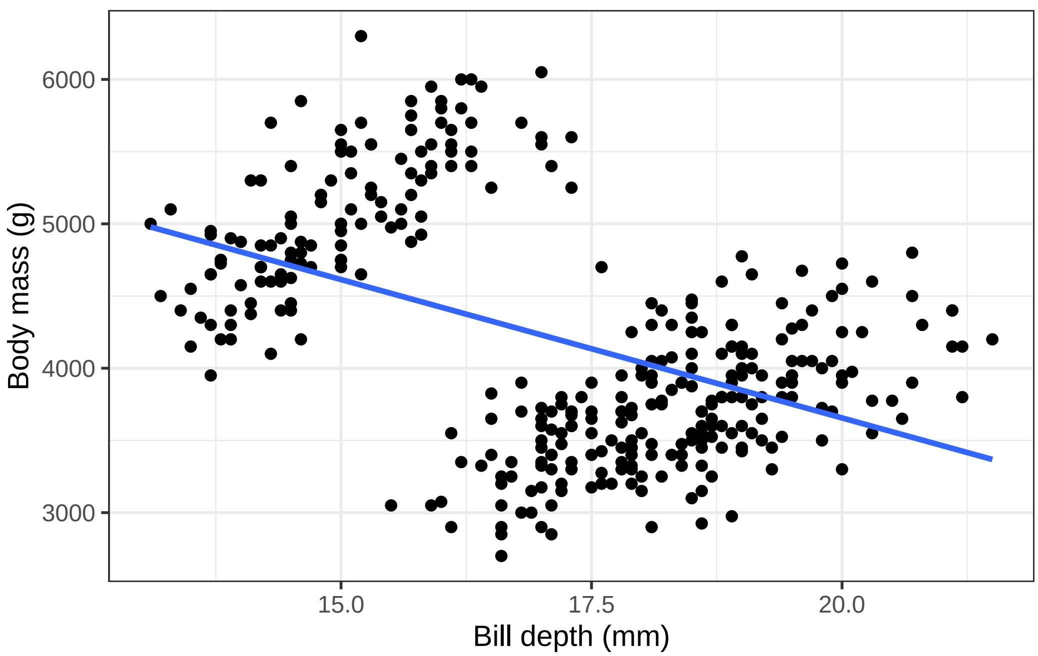
We could also make a histogram of values for each of the species. Here we would collect our data back into R before creating our plot.

```
penguins_db |>
  select("species", "body_mass_g") |>
  collect() |>
  ggplot(aes(group = species, fill = species)) +
  facet_grid(species ~ .) +
  geom_histogram(aes(body_mass_g), colour = "black", binwidth = 100) +
  xlab("Body mass (g)") +
  theme_bw() +
  theme(legend.position = "none")
```



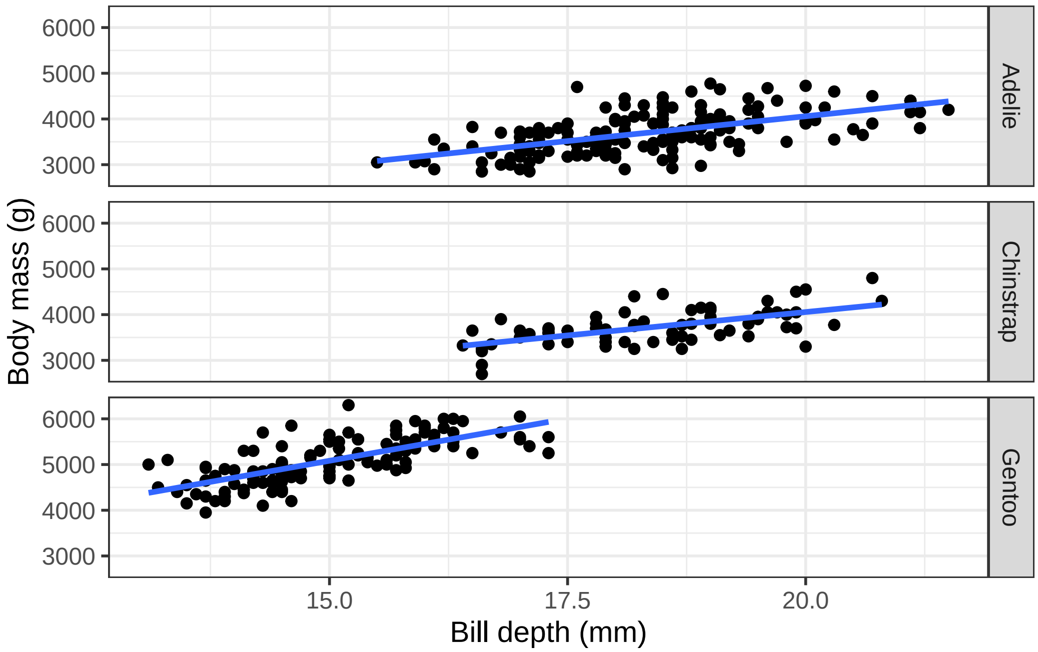
Now let's look at the relationship between body mass and bill depth.

```
penguins |>
  select("species", "body_mass_g", "bill_depth_mm") |>
  collect() |>
  ggplot(aes(x = bill_depth_mm, y = body_mass_g)) +
  geom_point() +
  geom_smooth(method = "lm", se = FALSE) +
  xlab("Bill depth (mm)") +
  ylab("Body mass (g)") +
  theme_bw() +
  theme(legend.position = "none")
```



Here we see a negative correlation between body mass and bill depth which seems rather unexpected. But what about if we stratify this query by species?

```
penguins |>
  select("species", "body_mass_g", "bill_depth_mm") |>
  collect() |>
  ggplot(aes(x = bill_depth_mm, y = body_mass_g)) +
  facet_grid(species ~ .) +
  geom_point() +
  geom_smooth(method = "lm", se = FALSE) +
  xlab("Bill depth (mm)") +
  ylab("Body mass (g)") +
  theme_bw() +
  theme(legend.position = "none")
```



As well as having an example of working with data in database from R, you also have an example of Simpson's paradox!

1.6 Disconnecting from the database

Now that we've reached the end of this example, we can close our connection to the database using the DBI package.

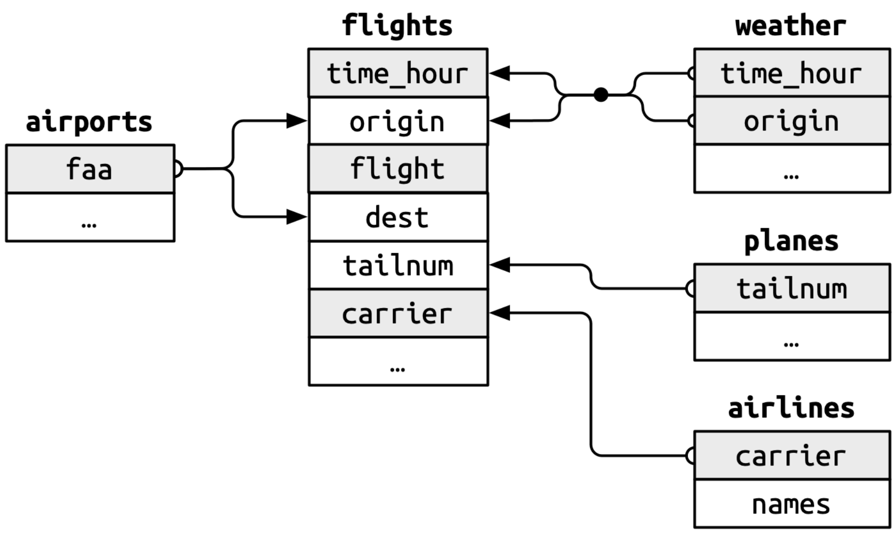
```
dbDisconnect(db)
```

1.7 Further reading

- R for Data Science (Chapter 13: Relational data)
- Writing SQL with dbplyr
- Data Carpentry: SQL databases and R

2 Core verbs for analytic pipelines utilising a database

We saw in the previous chapter that we can use familiar `dplyr` verbs with data held in a database. In the last chapter we were working with just a single table which we loaded into the database. When working with databases we will though typically be working with multiple tables (as we'll see later when working with data in the OMOP CDM format). For this chapter we will see more tidyverse functionality that can be used with data in a database, this time using the `nycflights13` data. As we can see, now we have a set of related tables with data on flights departing from New York City airports in 2013.



Let's load the required libraries, add our data to a duckdb database, and then create references to each of these tables.

```
library(dplyr)
library(dbplyr)
library(tidyr)
library(duckdb)
library(DBI)
```

```r
db <- dbConnect(duckdb(), dbdir = ":memory:")
copy_nycflights13(db)

airports_db <- tbl(db, "airports")
airports_db |> glimpse()
```

```
Rows: ??
Columns: 8
Database: DuckDB v1.2.1 [unknown@Linux 6.11.0-1012-azure:R 4.5.0/:memory:]
$ faa   <chr> "04G", "06A", "06C", "06N", "09J", "0A9", "0G6", "0G7", "0P2", "~
$ name  <chr> "Lansdowne Airport", "Moton Field Municipal Airport", "Schaumbur~
$ lat   <dbl> 41.13047, 32.46057, 41.98934, 41.43191, 31.07447, 36.37122, 41.4~
$ lon   <dbl> -80.61958, -85.68003, -88.10124, -74.39156, -81.42778, -82.17342~
$ alt   <dbl> 1044, 264, 801, 523, 11, 1593, 730, 492, 1000, 108, 409, 875, 10~
$ tz    <dbl> -5, -6, -6, -5, -5, -5, -5, -5, -5, -8, -5, -6, -5, -5, -5, -5, ~
$ dst   <chr> "A", "A", "A", "A", "A", "A", "A", "A", "U", "A", "A", "U", "A",~
$ tzone <chr> "America/New_York", "America/Chicago", "America/Chicago", "Ameri~
```

```r
flights_db <- tbl(db, "flights")
flights_db |> glimpse()
```

```
Rows: ??
Columns: 19
Database: DuckDB v1.2.1 [unknown@Linux 6.11.0-1012-azure:R 4.5.0/:memory:]
$ year           <int> 2013, 2013, 2013, 2013, 2013, 2013, 2013, 2013, 2013, 2~
$ month          <int> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1~
$ day            <int> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1~
$ dep_time       <int> 517, 533, 542, 544, 554, 554, 555, 557, 557, 558, 558, ~
$ sched_dep_time <int> 515, 529, 540, 545, 600, 558, 600, 600, 600, 600, 600, ~
$ dep_delay      <dbl> 2, 4, 2, -1, -6, -4, -5, -3, -3, -2, -2, -2, -2, -2, -1~
$ arr_time       <int> 830, 850, 923, 1004, 812, 740, 913, 709, 838, 753, 849,~
$ sched_arr_time <int> 819, 830, 850, 1022, 837, 728, 854, 723, 846, 745, 851,~
$ arr_delay      <dbl> 11, 20, 33, -18, -25, 12, 19, -14, -8, 8, -2, -3, 7, -1~
$ carrier        <chr> "UA", "UA", "AA", "B6", "DL", "UA", "B6", "EV", "B6", "~
$ flight         <int> 1545, 1714, 1141, 725, 461, 1696, 507, 5708, 79, 301, 4~
$ tailnum        <chr> "N14228", "N24211", "N619AA", "N804JB", "N668DN", "N394~
$ origin         <chr> "EWR", "LGA", "JFK", "JFK", "LGA", "EWR", "EWR", "LGA",~
$ dest           <chr> "IAH", "IAH", "MIA", "BQN", "ATL", "ORD", "FLL", "IAD",~
$ air_time       <dbl> 227, 227, 160, 183, 116, 150, 158, 53, 140, 138, 149, 1~
$ distance       <dbl> 1400, 1416, 1089, 1576, 762, 719, 1065, 229, 944, 733, ~
$ hour           <dbl> 5, 5, 5, 5, 6, 5, 6, 6, 6, 6, 6, 6, 6, 6, 6, 5, 6, 6, 6~
```

```
$ minute         <dbl> 15, 29, 40, 45, 0, 58, 0, 0, 0, 0, 0, 0, 0, 0, 0, 59, 0~
$ time_hour      <dttm> 2013-01-01 10:00:00, 2013-01-01 10:00:00, 2013-01-01 1~
```

```
weather_db <- tbl(db, "weather")
weather_db |> glimpse()
```

```
Rows: ??
Columns: 15
Database: DuckDB v1.2.1 [unknown@Linux 6.11.0-1012-azure:R 4.5.0/:memory:]
$ origin     <chr> "EWR", "EWR", "EWR", "EWR", "EWR", "EWR", "EWR", "EWR", "EW~
$ year       <int> 2013, 2013, 2013, 2013, 2013, 2013, 2013, 2013, 2013, 2013,~
$ month      <int> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,~
$ day        <int> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,~
$ hour       <int> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 13, 14, 15, 16, 17, 18, ~
$ temp       <dbl> 39.02, 39.02, 39.02, 39.92, 39.02, 37.94, 39.02, 39.92, 39.~
$ dewp       <dbl> 26.06, 26.96, 28.04, 28.04, 28.04, 28.04, 28.04, 28.04, 28.~
$ humid      <dbl> 59.37, 61.63, 64.43, 62.21, 64.43, 67.21, 64.43, 62.21, 62.~
$ wind_dir   <dbl> 270, 250, 240, 250, 260, 240, 240, 250, 260, 260, 260, 330,~
$ wind_speed <dbl> 10.35702, 8.05546, 11.50780, 12.65858, 12.65858, 11.50780, ~
$ wind_gust  <dbl> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, 20.~
$ precip     <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,~
$ pressure   <dbl> 1012.0, 1012.3, 1012.5, 1012.2, 1011.9, 1012.4, 1012.2, 101~
$ visib      <dbl> 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10,~
$ time_hour  <dttm> 2013-01-01 06:00:00, 2013-01-01 07:00:00, 2013-01-01 08:00~
```

```
planes_db <- tbl(db, "planes")
planes_db |> glimpse()
```

```
Rows: ??
Columns: 9
Database: DuckDB v1.2.1 [unknown@Linux 6.11.0-1012-azure:R 4.5.0/:memory:]
$ tailnum      <chr> "N10156", "N102UW", "N103US", "N104UW", "N10575", "N105UW~
$ year         <int> 2004, 1998, 1999, 1999, 2002, 1999, 1999, 1999, 1999, 199~
$ type         <chr> "Fixed wing multi engine", "Fixed wing multi engine", "Fi~
$ manufacturer <chr> "EMBRAER", "AIRBUS INDUSTRIE", "AIRBUS INDUSTRIE", "AIRBU~
$ model        <chr> "EMB-145XR", "A320-214", "A320-214", "A320-214", "EMB-145~
$ engines      <int> 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, ~
$ seats        <int> 55, 182, 182, 182, 55, 182, 182, 182, 182, 182, 55, 55, 5~
$ speed        <int> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, N~
$ engine       <chr> "Turbo-fan", "Turbo-fan", "Turbo-fan", "Turbo-fan", "Turb~
```

```r
airlines_db <- tbl(db, "airlines")
airlines_db |> glimpse()
```

```
Rows: ??
Columns: 2
Database: DuckDB v1.2.1 [unknown@Linux 6.11.0-1012-azure:R 4.5.0/:memory:]
$ carrier <chr> "9E", "AA", "AS", "B6", "DL", "EV", "F9", "FL", "HA", "MQ", "O~
$ name    <chr> "Endeavor Air Inc.", "American Airlines Inc.", "Alaska Airline~
```

2.0.1 Tidyverse functions

For almost all analyses we want to go from having our starting data spread out across multiple tables in the database to a single tidy table containing all the data we need for the specific analysis. We can often get to our tidy analytic dataset using the below tidyverse functions (most of which coming from `dplyr`, but a couple also from the `tidyr` package). These functions all work with data in a database by generating SQL that will have the same purpose as if these functions were being run against data in R.

> **! Important**
>
> Remember, until we use `compute()` or `collect()` (or printing the first few rows of the result) all we're doing is translating R code into SQL.

Purpose	Functions	Description
Selecting rows	filter, distinct	To select rows in a table.
Ordering rows	arrange	To order rows in a table.
Column Transformation	mutate, select, relocate, rename	To create new columns or change existing ones.
Grouping and ungrouping	group_by, rowwise, ungroup	To group data by one or more variables and to remove grouping.
Aggregation	count, tally, summarise	These functions are used for summarising data.

Purpose	Functions	Description
Data merging and joining	inner_join, left_join, right_join, full_join, anti_join, semi_join, cross_join	These functions are used to combine data from different tables based on common columns.
Data reshaping	pivot_wider, pivot_longer	These functions are used to reshape data between wide and long formats.
Data union	union_all, union	This function combines two tables.
Randomly selects rows	slice_sample	We can use this to take a random subset a table.

Behind the scenes

By using the above functions we can use the same code regardless of whether the data is held in the database or locally in R. This is because the functions used above are generic functions which behave differently depending on the type of input they are given. Let's take `inner_join()` for example. We can see that this function is a S3 generic function (with S3 being the most common object-oriented system used in R).

```
library(sloop)
ftype(inner_join)
```

```
[1] "S3"      "generic"
```

Among others, the references we create to tables in a database have `tbl_lazy` as a class attribute. Meanwhile, we can see that when collected into r the object changes to have different attributes, one of which being `data.frame` :

```
class(flights_db)
```

```
[1] "tbl_duckdb_connection" "tbl_dbi"                "tbl_sql"
[4] "tbl_lazy"              "tbl"
```

```
class(flights_db |> head(1) |> collect())
```

```
[1] "tbl_df"     "tbl"        "data.frame"
```

We can see that `inner_join()` has different methods for `tbl_lazy` and `data.frame`.

```
s3_methods_generic("inner_join")
```

```
# A tibble: 2 x 4
  generic    class      visible source
  <chr>      <chr>      <lgl>   <chr>
1 inner_join data.frame FALSE   registered S3method
2 inner_join tbl_lazy   FALSE   registered S3method
```

When working with references to tables in the database the `tbl_lazy` method will be used.

```
s3_dispatch(flights_db |>
              inner_join(planes_db))
```

```
   inner_join.tbl_duckdb_connection
   inner_join.tbl_dbi
   inner_join.tbl_sql
=> inner_join.tbl_lazy
   inner_join.tbl
   inner_join.default
```

But once we bring data into R, the `data.frame` method will be used.

```
s3_dispatch(flights_db |> head(1) |> collect() |>
              inner_join(planes_db |> head(1) |> collect()))
```

```
   inner_join.tbl_df
   inner_join.tbl
=> inner_join.data.frame
   inner_join.default
```

2.1 Getting to an analytic dataset

To see a little more on how we can use the above functions, let's say we want to do an analysis of late flights from JFK airport. We want to see whether there is some relationship between plane characteristics and the risk of delay.

For this we'll first use the `filter()` and `select()` `dplyr` verbs to get the data from the flights table. Note, we'll rename arr_delay to just delay.

```
delayed_flights_db <- flights_db |>
  filter(!is.na(arr_delay),
         origin == "JFK") |>
  select(dest,
         distance,
         carrier,
         tailnum,
         "delay" = "arr_delay")
```

Show query

```
<SQL>
SELECT dest, distance, carrier, tailnum, arr_delay AS delay
FROM flights
WHERE (NOT((arr_delay IS NULL))) AND (origin = 'JFK')
```

When executed, our results will look like the following:

```
delayed_flights_db
```

```
# Source:   SQL [?? x 5]
# Database: DuckDB v1.2.1 [unknown@Linux 6.11.0-1012-azure:R 4.5.0/:memory:]
   dest  distance carrier tailnum delay
   <chr>    <dbl> <chr>   <chr>   <dbl>
 1 MIA       1089 AA      N619AA     33
 2 BQN       1576 B6      N804JB    -18
 3 MCO        944 B6      N593JB     -8
 4 PBI       1028 B6      N793JB     -2
 5 TPA       1005 B6      N657JB     -3
 6 LAX       2475 UA      N29129      7
 7 BOS        187 B6      N708JB     -4
 8 ATL        760 DL      N3739P     -8
 9 SFO       2586 UA      N532UA     14
10 RSW       1074 B6      N635JB      4
# i more rows
```

Now we'll add plane characteristics from the planes table. We will use an inner join so that only records for which we have the plane characteristics are kept.

```r
delayed_flights_db <- delayed_flights_db |>
  inner_join(planes_db |>
               select(tailnum,
                      seats),
             by = join_by(tailnum))
```

Note that our first query was not executed, as we didn't use either `compute()` or `collect()`, so we'll now have added our join to the original query.

> **Show query**
>
> ```
> <SQL>
> SELECT LHS.*, seats
> FROM (
>   SELECT dest, distance, carrier, tailnum, arr_delay AS delay
>   FROM flights
>   WHERE (NOT((arr_delay IS NULL))) AND (origin = 'JFK')
> ) LHS
> INNER JOIN planes
>   ON (LHS.tailnum = planes.tailnum)
> ```

And when executed, our results will look like the following:

```r
delayed_flights_db
```

```
# Source:   SQL [?? x 6]
# Database: DuckDB v1.2.1 [unknown@Linux 6.11.0-1012-azure:R 4.5.0/:memory:]
   dest  distance carrier tailnum delay seats
   <chr>    <dbl> <chr>   <chr>   <dbl> <int>
 1 BQN       1576 B6      N804JB    -18   200
 2 MCO        944 B6      N593JB     -8   200
 3 PBI       1028 B6      N793JB     -2   200
 4 BOS        187 B6      N708JB     -4   200
 5 ATL        760 DL      N3739P     -8   189
 6 SJU       1598 B6      N794JB    -21   200
 7 PHX       2153 US      N535UW      0   379
 8 BOS        187 B6      N805JB    -10   200
 9 LAS       2248 B6      N558JB     -6   200
10 SLC       1990 DL      N3763D     -9   189
# i more rows
```

Getting to this tidy dataset has been done in the database via R code translated to SQL. With this, we can now collect our analytic dataset into R and go from there (for example, to perform locally statistical analyses which might not be possible to run in a database).

```
delayed_flights <- delayed_flights_db |>
  collect()

delayed_flights |>
 glimpse()
```

```
Rows: 93,298
Columns: 6
$ dest     <chr> "LAX", "CLT", "SFO", "ATL", "FLL", "BUF", "RSW", "LAS", "PHX"~
$ distance <dbl> 2475, 541, 2586, 760, 1069, 301, 1074, 2248, 2153, 1005, 2475~
$ carrier  <chr> "UA", "US", "UA", "DL", "B6", "B6", "B6", "B6", "US", "B6", "~
$ tailnum  <chr> "N34137", "N117UW", "N502UA", "N681DA", "N568JB", "N236JB", "~
$ delay    <dbl> -10, -34, 7, -12, -3, 2, 2, 0, -35, 7, -12, 11, -20, -10, -1,~
$ seats    <int> 178, 182, 178, 178, 200, 20, 200, 200, 379, 200, 200, 178, 17~
```

3 Supported expressions for database queries

In the previous chapter, Chapter 2, we saw that there are a core set of tidyverse functions that can be used with databases to extract data for analysis. The SQL code used in the previous chapter would be the same for all database management systems, with only joins and variable selection being used.

For more complex data pipleines we will, however, often need to incorporate additional expressions within these functions. Because of differences across database management systems, the SQL these pipelines get translated to can vary. Moreover, some expressions may only be supported for some subset of databases. When writing code which we want to work across different database management systems we therefore need to keep in mind what is supported where. To help with this, the sections below show the available translations for common expressions we might wish to use.

Let's first load the packages which these expressions come from. In addition to base R types, `bit64` adds support for integer64. The `stringr` package provides functions for working with strings, while `clock` has various functions for working with dates. Many other useful expressions will come from `dplyr` itself.

```
library(duckdb)
library(bit64)
library(dplyr)
library(dbplyr)
library(stringr)
library(clock)

options(dplyr.strict_sql = TRUE) # force error if no known translation
```

3.1 Data types

Commonly used data types are consistently supported across database backends. We can use the base `as.numeric()`, `as.integer()`, `as.charater()`, `as.Date()`, and `as.POSIXct()`. We can also use `as.integer64()` from the `bit64` package to coerce to integer64, and the `as_date()` and `as_datetime()` from the `clock` package instead of `as.Date()` and `as.POSIXct()`, respectively.

Show SQL

3.1.1 duckdb

```
translate_sql(as.numeric(var),
              con = simulate_duckdb())
```

```
<SQL> CAST(`var` AS NUMERIC)
```

```
translate_sql(as.integer(var),
              con = simulate_duckdb())
```

```
<SQL> CAST(`var` AS INTEGER)
```

```
translate_sql(as.integer64(var),
              con = simulate_duckdb())
```

```
<SQL> CAST(`var` AS BIGINT)
```

```
translate_sql(as.character(var),
              con = simulate_duckdb())
```

```
<SQL> CAST(`var` AS TEXT)
```

```
translate_sql(as.Date(var),
              con = simulate_duckdb())
```

```
<SQL> CAST(`var` AS DATE)
```

```
translate_sql(as_date(var),
              con = simulate_duckdb())
```

```
<SQL> CAST(`var` AS DATE)
```

```
translate_sql(as.POSIXct(var),
              con = simulate_duckdb())
```

```
<SQL> CAST(`var` AS TIMESTAMP)
```

```r
translate_sql(as_datetime(var),
              con = simulate_duckdb())
```

```
<SQL> CAST(`var` AS TIMESTAMP)
```

```r
translate_sql(as.logical(var),
              con = simulate_duckdb())
```

```
<SQL> CAST(`var` AS BOOLEAN)
```

3.1.2 Redshift

```r
translate_sql(as.numeric(var),
              con = simulate_redshift())
```

```
<SQL> CAST(`var` AS FLOAT)
```

```r
translate_sql(as.integer(var),
              con = simulate_redshift())
```

```
<SQL> CAST(`var` AS INTEGER)
```

```r
translate_sql(as.integer64(var),
              con = simulate_redshift())
```

```
<SQL> CAST(`var` AS BIGINT)
```

```r
translate_sql(as.character(var),
              con = simulate_redshift())
```

```
<SQL> CAST(`var` AS TEXT)
```

```r
translate_sql(as.Date(var),
              con = simulate_redshift())
```

```
<SQL> CAST(`var` AS DATE)
```

```r
translate_sql(as_date(var),
              con = simulate_redshift())
```

```
<SQL> CAST(`var` AS DATE)
```

```r
translate_sql(as.POSIXct(var),
              con = simulate_redshift())
```

```
<SQL> CAST(`var` AS TIMESTAMP)
```

```r
translate_sql(as_datetime(var),
              con = simulate_redshift())
```

```
<SQL> CAST(`var` AS TIMESTAMP)
```

```r
translate_sql(as.logical(var),
              con = simulate_redshift())
```

```
<SQL> CAST(`var` AS BOOLEAN)
```

3.1.3 Postgres

```r
translate_sql(as.numeric(var),
              con = simulate_postgres())
```

```
<SQL> CAST(`var` AS NUMERIC)
```

```r
translate_sql(as.integer(var),
              con = simulate_postgres())
```

```
<SQL> CAST(`var` AS INTEGER)
```

```r
translate_sql(as.integer64(var),
              con = simulate_postgres())
```

```
<SQL> CAST(`var` AS BIGINT)
```

```r
translate_sql(as.character(var),
              con = simulate_postgres())
```

```
<SQL> CAST(`var` AS TEXT)
```

```r
translate_sql(as.Date(var),
              con = simulate_postgres())
```

```
<SQL> CAST(`var` AS DATE)
```

```r
translate_sql(as_date(var),
              con = simulate_postgres())
```

```
<SQL> CAST(`var` AS DATE)
```

```r
translate_sql(as.POSIXct(var),
              con = simulate_postgres())
```

```
<SQL> CAST(`var` AS TIMESTAMP)
```

```r
translate_sql(as_datetime(var),
              con = simulate_postgres())
```

```
<SQL> CAST(`var` AS TIMESTAMP)
```

```r
translate_sql(as.logical(var),
              con = simulate_postgres())
```

```
<SQL> CAST(`var` AS BOOLEAN)
```

3.1.4 Snowflake

```r
translate_sql(as.numeric(var),
              con = simulate_snowflake())
```

```
<SQL> CAST(`var` AS DOUBLE)
```

```r
translate_sql(as.integer(var),
              con = simulate_snowflake())
```

```
<SQL> CAST(`var` AS INT)
```

```r
translate_sql(as.integer64(var),
              con = simulate_snowflake())
```

```
<SQL> CAST(`var` AS BIGINT)
```

```
translate_sql(as.character(var),
              con = simulate_snowflake())
```

```
<SQL> CAST(`var` AS STRING)
```

```
translate_sql(as.Date(var),
              con = simulate_snowflake())
```

```
<SQL> CAST(`var` AS DATE)
```

```
translate_sql(as_date(var),
              con = simulate_snowflake())
```

```
<SQL> CAST(`var` AS DATE)
```

```
translate_sql(as.POSIXct(var),
              con = simulate_snowflake())
```

```
<SQL> CAST(`var` AS TIMESTAMP)
```

```
translate_sql(as_datetime(var),
              con = simulate_snowflake())
```

```
<SQL> CAST(`var` AS TIMESTAMP)
```

```
translate_sql(as.logical(var),
              con = simulate_snowflake())
```

```
<SQL> CAST(`var` AS BOOLEAN)
```

3.1.5 Spark

```
translate_sql(as.numeric(var),
              con = simulate_spark_sql())
```

```
<SQL> CAST(`var` AS DOUBLE)
```

```r
translate_sql(as.integer(var),
              con = simulate_spark_sql())
```

```
<SQL> CAST(`var` AS INT)
```

```r
translate_sql(as.integer64(var),
              con = simulate_spark_sql())
```

```
<SQL> CAST(`var` AS BIGINT)
```

```r
translate_sql(as.character(var),
              con = simulate_spark_sql())
```

```
<SQL> CAST(`var` AS STRING)
```

```r
translate_sql(as.Date(var),
              con = simulate_spark_sql())
```

```
<SQL> CAST(`var` AS DATE)
```

```r
translate_sql(as_date(var),
              con = simulate_spark_sql())
```

```
<SQL> CAST(`var` AS DATE)
```

```r
translate_sql(as.POSIXct(var),
              con = simulate_spark_sql())
```

```
<SQL> CAST(`var` AS TIMESTAMP)
```

```r
translate_sql(as_datetime(var),
              con = simulate_spark_sql())
```

```
<SQL> CAST(`var` AS TIMESTAMP)
```

```r
translate_sql(as.logical(var),
              con = simulate_spark_sql())
```

```
<SQL> CAST(`var` AS BOOLEAN)
```

3.1.6 SQL Server

```
translate_sql(as.numeric(var),
              con = simulate_mssql())
```

```
<SQL> TRY_CAST(`var` AS FLOAT)
```

```
translate_sql(as.integer(var),
              con = simulate_mssql())
```

```
<SQL> TRY_CAST(TRY_CAST(`var` AS NUMERIC) AS INT)
```

```
translate_sql(as.integer64(var),
              con = simulate_mssql())
```

```
<SQL> TRY_CAST(TRY_CAST(`var` AS NUMERIC(38, 0)) AS BIGINT)
```

```
translate_sql(as.character(var),
              con = simulate_mssql())
```

```
<SQL> TRY_CAST(`var` AS VARCHAR(MAX))
```

```
translate_sql(as.Date(var),
              con = simulate_mssql())
```

```
<SQL> TRY_CAST(`var` AS DATE)
```

```
translate_sql(as_date(var),
              con = simulate_mssql())
```

```
<SQL> TRY_CAST(`var` AS DATE)
```

```
translate_sql(as.POSIXct(var),
              con = simulate_mssql())
```

```
<SQL> TRY_CAST(`var` AS DATETIME2)
```

```
translate_sql(as_datetime(var),
              con = simulate_mssql())
```

```
<SQL> TRY_CAST(`var` AS DATETIME2)
```

```
translate_sql(as.logical(var),
              con = simulate_mssql())
```

```
<SQL> TRY_CAST(`var` AS BIT)
```

3.2 Comparison and logical operators

Base R comparison operators, such as `<`, `<=`, `==`, `>=`, `>`, are also well supported in all database backends. Logical operators, such as `&` and `|` can also be used as if the data was in R.

Show SQL

3.2.1 duckdb

```
translate_sql(var_1 == var_2,
              con = simulate_duckdb())
```

```
<SQL> `var_1` = `var_2`
```

```
translate_sql(var_1 >= var_2,
              con = simulate_duckdb())
```

```
<SQL> `var_1` >= `var_2`
```

```
translate_sql(var_1 < 100,
              con = simulate_duckdb())
```

```
<SQL> `var_1` < 100.0
```

```
translate_sql(var_1 %in% c("a", "b", "c"),
              con = simulate_duckdb())
```

```
<SQL> `var_1` IN ('a', 'b', 'c')
```

```
translate_sql(!var_1 %in% c("a", "b", "c"),
              con = simulate_duckdb())
```

```
<SQL> NOT(`var_1` IN ('a', 'b', 'c'))
```

```
translate_sql(is.na(var_1),
              con = simulate_duckdb())
```

```
<SQL> (`var_1` IS NULL)
```

```
translate_sql(!is.na(var_1),
              con = simulate_duckdb())
```

```
<SQL> NOT((`var_1` IS NULL))
```

```
translate_sql(var_1 >= 100 & var_1  < 200,
              con = simulate_duckdb())
```

```
<SQL> `var_1` >= 100.0 AND `var_1` < 200.0
```

```
translate_sql(var_1 >= 100 | var_1  < 200,
              con = simulate_duckdb())
```

```
<SQL> `var_1` >= 100.0 OR `var_1` < 200.0
```

3.2.2 Redshift

```
translate_sql(var_1 == var_2,
              con = simulate_redshift())
```

```
<SQL> `var_1` = `var_2`
```

```
translate_sql(var_1 >= var_2,
              con = simulate_redshift())
```

```
<SQL> `var_1` >= `var_2`
```

```
translate_sql(var_1 < 100,
              con = simulate_redshift())
```

```
<SQL> `var_1` < 100.0
```

```r
translate_sql(var_1 %in% c("a", "b", "c"),
              con = simulate_redshift())
```

```
<SQL> `var_1` IN ('a', 'b', 'c')
```

```r
translate_sql(!var_1 %in% c("a", "b", "c"),
              con = simulate_redshift())
```

```
<SQL> NOT(`var_1` IN ('a', 'b', 'c'))
```

```r
translate_sql(is.na(var_1),
              con = simulate_redshift())
```

```
<SQL> (`var_1` IS NULL)
```

```r
translate_sql(!is.na(var_1),
              con = simulate_redshift())
```

```
<SQL> NOT((`var_1` IS NULL))
```

```r
translate_sql(var_1 >= 100 & var_1  < 200,
              con = simulate_redshift())
```

```
<SQL> `var_1` >= 100.0 AND `var_1` < 200.0
```

```r
translate_sql(var_1 >= 100 | var_1  < 200,
              con = simulate_redshift())
```

```
<SQL> `var_1` >= 100.0 OR `var_1` < 200.0
```

3.2.3 Postgres

```r
translate_sql(var_1 == var_2,
              con = simulate_postgres())
```

```
<SQL> `var_1` = `var_2`
```

```r
translate_sql(var_1 >= var_2,
              con = simulate_postgres())
```

```
<SQL> `var_1` >= `var_2`
```

```r
translate_sql(var_1 < 100,
              con = simulate_postgres())
```

```
<SQL> `var_1` < 100.0
```

```r
translate_sql(var_1 %in% c("a", "b", "c"),
              con = simulate_postgres())
```

```
<SQL> `var_1` IN ('a', 'b', 'c')
```

```r
translate_sql(!var_1 %in% c("a", "b", "c"),
              con = simulate_postgres())
```

```
<SQL> NOT(`var_1` IN ('a', 'b', 'c'))
```

```r
translate_sql(is.na(var_1),
              con = simulate_postgres())
```

```
<SQL> (`var_1` IS NULL)
```

```r
translate_sql(!is.na(var_1),
              con = simulate_postgres())
```

```
<SQL> NOT((`var_1` IS NULL))
```

```r
translate_sql(var_1 >= 100 & var_1  < 200,
              con = simulate_postgres())
```

```
<SQL> `var_1` >= 100.0 AND `var_1` < 200.0
```

```r
translate_sql(var_1 >= 100 | var_1  < 200,
              con = simulate_postgres())
```

```
<SQL> `var_1` >= 100.0 OR `var_1` < 200.0
```

3.2.4 Snowflake

```r
translate_sql(var_1 == var_2,
              con = simulate_snowflake())
```

```
<SQL> `var_1` = `var_2`
```

```r
translate_sql(var_1 >= var_2,
              con = simulate_snowflake())
```

```
<SQL> `var_1` >= `var_2`
```

```r
translate_sql(var_1 < 100,
              con = simulate_snowflake())
```

```
<SQL> `var_1` < 100.0
```

```r
translate_sql(var_1 %in% c("a", "b", "c"),
              con = simulate_snowflake())
```

```
<SQL> `var_1` IN ('a', 'b', 'c')
```

```r
translate_sql(!var_1 %in% c("a", "b", "c"),
              con = simulate_snowflake())
```

```
<SQL> NOT(`var_1` IN ('a', 'b', 'c'))
```

```r
translate_sql(is.na(var_1),
              con = simulate_snowflake())
```

```
<SQL> (`var_1` IS NULL)
```

```r
translate_sql(!is.na(var_1),
              con = simulate_snowflake())
```

```
<SQL> NOT((`var_1` IS NULL))
```

```r
translate_sql(var_1 >= 100 & var_1  < 200,
              con = simulate_snowflake())
```

```
<SQL> `var_1` >= 100.0 AND `var_1` < 200.0
```

```r
translate_sql(var_1 >= 100 | var_1  < 200,
              con = simulate_snowflake())
```

```
<SQL> `var_1` >= 100.0 OR `var_1` < 200.0
```

3.2.5 Spark

```r
translate_sql(var_1 == var_2,
              con = simulate_spark_sql())
```

```
<SQL> `var_1` = `var_2`
```

```r
translate_sql(var_1 >= var_2,
              con = simulate_spark_sql())
```

```
<SQL> `var_1` >= `var_2`
```

```r
translate_sql(var_1 < 100,
              con = simulate_spark_sql())
```

```
<SQL> `var_1` < 100.0
```

```r
translate_sql(var_1 %in% c("a", "b", "c"),
              con = simulate_spark_sql())
```

```
<SQL> `var_1` IN ('a', 'b', 'c')
```

```r
translate_sql(!var_1 %in% c("a", "b", "c"),
              con = simulate_spark_sql())
```

```
<SQL> NOT(`var_1` IN ('a', 'b', 'c'))
```

```r
translate_sql(is.na(var_1),
              con = simulate_spark_sql())
```

```
<SQL> (`var_1` IS NULL)
```

```r
translate_sql(!is.na(var_1),
              con = simulate_spark_sql())
```

```
<SQL> NOT((`var_1` IS NULL))
```

```r
translate_sql(var_1 >= 100 & var_1  < 200,
              con = simulate_spark_sql())
```

```
<SQL> `var_1` >= 100.0 AND `var_1` < 200.0
```

```r
translate_sql(var_1 >= 100 | var_1  < 200,
              con = simulate_spark_sql())
```

```
<SQL> `var_1` >= 100.0 OR `var_1` < 200.0
```

3.2.6 SQL Server

```r
translate_sql(var_1 == var_2,
              con = simulate_mssql())
```

```
<SQL> `var_1` = `var_2`
```

```r
translate_sql(var_1 >= var_2,
              con = simulate_mssql())
```

```
<SQL> `var_1` >= `var_2`
```

```r
translate_sql(var_1 < 100,
              con = simulate_mssql())
```

```
<SQL> `var_1` < 100.0
```

```r
translate_sql(var_1 %in% c("a", "b", "c"),
              con = simulate_mssql())
```

```
<SQL> `var_1` IN ('a', 'b', 'c')
```

```r
translate_sql(!var_1 %in% c("a", "b", "c"),
              con = simulate_mssql())
```

```
<SQL> NOT(`var_1` IN ('a', 'b', 'c'))
```

```
translate_sql(is.na(var_1),
              con = simulate_mssql())
```

```
<SQL> (`var_1` IS NULL)
```

```
translate_sql(!is.na(var_1),
              con = simulate_mssql())
```

```
<SQL> NOT((`var_1` IS NULL))
```

```
translate_sql(var_1 >= 100 & var_1  < 200,
              con = simulate_mssql())
```

```
<SQL> `var_1` >= 100.0 AND `var_1` < 200.0
```

```
translate_sql(var_1 >= 100 | var_1  < 200,
              con = simulate_mssql())
```

```
<SQL> `var_1` >= 100.0 OR `var_1` < 200.0
```

3.3 Conditional statements

The base `ifelse` function, along with `if_else` and `case_when` from `dplyr` are translated for each database backend. As can be seen in the translations, `case_when` maps to the SQL CASE WHEN statement.

Show SQL

3.3.1 duckdb

```
translate_sql(ifelse(var == "a", 1L, 2L),
              con = simulate_duckdb())
```

```
<SQL> CASE WHEN (`var` = 'a') THEN 1 WHEN NOT (`var` = 'a') THEN 2 END
```

```r
translate_sql(if_else(var == "a", 1L, 2L),
              con = simulate_duckdb())
```

```
<SQL> CASE WHEN (`var` = 'a') THEN 1 WHEN NOT (`var` = 'a') THEN 2 END
```

```r
translate_sql(case_when(var == "a" ~ 1L, .default = 2L),
              con = simulate_duckdb())
```

```
<SQL> CASE WHEN (`var` = 'a') THEN 1 ELSE 2 END
```

```r
translate_sql(case_when(var == "a" ~ 1L,
                        var == "b" ~ 2L,
                        var == "c" ~ 3L,
                        .default = NULL),
              con = simulate_duckdb())
```

```
<SQL> CASE
WHEN (`var` = 'a') THEN 1
WHEN (`var` = 'b') THEN 2
WHEN (`var` = 'c') THEN 3
END
```

```r
translate_sql(case_when(var == "a" ~ 1L,
                        var == "b" ~ 2L,
                        var == "c" ~ 3L,
                        .default = "something else"),
              con = simulate_duckdb())
```

```
<SQL> CASE
WHEN (`var` = 'a') THEN 1
WHEN (`var` = 'b') THEN 2
WHEN (`var` = 'c') THEN 3
ELSE 'something else'
END
```

3.3.2 Redshift

```r
translate_sql(ifelse(var == "a", 1L, 2L),
              con = simulate_redshift())
```

```
<SQL> CASE WHEN (`var` = 'a') THEN 1 WHEN NOT (`var` = 'a') THEN 2 END
```

```
translate_sql(if_else(var == "a", 1L, 2L),
              con = simulate_redshift())
```

```
<SQL> CASE WHEN (`var` = 'a') THEN 1 WHEN NOT (`var` = 'a') THEN 2 END
```

```
translate_sql(case_when(var == "a" ~ 1L, .default = 2L),
              con = simulate_redshift())
```

```
<SQL> CASE WHEN (`var` = 'a') THEN 1 ELSE 2 END
```

```
translate_sql(case_when(var == "a" ~ 1L,
                        var == "b" ~ 2L,
                        var == "c" ~ 3L,
                        .default = NULL),
              con = simulate_redshift())
```

```
<SQL> CASE
WHEN (`var` = 'a') THEN 1
WHEN (`var` = 'b') THEN 2
WHEN (`var` = 'c') THEN 3
END
```

```
translate_sql(case_when(var == "a" ~ 1L,
                        var == "b" ~ 2L,
                        var == "c" ~ 3L,
                        .default = "something else"),
              con = simulate_redshift())
```

```
<SQL> CASE
WHEN (`var` = 'a') THEN 1
WHEN (`var` = 'b') THEN 2
WHEN (`var` = 'c') THEN 3
ELSE 'something else'
END
```

3.3.3 Postgres

```
translate_sql(ifelse(var == "a", 1L, 2L),
              con = simulate_postgres())
```

```
<SQL> CASE WHEN (`var` = 'a') THEN 1 WHEN NOT (`var` = 'a') THEN 2 END
```

```r
translate_sql(if_else(var == "a", 1L, 2L),
              con = simulate_postgres())
```

```
<SQL> CASE WHEN (`var` = 'a') THEN 1 WHEN NOT (`var` = 'a') THEN 2 END
```

```r
translate_sql(case_when(var == "a" ~ 1L, .default = 2L),
              con = simulate_postgres())
```

```
<SQL> CASE WHEN (`var` = 'a') THEN 1 ELSE 2 END
```

```r
translate_sql(case_when(var == "a" ~ 1L,
                        var == "b" ~ 2L,
                        var == "c" ~ 3L,
                        .default = NULL),
              con = simulate_postgres())
```

```
<SQL> CASE
WHEN (`var` = 'a') THEN 1
WHEN (`var` = 'b') THEN 2
WHEN (`var` = 'c') THEN 3
END
```

```r
translate_sql(case_when(var == "a" ~ 1L,
                        var == "b" ~ 2L,
                        var == "c" ~ 3L,
                        .default = "something else"),
              con = simulate_postgres())
```

```
<SQL> CASE
WHEN (`var` = 'a') THEN 1
WHEN (`var` = 'b') THEN 2
WHEN (`var` = 'c') THEN 3
ELSE 'something else'
END
```

3.3.4 Snowflake

```r
translate_sql(ifelse(var == "a", 1L, 2L),
              con = simulate_snowflake())
```

```
<SQL> CASE WHEN (`var` = 'a') THEN 1 WHEN NOT (`var` = 'a') THEN 2 END
```

```r
translate_sql(if_else(var == "a", 1L, 2L),
              con = simulate_snowflake())
```

```
<SQL> CASE WHEN (`var` = 'a') THEN 1 WHEN NOT (`var` = 'a') THEN 2 END
```

```r
translate_sql(case_when(var == "a" ~ 1L, .default = 2L),
              con = simulate_snowflake())
```

```
<SQL> CASE WHEN (`var` = 'a') THEN 1 ELSE 2 END
```

```r
translate_sql(case_when(var == "a" ~ 1L,
                        var == "b" ~ 2L,
                        var == "c" ~ 3L,
                        .default = NULL),
              con = simulate_snowflake())
```

```
<SQL> CASE
WHEN (`var` = 'a') THEN 1
WHEN (`var` = 'b') THEN 2
WHEN (`var` = 'c') THEN 3
END
```

```r
translate_sql(case_when(var == "a" ~ 1L,
                        var == "b" ~ 2L,
                        var == "c" ~ 3L,
                        .default = "something else"),
              con = simulate_snowflake())
```

```
<SQL> CASE
WHEN (`var` = 'a') THEN 1
WHEN (`var` = 'b') THEN 2
WHEN (`var` = 'c') THEN 3
ELSE 'something else'
END
```

3.3.5 Spark

```r
translate_sql(ifelse(var == "a", 1L, 2L),
              con = simulate_spark_sql())
```

```
<SQL> CASE WHEN (`var` = 'a') THEN 1 WHEN NOT (`var` = 'a') THEN 2 END
```

```
translate_sql(if_else(var == "a", 1L, 2L),
              con = simulate_spark_sql())
```

```
<SQL> CASE WHEN (`var` = 'a') THEN 1 WHEN NOT (`var` = 'a') THEN 2 END
```

```
translate_sql(case_when(var == "a" ~ 1L, .default = 2L),
              con = simulate_spark_sql())
```

```
<SQL> CASE WHEN (`var` = 'a') THEN 1 ELSE 2 END
```

```
translate_sql(case_when(var == "a" ~ 1L,
                        var == "b" ~ 2L,
                        var == "c" ~ 3L,
                        .default = NULL),
              con = simulate_spark_sql())
```

```
<SQL> CASE
WHEN (`var` = 'a') THEN 1
WHEN (`var` = 'b') THEN 2
WHEN (`var` = 'c') THEN 3
END
```

```
translate_sql(case_when(var == "a" ~ 1L,
                        var == "b" ~ 2L,
                        var == "c" ~ 3L,
                        .default = "something else"),
              con = simulate_spark_sql())
```

```
<SQL> CASE
WHEN (`var` = 'a') THEN 1
WHEN (`var` = 'b') THEN 2
WHEN (`var` = 'c') THEN 3
ELSE 'something else'
END
```

3.3.6 SQL Server

```
translate_sql(ifelse(var == "a", 1L, 2L),
              con = simulate_mssql())
```

```
<SQL> IIF(`var` = 'a', 1, 2)
```

```
translate_sql(if_else(var == "a", 1L, 2L),
              con = simulate_mssql())
```

```
<SQL> IIF(`var` = 'a', 1, 2)
```

```
translate_sql(case_when(var == "a" ~ 1L, .default = 2L),
              con = simulate_mssql())
```

```
<SQL> CASE WHEN (`var` = 'a') THEN 1 ELSE 2 END
```

```
translate_sql(case_when(var == "a" ~ 1L,
                        var == "b" ~ 2L,
                        var == "c" ~ 3L,
                        .default = NULL),
              con = simulate_mssql())
```

```
<SQL> CASE
WHEN (`var` = 'a') THEN 1
WHEN (`var` = 'b') THEN 2
WHEN (`var` = 'c') THEN 3
END
```

```
translate_sql(case_when(var == "a" ~ 1L,
                        var == "b" ~ 2L,
                        var == "c" ~ 3L,
                        .default = "something else"),
              con = simulate_mssql())
```

```
<SQL> CASE
WHEN (`var` = 'a') THEN 1
WHEN (`var` = 'b') THEN 2
WHEN (`var` = 'c') THEN 3
ELSE 'something else'
END
```

3.4 Working with strings

Compared to the previous sections, there is much more variation in support of functions to work with strings across database management systems. In particular, although various useful `stringr` functions do have translations ubiquitously it can be seen below that more translations are available for some databases compared to others.

Show SQL

3.4.1 duckdb

```r
translate_sql(nchar(var),
              con = simulate_duckdb())
```

```
<SQL> LENGTH(`var`)
```

```r
translate_sql(nzchar(var),
              con = simulate_duckdb())
```

```
<SQL> ((`var` IS NULL) OR `var` != '')
```

```r
translate_sql(substr(var, 1, 2),
              con = simulate_duckdb())
```

```
<SQL> SUBSTR(`var`, 1, 2)
```

```r
translate_sql(trimws(var),
              con = simulate_duckdb())
```

```
<SQL> LTRIM(RTRIM(`var`))
```

```r
translate_sql(tolower(var),
              con = simulate_duckdb())
```

```
<SQL> LOWER(`var`)
```

```r
translate_sql(str_to_lower(var),
              con = simulate_duckdb())
```

```
<SQL> LOWER(`var`)
```

```r
translate_sql(toupper(var),
              con = simulate_duckdb())
```

```
<SQL> UPPER(`var`)
```

```r
translate_sql(str_to_upper(var),
              con = simulate_duckdb())
```

```
<SQL> UPPER(`var`)
```

```r
translate_sql(str_to_title(var),
              con = simulate_duckdb())
```

```
<SQL> INITCAP(`var`)
```

```r
translate_sql(str_trim(var),
              con = simulate_duckdb())
```

```
<SQL> LTRIM(RTRIM(`var`))
```

```r
translate_sql(str_squish(var),
              con = simulate_duckdb())
```

```
<SQL> TRIM(REGEXP_REPLACE(`var`, '\s+', ' ', 'g'))
```

```r
translate_sql(str_detect(var, "b"),
              con = simulate_duckdb())
```

```
<SQL> REGEXP_MATCHES(`var`, 'b')
```

```r
translate_sql(str_detect(var, "b", negate = TRUE),
              con = simulate_duckdb())
```

```
<SQL> (NOT(REGEXP_MATCHES(`var`, 'b')))
```

```r
translate_sql(str_detect(var, "[aeiou]"),
              con = simulate_duckdb())
```

```
<SQL> REGEXP_MATCHES(`var`, '[aeiou]')
```

```r
translate_sql(str_replace(var, "a", "b"),
              con = simulate_duckdb())
```

```
<SQL> REGEXP_REPLACE(`var`, 'a', 'b')
```

```r
translate_sql(str_replace_all(var, "a", "b"),
              con = simulate_duckdb())
```

```
<SQL> REGEXP_REPLACE(`var`, 'a', 'b', 'g')
```

```r
translate_sql(str_remove(var, "a"),
              con = simulate_duckdb())
```

```
<SQL> REGEXP_REPLACE(`var`, 'a', '')
```

```r
translate_sql(str_remove_all(var, "a"),
              con = simulate_duckdb())
```

```
<SQL> REGEXP_REPLACE(`var`, 'a', '', 'g')
```

```r
translate_sql(str_like(var, "a"),
              con = simulate_duckdb())
```

```
<SQL> `var` LIKE 'a'
```

```r
translate_sql(str_starts(var, "a"),
              con = simulate_duckdb())
```

```
<SQL> REGEXP_MATCHES(`var`,'^(?:'||'a'))
```

```r
translate_sql(str_ends(var, "a"),
              con = simulate_duckdb())
```

```
<SQL> REGEXP_MATCHES((?:`var`,'a'||')$')
```

3.4.2 Redshift

```
translate_sql(nchar(var),
              con = simulate_redshift())
```

```
<SQL> LENGTH(`var`)
```

```
translate_sql(nzchar(var),
              con = simulate_redshift())
```

```
<SQL> ((`var` IS NULL) OR `var` != '')
```

```
translate_sql(substr(var, 1, 2),
              con = simulate_redshift())
```

```
<SQL> SUBSTRING(`var`, 1, 2)
```

```
translate_sql(trimws(var),
              con = simulate_redshift())
```

```
<SQL> LTRIM(RTRIM(`var`))
```

```
translate_sql(tolower(var),
              con = simulate_redshift())
```

```
<SQL> LOWER(`var`)
```

```
translate_sql(str_to_lower(var),
              con = simulate_redshift())
```

```
<SQL> LOWER(`var`)
```

```
translate_sql(toupper(var),
              con = simulate_redshift())
```

```
<SQL> UPPER(`var`)
```

```
translate_sql(str_to_upper(var),
              con = simulate_redshift())
```

```
<SQL> UPPER(`var`)
```

```r
translate_sql(str_to_title(var),
              con = simulate_redshift())
```

```
<SQL> INITCAP(`var`)
```

```r
translate_sql(str_trim(var),
              con = simulate_redshift())
```

```
<SQL> LTRIM(RTRIM(`var`))
```

```r
translate_sql(str_squish(var),
              con = simulate_redshift())
```

```
<SQL> LTRIM(RTRIM(REGEXP_REPLACE(`var`, '\s+', ' ', 'g')))
```

```r
translate_sql(str_detect(var, "b"),
              con = simulate_redshift())
```

```
<SQL> `var` ~ 'b'
```

```r
translate_sql(str_detect(var, "b", negate = TRUE),
              con = simulate_redshift())
```

```
<SQL> !(`var` ~ 'b')
```

```r
translate_sql(str_detect(var, "[aeiou]"),
              con = simulate_redshift())
```

```
<SQL> `var` ~ '[aeiou]'
```

```r
translate_sql(str_replace(var, "a", "b"),
              con = simulate_redshift())
```

```
Error in `str_replace()`:
! `str_replace()` is not available in this SQL variant.
```

```r
translate_sql(str_replace_all(var, "a", "b"),
              con = simulate_redshift())
```

```
<SQL> REGEXP_REPLACE(`var`, 'a', 'b')
```

```
translate_sql(str_remove(var, "a"),
              con = simulate_redshift())
```

```
<SQL> REGEXP_REPLACE(`var`, 'a', '')
```

```
translate_sql(str_remove_all(var, "a"),
              con = simulate_redshift())
```

```
<SQL> REGEXP_REPLACE(`var`, 'a', '', 'g')
```

```
translate_sql(str_like(var, "a"),
              con = simulate_redshift())
```

```
<SQL> `var` ILIKE 'a'
```

```
translate_sql(str_starts(var, "a"),
              con = simulate_redshift())
```

```
Error in `str_starts()`:
! Only fixed patterns are supported on database backends.
```

```
translate_sql(str_ends(var, "a"),
              con = simulate_redshift())
```

```
Error in `str_ends()`:
! Only fixed patterns are supported on database backends.
```

3.4.3 Postgres

```
translate_sql(nchar(var),
              con = simulate_postgres())
```

```
<SQL> LENGTH(`var`)
```

```
translate_sql(nzchar(var),
              con = simulate_postgres())
```

```
<SQL> ((`var` IS NULL) OR `var` != '')
```

```r
translate_sql(substr(var, 1, 2),
              con = simulate_postgres())
```

```
<SQL> SUBSTR(`var`, 1, 2)
```

```r
translate_sql(trimws(var),
              con = simulate_postgres())
```

```
<SQL> LTRIM(RTRIM(`var`))
```

```r
translate_sql(tolower(var),
              con = simulate_postgres())
```

```
<SQL> LOWER(`var`)
```

```r
translate_sql(str_to_lower(var),
              con = simulate_postgres())
```

```
<SQL> LOWER(`var`)
```

```r
translate_sql(toupper(var),
              con = simulate_postgres())
```

```
<SQL> UPPER(`var`)
```

```r
translate_sql(str_to_upper(var),
              con = simulate_postgres())
```

```
<SQL> UPPER(`var`)
```

```r
translate_sql(str_to_title(var),
              con = simulate_postgres())
```

```
<SQL> INITCAP(`var`)
```

```r
translate_sql(str_trim(var),
              con = simulate_postgres())
```

```
<SQL> LTRIM(RTRIM(`var`))
```

```
translate_sql(str_squish(var),
              con = simulate_postgres())
```

```
<SQL> LTRIM(RTRIM(REGEXP_REPLACE(`var`, '\s+', ' ', 'g')))
```

```
translate_sql(str_detect(var, "b"),
              con = simulate_postgres())
```

```
<SQL> `var` ~ 'b'
```

```
translate_sql(str_detect(var, "b", negate = TRUE),
              con = simulate_postgres())
```

```
<SQL> !(`var` ~ 'b')
```

```
translate_sql(str_detect(var, "[aeiou]"),
              con = simulate_postgres())
```

```
<SQL> `var` ~ '[aeiou]'
```

```
translate_sql(str_replace(var, "a", "b"),
              con = simulate_postgres())
```

```
<SQL> REGEXP_REPLACE(`var`, 'a', 'b')
```

```
translate_sql(str_replace_all(var, "a", "b"),
              con = simulate_postgres())
```

```
<SQL> REGEXP_REPLACE(`var`, 'a', 'b', 'g')
```

```
translate_sql(str_remove(var, "a"),
              con = simulate_postgres())
```

```
<SQL> REGEXP_REPLACE(`var`, 'a', '')
```

```
translate_sql(str_remove_all(var, "a"),
              con = simulate_postgres())
```

```
<SQL> REGEXP_REPLACE(`var`, 'a', '', 'g')
```

```r
translate_sql(str_like(var, "a"),
              con = simulate_postgres())
```

```
<SQL> `var` ILIKE 'a'
```

```r
translate_sql(str_starts(var, "a"),
              con = simulate_postgres())
```

```
Error in `str_starts()`:
! Only fixed patterns are supported on database backends.
```

```r
translate_sql(str_ends(var, "a"),
              con = simulate_postgres())
```

```
Error in `str_ends()`:
! Only fixed patterns are supported on database backends.
```

3.4.4 Snowflake

```r
translate_sql(nchar(var),
              con = simulate_snowflake())
```

```
<SQL> LENGTH(`var`)
```

```r
translate_sql(nzchar(var),
              con = simulate_snowflake())
```

```
<SQL> ((`var` IS NULL) OR `var` != '')
```

```r
translate_sql(substr(var, 1, 2),
              con = simulate_snowflake())
```

```
<SQL> SUBSTR(`var`, 1, 2)
```

```r
translate_sql(trimws(var),
              con = simulate_snowflake())
```

```
<SQL> LTRIM(RTRIM(`var`))
```

```
translate_sql(tolower(var),
              con = simulate_snowflake())
```

```
<SQL> LOWER(`var`)
```

```
translate_sql(str_to_lower(var),
              con = simulate_snowflake())
```

```
<SQL> LOWER(`var`)
```

```
translate_sql(toupper(var),
              con = simulate_snowflake())
```

```
<SQL> UPPER(`var`)
```

```
translate_sql(str_to_upper(var),
              con = simulate_snowflake())
```

```
<SQL> UPPER(`var`)
```

```
translate_sql(str_to_title(var),
              con = simulate_snowflake())
```

```
<SQL> INITCAP(`var`)
```

```
translate_sql(str_trim(var),
              con = simulate_snowflake())
```

```
<SQL> TRIM(`var`)
```

```
translate_sql(str_squish(var),
              con = simulate_snowflake())
```

```
<SQL> REGEXP_REPLACE(TRIM(`var`), '\\s+', ' ')
```

```
translate_sql(str_detect(var, "b"),
              con = simulate_snowflake())
```

```
Error in `REGEXP_INSTR()`:
! Don't know how to translate `REGEXP_INSTR()`
```

```r
translate_sql(str_detect(var, "b", negate = TRUE),
              con = simulate_snowflake())
```

```
Error in `REGEXP_INSTR()`:
! Don't know how to translate `REGEXP_INSTR()`
```

```r
translate_sql(str_detect(var, "[aeiou]"),
              con = simulate_snowflake())
```

```
Error in `REGEXP_INSTR()`:
! Don't know how to translate `REGEXP_INSTR()`
```

```r
translate_sql(str_replace(var, "a", "b"),
              con = simulate_snowflake())
```

```
<SQL> REGEXP_REPLACE(`var`, 'a', 'b', 1.0, 1.0)
```

```r
translate_sql(str_replace_all(var, "a", "b"),
              con = simulate_snowflake())
```

```
<SQL> REGEXP_REPLACE(`var`, 'a', 'b')
```

```r
translate_sql(str_remove(var, "a"),
              con = simulate_snowflake())
```

```
<SQL> REGEXP_REPLACE(`var`, 'a', '', 1.0, 1.0)
```

```r
translate_sql(str_remove_all(var, "a"),
              con = simulate_snowflake())
```

```
<SQL> REGEXP_REPLACE(`var`, 'a')
```

```r
translate_sql(str_like(var, "a"),
              con = simulate_snowflake())
```

```
<SQL> `var` LIKE 'a'
```

```
translate_sql(str_starts(var, "a"),
              con = simulate_snowflake())
```

```
Error in `REGEXP_INSTR()`:
! Don't know how to translate `REGEXP_INSTR()`
```

```
translate_sql(str_ends(var, "a"),
              con = simulate_snowflake())
```

```
Error in `REGEXP_INSTR()`:
! Don't know how to translate `REGEXP_INSTR()`
```

3.4.5 Spark

```
translate_sql(nchar(var),
              con = simulate_spark_sql())
```

```
<SQL> LENGTH(`var`)
```

```
translate_sql(nzchar(var),
              con = simulate_spark_sql())
```

```
<SQL> ((`var` IS NULL) OR `var` != '')
```

```
translate_sql(substr(var, 1, 2),
              con = simulate_spark_sql())
```

```
<SQL> SUBSTR(`var`, 1, 2)
```

```
translate_sql(trimws(var),
              con = simulate_spark_sql())
```

```
<SQL> LTRIM(RTRIM(`var`))
```

```
translate_sql(tolower(var),
              con = simulate_spark_sql())
```

```
<SQL> LOWER(`var`)
```

```r
translate_sql(str_to_lower(var),
              con = simulate_spark_sql())
```

```
<SQL> LOWER(`var`)
```

```r
translate_sql(toupper(var),
              con = simulate_spark_sql())
```

```
<SQL> UPPER(`var`)
```

```r
translate_sql(str_to_upper(var),
              con = simulate_spark_sql())
```

```
<SQL> UPPER(`var`)
```

```r
translate_sql(str_to_title(var),
              con = simulate_spark_sql())
```

```
<SQL> INITCAP(`var`)
```

```r
translate_sql(str_trim(var),
              con = simulate_spark_sql())
```

```
<SQL> LTRIM(RTRIM(`var`))
```

```r
translate_sql(str_squish(var),
              con = simulate_spark_sql())
```

```
Error in `str_squish()`:
! `str_squish()` is not available in this SQL variant.
```

```r
translate_sql(str_detect(var, "b"),
              con = simulate_spark_sql())
```

```
Error in `str_detect()`:
! Only fixed patterns are supported on database backends.
```

```r
translate_sql(str_detect(var, "b", negate = TRUE),
              con = simulate_spark_sql())
```

```
Error in `str_detect()`:
! Only fixed patterns are supported on database backends.
```

```r
translate_sql(str_detect(var, "[aeiou]"),
              con = simulate_spark_sql())
```

```
Error in `str_detect()`:
! Only fixed patterns are supported on database backends.
```

```r
translate_sql(str_replace(var, "a", "b"),
              con = simulate_spark_sql())
```

```
Error in `str_replace()`:
! `str_replace()` is not available in this SQL variant.
```

```r
translate_sql(str_replace_all(var, "a", "b"),
              con = simulate_spark_sql())
```

```
Error in `str_replace_all()`:
! `str_replace_all()` is not available in this SQL variant.
```

```r
translate_sql(str_remove(var, "a"),
              con = simulate_spark_sql())
```

```
Error in `str_remove()`:
! `str_remove()` is not available in this SQL variant.
```

```r
translate_sql(str_remove_all(var, "a"),
              con = simulate_spark_sql())
```

```
Error in `str_remove_all()`:
! `str_remove_all()` is not available in this SQL variant.
```

```r
translate_sql(str_like(var, "a"),
              con = simulate_spark_sql())
```

```
<SQL> `var` LIKE 'a'
```

```r
translate_sql(str_starts(var, "a"),
              con = simulate_spark_sql())
```

```
Error in `str_starts()`:
! Only fixed patterns are supported on database backends.
```

```r
translate_sql(str_ends(var, "a"),
              con = simulate_spark_sql())
```

```
Error in `str_ends()`:
! Only fixed patterns are supported on database backends.
```

3.4.6 SQL Server

```r
translate_sql(nchar(var),
              con = simulate_mssql())
```

```
<SQL> LEN(`var`)
```

```r
translate_sql(nzchar(var),
              con = simulate_mssql())
```

```
<SQL> ((`var` IS NULL) OR `var` != '')
```

```r
translate_sql(substr(var, 1, 2),
              con = simulate_mssql())
```

```
<SQL> SUBSTRING(`var`, 1, 2)
```

```r
translate_sql(trimws(var),
              con = simulate_mssql())
```

```
<SQL> LTRIM(RTRIM(`var`))
```

```r
translate_sql(tolower(var),
              con = simulate_mssql())
```

```
<SQL> LOWER(`var`)
```

```r
translate_sql(str_to_lower(var),
              con = simulate_mssql())
```

```
<SQL> LOWER(`var`)
```

```r
translate_sql(toupper(var),
              con = simulate_mssql())
```

```
<SQL> UPPER(`var`)
```

```r
translate_sql(str_to_upper(var),
              con = simulate_mssql())
```

```
<SQL> UPPER(`var`)
```

```r
translate_sql(str_to_title(var),
              con = simulate_mssql())
```

```
Error in `str_to_title()`:
! `str_to_title()` is not available in this SQL variant.
```

```r
translate_sql(str_trim(var),
              con = simulate_mssql())
```

```
<SQL> LTRIM(RTRIM(`var`))
```

```r
translate_sql(str_squish(var),
              con = simulate_mssql())
```

```
Error in `str_squish()`:
! `str_squish()` is not available in this SQL variant.
```

```r
translate_sql(str_detect(var, "b"),
              con = simulate_mssql())
```

```
Error in `str_detect()`:
! Only fixed patterns are supported on database backends.
```

```r
translate_sql(str_detect(var, "b", negate = TRUE),
              con = simulate_mssql())
```

```
Error in `str_detect()`:
! Only fixed patterns are supported on database backends.
```

```r
translate_sql(str_detect(var, "[aeiou]"),
              con = simulate_mssql())
```

```
Error in `str_detect()`:
! Only fixed patterns are supported on database backends.
```

```r
translate_sql(str_replace(var, "a", "b"),
              con = simulate_mssql())
```

```
Error in `str_replace()`:
! `str_replace()` is not available in this SQL variant.
```

```r
translate_sql(str_replace_all(var, "a", "b"),
              con = simulate_mssql())
```

```
Error in `str_replace_all()`:
! `str_replace_all()` is not available in this SQL variant.
```

```r
translate_sql(str_remove(var, "a"),
              con = simulate_mssql())
```

```
Error in `str_remove()`:
! `str_remove()` is not available in this SQL variant.
```

```r
translate_sql(str_remove_all(var, "a"),
              con = simulate_mssql())
```

```
Error in `str_remove_all()`:
! `str_remove_all()` is not available in this SQL variant.
```

```r
translate_sql(str_like(var, "a"),
              con = simulate_mssql())
```

```
<SQL> `var` LIKE 'a'
```

```r
translate_sql(str_starts(var, "a"),
              con = simulate_mssql())
```

```
Error in `str_starts()`:
! Only fixed patterns are supported on database backends.
```

```r
translate_sql(str_ends(var, "a"),
              con = simulate_mssql())
```

```
Error in `str_ends()`:
! Only fixed patterns are supported on database backends.
```

3.5 Working with dates

Like with strings, support for working with dates is somewhat mixed. In general, we would use functions from the `clock` package such as `get_day()`, `get_month()`, `get_year()` to extract parts from a date, `add_days()` to add or subtract days to a date, and `date_count_between()` to get the number of days between two date variables.

Show SQL

3.5.1 duckdb

```r
translate_sql(get_day(date_1),
              con = simulate_duckdb())
```

```
<SQL> DATE_PART('day', `date_1`)
```

```r
translate_sql(get_month(date_1),
              con = simulate_duckdb())
```

```
<SQL> DATE_PART('month', `date_1`)
```

```r
translate_sql(get_year(date_1),
              con = simulate_duckdb())
```

```
<SQL> DATE_PART('year', `date_1`)
```

```r
translate_sql(add_days(date_1, 1),
              con = simulate_duckdb())
```

```
<SQL> DATE_ADD(`date_1`, INTERVAL (1.0) day)
```

```r
translate_sql(add_years(date_1, 1),
              con = simulate_duckdb())
```

```
<SQL> DATE_ADD(`date_1`, INTERVAL (1.0) year)
```

```r
translate_sql(difftime(date_1, date_2),
              con = simulate_duckdb())
```

```
Error in `difftime()`:
! Don't know how to translate `difftime()`
```

```r
translate_sql(date_count_between(date_1, date_2, "day"),
              con = simulate_duckdb())
```

```
<SQL> DATEDIFF('day', `date_1`, `date_2`)
```

```r
translate_sql(date_count_between(date_1, date_2, "year"),
              con = simulate_duckdb())
```

```
Error in date_count_between(date_1, date_2, "year"): The only supported value for `precisio
```

3.5.2 Redshift

```r
translate_sql(get_day(date_1),
              con = simulate_redshift())
```

```
<SQL> DATE_PART('day', `date_1`)
```

```r
translate_sql(get_month(date_1),
              con = simulate_redshift())
```

```
<SQL> DATE_PART('month', `date_1`)
```

```r
translate_sql(get_year(date_1),
              con = simulate_redshift())
```

```
<SQL> DATE_PART('year', `date_1`)
```

```r
translate_sql(add_days(date_1, 1),
              con = simulate_redshift())
```

```
<SQL> DATEADD(DAY, 1.0, `date_1`)
```

```r
translate_sql(add_years(date_1, 1),
              con = simulate_redshift())
```

```
<SQL> DATEADD(YEAR, 1.0, `date_1`)
```

```r
translate_sql(difftime(date_1, date_2),
              con = simulate_redshift())
```

```
<SQL> DATEDIFF(DAY, `date_1`, `date_2`)
```

```r
translate_sql(date_count_between(date_1, date_2, "day"),
              con = simulate_redshift())
```

```
Error in `date_count_between()`:
! Don't know how to translate `date_count_between()`
```

```r
translate_sql(date_count_between(date_1, date_2, "year"),
              con = simulate_redshift())
```

```
Error in `date_count_between()`:
! Don't know how to translate `date_count_between()`
```

3.5.3 Postgres

```r
translate_sql(get_day(date_1),
              con = simulate_postgres())
```

```
<SQL> DATE_PART('day', `date_1`)
```

```r
translate_sql(get_month(date_1),
              con = simulate_postgres())
```

```
<SQL> DATE_PART('month', `date_1`)
```

```r
translate_sql(get_year(date_1),
              con = simulate_postgres())
```

```
<SQL> DATE_PART('year', `date_1`)
```

```r
translate_sql(add_days(date_1, 1),
              con = simulate_postgres())
```

```
<SQL> (`date_1` + 1.0*INTERVAL'1 day')
```

```r
translate_sql(add_years(date_1, 1),
              con = simulate_postgres())
```

```
<SQL> (`date_1` + 1.0*INTERVAL'1 year')
```

```r
translate_sql(difftime(date_1, date_2),
              con = simulate_postgres())
```

```
<SQL> (CAST(`date_2` AS DATE) - CAST(`date_1` AS DATE))
```

```r
translate_sql(date_count_between(date_1, date_2, "day"),
              con = simulate_postgres())
```

```
Error in `date_count_between()`:
! Don't know how to translate `date_count_between()`
```

```r
translate_sql(date_count_between(date_1, date_2, "year"),
              con = simulate_postgres())
```

```
Error in `date_count_between()`:
! Don't know how to translate `date_count_between()`
```

3.5.4 Snowflake

```r
translate_sql(get_day(date_1),
              con = simulate_snowflake())
```

```
<SQL> DATE_PART(DAY, `date_1`)
```

```r
translate_sql(get_month(date_1),
              con = simulate_snowflake())
```

```
<SQL> DATE_PART(MONTH, `date_1`)
```

```r
translate_sql(get_year(date_1),
              con = simulate_snowflake())
```

```
<SQL> DATE_PART(YEAR, `date_1`)
```

```r
translate_sql(add_days(date_1, 1),
              con = simulate_snowflake())
```

```
<SQL> DATEADD(DAY, 1.0, `date_1`)
```

```r
translate_sql(add_years(date_1, 1),
              con = simulate_snowflake())
```

```
<SQL> DATEADD(YEAR, 1.0, `date_1`)
```

```r
translate_sql(difftime(date_1, date_2),
              con = simulate_snowflake())
```

```
<SQL> DATEDIFF(DAY, `date_1`, `date_2`)
```

```r
translate_sql(date_count_between(date_1, date_2, "day"),
              con = simulate_snowflake())
```

```
Error in `date_count_between()`:
! Don't know how to translate `date_count_between()`
```

```r
translate_sql(date_count_between(date_1, date_2, "year"),
              con = simulate_snowflake())
```

```
Error in `date_count_between()`:
! Don't know how to translate `date_count_between()`
```

3.5.5 Spark

```r
translate_sql(get_day(date_1),
              con = simulate_spark_sql())
```

```
<SQL> DATE_PART('DAY', `date_1`)
```

```r
translate_sql(get_month(date_1),
              con = simulate_spark_sql())
```

```
<SQL> DATE_PART('MONTH', `date_1`)
```

```r
translate_sql(get_year(date_1),
              con = simulate_spark_sql())
```

```
<SQL> DATE_PART('YEAR', `date_1`)
```

```r
translate_sql(add_days(date_1, 1),
              con = simulate_spark_sql())
```

```
<SQL> DATE_ADD(`date_1`, 1.0)
```

```r
translate_sql(add_years(date_1, 1),
              con = simulate_spark_sql())
```

```
<SQL> ADD_MONTHS('`date_1`', 1.0 * 12.0)
```

```r
translate_sql(difftime(date_1, date_2),
              con = simulate_spark_sql())
```

```
<SQL> DATEDIFF(`date_2`, `date_1`)
```

```r
translate_sql(date_count_between(date_1, date_2, "day"),
              con = simulate_spark_sql())
```

```
Error in `date_count_between()`:
! Don't know how to translate `date_count_between()`
```

```r
translate_sql(date_count_between(date_1, date_2, "year"),
              con = simulate_spark_sql())
```

```
Error in `date_count_between()`:
! Don't know how to translate `date_count_between()`
```

3.5.6 SQL Server

```r
translate_sql(get_day(date_1),
              con = simulate_mssql())
```

```
<SQL> DATEPART(DAY, `date_1`)
```

```r
translate_sql(get_month(date_1),
              con = simulate_mssql())
```

```
<SQL> DATEPART(MONTH, `date_1`)
```

```r
translate_sql(get_year(date_1),
              con = simulate_mssql())
```

```
<SQL> DATEPART(YEAR, `date_1`)
```

```r
translate_sql(add_days(date_1, 1),
              con = simulate_mssql())
```

```
<SQL> DATEADD(DAY, 1.0, `date_1`)
```

```r
translate_sql(add_years(date_1, 1),
              con = simulate_mssql())
```

```
<SQL> DATEADD(YEAR, 1.0, `date_1`)
```

```r
translate_sql(difftime(date_1, date_2),
              con = simulate_mssql())
```

```
<SQL> DATEDIFF(DAY, `date_1`, `date_2`)
```

```r
translate_sql(date_count_between(date_1, date_2, "day"),
              con = simulate_mssql())
```

```
Error in `date_count_between()`:
! Don't know how to translate `date_count_between()`
```

```r
translate_sql(date_count_between(date_1, date_2, "year"),
              con = simulate_mssql())
```

```
Error in `date_count_between()`:
! Don't know how to translate `date_count_between()`
```

3.6 Data aggregation

Within the context of using `summarise()`, we can get aggregated results across entire columns using functions such as `n()`, `n_distinct()`, `sum()`, `min()`, `max()`, `mean()`, and `sd()`. As can be seen below, the SQL for these calculations is similar across different database management systems.

Show SQL

3.6.1 duckdb

```
lazy_frame(x = c(1,2), con = simulate_duckdb()) %>%
  summarise(
          n = n(),
          n_unique = n_distinct(x),
          sum = sum(x, na.rm = TRUE),
          sum_is_1 = sum(x == 1, na.rm = TRUE),
          min = min(x, na.rm = TRUE),
          mean = mean(x, na.rm = TRUE),
          max = max(x, na.rm = TRUE),
          sd = sd(x, na.rm = TRUE)) |>
  show_query()
```

```
<SQL>
SELECT
  COUNT(*) AS `n`,
  COUNT(DISTINCT row(`x`)) AS `n_unique`,
  SUM(`x`) AS `sum`,
  SUM(`x` = 1.0) AS `sum_is_1`,
  MIN(`x`) AS `min`,
  AVG(`x`) AS `mean`,
  MAX(`x`) AS `max`,
  STDDEV(`x`) AS `sd`
FROM `df`
```

3.6.2 postgres

```r
lazy_frame(x = c(1,2), con = simulate_postgres()) %>%
  summarise(
          n = n(),
          n_unique = n_distinct(x),
          sum = sum(x, na.rm = TRUE),
          sum_is_1 = sum(x == 1, na.rm = TRUE),
          min = min(x, na.rm = TRUE),
          mean = mean(x, na.rm = TRUE),
          max = max(x, na.rm = TRUE),
          sd = sd(x, na.rm = TRUE)) |>
  show_query()
```

```
<SQL>
SELECT
  COUNT(*) AS `n`,
  COUNT(DISTINCT `x`) AS `n_unique`,
  SUM(`x`) AS `sum`,
  SUM(`x` = 1.0) AS `sum_is_1`,
  MIN(`x`) AS `min`,
  AVG(`x`) AS `mean`,
  MAX(`x`) AS `max`,
  STDDEV_SAMP(`x`) AS `sd`
FROM `df`
```

3.6.3 redshift

```r
lazy_frame(x = c(1,2), con = simulate_redshift()) %>%
  summarise(
          n = n(),
          n_unique = n_distinct(x),
          sum = sum(x, na.rm = TRUE),
          sum_is_1 = sum(x == 1, na.rm = TRUE),
          min = min(x, na.rm = TRUE),
          mean = mean(x, na.rm = TRUE),
          max = max(x, na.rm = TRUE),
          sd = sd(x, na.rm = TRUE)) |>
  show_query()
```

```
<SQL>
SELECT
  COUNT(*) AS `n`,
```

```
  COUNT(DISTINCT `x`) AS `n_unique`,
  SUM(`x`) AS `sum`,
  SUM(`x` = 1.0) AS `sum_is_1`,
  MIN(`x`) AS `min`,
  AVG(`x`) AS `mean`,
  MAX(`x`) AS `max`,
  STDDEV_SAMP(`x`) AS `sd`
FROM `df`
```

3.6.4 Snowflake

```
lazy_frame(x = c(1,2), con = simulate_snowflake()) %>%
  summarise(
          n = n(),
          n_unique = n_distinct(x),
          sum = sum(x, na.rm = TRUE),
          sum_is_1 = sum(x == 1, na.rm = TRUE),
          min = min(x, na.rm = TRUE),
          mean = mean(x, na.rm = TRUE),
          max = max(x, na.rm = TRUE),
          sd = sd(x, na.rm = TRUE)) |>
  show_query()
```

```
<SQL>
SELECT
  COUNT(*) AS `n`,
  COUNT(DISTINCT `x`) AS `n_unique`,
  SUM(`x`) AS `sum`,
  SUM(`x` = 1.0) AS `sum_is_1`,
  MIN(`x`) AS `min`,
  AVG(`x`) AS `mean`,
  MAX(`x`) AS `max`,
  STDDEV(`x`) AS `sd`
FROM `df`
```

3.6.5 Spark

```
lazy_frame(x = c(1,2), con = simulate_spark_sql()) %>%
  summarise(
          n = n(),
          n_unique = n_distinct(x),
          sum = sum(x, na.rm = TRUE),
          sum_is_1 = sum(x == 1, na.rm = TRUE),
          min = min(x, na.rm = TRUE),
          mean = mean(x, na.rm = TRUE),
          max = max(x, na.rm = TRUE),
          sd = sd(x, na.rm = TRUE)) |>
  show_query()
```

```
<SQL>
SELECT
  COUNT(*) AS `n`,
  COUNT(DISTINCT `x`) AS `n_unique`,
  SUM(`x`) AS `sum`,
  SUM(`x` = 1.0) AS `sum_is_1`,
  MIN(`x`) AS `min`,
  AVG(`x`) AS `mean`,
  MAX(`x`) AS `max`,
  STDDEV_SAMP(`x`) AS `sd`
FROM `df`
```

3.6.6 SQL Server

```
lazy_frame(x = c(1,2), a = "a", con = simulate_mssql()) %>%
  summarise(
          n = n(),
          n_unique = n_distinct(x),
          sum = sum(x, na.rm = TRUE),
          sum_is_1 = sum(x == 1, na.rm = TRUE),
          min = min(x, na.rm = TRUE),
          mean = mean(x, na.rm = TRUE),
          max = max(x, na.rm = TRUE),
          sd = sd(x, na.rm = TRUE)) |>
  show_query()
```

```
<SQL>
SELECT
  COUNT(*) AS `n`,
```

```
  COUNT(DISTINCT `x`) AS `n_unique`,
  SUM(`x`) AS `sum`,
  SUM(CAST(IIF(`x` = 1.0, 1, 0) AS BIT)) AS `sum_is_1`,
  MIN(`x`) AS `min`,
  AVG(`x`) AS `mean`,
  MAX(`x`) AS `max`,
  STDEV(`x`) AS `sd`
FROM `df`
```

3.7 Window functions

In the previous section we saw how aggregate functions can be used to perform operations across entire columns. Window functions differ in that they perform calculations across rows that are in some way related to a current row. For these we now use `mutate()` instead of using `summarise()`.

We can use window functions like `cumsum()` and `cummean()` to calculate running totals and averages, or `lag()` and `lead()` to help compare rows to their preceding or following rows.

Given that window functions compare rows to rows before or after them, we will often use `arrange()` to specify the order of rows. This will translate into a ORDER BY clause in the SQL. In addition, we may well also want to apply window functions within some specific groupings in our data. Using `group_by()` would result in a PARTITION BY clause in the translated SQL so that window function operates on each group independently.

Show SQL

3.7.1 duckdb

```r
lazy_frame(x = c(10, 20, 30),
           z = c(1, 2, 3),
           con = simulate_duckdb()) %>%
  window_order(z) |>
  mutate(sum_x = cumsum(x),
         mean_x = cummean(x),
         lag_x = lag(x),
         lead_x = lead(x)) |>
  show_query()
```

```
<SQL>
SELECT
```

```
  `df`.*,
  SUM(`x`) OVER (ORDER BY `z` ROWS UNBOUNDED PRECEDING) AS `sum_x`,
  AVG(`x`) OVER (ORDER BY `z` ROWS UNBOUNDED PRECEDING) AS `mean_x`,
  LAG(`x`, 1, NULL) OVER (ORDER BY `z`) AS `lag_x`,
  LEAD(`x`, 1, NULL) OVER (ORDER BY `z`) AS `lead_x`
FROM `df`
```

```
lazy_frame(x = c(10, 20, 30),
           y = c("a", "a", "b"),
           z = c(1, 2, 3),
           con = simulate_duckdb()) %>%
  window_order(z) |>
  group_by(y) |>
  mutate(sum_x = cumsum(x),
         mean_x = cummean(x),
         lag_x = lag(x),
         lead_x = lead(x)) |>
  show_query()
```

```
<SQL>
SELECT
  `df`.*,
  SUM(`x`) OVER (PARTITION BY `y` ORDER BY `z` ROWS UNBOUNDED PRECEDING) AS `sum_x`,
  AVG(`x`) OVER (PARTITION BY `y` ORDER BY `z` ROWS UNBOUNDED PRECEDING) AS `mean_x`,
  LAG(`x`, 1, NULL) OVER (PARTITION BY `y` ORDER BY `z`) AS `lag_x`,
  LEAD(`x`, 1, NULL) OVER (PARTITION BY `y` ORDER BY `z`) AS `lead_x`
FROM `df`
```

3.7.2 postgres

```
lazy_frame(x = c(10, 20, 30),
           z = c(1, 2, 3),
           con = simulate_postgres()) %>%
  window_order(z) |>
  mutate(sum_x = cumsum(x),
         mean_x = cummean(x),
         lag_x = lag(x),
         lead_x = lead(x)) |>
  show_query()
```

```
<SQL>
```

```
SELECT
  `df`.*,
  SUM(`x`) OVER `win1` AS `sum_x`,
  AVG(`x`) OVER `win1` AS `mean_x`,
  LAG(`x`, 1, NULL) OVER `win2` AS `lag_x`,
  LEAD(`x`, 1, NULL) OVER `win2` AS `lead_x`
FROM `df`
WINDOW
  `win1` AS (ORDER BY `z` ROWS UNBOUNDED PRECEDING),
  `win2` AS (ORDER BY `z`)
```

```
lazy_frame(x = c(10, 20, 30),
           y = c("a", "a", "b"),
           z = c(1, 2, 3),
           con = simulate_postgres()) %>%
  window_order(z) |>
  group_by(y) |>
  mutate(sum_x = cumsum(x),
         mean_x = cummean(x),
         lag_x = lag(x),
         lead_x = lead(x)) |>
  show_query()
```

```
<SQL>
SELECT
  `df`.*,
  SUM(`x`) OVER `win1` AS `sum_x`,
  AVG(`x`) OVER `win1` AS `mean_x`,
  LAG(`x`, 1, NULL) OVER `win2` AS `lag_x`,
  LEAD(`x`, 1, NULL) OVER `win2` AS `lead_x`
FROM `df`
WINDOW
  `win1` AS (PARTITION BY `y` ORDER BY `z` ROWS UNBOUNDED PRECEDING),
  `win2` AS (PARTITION BY `y` ORDER BY `z`)
```

3.7.3 redshift

```r
lazy_frame(x = c(10, 20, 30),
           z = c(1, 2, 3),
           con = simulate_redshift()) %>%
  window_order(z) |>
  mutate(sum_x = cumsum(x),
         mean_x = cummean(x),
         lag_x = lag(x),
         lead_x = lead(x)) |>
  show_query()
```

```
<SQL>
SELECT
  `df`.*,
  SUM(`x`) OVER (ORDER BY `z` ROWS UNBOUNDED PRECEDING) AS `sum_x`,
  AVG(`x`) OVER (ORDER BY `z` ROWS UNBOUNDED PRECEDING) AS `mean_x`,
  LAG(`x`, 1) OVER (ORDER BY `z`) AS `lag_x`,
  LEAD(`x`, 1) OVER (ORDER BY `z`) AS `lead_x`
FROM `df`
```

```r
lazy_frame(x = c(10, 20, 30),
           y = c("a", "a", "b"),
           z = c(1, 2, 3),
           con = simulate_redshift()) %>%
  window_order(z) |>
  group_by(y) |>
  mutate(sum_x = cumsum(x),
         mean_x = cummean(x),
         lag_x = lag(x),
         lead_x = lead(x)) |>
  show_query()
```

```
<SQL>
SELECT
  `df`.*,
  SUM(`x`) OVER (PARTITION BY `y` ORDER BY `z` ROWS UNBOUNDED PRECEDING) AS `sum_x`,
  AVG(`x`) OVER (PARTITION BY `y` ORDER BY `z` ROWS UNBOUNDED PRECEDING) AS `mean_x`,
  LAG(`x`, 1) OVER (PARTITION BY `y` ORDER BY `z`) AS `lag_x`,
  LEAD(`x`, 1) OVER (PARTITION BY `y` ORDER BY `z`) AS `lead_x`
FROM `df`
```

3.7.4 Snowflake

```
lazy_frame(x = c(10, 20, 30),
           z = c(1, 2, 3),
           con = simulate_snowflake()) %>%
  window_order(z) |>
  mutate(sum_x = cumsum(x),
         mean_x = cummean(x),
         lag_x = lag(x),
         lead_x = lead(x)) |>
  show_query()
```

```
<SQL>
SELECT
  `df`.*,
  SUM(`x`) OVER (ORDER BY `z` ROWS UNBOUNDED PRECEDING) AS `sum_x`,
  AVG(`x`) OVER (ORDER BY `z` ROWS UNBOUNDED PRECEDING) AS `mean_x`,
  LAG(`x`, 1, NULL) OVER (ORDER BY `z`) AS `lag_x`,
  LEAD(`x`, 1, NULL) OVER (ORDER BY `z`) AS `lead_x`
FROM `df`
```

```
lazy_frame(x = c(10, 20, 30),
           y = c("a", "a", "b"),
           z = c(1, 2, 3),
           con = simulate_snowflake()) %>%
  window_order(z) |>
  group_by(y) |>
  mutate(sum_x = cumsum(x),
         mean_x = cummean(x),
         lag_x = lag(x),
         lead_x = lead(x)) |>
  show_query()
```

```
<SQL>
SELECT
  `df`.*,
  SUM(`x`) OVER (PARTITION BY `y` ORDER BY `z` ROWS UNBOUNDED PRECEDING) AS `sum_x`,
  AVG(`x`) OVER (PARTITION BY `y` ORDER BY `z` ROWS UNBOUNDED PRECEDING) AS `mean_x`,
  LAG(`x`, 1, NULL) OVER (PARTITION BY `y` ORDER BY `z`) AS `lag_x`,
  LEAD(`x`, 1, NULL) OVER (PARTITION BY `y` ORDER BY `z`) AS `lead_x`
FROM `df`
```

3.7.5 Spark

```r
lazy_frame(x = c(10, 20, 30),
           z = c(1, 2, 3),
           con = simulate_spark_sql()) %>%
  window_order(z) |>
  mutate(sum_x = cumsum(x),
         mean_x = cummean(x),
         lag_x = lag(x),
         lead_x = lead(x)) |>
  show_query()
```

```
<SQL>
SELECT
  `df`.*,
  SUM(`x`) OVER `win1` AS `sum_x`,
  AVG(`x`) OVER `win1` AS `mean_x`,
  LAG(`x`, 1, NULL) OVER `win2` AS `lag_x`,
  LEAD(`x`, 1, NULL) OVER `win2` AS `lead_x`
FROM `df`
WINDOW
  `win1` AS (ORDER BY `z` ROWS UNBOUNDED PRECEDING),
  `win2` AS (ORDER BY `z`)
```

```r
lazy_frame(x = c(10, 20, 30),
           y = c("a", "a", "b"),
           z = c(1, 2, 3),
           con = simulate_spark_sql()) %>%
  window_order(z) |>
  group_by(y) |>
  mutate(sum_x = cumsum(x),
         mean_x = cummean(x),
         lag_x = lag(x),
         lead_x = lead(x)) |>
  show_query()
```

```
<SQL>
SELECT
  `df`.*,
  SUM(`x`) OVER `win1` AS `sum_x`,
  AVG(`x`) OVER `win1` AS `mean_x`,
```

```
  LAG(`x`, 1, NULL) OVER `win2` AS `lag_x`,
  LEAD(`x`, 1, NULL) OVER `win2` AS `lead_x`
FROM `df`
WINDOW
  `win1` AS (PARTITION BY `y` ORDER BY `z` ROWS UNBOUNDED PRECEDING),
  `win2` AS (PARTITION BY `y` ORDER BY `z`)
```

3.7.6 SQL Server

```
lazy_frame(x = c(10, 20, 30),
           z = c(1, 2, 3),
           con = simulate_mssql()) %>%
  window_order(z) |>
  mutate(sum_x = cumsum(x),
         mean_x = cummean(x),
         lag_x = lag(x),
         lead_x = lead(x)) |>
  show_query()
```

```
<SQL>
SELECT
  `df`.*,
  SUM(`x`) OVER (ORDER BY `z` ROWS UNBOUNDED PRECEDING) AS `sum_x`,
  AVG(`x`) OVER (ORDER BY `z` ROWS UNBOUNDED PRECEDING) AS `mean_x`,
  LAG(`x`, 1, NULL) OVER (ORDER BY `z`) AS `lag_x`,
  LEAD(`x`, 1, NULL) OVER (ORDER BY `z`) AS `lead_x`
FROM `df`
```

```
lazy_frame(x = c(10, 20, 30),
           y = c("a", "a", "b"),
           z = c(1, 2, 3),
           con = simulate_mssql()) %>%
  window_order(z) |>
  group_by(y) |>
  mutate(sum_x = cumsum(x),
         mean_x = cummean(x),
         lag_x = lag(x),
         lead_x = lead(x)) |>
  show_query()
```

```
<SQL>
```

```
SELECT
  `df`.*,
  SUM(`x`) OVER (PARTITION BY `y` ORDER BY `z` ROWS UNBOUNDED PRECEDING) AS `sum_x`,
  AVG(`x`) OVER (PARTITION BY `y` ORDER BY `z` ROWS UNBOUNDED PRECEDING) AS `mean_x`,
  LAG(`x`, 1, NULL) OVER (PARTITION BY `y` ORDER BY `z`) AS `lag_x`,
  LEAD(`x`, 1, NULL) OVER (PARTITION BY `y` ORDER BY `z`) AS `lead_x`
FROM `df`
```

3.8 Calculating quantiles, including the median

So far we've seen that we can perform various data manipulations and calculate summary statistics for different database management systems using the same R code. Although the translated SQL has been different, the databases all supported similar approaches to perform these queries.

A case where this is not the case is when we are interested in summarising distributions of the data and estimating quantiles. For example, let's take estimating the median as an example. Some databases only support calculating the median as an aggregation function similar to how min, mean, and max were calculated above. However, some others only support it as a window function like lead and lag above. Unfortunately this means that for some databases quantiles can only be calculated using the summarise aggregation approach, while in others only the mutate window approach can be used.

Show SQL

3.8.1 duckdb

```r
lazy_frame(x = c(1,2), con = simulate_duckdb()) %>%
  summarise(median = median(x, na.rm = TRUE)) |>
  show_query()
```

```
<SQL>
SELECT MEDIAN(`x`) AS `median`
FROM `df`
```

```r
lazy_frame(x = c(1,2), con = simulate_duckdb()) %>%
  mutate(median = median(x, na.rm = TRUE)) |>
  show_query()
```

```
<SQL>
```

```
SELECT `df`.*, MEDIAN(`x`) OVER () AS `median`
FROM `df`
```

3.8.2 postgres

```r
lazy_frame(x = c(1,2), con = simulate_postgres()) %>%
  summarise(median = median(x, na.rm = TRUE)) |>
  show_query()
```

```
<SQL>
SELECT PERCENTILE_CONT(0.5) WITHIN GROUP (ORDER BY `x`) AS `median`
FROM `df`
```

```r
lazy_frame(x = c(1,2), con = simulate_postgres()) %>%
  mutate(median = median(x, na.rm = TRUE)) |>
  show_query()
```

```
Error in `median()`:
! Translation of `median()` in `mutate()` is not supported for
  PostgreSQL.
i Use a combination of `summarise()` and `left_join()` instead:
  `df %>% left_join(summarise(<col> = median(x, na.rm = TRUE)))`.
```

3.8.3 redshift

```r
lazy_frame(x = c(1,2), con = simulate_redshift()) %>%
  summarise(median = median(x, na.rm = TRUE)) |>
  show_query()
```

```
<SQL>
SELECT PERCENTILE_CONT(0.5) WITHIN GROUP (ORDER BY `x`) AS `median`
FROM `df`
```

```r
lazy_frame(x = c(1,2), con = simulate_redshift()) %>%
  mutate(median = median(x, na.rm = TRUE)) |>
  show_query()
```

```
Error in `median()`:
! Translation of `median()` in `mutate()` is not supported for
  PostgreSQL.
i Use a combination of `summarise()` and `left_join()` instead:
  `df %>% left_join(summarise(<col> = median(x, na.rm = TRUE)))`.
```

3.8.4 Snowflake

```
lazy_frame(x = c(1,2), con = simulate_snowflake()) %>%
  summarise(median = median(x, na.rm = TRUE)) |>
  show_query()
```

```
<SQL>
SELECT PERCENTILE_CONT(0.5) WITHIN GROUP (ORDER BY `x`) AS `median`
FROM `df`
```

```
lazy_frame(x = c(1,2), con = simulate_snowflake()) %>%
  mutate(median = median(x, na.rm = TRUE)) |>
  show_query()
```

```
<SQL>
SELECT
  `df`.*,
  PERCENTILE_CONT(0.5) WITHIN GROUP (ORDER BY `x`) OVER () AS `median`
FROM `df`
```

3.8.5 Spark

```
lazy_frame(x = c(1,2), con = simulate_spark_sql()) %>%
  summarise(median = median(x, na.rm = TRUE)) |>
  show_query()
```

```
<SQL>
SELECT MEDIAN(`x`) AS `median`
FROM `df`
```

```
lazy_frame(x = c(1,2), con = simulate_spark_sql()) %>%
  mutate(median = median(x, na.rm = TRUE)) |>
  show_query()
```

```
<SQL>
SELECT `df`.*, MEDIAN(`x`) OVER () AS `median`
FROM `df`
```

3.8.6 SQL Server

```r
lazy_frame(x = c(1,2), con = simulate_mssql()) %>%
  summarise(median = median(x, na.rm = TRUE)) |>
  show_query()
```

```
Error in `median()`:
! Translation of `median()` in `summarise()` is not supported for SQL
  Server.
i Use a combination of `distinct()` and `mutate()` for the same result:
  `mutate(<col> = median(x, na.rm = TRUE)) %>% distinct(<col>)`
```

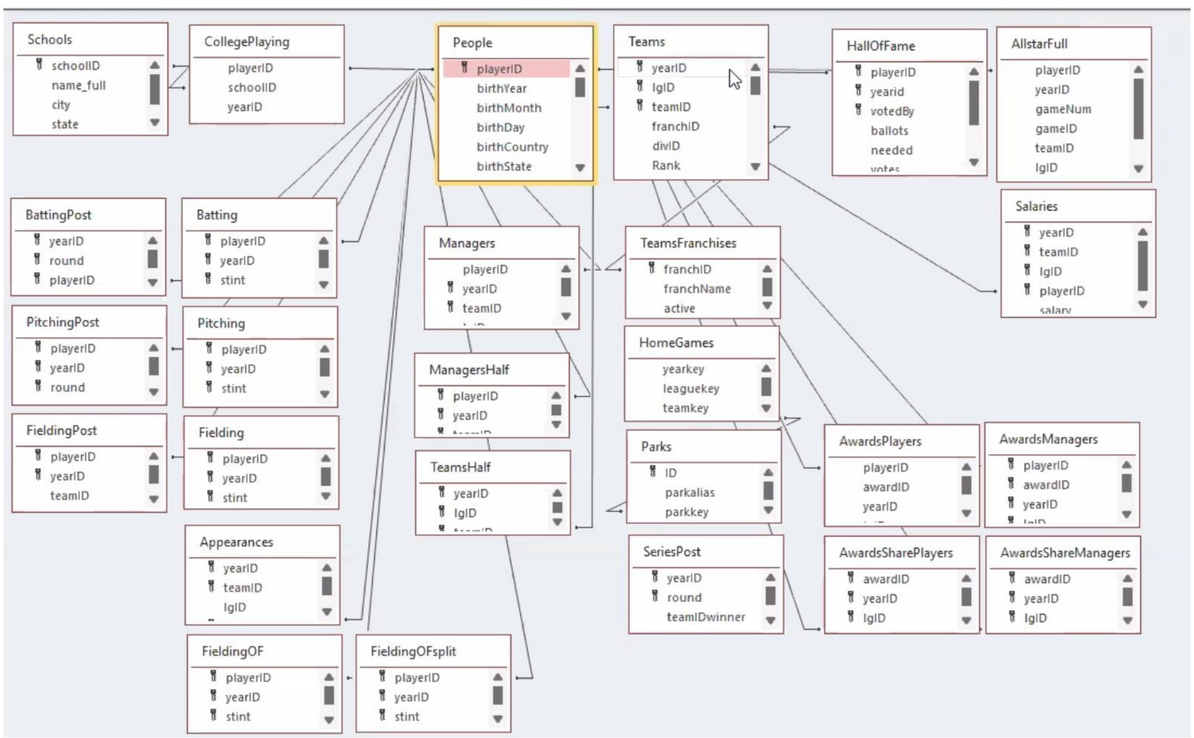
```r
lazy_frame(x = c(1,2), con = simulate_mssql()) %>%
  mutate(median = median(x, na.rm = TRUE)) |>
  show_query()
```

```
<SQL>
SELECT
  `df`.*,
  PERCENTILE_CONT(0.5) WITHIN GROUP (ORDER BY `x`) OVER () AS `median`
FROM `df`
```

4 Building analytic pipelines for a data model

In the previous chapters we've seen that after connecting to a database we can create references to the various tables we've interested in it and write bespoke analytic code to query them. However, if we are working with the same database over and over again we are likely to want to build some tooling for tasks we are often performing.

To see how we can develop a data model with associated methods and functions we'll use the Lahman baseball data. We can see below how the data is stored across various related tables.



4.1 Defining a data model

```r
library(DBI)
library(duckdb)
library(dplyr)
library(tidyr)
library(purrr)
library(cli)
library(dbplyr)
library(Lahman)

db <- dbConnect(duckdb(), dbdir = ":memory:")
copy_lahman(db)
```

Instead of manually creating references to tables of interest as we go, we will write a function to create a single reference to the Lahman data.

```r
lahmanFromCon <- function(con) {
  lahmanRef <- c(
    "AllstarFull", "Appearances", "AwardsManagers", "AwardsPlayers", "AwardsManagers",
    "AwardsShareManagers", "Batting", "BattingPost", "CollegePlaying", "Fielding",
    "FieldingOF", "FieldingOFsplit", "FieldingPost", "HallOfFame", "HomeGames",
    "LahmanData", "Managers", "ManagersHalf", "Parks", "People", "Pitching",
    "PitchingPost", "Salaries", "Schools", "SeriesPost", "Teams", "TeamsFranchises",
    "TeamsHalf"
  ) |>
    set_names() |>
    map(\(x) tbl(con, x))
  class(lahmanRef) <- c("lahman_ref", class(lahmanRef))
  lahmanRef
}
```

With this function we can now easily get references to all our lahman tables in one go using our `lahmanFromCon()` function.

```r
lahman <- lahmanFromCon(db)

lahman$People |>
  glimpse()
```

```
Rows: ??
Columns: 26
```

```
Database: DuckDB v1.2.1 [unknown@Linux 6.11.0-1012-azure:R 4.5.0/:memory:]
$ playerID     <chr> "aardsda01", "aaronha01", "aaronto01", "aasedo01", "abada~
$ birthYear    <int> 1981, 1934, 1939, 1954, 1972, 1985, 1850, 1877, 1869, 186~
$ birthMonth   <int> 12, 2, 8, 9, 8, 12, 11, 4, 11, 10, 9, 3, 10, 2, 8, 9, 6, ~
$ birthDay     <int> 27, 5, 5, 8, 25, 17, 4, 15, 11, 14, 20, 16, 22, 16, 17, 1~
$ birthCity    <chr> "Denver", "Mobile", "Mobile", "Orange", "Palm Beach", "La~
$ birthCountry <chr> "USA", "USA", "USA", "USA", "USA", "D.R.", "USA", "USA", ~
$ birthState   <chr> "CO", "AL", "AL", "CA", "FL", "La Romana", "PA", "PA", "V~
$ deathYear    <int> NA, 2021, 1984, NA, NA, NA, 1905, 1957, 1962, 1926, NA, 1~
$ deathMonth   <int> NA, 1, 8, NA, NA, NA, 5, 1, 6, 4, NA, 2, 6, NA, NA, NA, N~
$ deathDay     <int> NA, 22, 16, NA, NA, NA, 17, 6, 11, 27, NA, 13, 11, NA, NA~
$ deathCountry <chr> NA, "USA", "USA", NA, NA, NA, "USA", "USA", "USA", "USA",~
$ deathState   <chr> NA, "GA", "GA", NA, NA, NA, "NJ", "FL", "VT", "CA", NA, "~
$ deathCity    <chr> NA, "Atlanta", "Atlanta", NA, NA, NA, "Pemberton", "Fort ~
$ nameFirst    <chr> "David", "Hank", "Tommie", "Don", "Andy", "Fernando", "Jo~
$ nameLast     <chr> "Aardsma", "Aaron", "Aaron", "Aase", "Abad", "Abad", "Aba~
$ nameGiven    <chr> "David Allan", "Henry Louis", "Tommie Lee", "Donald Willi~
$ weight       <int> 215, 180, 190, 190, 184, 235, 192, 170, 175, 169, 220, 19~
$ height       <int> 75, 72, 75, 75, 73, 74, 72, 71, 71, 68, 74, 71, 70, 78, 7~
$ bats         <fct> R, R, R, R, L, L, R, R, R, L, R, R, R, R, R, L, R, L, L, ~
$ throws       <fct> R, R, R, R, L, L, R, R, R, L, R, R, R, R, L, L, R, L, R, ~
$ debut        <chr> "2004-04-06", "1954-04-13", "1962-04-10", "1977-07-26", "~
$ bbrefID      <chr> "aardsda01", "aaronha01", "aaronto01", "aasedo01", "abada~
$ finalGame    <chr> "2015-08-23", "1976-10-03", "1971-09-26", "1990-10-03", "~
$ retroID      <chr> "aardd001", "aaroh101", "aarot101", "aased001", "abada001~
$ deathDate    <date> NA, 2021-01-22, 1984-08-16, NA, NA, NA, 1905-05-17, 1957~
$ birthDate    <date> 1981-12-27, 1934-02-05, 1939-08-05, 1954-09-08, 1972-08-~
```

The dm package

In this chapter we will be creating a bespoke data model for our database. This approach can be further extended using the `dm` package, which also provides various helpful functions for creating a data model and working with it.
Similar to above, we can use `dm` to create a single object to access our database tables.

```r
library(dm)
lahman_dm <- dm(batting = tbl(db, "Batting"),
                people = tbl(db, "People"))
lahman_dm
```

```
-- Table source ---------------------------------------------------------------
src:  DuckDB v1.2.1 [unknown@Linux 6.11.0-1012-azure:R 4.5.0/:memory:]
```

```
-- Metadata -------------------------------------------------------------------
Tables: `batting`, `people`
Columns: 48
Primary keys: 0
Foreign keys: 0
```

Using this approach, we can make use of various utility functions. For example here we specify primary and foreign keys and then check that the key constraints are satisfied.

```r
lahman_dm <- lahman_dm %>%
  dm_add_pk(people, playerID) %>%
  dm_add_fk(batting, playerID, people)

lahman_dm
```

```
-- Table source ---------------------------------------------------------------
src:  DuckDB v1.2.1 [unknown@Linux 6.11.0-1012-azure:R 4.5.0/:memory:]
-- Metadata -------------------------------------------------------------------
Tables: `batting`, `people`
Columns: 48
Primary keys: 1
Foreign keys: 1
```

```r
dm_examine_constraints(lahman_dm)
```

```
i All constraints satisfied.
```

For more information on the dm package see https://dm.cynkra.com/index.html

4.2 Creating functions for the data model

We can also now make various functions specific to our Lahman data model to facilitate data analyses. Given we know the structure of the data, we can build a set of functions that abstract away some of the complexities of working with data in a database.

Let's start by making a small function to get the teams players have played for. We can see that the code we use follows on from the last couple of chapters.

```r
getTeams <- function(lahman, name = "Barry Bonds") {
  lahman$Batting |>
```

```
    inner_join(
      lahman$People |>
        mutate(full_name = paste0(nameFirst, " ", nameLast)) |>
        filter(full_name %in% name) |>
        select("playerID"),
      by = join_by(playerID)
    ) |>
    select(
      "teamID",
      "yearID"
    ) |>
    distinct() |>
    left_join(lahman$Teams,
      by = join_by(teamID, yearID)
    ) |>
    select("name") |>
    distinct()
}
```

Now we can easily get the different teams a player represented. We can see how changing the player name changes the SQL that is getting run behind the scenes.

```
getTeams(lahman, "Babe Ruth")
```

```
# Source:   SQL [?? x 1]
# Database: DuckDB v1.2.1 [unknown@Linux 6.11.0-1012-azure:R 4.5.0/:memory:]
  name
  <chr>
1 Boston Red Sox
2 New York Yankees
3 Boston Braves
```

Show query

```
<SQL>
SELECT DISTINCT q01.*
FROM (
  SELECT "name"
  FROM (
    SELECT DISTINCT q01.*
    FROM (
```

```
      SELECT teamID, yearID
      FROM Batting
      INNER JOIN (
        SELECT playerID
        FROM (
          SELECT People.*, CONCAT_WS('', nameFirst, ' ', nameLast) AS full_name
          FROM People
        ) q01
        WHERE (full_name IN ('Babe Ruth'))
      ) RHS
        ON (Batting.playerID = RHS.playerID)
    ) q01
  ) LHS
  LEFT JOIN Teams
    ON (LHS.teamID = Teams.teamID AND LHS.yearID = Teams.yearID)
) q01
```

```
getTeams(lahman, "Barry Bonds")
```

```
# Source:   SQL [?? x 1]
# Database: DuckDB v1.2.1 [unknown@Linux 6.11.0-1012-azure:R 4.5.0/:memory:]
  name
  <chr>
1 San Francisco Giants
2 Pittsburgh Pirates
```

Show query

```
<SQL>
SELECT DISTINCT q01.*
FROM (
  SELECT "name"
  FROM (
    SELECT DISTINCT q01.*
    FROM (
      SELECT teamID, yearID
      FROM Batting
      INNER JOIN (
        SELECT playerID
        FROM (
          SELECT People.*, CONCAT_WS('', nameFirst, ' ', nameLast) AS full_name
```

```
          FROM People
        ) q01
        WHERE (full_name IN ('Barry Bonds'))
      ) RHS
        ON (Batting.playerID = RHS.playerID)
    ) q01
  ) LHS
  LEFT JOIN Teams
    ON (LHS.teamID = Teams.teamID AND LHS.yearID = Teams.yearID)
) q01
```

Choosing the right time to collect data into R

The function `collect()` brings data out of the database and into R. When working with large datasets, as is often the case when interacting with a database, we typically want to keep as much computation as possible on the database side. In the case of our `getTeams()` function, for example, it does everything on the database side and so collecting will just bring out the result of the teams the person played for. In this case we could also use `pull()` to get our result out as a vector rather that a data frame.

```
getTeams(lahman, "Barry Bonds") |>
  collect()
```

```
# A tibble: 2 x 1
  name
  <chr>
1 San Francisco Giants
2 Pittsburgh Pirates
```

```
getTeams(lahman, "Barry Bonds") |>
  pull()
```

```
[1] "Pittsburgh Pirates"   "San Francisco Giants"
```

In other cases however we may need to collect data so as to perform further analysis steps that are not possible using SQL. This might be the case for plotting or for other analytic steps like fitting statistical models. In such cases we should try to only bring out the data that we need (as we will likely have much less memory available on our local computer than is available for the database).

Similarly we could make a function to add the a player's year of birth to a table.

```r
addBirthCountry <- function(lahmanTbl){
  lahmanTbl |>
    left_join(lahman$People |>
                select("playerID", "birthCountry"),
                join_by("playerID"))
}
```

```r
lahman$Batting |>
  addBirthCountry()
```

```
# Source:   SQL [?? x 23]
# Database: DuckDB v1.2.1 [unknown@Linux 6.11.0-1012-azure:R 4.5.0/:memory:]
   playerID  yearID stint teamID lgID      G    AB     R     H   X2B   X3B    HR
   <chr>      <int> <int> <fct>  <fct> <int> <int> <int> <int> <int> <int> <int>
 1 aardsda01   2004     1 SFN    NL       11     0     0     0     0     0     0
 2 aardsda01   2006     1 CHN    NL       45     2     0     0     0     0     0
 3 aardsda01   2007     1 CHA    AL       25     0     0     0     0     0     0
 4 aardsda01   2008     1 BOS    AL       47     1     0     0     0     0     0
 5 aardsda01   2009     1 SEA    AL       73     0     0     0     0     0     0
 6 aardsda01   2010     1 SEA    AL       53     0     0     0     0     0     0
 7 aardsda01   2012     1 NYA    AL        1     0     0     0     0     0     0
 8 aardsda01   2013     1 NYN    NL       43     0     0     0     0     0     0
 9 aardsda01   2015     1 ATL    NL       33     1     0     0     0     0     0
10 aaronha01   1954     1 ML1    NL      122   468    58   131    27     6    13
# i more rows
# i 11 more variables: RBI <int>, SB <int>, CS <int>, BB <int>, SO <int>,
#   IBB <int>, HBP <int>, SH <int>, SF <int>, GIDP <int>, birthCountry <chr>
```

Show query

```
<SQL>
SELECT Batting.*, birthCountry
FROM Batting
LEFT JOIN People
  ON (Batting.playerID = People.playerID)
```

```r
lahman$Pitching |>
  addBirthCountry()
```

```
# Source:   SQL [?? x 31]
```

```
# Database: DuckDB v1.2.1 [unknown@Linux 6.11.0-1012-azure:R 4.5.0/:memory:]
   playerID  yearID stint teamID lgID      W     L     G    GS    CG   SHO    SV
   <chr>      <int> <int> <fct>  <fct> <int> <int> <int> <int> <int> <int> <int>
 1 aardsda01   2004     1 SFN    NL        1     0    11     0     0     0     0
 2 aardsda01   2006     1 CHN    NL        3     0    45     0     0     0     0
 3 aardsda01   2007     1 CHA    AL        2     1    25     0     0     0     0
 4 aardsda01   2008     1 BOS    AL        4     2    47     0     0     0     0
 5 aardsda01   2009     1 SEA    AL        3     6    73     0     0     0    38
 6 aardsda01   2010     1 SEA    AL        0     6    53     0     0     0    31
 7 aardsda01   2012     1 NYA    AL        0     0     1     0     0     0     0
 8 aardsda01   2013     1 NYN    NL        2     2    43     0     0     0     0
 9 aardsda01   2015     1 ATL    NL        1     1    33     0     0     0     0
10 aasedo01    1977     1 BOS    AL        6     2    13    13     4     2     0
# i more rows
# i 19 more variables: IPouts <int>, H <int>, ER <int>, HR <int>, BB <int>,
#   SO <int>, BAOpp <dbl>, ERA <dbl>, IBB <int>, WP <int>, HBP <int>, BK <int>,
#   BFP <int>, GF <int>, R <int>, SH <int>, SF <int>, GIDP <int>,
#   birthCountry <chr>
```

Show query

```
<SQL>
SELECT Pitching.*, birthCountry
FROM Pitching
LEFT JOIN People
  ON (Pitching.playerID = People.playerID)
```

We could then use our addBirthCountry() function as part of a larger query to summarise the proportion of players from each country over time (based on their presence in the batting table).

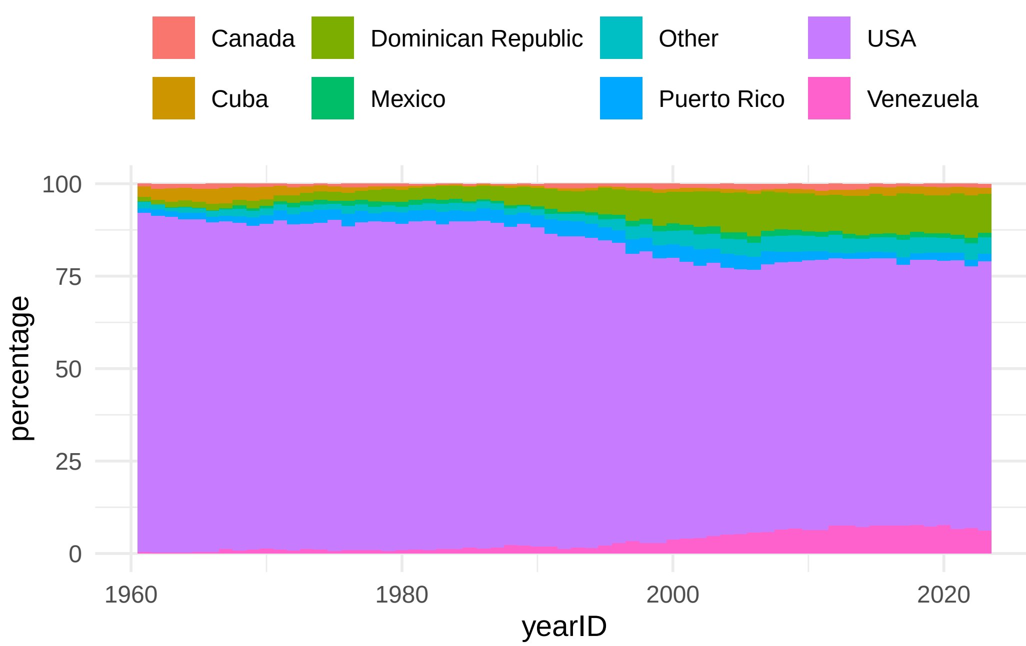
```
plot_data <- lahman$Batting |>
  select(playerID, yearID) |>
  addBirthCountry() |>
  filter(yearID > 1960) |>
  mutate(birthCountry = case_when(
    birthCountry == "USA" ~ "USA",
    birthCountry == "D.R." ~ "Dominican Republic",
    birthCountry == "Venezuela" ~ "Venezuela",
    birthCountry == "P.R." ~ "Puerto Rico ",
    birthCountry == "Cuba" ~ "Cuba",
    birthCountry == "CAN" ~ "Canada",
```

```r
    birthCountry == "Mexico" ~ "Mexico",
    .default = "Other"
  )) |>
  summarise(n = n(), .by = c("yearID", "birthCountry")) |>
  group_by(yearID) |>
  mutate(percentage = n / sum(n) * 100) |>
  ungroup() |>
  collect()
```

Show query

```sql
<SQL>
SELECT q01.*, (n / SUM(n) OVER (PARTITION BY yearID)) * 100.0 AS percentage
FROM (
  SELECT yearID, birthCountry, COUNT(*) AS n
  FROM (
    SELECT
      playerID,
      yearID,
      CASE
WHEN (birthCountry = 'USA') THEN 'USA'
WHEN (birthCountry = 'D.R.') THEN 'Dominican Republic'
WHEN (birthCountry = 'Venezuela') THEN 'Venezuela'
WHEN (birthCountry = 'P.R.') THEN 'Puerto Rico '
WHEN (birthCountry = 'Cuba') THEN 'Cuba'
WHEN (birthCountry = 'CAN') THEN 'Canada'
WHEN (birthCountry = 'Mexico') THEN 'Mexico'
ELSE 'Other'
END AS birthCountry
    FROM (
      SELECT Batting.playerID AS playerID, yearID, birthCountry
      FROM Batting
      LEFT JOIN People
        ON (Batting.playerID = People.playerID)
    ) q01
    WHERE (yearID > 1960.0)
  ) q01
  GROUP BY yearID, birthCountry
) q01
```

```r
library(ggplot2)
plot_data |>
  ggplot() +
  geom_col(aes(yearID,
               percentage,
               fill = birthCountry), width=1) +
  theme_minimal() +
  theme(legend.title = element_blank(),
        legend.position = "top")
```



Defining methods for the data model

As part of our `lahmanFromCon()` function our data model object has the class "lahman_ref". Therefore as well as creating user-facing functions to work with our lahman data model, we can also define methods for this object.

```r
class(lahman)
```

```
[1] "lahman_ref" "list"
```

With this we can make some specific methods for a "lahman_ref" object. For example, we can define a print method like so:

```
print.lahman_ref <- function(x, ...) {
  len <- length(names(x))
  cli_h1("# Lahman reference - {len} tables")
  cli_li(paste(
    "{.strong tables:}",
    paste(names(x), collapse = ", ")
  ))
  invisible(x)
}
```

Now we can see a summary of our lahman data model when we print the object.

```
lahman
```

```
-- # Lahman reference - 28 tables ----------------------------------------------

* tables: AllstarFull, Appearances, AwardsManagers, AwardsPlayers,
AwardsManagers, AwardsShareManagers, Batting, BattingPost, CollegePlaying,
Fielding, FieldingOF, FieldingOFsplit, FieldingPost, HallOfFame, HomeGames,
LahmanData, Managers, ManagersHalf, Parks, People, Pitching, PitchingPost,
Salaries, Schools, SeriesPost, Teams, TeamsFranchises, TeamsHalf
```

And we can see that this print is being done by the method we defined.

```
library(sloop)
s3_dispatch(print(lahman))
```

```
=> print.lahman_ref
   print.list
 * print.default
```

4.3 Building efficient analytic pipelines

4.3.1 The risk of "clean" R code

Following on from the above approach, we might think it a good idea to make another function `addBirthYear()`. We can then use it along with our `addBirthCountry()` to get a summarise average salary by birth country and birth year.

```r
addBirthYear <- function(lahmanTbl){
  lahmanTbl |>
    left_join(lahman$People |>
              select("playerID", "birthYear"),
              join_by("playerID"))
}

lahman$Salaries |>
  addBirthCountry() |>
  addBirthYear() |>
  summarise(average_salary = mean(salary),
            .by = c("birthCountry", "birthYear"))
```

```
# Source:   SQL [?? x 3]
# Database: DuckDB v1.2.1 [unknown@Linux 6.11.0-1012-azure:R 4.5.0/:memory:]
   birthCountry birthYear average_salary
   <chr>            <int>          <dbl>
 1 USA               1960       1030321.
 2 USA               1952        498378.
 3 USA               1956        986760.
 4 USA               1961        811250.
 5 USA               1950        625076.
 6 Nicaragua         1954       2083440.
 7 Panama            1945        875000
 8 CAN               1961       1080292.
 9 Venezuela         1948        632500
10 Cuba              1942        250000
# i more rows
```

Although the R code on the face of it looks fine, when we look at the SQL we can see that our query has two joins to the People table. One join gets information on the birth country and the other on the birth year.

Show query

```
<SQL>
SELECT birthCountry, birthYear, AVG(salary) AS average_salary
FROM (
  SELECT
    Salaries.*,
    "People...2".birthCountry AS birthCountry,
```

```
    "People...3".birthYear AS birthYear
  FROM Salaries
  LEFT JOIN People "People...2"
    ON (Salaries.playerID = "People...2".playerID)
  LEFT JOIN People "People...3"
    ON (Salaries.playerID = "People...3".playerID)
) q01
GROUP BY birthCountry, birthYear
```

To improve performance, we could instead have a single function to get both of these, birth country and birth year, at the same time.

```r
addCharacteristics <- function(lahmanTbl){
  lahmanTbl |>
    left_join(lahman$People |>
              select("playerID", "birthYear", "birthCountry"),
              join_by("playerID"))
}

lahman$Salaries |>
  addCharacteristics() |>
  summarise(average_salary = mean(salary),
            .by = c("birthCountry", "birthYear"))
```

```
# Source:   SQL [?? x 3]
# Database: DuckDB v1.2.1 [unknown@Linux 6.11.0-1012-azure:R 4.5.0/:memory:]
   birthCountry birthYear average_salary
   <chr>            <int>          <dbl>
 1 D.R.              1985       1531438.
 2 USA               1966       1761151.
 3 Venezuela         1974       4269365.
 4 Cuba              1987       4932700.
 5 Panama            1981        555833.
 6 USA               1978       3133596.
 7 CAN               1985        501000
 8 P.R.              1959        297786.
 9 USA               1961        811250.
10 USA               1990        728740.
# i more rows
```

Show query

```
<SQL>
SELECT birthCountry, birthYear, AVG(salary) AS average_salary
FROM (
  SELECT Salaries.*, birthYear, birthCountry
  FROM Salaries
  LEFT JOIN People
    ON (Salaries.playerID = People.playerID)
) q01
GROUP BY birthCountry, birthYear
```

Now this query outputs the same result but is simpler than the previous one, thus lowering the computational cost of the analysis. All this is to show that when working with databases we should keep in mind what is going on behind the scenes in terms of the SQL code actually being executed.

4.3.2 Piping and SQL

Although piping functions has little impact on performance when using R with data in memory, when working with a database the SQL generated will differ when using multiple function calls (with a separate operation specified in each) instead of multiple operations within a single function call.

For example, a single mutate function creating two new variables would generate the below SQL.

```
lahman$People |>
  mutate(birthDatePlus1 =
           add_years(birthDate, 1L),
         birthDatePlus10 =
           add_years(birthDate, 10L)) |>
  select("playerID",
         "birthDatePlus1",
         "birthDatePlus10") |>
  show_query()
```

```
<SQL>
SELECT
  playerID,
  DATE_ADD(birthDate, INTERVAL (1) year) AS birthDatePlus1,
  DATE_ADD(birthDate, INTERVAL (10) year) AS birthDatePlus10
```

```
FROM People
```

Whereas the SQL will be different if these were created using multiple mutate calls (with now one being created in a sub-query).

```
lahman$People |>
  mutate(birthDatePlus1 =
           add_years(birthDate, 1L)) |>
  mutate(birthDatePlus10 =
           add_years(birthDate, 10L)) |>
  select("playerID",
         "birthDatePlus1",
         "birthDatePlus10") |>
  show_query()
```

```
<SQL>
SELECT
  playerID,
  birthDatePlus1,
  DATE_ADD(birthDate, INTERVAL (10) year) AS birthDatePlus10
FROM (
  SELECT People.*, DATE_ADD(birthDate, INTERVAL (1) year) AS birthDatePlus1
  FROM People
) q01
```

4.3.3 Computing intermediate queries

Let's say we want to summarise home runs in the batting table and stike outs in the pitching table by the college players attended and their birth year. We could do this like so:

```
players_with_college <- lahman$People |>
  select(playerID, birthYear) |>
  inner_join(lahman$CollegePlaying |>
               filter(!is.na(schoolID)) |>
               select(playerID, schoolID) |>
               distinct(),
             by = join_by(playerID))

lahman$Batting |>
  left_join(players_with_college,
            by = join_by(playerID)) |>
```

```r
  summarise(home_runs = sum(H, na.rm = TRUE),
                      .by = c(schoolID, birthYear)) |>
  collect()
```

```
# A tibble: 6,206 x 3
   schoolID   birthYear home_runs
   <chr>          <int>     <dbl>
 1 rice            1981         0
 2 virginia        1987        27
 3 cacerri         1971         3
 4 usc             1947        11
 5 lsu             1927      1832
 6 wake            1915        72
 7 pepperdine      1969         1
 8 lsu             1978         2
 9 miamidade       1982         0
10 cincy           1950         5
# i 6,196 more rows
```

```r
lahman$Pitching |>
  left_join(players_with_college,
            by = join_by(playerID)) |>
  summarise(strike_outs = sum(SO, na.rm = TRUE),
                        .by = c(schoolID, birthYear))|>
  collect()
```

```
# A tibble: 3,662 x 3
   schoolID   birthYear strike_outs
   <chr>          <int>       <dbl>
 1 michigan        1967         888
 2 texas           1958         549
 3 nmstate         1968          98
 4 stanford        1972         218
 5 beloitwi        1872           3
 6 upenn           1964          14
 7 arkansas        1962         537
 8 mntclairst      1961          46
 9 incante         1893         526
10 illinois        1979          19
# i 3,652 more rows
```

Looking at the SQL we can see, however, that there is some duplication, because as part of each full query we have run our players_with_college query.

Show query

```
<SQL>
SELECT schoolID, birthYear, SUM(H) AS home_runs
FROM (
  SELECT Batting.*, birthYear, schoolID
  FROM Batting
  LEFT JOIN (
    SELECT People.playerID AS playerID, birthYear, schoolID
    FROM People
    INNER JOIN (
      SELECT DISTINCT playerID, schoolID
      FROM CollegePlaying
      WHERE (NOT((schoolID IS NULL)))
    ) RHS
      ON (People.playerID = RHS.playerID)
  ) RHS
    ON (Batting.playerID = RHS.playerID)
) q01
GROUP BY schoolID, birthYear

<SQL>
SELECT schoolID, birthYear, SUM(SO) AS strike_outs
FROM (
  SELECT Pitching.*, birthYear, schoolID
  FROM Pitching
  LEFT JOIN (
    SELECT People.playerID AS playerID, birthYear, schoolID
    FROM People
    INNER JOIN (
      SELECT DISTINCT playerID, schoolID
      FROM CollegePlaying
      WHERE (NOT((schoolID IS NULL)))
    ) RHS
      ON (People.playerID = RHS.playerID)
  ) RHS
    ON (Pitching.playerID = RHS.playerID)
) q01
GROUP BY schoolID, birthYear
```

To avoid this we could instead make use of the `compute()` function to force the computation of this first, intermediate, query to a temporary table in the database.

```
players_with_college <- players_with_college |>
  compute()
```

Now we have a temporary table with the result of our players_with_college query, and we can use this in both of our aggregation queries.

```
players_with_college |>
  show_query()
```

```
<SQL>
SELECT *
FROM dbplyr_1FJqLh3epu
```

```
lahman$Batting |>
  left_join(players_with_college,
            by = join_by(playerID)) |>
  summarise(home_runs = sum(H, na.rm = TRUE),
                        .by = c(schoolID, birthYear)) |>
  collect()
```

```
# A tibble: 6,206 x 3
   schoolID  birthYear home_runs
   <chr>         <int>     <dbl>
 1 kentucky       1972       157
 2 elon           1921         1
 3 lehigh         1901         1
 4 ucla           1952       306
 5 usc            1947        11
 6 tamukvill      1978         0
 7 stanford       1972        55
 8 lsu            1927      1832
 9 wake           1915        72
10 upenn          1964         0
# i 6,196 more rows
```

```r
lahman$Pitching |>
  left_join(players_with_college,
            by = join_by(playerID)) |>
  summarise(strike_outs = sum(SO, na.rm = TRUE),
                        .by = c(schoolID, birthYear))|>
  collect()
```

```
# A tibble: 3,662 x 3
   schoolID  birthYear strike_outs
   <chr>         <int>       <dbl>
 1 elon           1921          13
 2 lehigh         1901           1
 3 usc            1947         275
 4 tamukvill      1978         409
 5 stanford       1972         218
 6 upenn          1964          14
 7 arkansas       1962         537
 8 kentucky       1985          91
 9 txsjjcn        1983         571
10 rhodestn       1888         457
# i 3,652 more rows
```

Show query

```sql
<SQL>
SELECT schoolID, birthYear, SUM(H) AS home_runs
FROM (
  SELECT Batting.*, birthYear, schoolID
  FROM Batting
  LEFT JOIN dbplyr_1FJqLh3epu
    ON (Batting.playerID = dbplyr_1FJqLh3epu.playerID)
) q01
GROUP BY schoolID, birthYear

<SQL>
SELECT schoolID, birthYear, SUM(SO) AS strike_outs
FROM (
  SELECT Pitching.*, birthYear, schoolID
  FROM Pitching
  LEFT JOIN dbplyr_1FJqLh3epu
    ON (Pitching.playerID = dbplyr_1FJqLh3epu.playerID)
) q01
```

```
GROUP BY schoolID, birthYear
```

In this case the SQL from our initial approach was not so complicated. However, you can imagine that without using computation to intermediate tables, the SQL associated with a series of data manipulations could quickly become unmanageable. Moreover, we can end up with inefficient code that repeatedly gets the same result as part of a larger query. Therefore although we don't want to overuse computation of intermediate queries, it is often a necessity when creating our analytic pipelines.

Part II

Working with the OMOP CDM from R

In this second half of the book we will see how we can work with data in the OMOP CDM format from R.

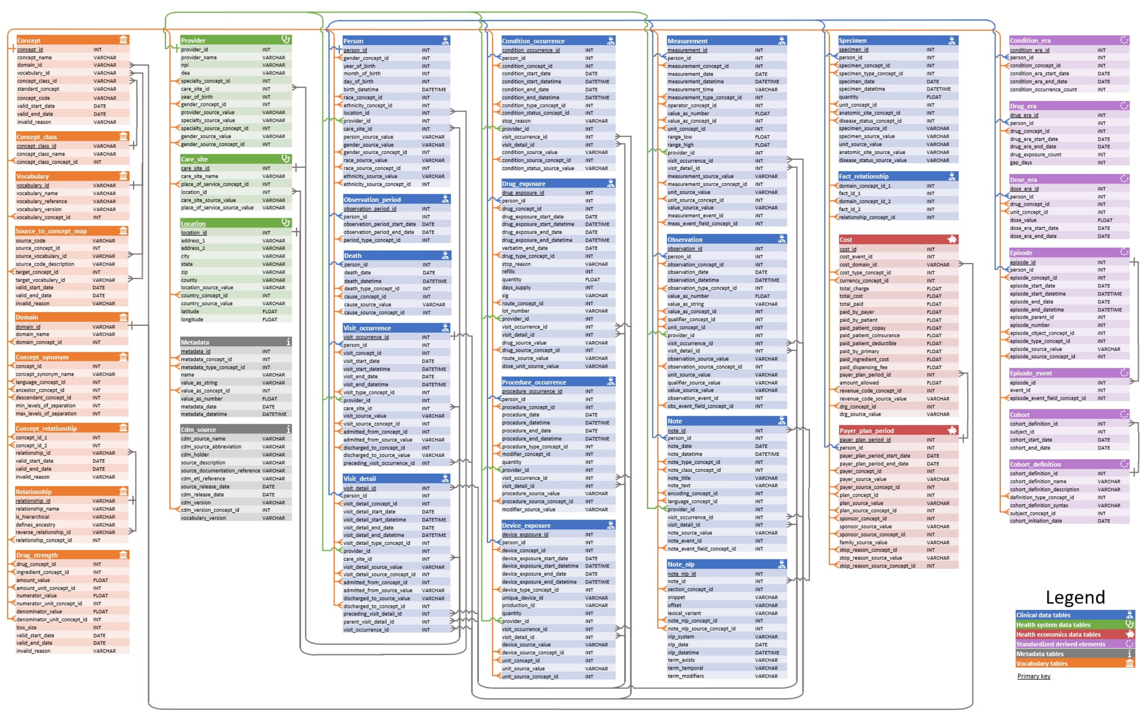
- In Chapter 5 we will see how to create a cdm_reference in R, a data model that contains references to the OMOP CDM tables and provides the foundation for analysis.
- The OMOP CDM is a person-centric model, and the person and observation period tables are two key tables for any analysis. In **?@sec-omop_person_obs_period** we will see more on how these tables can be used as the starting point for identifying your study participants.
- The OMOP CDM standarises the content of health care data via the OMOP CDM vocabulary tables, which provides a set of standard concepts to represent different clinical events. The vocabulary tables are described in **?@sec-omop_vocabularies**, with these tables playing a fundamental role when we identify the clinical events of interest for our study.
- Clinical records associated with individuals are spread across various OMOP CDM tables, covering various domains. In **?@sec-omop_clinical_tables** we will see how these tables represent events and link back to the person and vocabulary tables.

5 Creating a CDM reference

5.1 The OMOP common data model (CDM) layout

The OMOP CDM standardises the structure of healthcare data. Data is stored across a system of tables with established relationships between them. In other words, the OMOP CDM provides a relational database structure, with version 5.4 of the OMOP CDM shown below.

OMOP Common Data Model 5.4



5.2 Creating a reference to the OMOP CDM

As we saw in Chapter 4, creating a data model in R to represent the OMOP CDM can provide a basis for analytic pipelines using the data. Luckily for us, we won't have to create functions and methods for this ourselves. Instead, we will use the `omopgenerics` package which defines a data model for OMOP CDM data and the `CDMConnector` package which provides functions for connecting to a OMOP CDM data held in a database.

To see how this works we will use the `omock` package to create example data in the format of the OMOP CDM, which we will then copy to a `duckdb` database.

```
library(DBI)
library(duckdb)
library(here)
library(dplyr)
library(omock)
library(omopgenerics)
library(CDMConnector)
library(palmerpenguins)

cdm_local <- mockCdmReference() |>
    mockPerson(nPerson = 100) |>
    mockObservationPeriod() |>
    mockConditionOccurrence() |>
    mockDrugExposure() |>
    mockObservation() |>
    mockMeasurement() |>
    mockVisitOccurrence() |>
    mockProcedureOccurrence()

db <- dbConnect(drv = duckdb())

cdm <- insertCdmTo(cdm = cdm_local,
                   to = dbSource(con = db, writeSchema = "main"))
```

Now that we have OMOP CDM data in a database, we can use the function `cdmFromCon()` from `CDMConnector` to create our cdm reference. Note that as well as specifying the schema containing our OMOP CDM tables, we will also specify a write schema where any database tables we create during our analysis will be stored. Often our OMOP CDM tables will be in a schema that we only have read-access to and we'll have another schema where we can have write-access and where intermediate tables can be created for a given study.

```
cdm <- cdmFromCon(db,
                  cdmSchema = "main",
                  writeSchema = "main",
                  cdmName = "example_data")
```

```r
cdm
```

```
-- # OMOP CDM reference (duckdb) of example_data ------------------------------

* omop tables: person, observation_period, visit_occurrence,
condition_occurrence, drug_exposure, procedure_occurrence, measurement,
observation, cdm_source, concept, vocabulary, concept_relationship,
concept_synonym, concept_ancestor, drug_strength

* cohort tables: -

* achilles tables: -

* other tables: -
```

> **Setting a write prefix**
>
> We can also specify a write prefix and this will be used whenever permanent tables are created in the write schema. This can be useful when we're sharing our write schema with others and want to avoid table name conflicts and easily drop tables created as part of a particular study.
>
> ```r
> cdm <- cdmFromCon(con = db,
>                   cdmSchema = "main",
>                   writeSchema = "main",
>                   writePrefix = "my_study_",
>                   cdmName = "example_data")
> ```

We can see that we now have an object that contains references to all the OMOP CDM tables. We can reference specific tables using the "$" or "[[…]]" operators.

```r
cdm$person
```

```
# Source:   table<person> [?? x 18]
# Database: DuckDB v1.2.1 [unknown@Linux 6.11.0-1012-azure:R 4.5.0/:memory:]
   person_id gender_concept_id year_of_birth month_of_birth day_of_birth
       <int>             <int>         <int>          <int>        <int>
```

```
 1          1              8507          1951              9            23
 2          2              8532          2000             12            19
 3          3              8507          1957              6            22
 4          4              8507          1963              1            19
 5          5              8507          1970              3            17
 6          6              8507          1987              4            20
 7          7              8507          1982              3             4
 8          8              8507          1988              1             9
 9          9              8532          1967              2             6
10         10              8532          1992             12            24
# i more rows
# i 13 more variables: race_concept_id <int>, ethnicity_concept_id <int>,
#   birth_datetime <dttm>, location_id <int>, provider_id <int>,
#   care_site_id <int>, person_source_value <chr>, gender_source_value <chr>,
#   gender_source_concept_id <int>, race_source_value <chr>,
#   race_source_concept_id <int>, ethnicity_source_value <chr>,
#   ethnicity_source_concept_id <int>
```

```
cdm[["observation_period"]]
```

```
# Source:   table<observation_period> [?? x 5]
# Database: DuckDB v1.2.1 [unknown@Linux 6.11.0-1012-azure:R 4.5.0/:memory:]
   observation_period_id person_id observation_period_s~1 observation_period_e~2
                   <int>     <int> <date>                 <date>
 1                     1         1 1998-01-29             2004-01-31
 2                     2         2 2005-09-04             2017-06-17
 3                     3         3 2001-08-25             2019-08-12
 4                     4         4 1967-12-17             2015-10-20
 5                     5         5 1982-04-17             1995-02-13
 6                     6         6 2005-07-25             2010-09-17
 7                     7         7 2008-12-10             2015-09-22
 8                     8         8 2008-08-14             2014-09-22
 9                     9         9 2013-03-25             2019-08-16
10                    10        10 1997-04-15             2018-08-02
# i more rows
# i abbreviated names: 1: observation_period_start_date,
#   2: observation_period_end_date
# i 1 more variable: period_type_concept_id <int>
```

Note that here we have first created a local version of the cdm with all the tables of interest with `omock`, then copied it to a `duckdb` database, and finally crated a reference to it with `CDMConnector`, so that we can work with the final `cdm` object as we normally would for one created with our own healthcare data. In that case we would directly use `cdmFromCon` with our own database information. Throughout this chapter, however, we will keep working with the mock dataset.

5.3 CDM attributes

5.3.1 CDM name

Our cdm reference will be associated with a name. By default this name will be taken from the `cdm_source_name` field from the `cdm_source` table. We will use the function `cdmName` from `omopgenerics` to get it.

```
cdm <- cdmFromCon(db,
  cdmSchema = "main",
  writeSchema = "main")
cdm$cdm_source
```

```
# Source:   table<cdm_source> [?? x 10]
# Database: DuckDB v1.2.1 [unknown@Linux 6.11.0-1012-azure:R 4.5.0/:memory:]
  cdm_source_name cdm_source_abbreviation cdm_holder source_description
  <chr>           <chr>                   <chr>      <chr>
1 mock            <NA>                    <NA>       <NA>
# i 6 more variables: source_documentation_reference <chr>,
#   cdm_etl_reference <chr>, source_release_date <date>,
#   cdm_release_date <date>, cdm_version <chr>, vocabulary_version <chr>
```

```
cdmName(cdm)
```

```
[1] "mock"
```

However, we can instead set this name to whatever else we want when creating our cdm reference.

```
cdm <- cdmFromCon(db,
  cdmSchema = "main",
  writeSchema = "main",
  cdmName = "my_cdm")
cdmName(cdm)
```

```
[1] "my_cdm"
```

Note that we can also get our cdm name from any of the tables in our cdm reference.

```r
cdmName(cdm$person)
```

```
[1] "my_cdm"
```

> Behind the scenes
>
> The class of the cdm reference itself is cdm_reference.
>
> ```r
> class(cdm)
> ```
>
> ```
> [1] "cdm_reference"
> ```
>
> ```r
> class(cdm$person)
> ```
>
> ```
> [1] "omop_table"              "cdm_table"               "tbl_duckdb_connection"
> [4] "tbl_dbi"                 "tbl_sql"                 "tbl_lazy"
> [7] "tbl"
> ```
>
> Each of the tables has class cdm_table. If the table is one of the standard OMOP CDM tables it will also have class omop_table. This latter class is defined so that we can allow different behaviour for these core tables (person, condition_occurrence, observation_period, etc.) compared to other tables that are added to the cdm reference during the course of running a study.
>
> ```r
> class(cdm$person)
> ```
>
> ```
> [1] "omop_table"              "cdm_table"               "tbl_duckdb_connection"
> [4] "tbl_dbi"                 "tbl_sql"                 "tbl_lazy"
> [7] "tbl"
> ```
>
> We can see that `cdmName()` is a generic function, which works for both the cdm reference as a whole and individual tables.
>
> ```r
> library(sloop)
> s3_dispatch(cdmName(cdm))
> ```
>
> ```
> => cdmName.cdm_reference
>  * cdmName.default
> ```

```
s3_dispatch(cdmName(cdm$person))
```

```
   cdmName.omop_table
=> cdmName.cdm_table
   cdmName.tbl_duckdb_connection
   cdmName.tbl_dbi
   cdmName.tbl_sql
   cdmName.tbl_lazy
   cdmName.tbl
 * cdmName.default
```

5.3.2 CDM version

We can also easily check the OMOP CDM version that is being used with the function `cdmVersion` from `omopgenerics` like so:

```
cdmVersion(cdm)
```

```
[1] "5.3"
```

5.4 Including cohort tables in the cdm reference

We'll be seeing how to create cohorts in more detail in **?@sec-creating_cohorts**. For the moment, let's just outline how we can include a cohort in our cdm reference. For this we'll use `omock` to add a cohort to our local cdm and upload that to a `duckdb` database again.

```
cdm_local <- cdm_local |>
  mockCohort(name = "my_study_cohort")
db <- dbConnect(drv = duckdb())
cdm <- insertCdmTo(cdm = cdm_local,
                   to = dbSource(con = db, writeSchema = "main"))
```

Now we can specify we want to include this existing cohort table to our cdm object when creating our cdm reference.

```
cdm <- cdmFromCon(db,
                  cdmSchema = "main",
                  writeSchema = "main",
                  cohortTables = "my_study_cohort",
                  cdmName = "example_data")
cdm
```

```
cdm$my_study_cohort |>
  glimpse()
```

```
Rows: ??
Columns: 4
Database: DuckDB v1.2.1 [unknown@Linux 6.11.0-1012-azure:R 4.5.0/:memory:]
$ cohort_definition_id <int> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1~
$ subject_id           <int> 1, 2, 2, 2, 3, 4, 4, 4, 4, 4, 5, 5, 5, 5, 6, 8, 8~
$ cohort_start_date    <date> 1999-08-26, 2006-12-08, 2006-12-14, 2007-08-24, ~
$ cohort_end_date      <date> 2001-07-03, 2006-12-13, 2007-08-23, 2012-06-01, ~
```

5.5 Including achilles tables in the cdm reference

If we have the results tables from the Achilles R package in our database, we can also include these in our cdm reference.

Just to show how this can be done let's upload some empty results tables in the Achilles format.

```
dbWriteTable(db,
             "achilles_analysis",
             tibble(
               analysis_id = NA_integer_,
               analysis_name = NA_character_,
               stratum_1_name = NA_character_,
               stratum_2_name = NA_character_,
               stratum_3_name = NA_character_,
               stratum_4_name = NA_character_,
               stratum_5_name = NA_character_,
               is_default = NA_character_,
               category = NA_character_))
dbWriteTable(db,
             "achilles_results",
```

```
             tibble(
               analysis_id = NA_integer_,
               stratum_1 = NA_character_,
               stratum_2 = NA_character_,
               stratum_3 = NA_character_,
               stratum_4 = NA_character_,
               stratum_5 = NA_character_,
               count_value = NA_character_))
dbWriteTable(db,
             "achilles_results_dist",
             tibble(
               analysis_id = NA_integer_,
               stratum_1 = NA_character_,
               stratum_2 = NA_character_,
               stratum_3 = NA_character_,
               stratum_4 = NA_character_,
               stratum_5 = NA_character_,
               count_value = NA_character_,
               min_value = NA_character_,
               max_value = NA_character_,
               avg_value = NA_character_,
               stdev_value = NA_character_,
               median_value = NA_character_,
               p10_value = NA_character_,
               p25_value = NA_character_,
               p75_value = NA_character_,
               p90_value = NA_character_))
```

We can now include these achilles table in our cdm reference as in the previous case.

```
cdm <- cdmFromCon(db,
                  cdmSchema = "main",
                  writeSchema = "main",
                  cohortTables = "my_study_cohort",
                  achillesSchema = "main",
                  cdmName = "example_data")
cdm
```

5.6 Adding other tables to the cdm reference

Let's say we have some additional local data that we want to add to our cdm reference. We can add this both to the same source (in this case a database) and to our cdm reference using `insertTable` from `omopgenerics`. We will show this with the dataset `cars` in-built in R.

```
cars |>
  glimpse()
```

```
Rows: 50
Columns: 2
$ speed <dbl> 4, 4, 7, 7, 8, 9, 10, 10, 10, 11, 11, 12, 12, 12, 12, 13, 13, 13~
$ dist  <dbl> 2, 10, 4, 22, 16, 10, 18, 26, 34, 17, 28, 14, 20, 24, 28, 26, 34~
```

```
cdm <- insertTable(cdm = cdm,
                   name = "cars",
                   table = cars,
                   temporary = FALSE)
```

We can see that now this extra table has been uploaded to the database behind our cdm reference and also added to our reference.

```
cdm
```

```
-- # OMOP CDM reference (duckdb) of example_data -------------------------------

* omop tables: person, observation_period, visit_occurrence,
condition_occurrence, drug_exposure, procedure_occurrence, measurement,
observation, cdm_source, concept, vocabulary, concept_relationship,
concept_synonym, concept_ancestor, drug_strength

* cohort tables: my_study_cohort

* achilles tables: achilles_analysis, achilles_results, achilles_results_dist

* other tables: cars
```

```
cdm$cars
```

```
# Source:   table<cars> [?? x 2]
# Database: DuckDB v1.2.1 [unknown@Linux 6.11.0-1012-azure:R 4.5.0/:memory:]
   speed  dist
   <dbl> <dbl>
 1     4     2
 2     4    10
 3     7     4
 4     7    22
 5     8    16
 6     9    10
 7    10    18
 8    10    26
 9    10    34
10    11    17
# i more rows
```

If we already had the table in the database we could have instead just assigned it to our existing cdm reference. To see this let's upload the `penguins` table to our `duckdb` database.

```
dbWriteTable(db,
             "penguins",
             penguins)
```

Once we have this table in the database, we can just assign it to our cdm reference.

```
cdm$penguins <- tbl(db, "penguins")

cdm
```

```
-- # OMOP CDM reference (duckdb) of example_data -------------------------------

* omop tables: person, observation_period, visit_occurrence,
condition_occurrence, drug_exposure, procedure_occurrence, measurement,
observation, cdm_source, concept, vocabulary, concept_relationship,
concept_synonym, concept_ancestor, drug_strength
```

```
* cohort tables: my_study_cohort

* achilles tables: achilles_analysis, achilles_results, achilles_results_dist

* other tables: cars, penguins
```

5.7 Mutability of the cdm reference

An important characteristic of our cdm reference is that we can alter the tables in R, but the OMOP CDM data will not be affected. We will therefore only be transforming the data in our cdm object but the original datasets behind it will remain intact.

For example, let's say we want to perform a study with only people born in 1970. For this we could filter our person table to only people born in this year.

```r
cdm$person <- cdm$person |>
  filter(year_of_birth == 1970)

cdm$person
```

```
# Source:   SQL [?? x 18]
# Database: DuckDB v1.2.1 [unknown@Linux 6.11.0-1012-azure:R 4.5.0/:memory:]
  person_id gender_concept_id year_of_birth month_of_birth day_of_birth
      <int>             <int>         <int>          <int>        <int>
1         5              8507          1970              3           17
2        13              8532          1970              4           26
# i 13 more variables: race_concept_id <int>, ethnicity_concept_id <int>,
#   birth_datetime <dttm>, location_id <int>, provider_id <int>,
#   care_site_id <int>, person_source_value <chr>, gender_source_value <chr>,
#   gender_source_concept_id <int>, race_source_value <chr>,
#   race_source_concept_id <int>, ethnicity_source_value <chr>,
#   ethnicity_source_concept_id <int>
```

From now on, when we work with our cdm reference this restriction will continue to have been applied.

```r
cdm$person |>
    tally()
```

```
# Source:   SQL [?? x 1]
# Database: DuckDB v1.2.1 [unknown@Linux 6.11.0-1012-azure:R 4.5.0/:memory:]
      n
  <dbl>
1     2
```

The original OMOP CDM data itself however will remain unaffected. We can see that, indeed, if we create our reference again the underlying data is unchanged.

```
cdm <- cdmFromCon(con = db,
                  cdmSchema = "main",
                  writeSchema = "main",
                  cdmName = "Synthea Covid-19 data")
cdm$person |>
    tally()
```

```
# Source:   SQL [?? x 1]
# Database: DuckDB v1.2.1 [unknown@Linux 6.11.0-1012-azure:R 4.5.0/:memory:]
      n
  <dbl>
1   100
```

The mutability of our cdm reference is a useful feature for studies as it means we can easily tweak our OMOP CDM data if needed. Meanwhile, leaving the underlying data unchanged is essential so that other study code can run against the data, unaffected by any of our changes.

One thing we can't do, though, is alter the structure of OMOP CDM tables. For example, the following code would cause an error as the person table must always have the column person_id.

```
cdm$person <- cdm$person |>
    rename("new_id" = "person_id")
```

```
Error in `newOmopTable()`:
! person_id is not present in table person
```

In such a case we would have to call the table something else first, and then run the previous code:

```
cdm$person_new <- cdm$person |>
    rename("new_id" = "person_id") |>
    compute(name = "person_new",
            temporary = TRUE)
```

Now we would be allowed to have this new table as an additional table in our cdm reference, knowing it was not in the format of one of the core OMOP CDM tables.

```
cdm
```

```
-- # OMOP CDM reference (duckdb) of Synthea Covid-19 data -----------------------

* omop tables: person, observation_period, visit_occurrence,
condition_occurrence, drug_exposure, procedure_occurrence, measurement,
observation, cdm_source, concept, vocabulary, concept_relationship,
concept_synonym, concept_ancestor, drug_strength

* cohort tables: -

* achilles tables: -

* other tables: -
```

The package `omopgenerics` provides a comprehensive list of the required features of a valid cdm reference. You can read more about it here.

5.8 Working with temporary and permanent tables

When we create new tables and our cdm reference is in a database we have a choice between using temporary or permanent tables. In most cases we can work with these interchangeably. Below we create one temporary table and one permanent table. We can see that both of these tables have been added to our cdm reference and that we can use them in the same way. Note that any new computed table will by default be temporary unless otherwise specified.

```r
cdm$person_new_temp <- cdm$person |>
  head(5) |>
  compute()
```

```r
cdm$person_new_permanent <- cdm$person |>
  head(5) |>
  compute(name = "person_new_permanent",
          temporary = FALSE)
```

```r
cdm

cdm$person_new_temp
```

```
# Source:   table<og_001_1746389266> [?? x 18]
# Database: DuckDB v1.2.1 [unknown@Linux 6.11.0-1012-azure:R 4.5.0/:memory:]
  person_id gender_concept_id year_of_birth month_of_birth day_of_birth
      <int>             <int>         <int>          <int>        <int>
1         1              8507          1951              9           23
2         2              8532          2000             12           19
3         3              8507          1957              6           22
4         4              8507          1963              1           19
5         5              8507          1970              3           17
# i 13 more variables: race_concept_id <int>, ethnicity_concept_id <int>,
#   birth_datetime <dttm>, location_id <int>, provider_id <int>,
#   care_site_id <int>, person_source_value <chr>, gender_source_value <chr>,
#   gender_source_concept_id <int>, race_source_value <chr>,
#   race_source_concept_id <int>, ethnicity_source_value <chr>,
#   ethnicity_source_concept_id <int>
```

```r
cdm$person_new_permanent
```

```
# Source:   table<person_new_permanent> [?? x 18]
# Database: DuckDB v1.2.1 [unknown@Linux 6.11.0-1012-azure:R 4.5.0/:memory:]
  person_id gender_concept_id year_of_birth month_of_birth day_of_birth
      <int>             <int>         <int>          <int>        <int>
1         1              8507          1951              9           23
2         2              8532          2000             12           19
3         3              8507          1957              6           22
4         4              8507          1963              1           19
5         5              8507          1970              3           17
```

```
# i 13 more variables: race_concept_id <int>, ethnicity_concept_id <int>,
#   birth_datetime <dttm>, location_id <int>, provider_id <int>,
#   care_site_id <int>, person_source_value <chr>, gender_source_value <chr>,
#   gender_source_concept_id <int>, race_source_value <chr>,
#   race_source_concept_id <int>, ethnicity_source_value <chr>,
#   ethnicity_source_concept_id <int>
```

One benefit of working with temporary tables is that they will be automatically dropped at the end of the session, whereas the permanent tables will be left over in the database until explicitly dropped. This helps maintain the original database structure tidy and free of irrelevant data.

However, one disadvantage of using temporary tables is that we will generally accumulate more and more of them as we go (in a single R session), whereas we can overwrite permanent tables continuously. For example, if our study code contains a loop that requires a compute, we would either overwrite an intermediate permanent table 100 times or create 100 different temporary tables in the process. In the latter case we should be wary of consuming a lot of RAM, which could lead to performance issues or even crashes.

6 Disconnecting

Once we have finished our analysis we can close our connection to the database behind our cdm reference.

```
cdmDisconnect(cdm)
```

7 Further reading

- omopgenerics package
- CDMConnector package

8 Exploring the OMOP CDM

For this chapter, we'll use a synthetic Covid-19 dataset.

```
library(DBI)
library(dbplyr)
library(dplyr)
library(here)
library(CDMConnector)
library(ggplot2)
library(clock)
```

```
db<-dbConnect(duckdb::duckdb(),
              dbdir = eunomiaDir(datasetName = "synthea-covid19-10k"))
cdm <- cdmFromCon(db, cdmSchema = "main", writeSchema = "main")
```

```
cdm
```

```
-- # OMOP CDM reference (duckdb) of Synthea -----------------------------------

* omop tables: person, observation_period, visit_occurrence, visit_detail,
condition_occurrence, drug_exposure, procedure_occurrence, device_exposure,
measurement, observation, death, note, note_nlp, specimen, fact_relationship,
location, care_site, provider, payer_plan_period, cost, drug_era, dose_era,
condition_era, metadata, cdm_source, concept, vocabulary, domain,
concept_class, concept_relationship, relationship, concept_synonym,
concept_ancestor, source_to_concept_map, drug_strength, cohort_definition,
attribute_definition

* cohort tables: -

* achilles tables: -

* other tables: -
```

8.1 Counting people

The OMOP CDM is person-centric, with the person table containing records to uniquely identify each person in the database. As each row refers to a unique person, we can quickly get a count of the number of individuals in the database like so

```
cdm$person |>
  count()
```

```
# Source:   SQL [?? x 1]
# Database: DuckDB v1.2.1 [unknown@Linux 6.11.0-1012-azure:R 4.5.0//tmp/RtmpHwyyYa/file1f8a1(
      n
  <dbl>
1 10754
```

The person table also contains some demographic information, including a gender concept for each person. We can get a count grouped by this variable, but as this uses a concept we'll also need to join to the concept table to get the corresponding concept name for each concept id.

```
cdm$person |>
  group_by(gender_concept_id) |>
  count() |>
  left_join(cdm$concept,
            by=c("gender_concept_id" = "concept_id")) |>
              select("gender_concept_id", "concept_name", "n") |>
  collect()
```

```
# A tibble: 2 x 3
# Groups:   gender_concept_id [2]
  gender_concept_id concept_name     n
              <int> <chr>        <dbl>
1              8532 FEMALE        5165
2              8507 MALE          5589
```

Vocabulary tables

Above we've got counts by specific concept IDs recorded in the condition occurrence table. What these IDs represent is described in the concept table. Here we have the name associated with the concept, along with other information such as it's domain and vocabulary id.

```r
cdm$concept |>
  glimpse()
```

```
Rows: ??
Columns: 10
Database: DuckDB v1.2.1 [unknown@Linux 6.11.0-1012-azure:R 4.5.0//tmp/RtmpHwyyYa/file1f8a1
$ concept_id       <int> 45756805, 45756804, 45756803, 45756802, 45756801, 457~
$ concept_name     <chr> "Pediatric Cardiology", "Pediatric Anesthesiology", "~
$ domain_id        <chr> "Provider", "Provider", "Provider", "Provider", "Prov~
$ vocabulary_id    <chr> "ABMS", "ABMS", "ABMS", "ABMS", "ABMS", "ABMS", "ABMS~
$ concept_class_id <chr> "Physician Specialty", "Physician Specialty", "Physic~
$ standard_concept <chr> "S", "S", "S", "S", "S", "S", "S", "S", "S", "S", "S"~
$ concept_code     <chr> "OMOP4821938", "OMOP4821939", "OMOP4821940", "OMOP482~
$ valid_start_date <date> 1970-01-01, 1970-01-01, 1970-01-01, 1970-01-01, 1970~
$ valid_end_date   <date> 2099-12-31, 2099-12-31, 2099-12-31, 2099-12-31, 2099~
$ invalid_reason   <chr> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, N~
```

Other vocabulary tables capture other information about concepts, such as the direct relationships between concepts (the concept relationship table) and hierarchical relationships between (the concept ancestor table).

```r
cdm$concept_relationship |>
  glimpse()
```

```
Rows: ??
Columns: 6
Database: DuckDB v1.2.1 [unknown@Linux 6.11.0-1012-azure:R 4.5.0//tmp/RtmpHwyyYa/file1f8a1
$ concept_id_1     <int> 35804314, 35804314, 35804314, 35804327, 35804327, 358~
$ concept_id_2     <int> 912065, 42542145, 42542145, 35803584, 42542145, 42542~
$ relationship_id  <chr> "Has modality", "Has accepted use", "Is current in", ~
$ valid_start_date <date> 2021-01-26, 2019-08-29, 2019-08-29, 2019-05-27, 2019~
$ valid_end_date   <date> 2099-12-31, 2099-12-31, 2099-12-31, 2099-12-31, 2099~
$ invalid_reason   <chr> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, N~
```

```r
cdm$concept_ancestor |>
  glimpse()
```

```
Rows: ??
Columns: 4
```

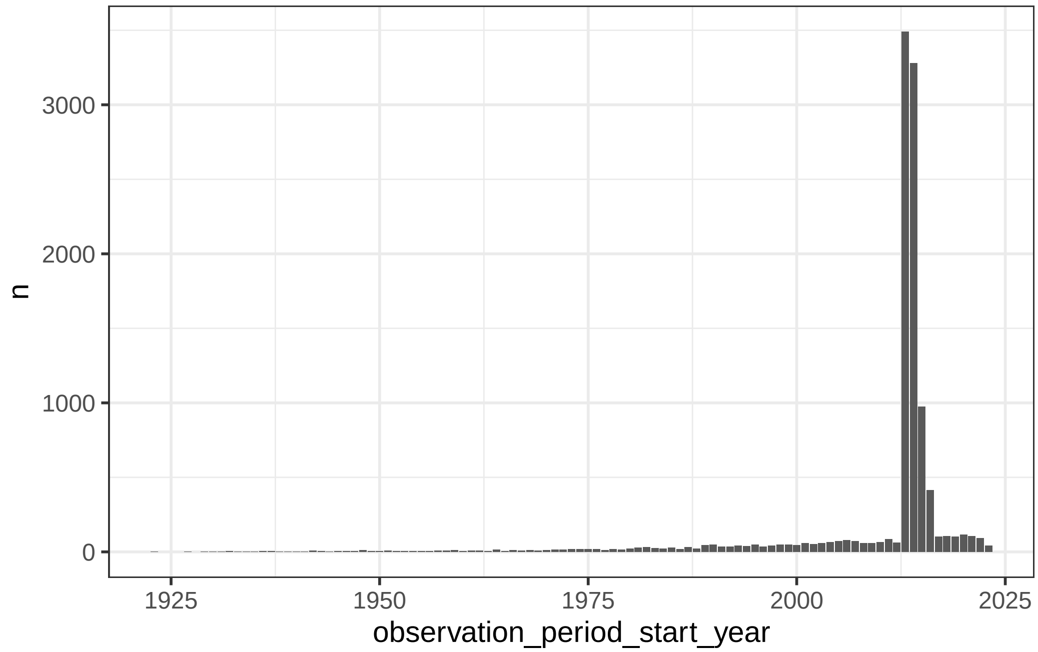
```
Database: DuckDB v1.2.1 [unknown@Linux 6.11.0-1012-azure:R 4.5.0//tmp/RtmpHwyyYa/file1f8a1(
$ ancestor_concept_id      <int> 375415, 727760, 735979, 438112, 529411, 14196~
$ descendant_concept_id    <int> 4335743, 2056453, 41070383, 36566114, 4326940~
$ min_levels_of_separation <int> 4, 1, 3, 2, 3, 3, 4, 3, 2, 5, 1, 3, 4, 2, 2, ~
$ max_levels_of_separation <int> 4, 1, 5, 3, 3, 6, 12, 3, 2, 10, 1, 3, 4, 2, 2~
```

More information on the vocabulary tables (as well as other tables in the OMOP CDM version 5.3) can be found at https://ohdsi.github.io/CommonDataModel/cdm53.html#Vocabulary_Tables.

8.2 Summarising observation periods

The observation period table contains records indicating spans of time over which clinical events can be reliably observed for the people in the person table. Someone can potentially have multiple observation periods. So say we wanted a count of people grouped by the year during which their first observation period started. We could do this like so:

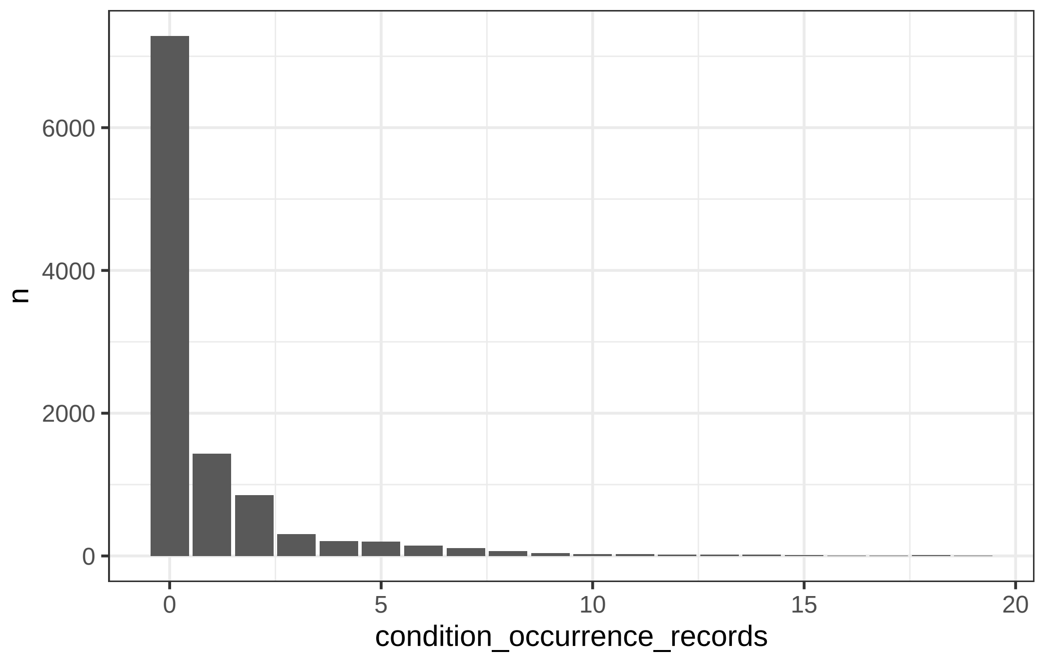
```
first_observation_period <- cdm$observation_period |>
    group_by(person_id) |>
    filter(row_number() == 1) |>
    compute()

cdm$person |>
  left_join(first_observation_period,
            by = "person_id") |>
  mutate(observation_period_start_year = get_year(observation_period_start_date)) |>
  group_by(observation_period_start_year) |>
  count() |>
  collect() |>
  ggplot() +
  geom_col(aes(observation_period_start_year, n)) +
  theme_bw()
```



8.3 Summarising clinical records

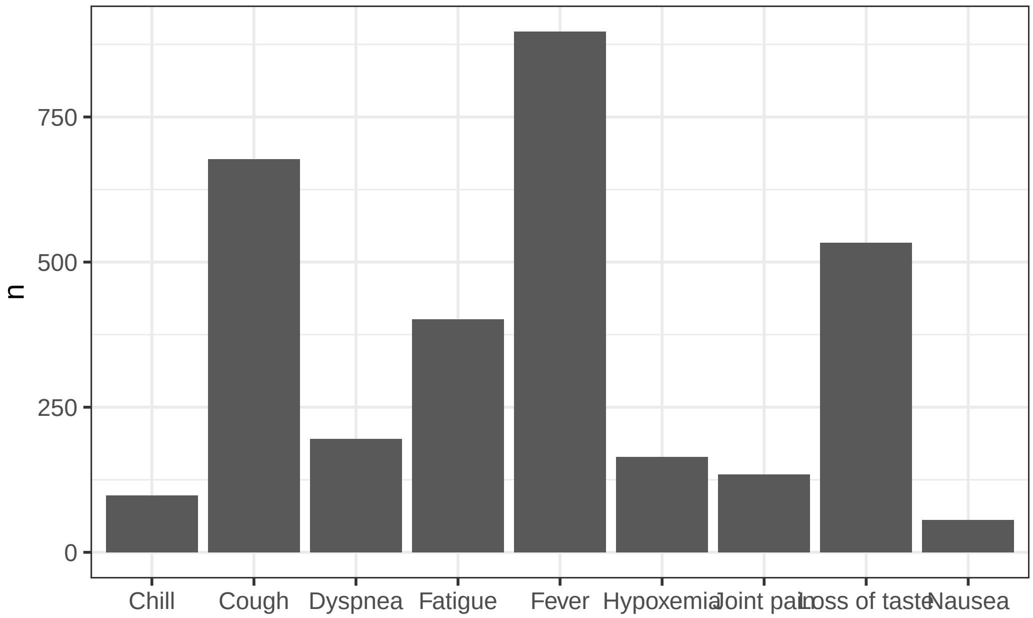
What's the number of condition occurrence records per person in the database? We can find this out like so

```
cdm$person |>
  left_join(cdm$condition_occurrence |>
  group_by(person_id) |>
  count(name = "condition_occurrence_records"),
  by="person_id") |>
  mutate(condition_occurrence_records = if_else(
    is.na(condition_occurrence_records), 0,
    condition_occurrence_records)) |>
  group_by(condition_occurrence_records) |>
  count() |>
  collect() |>
  ggplot() +
  geom_col(aes(condition_occurrence_records, n)) +
  theme_bw()
```



How about we were interested in getting record counts for some specific concepts related to Covid-19 symptoms?

```
cdm$condition_occurrence |>
  filter(condition_concept_id %in% c(437663,437390,31967,
                                      4289517,4223659, 312437,
                                      434490,254761,77074)) |>
  group_by(condition_concept_id) |>
  count() |>
  left_join(cdm$concept,
            by=c("condition_concept_id" = "concept_id")) |>
  collect() |>
  ggplot() +
  geom_col(aes(concept_name, n)) +
  theme_bw()+
  xlab("")
```



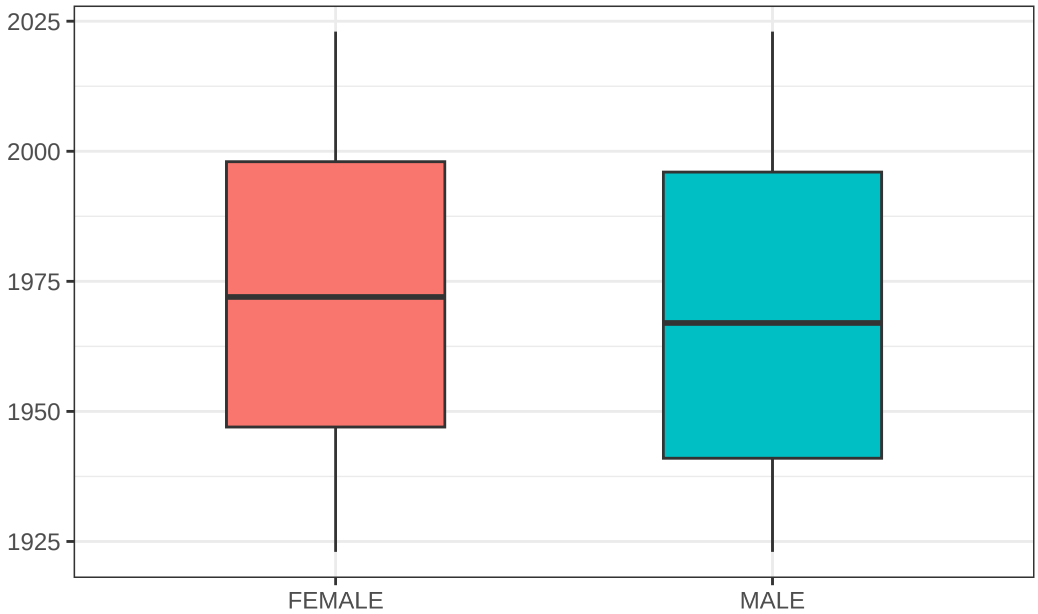
We can also use summarise for various other calculations

```
cdm$person |>
  summarise(min_year_of_birth = min(year_of_birth, na.rm=TRUE),
            q05_year_of_birth = quantile(year_of_birth, 0.05, na.rm=TRUE),
            mean_year_of_birth = round(mean(year_of_birth, na.rm=TRUE),0),
            median_year_of_birth = median(year_of_birth, na.rm=TRUE),
            q95_year_of_birth = quantile(year_of_birth, 0.95, na.rm=TRUE),
            max_year_of_birth = max(year_of_birth, na.rm=TRUE)) |>
  glimpse()
```

```
Rows: ??
Columns: 6
Database: DuckDB v1.2.1 [unknown@Linux 6.11.0-1012-azure:R 4.5.0//tmp/RtmpHwyyYa/file1f8a1069
$ min_year_of_birth    <int> 1923
$ q05_year_of_birth    <dbl> 1927
$ mean_year_of_birth   <dbl> 1971
$ median_year_of_birth <dbl> 1970
$ q95_year_of_birth    <dbl> 2018
$ max_year_of_birth    <int> 2023
```

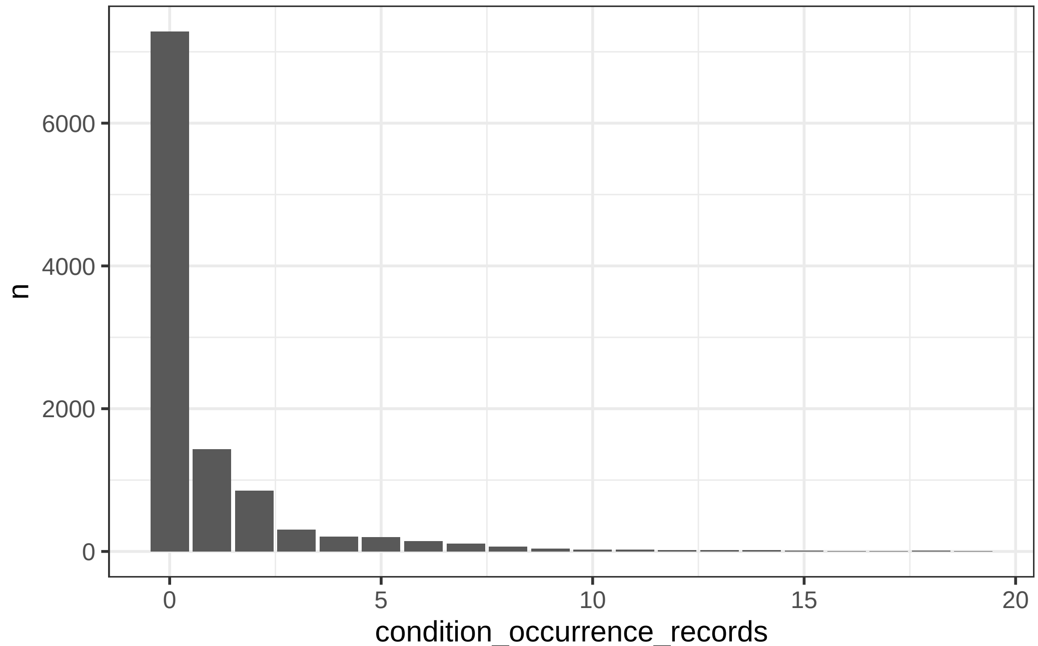
As we've seen before, we can also quickly get results for various groupings or restrictions

```
grouped_summary <- cdm$person |>
   group_by(gender_concept_id) |>
   summarise(min_year_of_birth = min(year_of_birth, na.rm=TRUE),
            q25_year_of_birth = quantile(year_of_birth, 0.25, na.rm=TRUE),
            median_year_of_birth = median(year_of_birth, na.rm=TRUE),
            q75_year_of_birth = quantile(year_of_birth, 0.75, na.rm=TRUE),
            max_year_of_birth = max(year_of_birth, na.rm=TRUE)) |>
  left_join(cdm$concept,
            by=c("gender_concept_id" = "concept_id")) |>
   collect()

grouped_summary |>
  ggplot(aes(x = concept_name, group = concept_name,
             fill = concept_name)) +
  geom_boxplot(aes(
    lower = q25_year_of_birth,
    upper = q75_year_of_birth,
    middle = median_year_of_birth,
    ymin = min_year_of_birth,
    ymax = max_year_of_birth),
    stat = "identity", width = 0.5) +
  theme_bw()+
  theme(legend.position = "none") +
  xlab("")
```



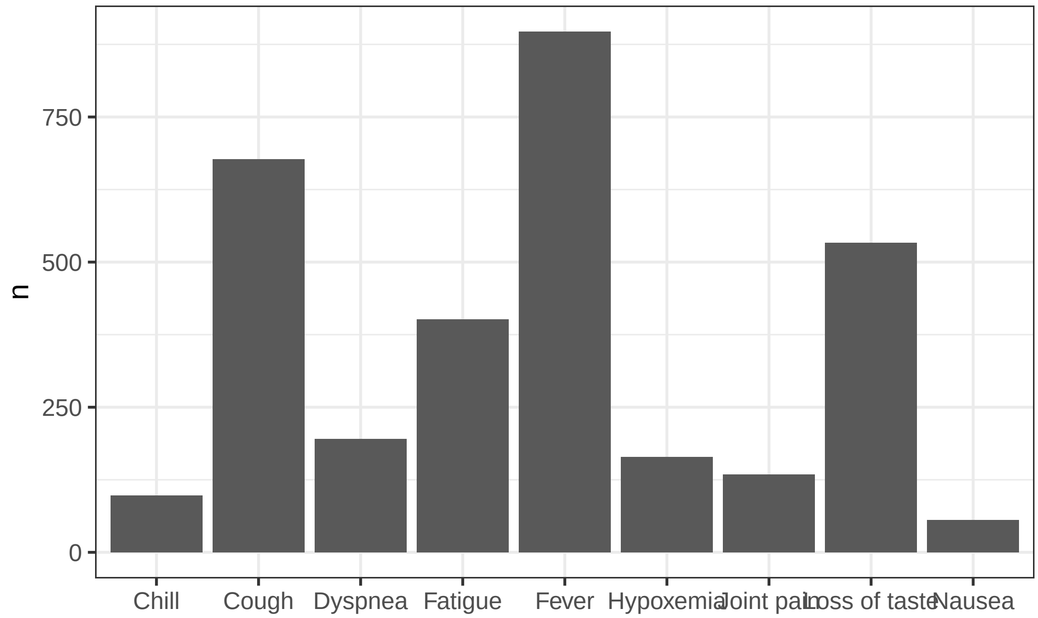
What's the number of condition occurrence records per person in the database? We can find this out like so

```
cdm$person |>
  left_join(cdm$condition_occurrence |>
  group_by(person_id) |>
  count(name = "condition_occurrence_records"),
  by="person_id") |>
  mutate(condition_occurrence_records = if_else(
    is.na(condition_occurrence_records), 0,
    condition_occurrence_records)) |>
  group_by(condition_occurrence_records) |>
  count() |>
  collect() |>
  ggplot() +
  geom_col(aes(condition_occurrence_records, n)) +
  theme_bw()
```



How about we were interested in getting record counts for some specific concepts related to Covid-19 symptoms?

```
cdm$condition_occurrence |>
  filter(condition_concept_id %in% c(437663,437390,31967,
                                     4289517,4223659, 312437,
                                     434490,254761,77074)) |>
  group_by(condition_concept_id) |>
  count() |>
  left_join(cdm$concept,
            by=c("condition_concept_id" = "concept_id")) |>
  collect() |>
  ggplot() +
  geom_col(aes(concept_name, n)) +
  theme_bw()+
  xlab("")
```


750
500
250
0
n
Chill
Cough
Dyspnea
Fatigue
Fever
Hypoxemia
Joint pain
Loss of taste
Nausea

9 Identifying patient characteristics

For this chapter, we'll again use our example COVID-19 dataset.

```
library(DBI)
library(duckdb)
library(dbplyr)
library(dplyr)
library(here)
library(CDMConnector)
library(PatientProfiles)
library(ggplot2)
```

```
db <- dbConnect(drv = duckdb(),
                dbdir = eunomiaDir(datasetName = "synthea-covid19-10k"))
cdm <- cdmFromCon(db, cdmSchema = "main", writeSchema = "main")
```

As part of an analysis we almost always have a need to identify certain characteristics related to the individuals in our data. These characteristics might be time-invariant (ie a characteristic that does not change as time passes and a person ages) or time-varying.[1]

9.1 Adding specific demographics

The `PatientProfiles` package makes it easy for us to add demographic information to tables in the OMOP CDM. Like the `CDMConnector` package we've seen previously, the fact that the structure of the OMOP CDM is known allows the `PatientProfiles` package to abstract away some common data manipulations required to do research with patient-level data.[2]

Let's say we are interested in individuals' age and sex at time of diagnosis with COVID-19. We can add these variables to the table like so (noting that because age is time-varying, we have to specify the variable with the date for which we want to calculate age relative to).

[1] In some datasets characteristics that could conceptually be considered as time-varying are encoded as time-invariant. One example for the latter is that in some cases an individual may be associated with a particular socioeconomic status or nationality that for the purposes of the data is treated as time-invariant.

[2] Although these manipulations can on the face of it seem quite simple, their implementation across different database platforms with different data granularity (for example whether day of birth has been filled in for all patients or not) presents challenges that the `PatientProfiles` package solves for us.

```r
cdm$condition_occurrence <- cdm$condition_occurrence |>
  addSex() |>
  addAge(indexDate = "condition_start_date")

cdm$condition_occurrence |>
  glimpse()
```

```
Rows: ??
Columns: 18
Database: DuckDB v1.2.1 [unknown@Linux 6.11.0-1012-azure:R 4.5.0//tmp/RtmpFr027c/file1fd562b
$ condition_occurrence_id       <int> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 1~
$ person_id                     <int> 2, 6, 7, 8, 8, 8, 8, 16, 16, 18, 18, 25,~
$ condition_concept_id          <int> 381316, 321042, 381316, 37311061, 437663~
$ condition_start_date          <date> 1986-09-08, 2021-06-23, 2021-04-07, 202~
$ condition_start_datetime      <dttm> 1986-09-08, 2021-06-23, 2021-04-07, 202~
$ condition_end_date            <date> 1986-09-08, 2021-06-23, 2021-04-07, 202~
$ condition_end_datetime        <dttm> 1986-09-08, 2021-06-23, 2021-04-07, 202~
$ condition_type_concept_id     <int> 38000175, 38000175, 38000175, 38000175, ~
$ condition_status_concept_id   <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0~
$ stop_reason                   <chr> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, ~
$ provider_id                   <int> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, ~
$ visit_occurrence_id           <int> 19, 55, 67, 79, 79, 79, 79, 168, 171, 19~
$ visit_detail_id               <int> 1000019, 1000055, 1000067, 1000079, 1000~
$ condition_source_value        <chr> "230690007", "410429000", "230690007", "~
$ condition_source_concept_id   <int> 381316, 321042, 381316, 37311061, 437663~
$ condition_status_source_value <chr> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, ~
$ sex                           <chr> "Female", "Male", "Male", "Male", "Male"~
$ age                           <int> 57, 25, 97, 2, 2, 2, 2, 75, 77, 57, 76, ~
```

```r
cdm$condition_occurrence |>
  addSexQuery() |>
  show_query()
```

```
Warning: ! The following columns will be overwritten: sex
```

```
<SQL>
SELECT
  condition_occurrence_id,
  og_002_1746389311.person_id AS person_id,
  condition_concept_id,
```

```
  condition_start_date,
  condition_start_datetime,
  condition_end_date,
  condition_end_datetime,
  condition_type_concept_id,
  condition_status_concept_id,
  stop_reason,
  provider_id,
  visit_occurrence_id,
  visit_detail_id,
  condition_source_value,
  condition_source_concept_id,
  condition_status_source_value,
  age,
  RHS.sex AS sex
FROM og_002_1746389311
LEFT JOIN (
  SELECT
    person_id,
    CASE
WHEN (gender_concept_id = 8507.0) THEN 'Male'
WHEN (gender_concept_id = 8532.0) THEN 'Female'
ELSE 'None'
END AS sex
  FROM person
) RHS
  ON (og_002_1746389311.person_id = RHS.person_id)
```

We now have two variables added containing values for age and sex.

```
cdm$condition_occurrence |>
  glimpse()
```

```
Rows: ??
Columns: 18
Database: DuckDB v1.2.1 [unknown@Linux 6.11.0-1012-azure:R 4.5.0//tmp/RtmpFr027c/file1fd562b
$ condition_occurrence_id       <int> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 1~
$ person_id                     <int> 2, 6, 7, 8, 8, 8, 8, 16, 16, 18, 18, 25,~
$ condition_concept_id          <int> 381316, 321042, 381316, 37311061, 437663~
$ condition_start_date          <date> 1986-09-08, 2021-06-23, 2021-04-07, 202~
$ condition_start_datetime      <dttm> 1986-09-08, 2021-06-23, 2021-04-07, 202~
$ condition_end_date            <date> 1986-09-08, 2021-06-23, 2021-04-07, 202~
```

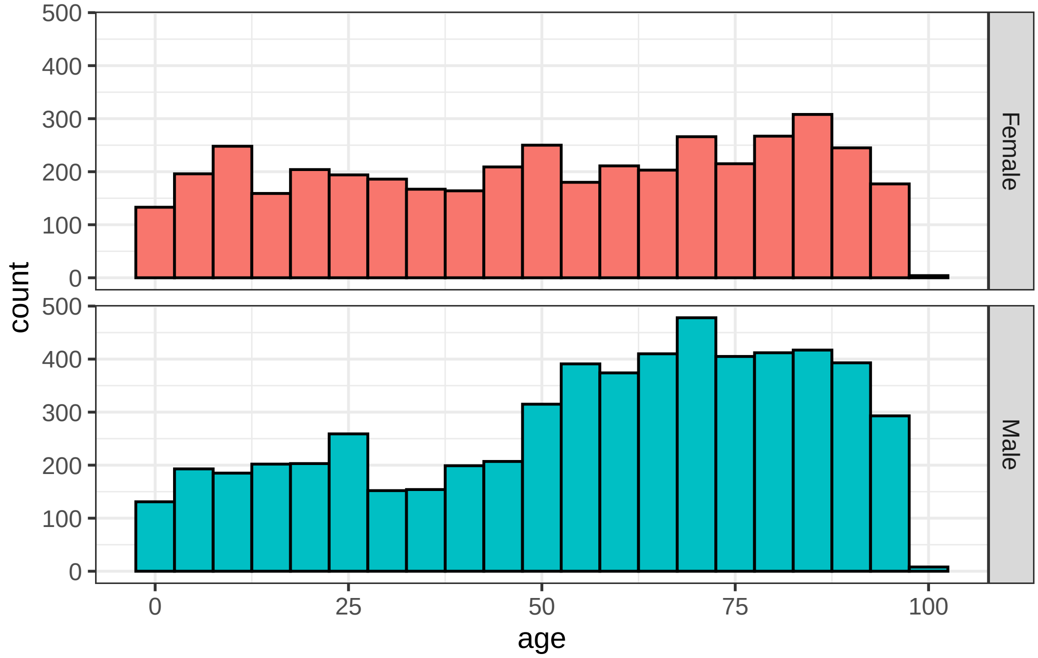
```
$ condition_end_datetime       <dttm> 1986-09-08, 2021-06-23, 2021-04-07, 202~
$ condition_type_concept_id    <int> 38000175, 38000175, 38000175, 38000175, ~
$ condition_status_concept_id  <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0~
$ stop_reason                  <chr> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, ~
$ provider_id                  <int> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, ~
$ visit_occurrence_id          <int> 19, 55, 67, 79, 79, 79, 79, 168, 171, 19~
$ visit_detail_id              <int> 1000019, 1000055, 1000067, 1000079, 1000~
$ condition_source_value       <chr> "230690007", "410429000", "230690007", "~
$ condition_source_concept_id  <int> 381316, 321042, 381316, 37311061, 437663~
$ condition_status_source_value <chr> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, ~
$ sex                          <chr> "Female", "Male", "Male", "Male", "Male"~
$ age                          <int> 57, 25, 97, 2, 2, 2, 2, 75, 77, 57, 76, ~
```

And with these now added it is straightforward to calculate mean age at condition start date by sex or even plot the distribution of age at diagnosis by sex.

```
cdm$condition_occurrence |>
  summarise(mean_age = mean(age, na.rm=TRUE), .by = "sex") |>
  collect()
```

```
# A tibble: 2 x 2
  sex    mean_age
  <chr>     <dbl>
1 Female     50.8
2 Male       56.5
```

```
cdm$condition_occurrence |>
  select("person_id", "age", "sex") |>
  collect()  |>
  ggplot(aes(fill = sex)) +
  facet_grid(sex ~ .) +
  geom_histogram(aes(age), colour = "black", binwidth = 5) +
  theme_bw() +
  theme(legend.position = "none")
```



9.2 Adding multiple demographics simultaneously

We've now seen individual functions from `PatientProfiles` to add age and sex, and the package has others to add other characteristics like days of prior observation in the database (rather unimaginatively named `addPriorObservation()`). In additional to these individuals functions, the package also provides a more general function to get all of these characteristics at the same time.[3]

```
cdm$drug_exposure <- cdm$drug_exposure |>
  addDemographics(indexDate = "drug_exposure_start_date")

cdm$drug_exposure |>
  glimpse()
```

```
Rows: ??
Columns: 27
Database: DuckDB v1.2.1 [unknown@Linux 6.11.0-1012-azure:R 4.5.0//tmp/RtmpFrO27c/file1fd562b
$ drug_exposure_id              <int> 245761, 245762, 245763, 245764, 245765, 2~
```

[3] This function also provides a more time efficient method that getting the characteristics one by one. This is because these characteristics are all derived from the OMOP CDM person and observation period tables and so can be identified simultaneously.

```
$ person_id                   <int> 7764, 7764, 7764, 7764, 7764, 7764, 7764,~
$ drug_concept_id             <int> 40213227, 40213201, 40213198, 40213154, 4~
$ drug_exposure_start_date    <date> 2015-02-08, 2010-01-10, 2010-01-10, 2017~
$ drug_exposure_start_datetime <dttm> 2015-02-08 22:40:04, 2010-01-10 22:40:04~
$ drug_exposure_end_date      <date> 2015-02-08, 2010-01-10, 2010-01-10, 2017~
$ drug_exposure_end_datetime  <dttm> 2015-02-08 22:40:04, 2010-01-10 22:40:04~
$ verbatim_end_date           <date> 2015-02-08, 2010-01-10, 2010-01-10, 2017~
$ drug_type_concept_id        <int> 32869, 32869, 32869, 32869, 32869, 32869,~
$ stop_reason                 <chr> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, N~
$ refills                     <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,~
$ quantity                    <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,~
$ days_supply                 <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,~
$ sig                         <chr> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, N~
$ route_concept_id            <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,~
$ lot_number                  <chr> "0", "0", "0", "0", "0", "0", "0", "0", "~
$ provider_id                 <int> 14656, 14656, 14656, 14656, 14656, 14656,~
$ visit_occurrence_id         <int> 80896, 80891, 80891, 80892, 80895, 80896,~
$ visit_detail_id             <int> 1080896, 1080891, 1080891, 1080892, 10808~
$ drug_source_value           <chr> "113", "33", "133", "140", "140", "140", ~
$ drug_source_concept_id      <int> 40213227, 40213201, 40213198, 40213154, 4~
$ route_source_value          <chr> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, N~
$ dose_unit_source_value      <chr> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, N~
$ age                         <int> 71, 66, 66, 73, 72, 71, 69, 67, 65, 70, 6~
$ sex                         <chr> "Male", "Male", "Male", "Male", "Male", "~
$ prior_observation           <int> 2597, 742, 742, 3339, 2968, 2597, 1855, 1~
$ future_observation          <int> 896, 2751, 2751, 154, 525, 896, 1638, 238~
```

With these characteristics now all added, we can now calculate mean age, prior observation (how many days have passed since the individual's most recent observation start date), and future observation (how many days until the individual's nearest observation end date) at drug exposure start date by sex.

```
cdm$drug_exposure |>
  summarise(mean_age = mean(age, na.rm=TRUE),
            mean_prior_observation = mean(prior_observation, na.rm=TRUE),
            mean_future_observation = mean(future_observation, na.rm=TRUE),
            .by = "sex") |>
  collect()
```

```
# A tibble: 2 x 4
  sex    mean_age mean_prior_observation mean_future_observation
  <chr>     <dbl>                  <dbl>                   <dbl>
```

```
1 Male        43.0                    2455.                   1768.
2 Female      39.4                    2096.                   1661.
```

Returning a query from `PatientProfiles` rather than the result

In the above examples the functions from PatientProfiles will execute queries with the results written to a table in the database (either temporary if no name is provided or a permanent table if one is given). We might though instead want to to instead just get the underlying query back so that we have more control over how and when the query will be executed.

```
cdm$visit_occurrence |>
  addSex() |>
  filter(sex == "Male") |>
  show_query()
```

```
<SQL>
SELECT og_004_1746389312.*
FROM og_004_1746389312
WHERE (sex = 'Male')
```

```
cdm$visit_occurrence |>
  addSex(name = "my_new_table") |>
  filter(sex == "Male") |>
  show_query()
```

```
<SQL>
SELECT my_new_table.*
FROM my_new_table
WHERE (sex = 'Male')
```

```
cdm$visit_occurrence |>
  addSexQuery() |>
  filter(sex == "Male") |>
  show_query()
```

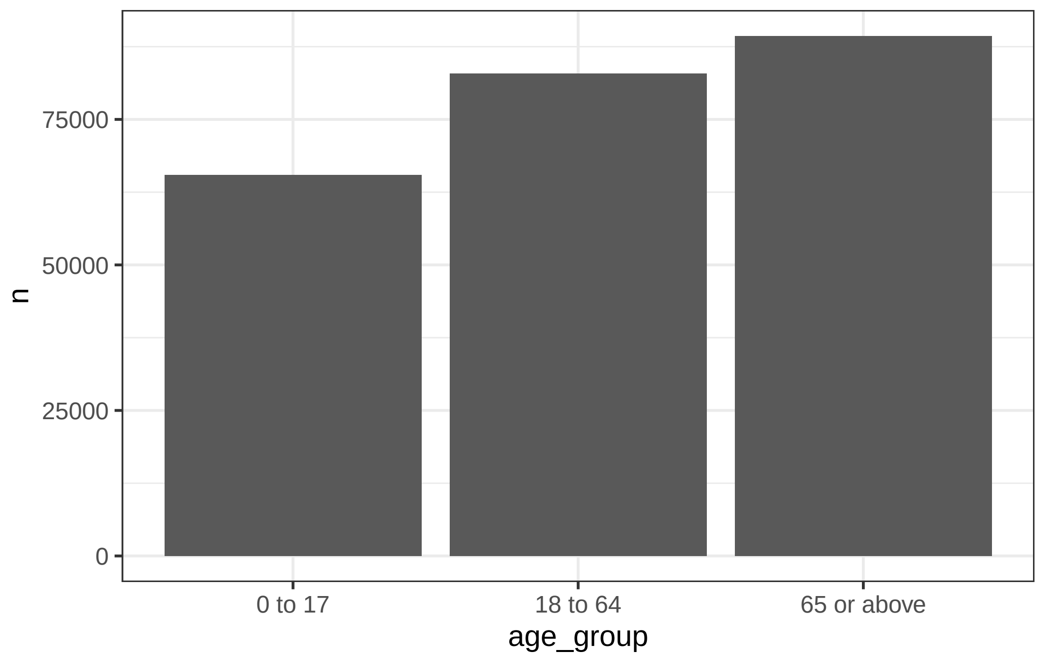
```
<SQL>
SELECT q01.*
FROM (
  SELECT visit_occurrence.*, sex
  FROM visit_occurrence
```

```
  LEFT JOIN (
    SELECT
      person_id,
      CASE
WHEN (gender_concept_id = 8507.0) THEN 'Male'
WHEN (gender_concept_id = 8532.0) THEN 'Female'
ELSE 'None'
END AS sex
    FROM person
  ) RHS
    ON (visit_occurrence.person_id = RHS.person_id)
) q01
WHERE (sex = 'Male')
```

9.3 Creating categories

When we add age, either via addAge or addDemographics, we can also add another variable containing age groups. These age groups are specified in a list of vectors, each of which contain the lower and upper bounds.

```
cdm$visit_occurrence <- cdm$visit_occurrence |>
  addAge(indexDate = "visit_start_date",
    ageGroup = list(c(0,17), c(18, 64),
                    c(65, Inf)))

cdm$visit_occurrence |>
  # data quality issues with our synthetic data means we have
  # some negative ages so will drop these
  filter(age >= 0) |>
  group_by(age_group) |>
  tally() |>
  collect() |>
  ggplot() +
  geom_col(aes(x = age_group, y = n)) +
  theme_bw()
```



`PatientProfiles` also provides a more general function for adding categories. Can you guess it's name? That's right, we have `addCategories()` for this.

```
cdm$condition_occurrence |>
  addPriorObservation(indexDate = "condition_start_date") |>
  addCategories(
    variable = "prior_observation",
    categories = list("prior_observation_group" = list(
      c(0, 364), c(365, Inf)
    ))
  ) |>
  glimpse()
```

```
Rows: ??
Columns: 20
Database: DuckDB v1.2.1 [unknown@Linux 6.11.0-1012-azure:R 4.5.0//tmp/RtmpFr027c/file1fd562b
$ condition_occurrence_id       <int> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 1~
$ person_id                     <int> 2, 6, 7, 8, 8, 8, 8, 16, 16, 18, 18, 25,~
$ condition_concept_id          <int> 381316, 321042, 381316, 37311061, 437663~
$ condition_start_date          <date> 1986-09-08, 2021-06-23, 2021-04-07, 202~
$ condition_start_datetime      <dttm> 1986-09-08, 2021-06-23, 2021-04-07, 202~
$ condition_end_date            <date> 1986-09-08, 2021-06-23, 2021-04-07, 202~
$ condition_end_datetime        <dttm> 1986-09-08, 2021-06-23, 2021-04-07, 202~
```

```
$ condition_type_concept_id     <int> 38000175, 38000175, 38000175, 38000175, ~
$ condition_status_concept_id   <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0~
$ stop_reason                   <chr> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, ~
$ provider_id                   <int> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, ~
$ visit_occurrence_id           <int> 19, 55, 67, 79, 79, 79, 79, 168, 171, 19~
$ visit_detail_id               <int> 1000019, 1000055, 1000067, 1000079, 1000~
$ condition_source_value        <chr> "230690007", "410429000", "230690007", "~
$ condition_source_concept_id   <int> 381316, 321042, 381316, 37311061, 437663~
$ condition_status_source_value <chr> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, ~
$ sex                           <chr> "Female", "Male", "Male", "Male", "Male"~
$ age                           <int> 57, 25, 97, 2, 2, 2, 2, 75, 77, 57, 76, ~
$ prior_observation             <int> 3437, 2898, 2842, 872, 872, 872, 872, 23~
$ prior_observation_group       <chr> "365 or above", "365 or above", "365 or ~
```

9.4 Adding custom variables

While `PatientProfiles` provides a range of functions that can help add characteristics of interest, you may also want to add other features . Obviously we can't cover here all possible custom characteristics you may wish to add. However, two common groups of custom features are those that are derived from other variables in the same table and others that are taken from other tables and joined to our particular table of interest.

In the first case where we want to add a new variable derived from other variables in our table we'll typically be using `mutate()` (from *dplyr* package). For example, perhaps we just want to add a new variable to our observation period table containing the year of individuals' observation period start date. This is rather straightforward.

```r
cdm$observation_period <- cdm$observation_period |>
  mutate(observation_period_start_year = get_year(observation_period_start_date))

cdm$observation_period |>
  glimpse()
```

```
Rows: ??
Columns: 6
Database: DuckDB v1.2.1 [unknown@Linux 6.11.0-1012-azure:R 4.5.0//tmp/RtmpFrO27c/file1fd562b
$ observation_period_id         <int> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 1~
$ person_id                     <int> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 1~
$ observation_period_start_date <date> 2014-05-09, 1977-04-11, 2014-04-19, 201~
$ observation_period_end_date   <date> 2023-05-12, 1986-09-15, 2023-04-22, 202~
$ period_type_concept_id        <int> 44814724, 44814724, 44814724, 44814724, ~
$ observation_period_start_year <dbl> 2014, 1977, 2014, 2014, 2013, 2013, 2013~
```

The second case is normally a more complex task where adding a new variable involves joining to some other table. This table may well have been created by some intermediate query that we wrote to derive the variable of interest. For example, lets say we want to add each number of condition occurrence records for each individual to the person table (remember that we saw how to calculate this in the previous chapter). For this we will need to do a join between the person and condition occurrence tables (as some people might not have any records in the condition occurrence table). Here we'll save the create a table containing just the information we're interested in and compute to a temporary table.

```
condition_summary <- cdm$person |>
  select("person_id") |>
  left_join(cdm$condition_occurrence |>
  group_by(person_id) |>
  count(name = "condition_occurrence_records"),
  by="person_id") |>
  select("person_id", "condition_occurrence_records") |>
  mutate(condition_occurrence_records = if_else(
    is.na(condition_occurrence_records),
    0, condition_occurrence_records)) |>
  compute()

condition_summary |>
  glimpse()
```

```
Rows: ??
Columns: 2
Database: DuckDB v1.2.1 [unknown@Linux 6.11.0-1012-azure:R 4.5.0//tmp/RtmpFrO27c/file1fd562b
$ person_id                   <int> 2, 7, 16, 18, 25, 36, 42, 44, 47, 51, 52,~
$ condition_occurrence_records <dbl> 1, 1, 2, 2, 1, 4, 3, 2, 5, 1, 3, 2, 1, 4,~
```

We can see what goes on behind the scenes by viewing the associated SQL.

```
cdm$person |>
  select("person_id") |>
  left_join(cdm$condition_occurrence |>
  group_by(person_id) |>
  count(name = "condition_occurrence_records"),
  by="person_id") |>
  select("person_id", "condition_occurrence_records") |>
  mutate(condition_occurrence_records = if_else(
    is.na(condition_occurrence_records),
```

```
    0, condition_occurrence_records)) |>
  show_query()
```

```
<SQL>
SELECT
  person_id,
  CASE WHEN ((condition_occurrence_records IS NULL)) THEN 0.0 WHEN NOT ((condition_occurrenc
FROM (
  SELECT person.person_id AS person_id, condition_occurrence_records
  FROM person
  LEFT JOIN (
    SELECT person_id, COUNT(*) AS condition_occurrence_records
    FROM og_002_1746389311
    GROUP BY person_id
  ) RHS
    ON (person.person_id = RHS.person_id)
) q01
```

Taking care with joins

When adding variables through joins we need to pay particular attention to the dimensions of the resulting table. While sometimes we may want to have additional rows added as well as new columns, this is often not desired. If we, for example, have a table with one row per person then a left join to a table with multiple rows per person can then result in a table with multiple rows per person.

Examples where to be careful include when joining to the observation period table, as individuals can have multiple observation periods, and when working with cohorts (which are the focus of the next chapter) as individuals can also enter the same study cohort multiple times.

Just to underline how problematic joins can become if we don't take care, here we join the condition occurrence table and the drug exposure table both of which have multiple records per person. Remember this is just with our small synthetic data, so when working with real patient data which is oftentimes much, much larger this would be extremely problematic (and would unlikely be needed to answer any research question). In other words, don't try this at home!

```
cdm$condition_occurrence |>
  tally()
```

```
# Source:   SQL [?? x 1]
# Database: DuckDB v1.2.1 [unknown@Linux 6.11.0-1012-azure:R 4.5.0//tmp/RtmpFr027c/file1fd5
```

```
      n
  <dbl>
1  9967
```

```r
cdm$drug_exposure |>
  tally()
```

```
# Source:   SQL [?? x 1]
# Database: DuckDB v1.2.1 [unknown@Linux 6.11.0-1012-azure:R 4.5.0//tmp/RtmpFr027c/file1fd5
       n
   <dbl>
1 337509
```

```r
cdm$condition_occurrence |>
  select(person_id, condition_start_date) |>
  left_join(cdm$drug_exposure |>
  select(person_id, drug_exposure_start_date),
  by = "person_id") |>
  tally()
```

```
# Source:   SQL [?? x 1]
# Database: DuckDB v1.2.1 [unknown@Linux 6.11.0-1012-azure:R 4.5.0//tmp/RtmpFr027c/file1fd5
       n
   <dbl>
1 410683
```

10 Further reading

- PatientProfiles package

11 Adding cohorts to the CDM

11.1 What is a cohort?

When performing research with the OMOP common data model we often want to identify groups of individuals who share some set of characteristics. The criteria for including individuals can range from the seemingly simple (e.g. people diagnosed with asthma) to the much more complicated (e.g. adults diagnosed with asthma who had a year of prior observation time in the database prior to their diagnosis, had no prior history of chronic obstructive pulmonary disease, and no history of use of short-acting beta-antagonists).

The set of people we identify are cohorts, and the OMOP CDM has a specific structure by which they can be represented, with a cohort table having four required fields: 1) cohort definition id (a unique identifier for each cohort), 2) subject id (a foreign key to the subject in the cohort - typically referring to records in the person table), 3) cohort start date, and 4) cohort end date. Individuals can enter a cohort multiple times, but the time periods in which they are in the cohort cannot overlap. Individuals will only be considered in a cohort when they have have an ongoing observation period.

It is beyond the scope of this book to describe all the different ways cohorts could be created, however in this chapter we provide a summary of some of the key building blocks for cohort creation. Cohort-building pipelines can be created following these principles to create a wide range of study cohorts.

11.2 Set up

We'll use our synthetic dataset for demonstrating how cohorts can be constructed.

```
library(DBI)
library(duckdb)
library(CDMConnector)
library(CodelistGenerator)
library(CohortConstructor)
library(CohortCharacteristics)
library(dplyr)
```

```r
db <- dbConnect(drv = duckdb(),
                dbdir = eunomiaDir(datasetName = "synthea-covid19-10k"))
cdm <- cdmFromCon(db, cdmSchema = "main", writeSchema = "main")
```

11.3 General concept based cohort

Often study cohorts will be based around a specific clinical event identified by some set of clinical codes. Here, for example, we use the `CohortConstructor` package to create a cohort of people with Covid-19. For this we are identifying any clinical records with the code 37311061.

```r
cdm$covid <- conceptCohort(cdm = cdm,
                           conceptSet = list("covid" = 37311061),
                           name = "covid")
cdm$covid
```

```
# Source:   table<covid> [?? x 4]
# Database: DuckDB v1.2.1 [unknown@Linux 6.11.0-1012-azure:R 4.5.0//tmp/RtmpaqSVSc/file20123e
   cohort_definition_id subject_id cohort_start_date cohort_end_date
                  <int>      <int> <date>            <date>
 1                    1       1606 2021-01-18        2021-02-13
 2                    1       2527 2021-08-22        2021-09-14
 3                    1       2695 2020-07-18        2020-07-31
 4                    1       1058 2020-06-29        2020-07-14
 5                    1       1532 2020-07-09        2020-08-10
 6                    1       3042 2020-12-09        2020-12-27
 7                    1       4606 2020-12-23        2021-01-12
 8                    1       5830 2021-06-25        2021-07-25
 9                    1       9409 2021-04-03        2021-05-01
10                    1       1068 2020-03-24        2020-04-23
# i more rows
```

Finding appropriate codes

In the defining the cohorts above we have needed to provide concept IDs to define our cohort. But, where do these come from?
We can search for codes of interest using the `CodelistGenerator` package. This can be done using a text search with the function `CodelistGenerator::getCandidateCodes()`. For example, we can have found the code we used above (and many others) like so:

```r
getCandidateCodes(cdm = cdm,
                  keywords = c("coronavirus","covid"),
                  domains = "condition",
                  includeDescendants = TRUE)
```

```
Limiting to domains of interest
Getting concepts to include
Adding descendants
Search completed. Finishing up.
v 37 candidate concepts identified

Time taken: 0 minutes and 1 seconds

# A tibble: 37 x 6
   concept_id found_from   concept_name domain_id vocabulary_id standard_concept
        <int> <chr>        <chr>        <chr>     <chr>         <chr>
 1     756039 From initia~ Respiratory~ Condition OMOP Extensi~ S
 2     756031 From initia~ Bronchitis ~ Condition OMOP Extensi~ S
 3    3661885 From initia~ Fever cause~ Condition SNOMED        S
 4   37310286 From initia~ Infection o~ Condition SNOMED        S
 5     703447 From initia~ High risk c~ Condition SNOMED        S
 6    3661632 From initia~ Thrombocyto~ Condition SNOMED        S
 7    3656667 From initia~ Cardiomyopa~ Condition SNOMED        S
 8    3656669 From initia~ Dyspnea cau~ Condition SNOMED        S
 9   37310284 From initia~ Encephalopa~ Condition SNOMED        S
10     703446 From initia~ Moderate ri~ Condition SNOMED        S
# i 27 more rows
```

We can also do automated searches that make use of the hierarchies in the vocabularies. Here, for example, we find the code for the drug ingredient Acetaminophen and all of it's descendants.

```r
getDrugIngredientCodes(cdm = cdm, name = "acetaminophen")
```

```
-- 1 codelist -----------------------------------------------------------------

- 161_acetaminophen (25747 codes)
```

Note that in practice clinical expertise is vital in the identification of appropriate codes so as to decide which the codes are in line with the clinical idea at hand.

We can see that as well as having the cohort entries above, our cohort table is associated with several attributes.

First, we can see the settings associated with cohort.

```
settings(cdm$covid) |>
  glimpse()
```

```
Rows: 1
Columns: 4
$ cohort_definition_id <int> 1
$ cohort_name          <chr> "covid"
$ cdm_version          <chr> "5.3"
$ vocabulary_version   <chr> "v5.0 22-JUN-22"
```

Second, we can get counts of the cohort.

```
cohortCount(cdm$covid) |>
  glimpse()
```

```
Rows: 1
Columns: 3
$ cohort_definition_id <int> 1
$ number_records       <int> 964
$ number_subjects      <int> 964
```

And last we can see attrition related to the cohort.

```
attrition(cdm$covid) |>
  glimpse()
```

```
Rows: 4
Columns: 7
$ cohort_definition_id <int> 1, 1, 1, 1
$ number_records       <int> 964, 964, 964, 964
$ number_subjects      <int> 964, 964, 964, 964
$ reason_id            <int> 1, 2, 3, 4
$ reason               <chr> "Initial qualifying events", "Record start <= rec~
$ excluded_records     <int> 0, 0, 0, 0
$ excluded_subjects    <int> 0, 0, 0, 0
```

As we will see below these attributes of the cohorts become particularly useful as we apply further restrictions on our cohort.

11.4 Applying inclusion criteria

11.4.1 Only include first cohort entry per person

Let's say we first want to restrict to first entry.

```
cdm$covid <- cdm$covid |>
     requireIsFirstEntry()
```

11.4.2 Restrict to study period

```
cdm$covid <- cdm$covid |>
   requireInDateRange(dateRange = c(as.Date("2020-09-01"), NA))
```

11.4.3 Applying demographic inclusion criteria

Say for our study we want to include people with a GI bleed who were aged 40 or over at the time. We can use the add variables with these characteristics as seen in chapter 4 and then filter accordingly. The function `CDMConnector::record_cohort_attrition()` will then update our cohort attributes as we can see below.

```
cdm$covid <- cdm$covid |>
   requireDemographics(ageRange = c(18, 64), sex = "Male")
```

11.4.4 Applying cohort-based inclusion criteria

As well as requirements about specific demographics, we may also want to use another cohort for inclusion criteria. Let's say we want to exclude anyone with a history of cardiac conditions before their Covid-19 cohort entry.

We can first generate this new cohort table with records of cardiac conditions.

```
cdm$cardiac <- conceptCohort(
  cdm = cdm,
  list("myocaridal_infarction" = c(
    317576, 313217, 321042, 4329847
  )),
name = "cardiac"
```

```
)
cdm$cardiac
```

```
# Source:   table<cardiac> [?? x 4]
# Database: DuckDB v1.2.1 [unknown@Linux 6.11.0-1012-azure:R 4.5.0//tmp/RtmpaqSVSc/file20123
   cohort_definition_id subject_id cohort_start_date cohort_end_date
                  <int>      <int> <date>            <date>
 1                    1        674 2001-08-12        2001-08-12
 2                    1       3846 1976-11-03        1976-11-03
 3                    1       4290 2018-05-07        2018-05-07
 4                    1       5842 1964-04-08        1964-04-08
 5                    1       5926 2006-02-14        2006-02-14
 6                    1       8649 2019-06-16        2019-06-16
 7                    1       8805 1977-10-24        1977-10-24
 8                    1      10252 2008-12-18        2008-12-18
 9                    1       1923 1995-11-13        1995-11-13
10                    1       3403 1989-04-03        1989-04-03
# i more rows
```

And now we can apply the inclusion criteria that individuals have zero intersections with the table in the time prior to their Covid-19 cohort entry.

```
cdm$covid <- cdm$covid |>
  requireCohortIntersect(targetCohortTable = "cardiac",
                         indexDate = "cohort_start_date",
                         window = c(-Inf, -1),
                         intersections = 0)
```

Note if we had wanted to have required that individuals did have a history of a cardiac condition we would instead have set `intersections = c(1, Inf)` above.

11.5 Cohort attributes

We can see that the attributes of the cohort were updated as we applied the inclusion criteria.

```
settings(cdm$covid) |>
  glimpse()
```

```
Rows: 1
Columns: 8
$ cohort_definition_id   <int> 1
$ cohort_name            <chr> "covid"
$ age_range              <chr> "18_64"
$ sex                    <chr> "Male"
$ min_prior_observation  <dbl> 0
$ min_future_observation <dbl> 0
$ cdm_version            <chr> "5.3"
$ vocabulary_version     <chr> "v5.0 22-JUN-22"
```

```r
cohortCount(cdm$covid) |>
  glimpse()
```

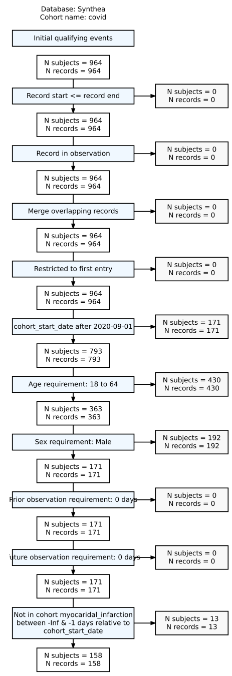
```
Rows: 1
Columns: 3
$ cohort_definition_id <int> 1
$ number_records       <int> 158
$ number_subjects      <int> 158
```

```r
attrition(cdm$covid) |>
  glimpse()
```

```
Rows: 11
Columns: 7
$ cohort_definition_id <int> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1
$ number_records       <int> 964, 964, 964, 964, 964, 793, 363, 171, 171, 171,~
$ number_subjects      <int> 964, 964, 964, 964, 964, 793, 363, 171, 171, 171,~
$ reason_id            <int> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11
$ reason               <chr> "Initial qualifying events", "Record start <= rec~
$ excluded_records     <int> 0, 0, 0, 0, 0, 171, 430, 192, 0, 0, 13
$ excluded_subjects    <int> 0, 0, 0, 0, 0, 171, 430, 192, 0, 0, 13
```

For attrition, we can use `CohortConstructor::summariseCohortAttrition()` and then `CohortConstructor::tableCohortAttrition()` to better view the impact of applying the additional inclusion criteria.

```r
attrition_summary <- summariseCohortAttrition(cdm$covid)
plotCohortAttrition(attrition_summary, type = 'png')
```



Database: Synthea
Cohort name: covid
Initial qualifying events
N subjects = 964
N records = 964
Record start <= record end
N subjects = 0
N records = 0
N subjects = 964
N records = 964
Record in observation
N subjects = 0
N records = 0
N subjects = 964
N records = 964
Merge overlapping records
N subjects = 0
N records = 0
N subjects = 964
N records = 964
Restricted to first entry
N subjects = 0
N records = 0
N subjects = 964
N records = 964
cohort_start_date after 2020-09-01
N subjects = 171
N records = 171
N subjects = 793
N records = 793
Age requirement: 18 to 64
N subjects = 430
N records = 430
N subjects = 363
N records = 363
Sex requirement: Male
N subjects = 192
N records = 192
N subjects = 171
N records = 171
Prior observation requirement: 0 days
N subjects = 0
N records = 0
N subjects = 171
N records = 171
Future observation requirement: 0 days
N subjects = 0
N records = 0
N subjects = 171
N records = 171
Not in cohort myocaridal_infarction between -Inf & -1 days relative to cohort_start_date
N subjects = 13
N records = 13
N subjects = 158
N records = 158

12 Further reading

- ...

13 Working with cohorts

13.1 Cohort intersections

PatientProfiles::addCohortIntersect()

13.2 Intersection between two cohorts

13.3 Set up

```
library(CDMConnector)
library(dplyr)
library(PatientProfiles)

# For this example we will use GiBleed data set
downloadEunomiaData(datasetName = "GiBleed")
db <- DBI::dbConnect(duckdb::duckdb(), eunomiaDir())

cdm <- cdmFromCon(db, cdmSchema = "main", writeSchema = "main")

# cdm <- cdm |>
#   generate_concept_cohort_set(concept_set = list("gi_bleed" = 192671),
#                               limit = "all",
#                               end = 30,
#                               name = "gi_bleed",
#                               overwrite = TRUE) |>
#   generate_concept_cohort_set(concept_set = list("acetaminophen" = c(1125315,
#                                                                      1127078,
#                                                                      1127433,
#                                                                      40229134,
#                                                                      40231925,
#                                                                      40162522,
#                                                                      19133768)),
```

```
#                                limit = "all",
#                              # end = "event_end_date",
#                              name = "acetaminophen",
#                              overwrite = TRUE)
```

13.3.1 Flag

```
# cdm$gi_bleed <- cdm$gi_bleed |>
#   addCohortIntersectFlag(targetCohortTable = "acetaminophen",
#                           window = list(c(-Inf, -1), c(0,0), c(1, Inf)))
#
# cdm$gi_bleed |>
#   summarise(acetaminophen_prior = sum(acetaminophen_minf_to_m1),
#             acetaminophen_index = sum(acetaminophen_0_to_0),
#             acetaminophen_post = sum(acetaminophen_1_to_inf)) |>
#   collect()
```

13.3.2 Count

13.3.3 Date and times

13.4 Intersection between a cohort and tables with patient data

14 Further reading

- ...