SQL A Quick Introduction

Introduction

DATABASE

- There are mainly two type of database
  1. Relational:
     Tables in relational database resemble Excel spreadsheets (Rows and Columns). Tables in relational database can have relation to each others and it is done by the concept `keys`.
  2. Non-Relational: Data can be organized in any format but not a table (non-tabular form, and tends to be more flexible than SQL-based) like JSON files (It is a collection of key-value pairs where the key must be a string type, and the value can be of any of the following types: Number, String.)
     Example of some simple JSON data

{ "course": "DATA613", "level": "Graduate", "credit": 3 }

To utilize data in a relational database we use `SQL` and for non-relational we use another language called `NOSQL` (Not Only SQL). `NOSQL` databases use `JSON` (JavaScript Object Notation), XML, YAML, or binary schema, facilitating unstructured data. Our focus here is on SQL!

SQL

SQL is a database query language - a language designed specifically for interacting with a database. It offers syntax for extracting data, updating data, replacing data, creating data, etc. For our purposes, it will typically be used when accessing data off a server database. If the database isn't too large, you can grab the entire data set and stick it in a data.frame. However, often the data are quite large so you interact with it piecemeal via SQL.

- SQL is how you download this subset. You choose which data frames ("tables" in SQL) to download, what subsets of these tables to download (by filtering rows), and whether to join tables together in this process.
- SQL allows you to do a lot that {dplr} does. It is industry standard for interacting with a relational database.
- One of the nice advantage of SQL is, you do not need to export data from the database into a file and then load it into R. And have to redo it again each time the data is updated. With SQL, we can get our code directly and get the most recent data straight out of the database.
- To work with relational database system we need special software known as a DataBase Management System (DBMS). It is a workspace for us to write SQL statement. There are different DBMS that you can use. For instance

  - MYSQL
  - Microsoft SQL Server
  - Oracle
  - Postgres SQL
  - and may more.

  The method of connecting with each database may differ, but they support SQL (specifically they support ANSI SQL). If you get familiar with one of these DBMS then transition from one server to another is not very hard.

- We will use R Studio in this lesson. But if you get really into SQL, a popular IDE is DBeaver , with a tutorial from DuckDB here .

  - The first step in using SQL is accessing the actual data. There are a few packages that might be useful in connecting

    * DBI
    * RODBC
    * dbConnect
    * RSQLite
    * RMySQL
    * RPostgreSQL

SQL for Database Management

A **DBMS (Database Management System)** is software that allows users to efficiently store, manage, and query data in databases. Important ones include **MySQL**, **PostgreSQL**, **SQL Server**, **Oracle**, and **SQLite**.

DBMS tools are software applications used to manage and interact with databases. Important ones include **DBeaver**, **MySQL,** ,and **Oracle SQL Developer**.

Database Management Focus: DBM tools are specifically designed for **database management** tasks, such as:

- Structuring and managing data.
- Writing and testing SQL queries.
- Performing tasks like joining tables, filtering, and data manipulation directly within the database, rather than relying on R's code-based approach.

What is DBeaver?

- **DBeaver** is an open-source, cross-platform database management tool designed for working with **SQL databases** and **NoSQL databases**.
- It provides a **graphical interface** to interact with databases, making it easy to manage and explore data, run SQL queries, and generate **ER diagrams** to visualize database structure.
- DBeaver supports a wide range of databases and provides tools for **SQL editing**, **query execution**, **data browsing**, **schema management**, and **database administration**.
- It's an ideal tool for both **beginners** learning SQL and **advanced users** working with complex databases.

SQL In R

- **Note:** In this class we learn
- Interface SQL with R through the `{DBI}` package.
- Write SQL code using the tidyverse and the `{dbplyr}` package.

Install and Load necessary packages

The first package we load is {DBI}, it is the basic database infrastructure. It let's R to talk to lots of different kind of dadtabases and perform required tasks.

- **{DBI}** – Acts as a bridge between R and databases, providing a consistent way to connect and send queries.
- **{DBI}** lets R talk to DuckDB.

```
library(DBI)
```

{duckdb}: It tells {DBI} package translate between R and database. There are other related packages for translating between R and other database management system like {duckdb} or {RSQLite}.

- **{duckdb}** – A fast, in-memory database that processes SQL queries efficiently without requiring an external database server.
- **{duckdb}** executes SQL queries efficiently.

```
library(duckdb)
```

{dbplyr}: If we want to interact with database directly using {dplyr} we need to load {dbplyr} (database plyr package). That will allow {dplyr} and databases to interact by using the package {DBI}.

- **{dplyr}** – Allows users to manipulate data using R functions instead of writing raw SQL, making database operations easier.
- **{dplyr}** enables SQL-like operations in R without writing SQL directly.

An overview example showing how `{dplyr}` allows you to perform `SQL` queries.

Scenario:

Suppose you have a `data.frame` in R with sales data, and you want to:

- Filter rows where the sales are greater than $100.

- Group the data by `region`.
- Calculate the average sales per region.

When you're working with a database connection, **{dplyr}** automatically detects that you're using a database and translates its functions (like `filter()`, `group_by()`, etc.) into SQL queries instead of running them in-memory as it would with a local `data.frame`.

Here's how the connection and detection process works:

1. **Set up the connection** with **{DBI}** and **{duckdb}**:

```r
# Connect to DuckDB (this creates an in-memory database)
dbcon <- dbConnect(duckdb::duckdb())
```

2. **Create a table in DuckDB** (optional, if you want to work with an actual database table):

```r
# Sample data frame
sales_data <- data.frame(
  region = c("North", "South", "East", "West", "North", "South"),
  sales = c(150, 120, 90, 200, 300, 80)
)
```

```r
# Copy the data into DuckDB
dbWriteTable(dbcon, "sales", sales_data)
```

```r
# Check if the connection is established
dbIsValid(dbcon)
```

```
[1] TRUE
```

3. **Use {dplyr} to query the database**:

```r
# Now use dplyr to interact with the database
result <- tbl(dbcon, "sales") %>%
  filter(sales > 100) %>%
  group_by(region) %>%
  summarise(avg_sales = mean(sales))

# Show the result
print(result)
```

```
Warning: Missing values are always removed in SQL aggregation functions.
Use `na.rm = TRUE` to silence this warning
This warning is displayed once every 8 hours.
```

```
# Source:   SQL [3 x 2]
# Database: DuckDB v1.1.3-dev165 [semiyari@Windows 10 x64:R 4.4.2/:memory:]
  region avg_sales
  <chr>      <dbl>
1 North        225
2 West         200
3 South        120
```

What happens behind the scenes:

- The `tbl()` function tells **{dplyr}** to treat the `"sales"` table as a database object (not a local `data.frame`).
- Once **{dplyr}** detects the connection (`dbcon`), it automatically knows you're working with a database and will translate the `filter()`, `group_by()`, and `summarise()` operations into the appropriate **SQL** commands instead of running them in R.

For instance, the query for the above operation would look something like this in SQL: SQL

```sql
SELECT region, AVG(sales) AS avg_sales
FROM sales
WHERE sales > 100
GROUP BY region
```

Table 1: 3 records

region	avg_sales
North	225
South	120
West	200

How does {dplyr} know?

- The `tbl()` function is the key. When you provide a **database connection** as an argument, **{dplyr}** recognizes that it should interact with the database and generate SQL queries.
- If you were using a local `data.frame`, it would just run the operations in R, not SQL.

So, **{dplyr}** translates your R code to SQL under the hood when it detects that you're working with a database connection.

Closing the connection

We are done with this example so we need to close the connection.

```
# Close the previous connection if it is open
if (dbIsValid(dbcon)) {
  dbDisconnect(dbcon)
  cat("Previous connection closed.")
} else {
  cat("No active connection to close.")
}
```

```
Previous connection closed.
```

Another Example:

Connecting using {duckdb}

Let's download a duck database from: https://data-science-master.github.io/lectures/data/flights.duckdb

```
<mark style="background-color: lightblue">R</mark>
```

```
# Download the DuckDB file from the provided URL

url <- "https://data-science-master.github.io/lectures/data/flights.duckdb"

download.file(url, destfile = "../data/flights.duckdb", mode = "wb")
```

```
Warning in download.file(url, destfile = "../data/flights.duckdb", mode =
"wb"): URL https://data-science-master.github.io/lectures/data/flights.duckdb:
cannot open destfile '../data/flights.duckdb', reason 'Permission denied'
```

```
Warning in download.file(url, destfile = "../data/flights.duckdb", mode =
"wb"): download had nonzero exit status
```

- The first argument is the driver from {duckdb} that helps translate between R and the database. The driver is loaded using the `duckdb()` function.
- The second argument is the path to our database file.

  R

```
conn <- dbConnect(duckdb(), "../data/flights.duckdb", read_only = TRUE)
```

Check the Connection

- If you look at the "environment pane" you will see the "Formal class duckdb_connect…" This means we have connected to this database.
- To check if the connection is closed use the `dbIsValid()` function in R. This function returns TRUE if the connection is valid (open) and FALSE if it is closed.

  R

```
dbIsValid(conn)
```

```
[1] TRUE
```

Basic Operations:

- Once we connected to database we can look at it to see what is going on by using `dbListTables()`, where the argument is the connection object we made. It will shows the tables we have in this database. The warning message says when finishing with your work you must disconnect.

  R

```
dbListTables(conn)
```

```
[1] "airlines" "airports" "flights"  "planes"   "weather"
```

- We also can find out the details of the individual tables by `dbListFields()`, where the first argument is the connection we made and the seconf wrapped in qutation is the name of the table that we are interested in

  R

```
dbListFields(conn, "flights")
```

```
 [1] "year"           "month"          "day"            "dep_time"
 [5] "sched_dep_time" "dep_delay"      "arr_time"       "sched_arr_time"
 [9] "arr_delay"      "carrier"        "flight"         "tailnum"
[13] "origin"         "dest"           "air_time"       "distance"
[17] "hour"           "minute"         "time_hour"
```

```
<mark style="background-color: lightblue">R</mark>
```

```
dbListFields(conn, "planes")
```

```
[1] "tailnum"      "year"         "type"         "manufacturer" "model"
[6] "engines"      "seats"        "speed"        "engine"
```

```
<mark style="background-color: lightblue">R</mark>
```

```
dbListFields(conn, "airports")
```

```
[1] "faa"   "name"  "lat"   "lon"   "alt"   "tz"    "dst"   "tzone"
```

- In addition to looking at a table in a dataframe we can also make direct connections to those individual tables and we can do that using `tbl()` from {dplyr}.
- Let's assume we want to make a connect link to "airports" table via `tbl()` from `{dplyr}`

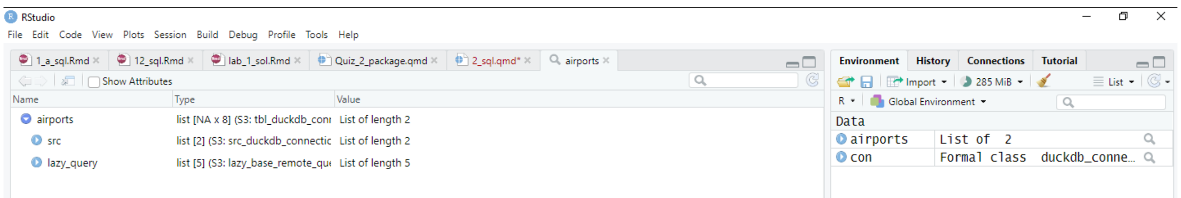
  R

```
tbl(conn, "airports") -> airports
airports
```

```
# Source:   table<airports> [?? x 8]
# Database: DuckDB v1.1.3-dev165 [semiyari@Windows 10 x64:R 4.4.2/C:\Users\semiyari\Desktop\
   faa   name                             lat   lon   alt    tz dst   tzone
   <chr> <chr>                          <dbl> <dbl> <dbl> <dbl> <chr> <chr>
 1 04G   Lansdowne Airport               41.1 -80.6  1044    -5 A     America/~
 2 06A   Moton Field Municipal Airport   32.5 -85.7   264    -6 A     America/~
 3 06C   Schaumburg Regional             42.0 -88.1   801    -6 A     America/~
 4 06N   Randall Airport                 41.4 -74.4   523    -5 A     America/~
 5 09J   Jekyll Island Airport           31.1 -81.4    11    -5 A     America/~
```

```
 6 0A9   Elizabethton Municipal Airport  36.4  -82.2  1593    -5 A     America/~
 7 0G6   Williams County Airport         41.5  -84.5   730    -5 A     America/~
 8 0G7   Finger Lakes Regional Airport   42.9  -76.8   492    -5 A     America/~
 9 0P2   Shoestring Aviation Airfield    39.8  -76.6  1000    -5 U     America/~
10 0S9   Jefferson County Intl           48.1 -123.    108    -8 A     America/~
# i more rows
```

- if you look at the the output you will see the number of rows is unknown.
- You will see something like `[??,8]` which indicates `??` rows and 8 columns. This is because R does not have the entire table. it only knows the first 10 rows as you can see from the output of the previous command.
- However, if you click the "airports" objects in the "environment" pane you will see some confusing output.




```r
View(airports)
```

If we want to bring this table to R we need to use `collect()` function

```r
airports |>
  collect() ->
  df_airports
df_airports
```

```
# A tibble: 1,458 x 8
   faa   name                             lat    lon   alt    tz dst   tzone
   <chr> <chr>                          <dbl>  <dbl> <dbl> <dbl> <chr> <chr>
 1 04G   Lansdowne Airport               41.1  -80.6  1044    -5 A     America/~
 2 06A   Moton Field Municipal Airport   32.5  -85.7   264    -6 A     America/~
 3 06C   Schaumburg Regional             42.0  -88.1   801    -6 A     America/~
 4 06N   Randall Airport                 41.4  -74.4   523    -5 A     America/~
 5 09J   Jekyll Island Airport           31.1  -81.4    11    -5 A     America/~
 6 0A9   Elizabethton Municipal Airport  36.4  -82.2  1593    -5 A     America/~
 7 0G6   Williams County Airport         41.5  -84.5   730    -5 A     America/~
```

```
 8 0G7   Finger Lakes Regional Airport   42.9  -76.8   492    -5 A      America/~
 9 0P2   Shoestring Aviation Airfield    39.8  -76.6  1000    -5 U      America/~
10 0S9   Jefferson County Intl           48.1 -123.    108    -8 A      America/~
# i 1,448 more rows
```

Now, if you click on `df_airports` in the 'Environment' pane, you will see exactly what you would expect from `read_csv()`, including a '`$`' sign followed by the variable name, the type of the variables, and more.

```
View(df_airports)
```

Running SQL From R

We can interact with the data in a database that we 've made a connection to.

- We want to learn how to write queries in `SQL`. If we want to interact with a database from R based on those queries, we start by writing the query as a **string**.
- **Therefore, the query must be enclosed in quotation marks.**
- A basic SQL code chunk looks like this (put SQL code between the chunks):

````
```{sql, connection=conn}

```
````

- By convention, SQL syntax is written in all UPPER CASE and variable names/database names are written in lower case.

Select Specific Columns

As you can see, the following query:

```
"SELECT tzone, name
 FROM airports"
```

```
[1] "SELECT tzone, name\n FROM airports"
```

is inside quotation marks in the above chunk of code.

There are three ways to run this query

1. dbGetQuery() From DBI

- Use the function `dbGetQuery()` from {DBI} package.
- Now let us run `dbGetQuery()` function

  R

```
"SELECT tzone, name
 FROM airports" %>%
  dbGetQuery(conn, .) ->
  tz_name
head(tz_name)
```

```
             tzone                            name
1 America/New_York               Lansdowne Airport
2  America/Chicago  Moton Field Municipal Airport
3  America/Chicago             Schaumburg Regional
4 America/New_York                 Randall Airport
5 America/New_York            Jekyll Island Airport
6 America/New_York Elizabethton Municipal Airport
```

As you can see, the query is inside quotation marks.

It will get run in database, select the two columns that we have requested from the table we have provided. So this is actually a dataframe that was passed back to R and if we store it , then it will be ready when we need it.

R

```
nrow(tz_name)
```

```
[1] 1458
```

R

```
names(tz_name)
```

```
[1] "tzone" "name"
```

R

```r
tz_name %>%
  head()
```

```
             tzone                            name
1 America/New_York               Lansdowne Airport
2  America/Chicago  Moton Field Municipal Airport
3  America/Chicago             Schaumburg Regional
4 America/New_York                 Randall Airport
5 America/New_York           Jekyll Island Airport
6 America/New_York Elizabethton Municipal Airport
```

2. `tbl()` From `dplyr`

(i) with `sql()` function

- We can use `tbl()` from {dplyr}

  R

```r
"SELECT tzone, name
 FROM airports" %>%
  sql() %>%
  tbl(conn, .)
```

```
# Source:   SQL [?? x 2]
# Database: DuckDB v1.1.3-dev165 [semiyari@Windows 10 x64:R 4.4.2/C:\Users\semiyari\Desktop\I
   tzone               name
   <chr>               <chr>
 1 America/New_York    Lansdowne Airport
 2 America/Chicago     Moton Field Municipal Airport
 3 America/Chicago     Schaumburg Regional
 4 America/New_York    Randall Airport
 5 America/New_York    Jekyll Island Airport
 6 America/New_York    Elizabethton Municipal Airport
 7 America/New_York    Williams County Airport
 8 America/New_York    Finger Lakes Regional Airport
 9 America/New_York    Shoestring Aviation Airfield
10 America/Los_Angeles Jefferson County Intl
# i more rows
```

As you can see, the query is inside quotation marks.

- This will create a table similar to one we had with `dbGetQuery()`. The difference is the **`dbGetQuery()` returns a dataframe back to R. `tbl()` function actually leaves the result table still in the database.** And we can see it R does not know how many rows there. on the top of the table you will see something similar to

Source:SQL [?? x 2]

Which implies R does not know the entire the table, it only knows the first 10 rows.

If we want to get the result of that query back to R we need to use `collect()` function

R

```
"SELECT tzone, name
 FROM airports" %>%
  sql() %>%
  tbl(conn, .) %>%
  collect()
```

```
# A tibble: 1,458 x 2
   tzone               name
   <chr>               <chr>
 1 America/New_York    Lansdowne Airport
 2 America/Chicago     Moton Field Municipal Airport
 3 America/Chicago     Schaumburg Regional
 4 America/New_York    Randall Airport
 5 America/New_York    Jekyll Island Airport
 6 America/New_York    Elizabethton Municipal Airport
 7 America/New_York    Williams County Airport
 8 America/New_York    Finger Lakes Regional Airport
 9 America/New_York    Shoestring Aviation Airfield
10 America/Los_Angeles Jefferson County Intl
# i 1,448 more rows
```

Now it will return the data as a datafram into R.

(ii) with `dplyr's` functions

R

```
tbl(conn, "airports") %>%
  select(tzone, name) %>%
  collect()
```

```
# A tibble: 1,458 x 2
   tzone               name
   <chr>               <chr>
 1 America/New_York    Lansdowne Airport
 2 America/Chicago     Moton Field Municipal Airport
 3 America/Chicago     Schaumburg Regional
 4 America/New_York    Randall Airport
 5 America/New_York    Jekyll Island Airport
 6 America/New_York    Elizabethton Municipal Airport
 7 America/New_York    Williams County Airport
 8 America/New_York    Finger Lakes Regional Airport
 9 America/New_York    Shoestring Aviation Airfield
10 America/Los_Angeles Jefferson County Intl
# i 1,448 more rows
```

Once **{dplyr}** detects the connection (`conn`), it automatically knows you're working with a database and will translate the `filter()`, `group_by()`, and `summarise()` operations into the appropriate **SQL** commands instead of running them in R.

3. Use Language SQL within chunk code

- We can use he curly braces `{}` to denote code chunks. Within these code chunks, you can specify the language of the code using the syntax
- `{sql, connection=conn}` indicates a SQL code chunk with additional parameters, such as specifying a connection object (conn in this case). ##### General
- Case does not matter (i.e. `select` is the same as `SELECT` is the same as `SeLeCt`), but it is standard to have all statements be in UPPERCASE (i.e. `SELECT`).
- The statements below **must** be in the following order: `SELECT`, `FROM`, `WHERE`, `GROUP BY`, `ORDER BY`.
- **New lines and white space don't matter**. But it is common to put those five commands above on new lines.
- **Character values must be in single quotes.**
- You can use **invalid variable names** by putting them in double quotes (same as using backticks in R).
  - Some folks always use double quotes because it is not always clear what is an invalid variable name in the database management system.
- Comments in SQL have two hyphens `--`.

- Make sure to put a semicolon `;` at the end of a SQL statement. This will allow you to have multiple SQL queries in one chunk.

Showing Tables

- The `SHOW TABLES` command can be used to get a list of all of the tables

  SQL

```
SHOW TABLEs;
```

Table 2: 5 records

name
airlines
airports
flights
planes
weather

- The `DESCRIBE` command can be used to show tables and the variables.

  SQL

```
DESCRIBE;
```

Table 3: 5 records

database	schema	name	column_names	column_types	temporary
flights	main	airlines	carrier, name	VARCHAR, VARCHAR	FALSE
flights	main	airports	faa, name , lat , lon , alt , tz , dst , tzone	VARCHAR, VARCHAR, DOUBLE , DOUBLE , DOUBLE , DOUBLE , VARCHAR, VARCHAR	FALSE

database	schema	name	column_names	column_types	temporary
flights	main	flights	year , month , day , dep_time , sched_dep_time, dep_delay , arr_time , sched_arr_time, arr_delay , carrier , flight , tailnum , origin , dest , air_time , distance , hour , minute , time_hour	INTEGER , INTEGER , INTEGER , INTEGER , INTEGER , DOUBLE , INTEGER , INTEGER , DOUBLE , VARCHAR , INTEGER , VARCHAR , VARCHAR , VARCHAR , DOUBLE , DOUBLE , DOUBLE , DOUBLE , TIMESTAMP	FALSE
flights	main	planes	tailnum , year , type , manufacturer, model , engines , seats , speed , engine	VARCHAR, INTEGER, VARCHAR, VARCHAR, VARCHAR, INTEGER, INTEGER, INTEGER, VARCHAR	FALSE
flights	main	weather	origin , year , month , day , hour , temp , dewp , humid , wind_dir , wind_speed, wind_gust , precip , pressure , visib , time_hour	VARCHAR , INTEGER , INTEGER , INTEGER , INTEGER , DOUBLE , DOUBLE , DOUBLE , DOUBLE , DOUBLE , DOUBLE , DOUBLE , DOUBLE , DOUBLE , TIMESTAMP	FALSE

`<mark style="background-color: #e24e2f">SQL</mark>`

```sql
DESCRIBE airports;
```

Table 4: 8 records

column_name	column_type	null	key	default	extra
faa	VARCHAR	YES	NA	NA	NA
name	VARCHAR	YES	NA	NA	NA
lat	DOUBLE	YES	NA	NA	NA
lon	DOUBLE	YES	NA	NA	NA
alt	DOUBLE	YES	NA	NA	NA
tz	DOUBLE	YES	NA	NA	NA
dst	VARCHAR	YES	NA	NA	NA
tzone	VARCHAR	YES	NA	NA	NA

Select Specific Columns

- To get the columns from a data frame, use the `SELECT` command.
- The syntax is like this

  SQL

  ```
  SELECT <column1>, <column2>, <column3>
  FROM <mytable>;
  ```

- Let's use this to get the `tzone`, and `name`variables from the `airports` table.

  SQL

```
SELECT "tzone", "name"
 FROM "airports"
```

Table 5: Displaying records 1 - 10

tzone	name
America/New_York	Lansdowne Airport
America/Chicago	Moton Field Municipal Airport
America/Chicago	Schaumburg Regional
America/New_York	Randall Airport
America/New_York	Jekyll Island Airport
America/New_York	Elizabethton Municipal Airport
America/New_York	Williams County Airport
America/New_York	Finger Lakes Regional Airport
America/New_York	Shoestring Aviation Airfield
America/Los_Angeles	Jefferson County Intl

In SQL, queries are not placed within quotation marks when written directly.

However, SQL requires invalid variable names to be enclosed in quotation marks. Some folks always use double quotes because it is not always clear what is an invalid variable name in the database management system (DBMS).

Additionally, character string values in SQL must be enclosed in single quotation marks (`'`), not double quotation marks (`"`).

In R, the `#` symbol is used to indicate comments, whereas in SQL, comments can be defined using `--` for single-line comments.

SQL

```sql
-- names are valid so can be written without quotation marks
SELECT tzone, name
 FROM airports
```

Table 6: Displaying records 1 - 10

tzone	name
America/New_York	Lansdowne Airport
America/Chicago	Moton Field Municipal Airport
America/Chicago	Schaumburg Regional
America/New_York	Randall Airport
America/New_York	Jekyll Island Airport
America/New_York	Elizabethton Municipal Airport
America/New_York	Williams County Airport
America/New_York	Finger Lakes Regional Airport
America/New_York	Shoestring Aviation Airfield
America/Los_Angeles	Jefferson County Intl

- We select every column by using * (Wild card):

  SQL

```sql
SELECT *
FROM airports;
```

Table 7: Displaying records 1 - 10

faa	name	lat	lon	alt	tz	dst	tzone
04G	Lansdowne Airport	41.13047	-80.61958	1044	-5	A	America/New_York
06A	Moton Field Municipal Airport	32.46057	-85.68003	264	-6	A	America/Chicago
06C	Schaumburg Regional	41.98934	-88.10124	801	-6	A	America/Chicago
06N	Randall Airport	41.43191	-74.39156	523	-5	A	America/New_York
09J	Jekyll Island Airport	31.07447	-81.42778	11	-5	A	America/New_York
0A9	Elizabethton Municipal Airport	36.37122	-82.17342	1593	-5	A	America/New_York
0G6	Williams County Airport	41.46731	-84.50678	730	-5	A	America/New_York
0G7	Finger Lakes Regional Airport	42.88356	-76.78123	492	-5	A	America/New_York

faa	name	lat	lon	alt	tz	dst	tzone
0P2	Shoestring Aviation Airfield	39.79482	-76.64719	1000	-5	U	America/New_York
0S9	Jefferson County Intl	48.05381	-122.81064	108	-8	A	America/Los_Angeles

Filter rows

R

```r
dbListFields(conn, "flights")
```

```
 [1] "year"           "month"          "day"            "dep_time"
 [5] "sched_dep_time" "dep_delay"      "arr_time"       "sched_arr_time"
 [9] "arr_delay"      "carrier"        "flight"         "tailnum"
[13] "origin"         "dest"           "air_time"       "distance"
[17] "hour"           "minute"         "time_hour"
```

- You use the `WHERE` command in SQL to filter by rows.

  SQL

```sql
    SELECT "flight", "distance", "origin", "dest"
    FROM flights
    WHERE "distance" < 50;
```

Table 8: 1 records

flight	distance	origin	dest
1632	17	EWR	LGA

R

```r
   "SELECT flight, distance, origin, dest
    FROM flights" %>%
  dbGetQuery(conn, .) %>%
  head()
```

```
  flight distance origin dest
1   1545     1400    EWR  IAH
2   1714     1416    LGA  IAH
3   1141     1089    JFK  MIA
4    725     1576    JFK  BQN
5    461      762    LGA  ATL
6   1696      719    EWR  ORD
```

- To test for equality, you just use one equals sign.

  SQL

```sql
SELECT "flight", "month"
FROM flights
WHERE "month" = 12;
```

Table 9: Displaying records 1 - 10

flight	month
745	12
839	12
1895	12
1487	12
2243	12
939	12
3819	12
1441	12
2167	12
605	12

- For characters you **must use single quotes**, not double.

  SQL

```sql
SELECT "flight", "origin"
FROM flights
WHERE "origin" = 'JFK';
```

Table 10: Displaying records 1 - 10

flight	origin
1141	JFK
725	JFK
79	JFK
49	JFK
71	JFK
194	JFK
1806	JFK
1743	JFK
303	JFK
135	JFK

- You can select multiple criteria using the `AND` command

  SQL

```sql
SELECT "flight", "origin", "dest"
FROM flights
WHERE "origin" = 'JFK' AND "dest" = 'CMH';
```

Table 11: Displaying records 1 - 10

flight	origin	dest
4146	JFK	CMH
3783	JFK	CMH
4146	JFK	CMH
3783	JFK	CMH
4146	JFK	CMH
3783	JFK	CMH
4146	JFK	CMH
3783	JFK	CMH
4146	JFK	CMH
3650	JFK	CMH

- You can use the `OR` logical operator too. Just put parentheses around your desired order of operations.

  SQL

```sql
SELECT "flight", "origin", "dest"
FROM flights
WHERE ("origin" = 'JFK' OR "origin" = 'LGA') AND dest = 'CMH';
```

Table 12: Displaying records 1 - 10

flight	origin	dest
4146	JFK	CMH
3783	JFK	CMH
4146	JFK	CMH
3783	JFK	CMH
4490	LGA	CMH
4485	LGA	CMH
4426	LGA	CMH
4429	LGA	CMH
4626	LGA	CMH
4555	LGA	CMH

- Missing data is `NULL` in SQL (instead of `NA`). We can remove them by the special command:

  SQL

```sql
SELECT "flight", "dep_delay"
FROM flights
WHERE "dep_delay" IS NOT NULL;
```

Table 13: Displaying records 1 - 10

flight	dep_delay
1545	2
1714	4
1141	2
725	-1
461	-6
1696	-4
507	-5
5708	-3
79	-3
301	-2

- Just use `IS` if you want only the missing data observations

  SQL

```sql
SELECT "flight", "dep_delay"
FROM flights
WHERE "dep_delay" IS NULL;
```

Table 14: Displaying records 1 - 10

flight	dep_delay
4308	NA
791	NA
1925	NA
125	NA
4352	NA
4406	NA
4434	NA
4935	NA
3849	NA
133	NA

- When you are building a query, you often want to subset the rows while you are finishing it (you don't want to return the whole table each time you are trouble shooting a query). Use `LIMIT` to show only the top subset.

  SQL

```sql
SELECT "flight", "origin", "dest"
FROM flights
LIMIT 5;
```

Table 15: 5 records

flight	origin	dest
1545	EWR	IAH
1714	LGA	IAH
1141	JFK	MIA
725	JFK	BQN
461	LGA	ATL

- You can also randomly sample rows via `USING SAMPLE`:

SQL

```sql
SELECT "flight", "origin", "dest"
FROM flights
USING SAMPLE 5 ROWS;
```

Table 16: 5 records

flight	origin	dest
269	JFK	MIA
2154	LGA	BOS
3273	EWR	ATL
1638	EWR	CLE
1695	EWR	IAH

Arranging Rows

- Use `ORDER BY` to rearrange the rows (let's remove missing values so we can see the ordering)

  SQL

```sql
SELECT "flight", "dep_delay"
FROM flights
WHERE "dep_delay" IS NOT NULL
ORDER BY "dep_delay";
```

Table 17: Displaying records 1 - 10

flight	dep_delay
97	-43
1715	-33
5713	-32
1435	-30
837	-27
3478	-26
4573	-25
4361	-25
3318	-24
375	-24

- Use `DESC` after the variable to arrange in descending order

  SQL

```sql
SELECT "flight", "dep_delay"
FROM flights
WHERE dep_delay IS NOT NULL
ORDER BY "dep_delay" DESC;
```

Table 18: Displaying records 1 - 10

flight	dep_delay
51	1301
3535	1137
3695	1126
177	1014
3075	1005
2391	960
2119	911
2007	899
2047	898
172	896

- You break ties by adding more variables in the `ORDER BY` statement

  SQL

```sql
SELECT "flight", "origin", "dep_delay"
FROM "flights"
WHERE "dep_delay" IS NOT NULL
ORDER BY "origin" DESC, "dep_delay";
```

Table 19: Displaying records 1 - 10

flight	origin	dep_delay
1715	LGA	-33
5713	LGA	-32
1435	LGA	-30
837	LGA	-27
3478	LGA	-26
4573	LGA	-25

flight	origin	dep_delay
375	LGA	-24
4065	LGA	-24
2223	LGA	-24
5956	LGA	-23

Mutate

- In SQL, you mutate variables while you SELECT. You use `AS` to specify what the new variable is called (choosing a variable name is called "aliasing" in SQL).

  SQL

  ```
  SELECT <expression> AS <myvariable>
  FROM <mytable>;
  ```

- Let's calculate average speed from the `flights` table. We'll also keep the flight number, distance, and air time variables.

  SQL

```
SELECT "flight", "distance" / "air_time" AS "speed", "distance", "air_time"
FROM flights;
```

Table 20: Displaying records 1 - 10

flight	speed	distance	air_time
1545	6.167401	1400	227
1714	6.237885	1416	227
1141	6.806250	1089	160
725	8.612022	1576	183
461	6.568966	762	116
1696	4.793333	719	150
507	6.740506	1065	158
5708	4.320755	229	53
79	6.742857	944	140
301	5.311594	733	138

Joining

- For joining, in the `SELECT` call, you write out all of the columns in **both** tables that you are joining.
- If there are shared column names, you need to distinguish between the two via `table1."var"` or `table2."var"` etc…
- Use `LEFT JOIN` to declare a left join, and `ON` to declare the keys.

  SQL

```sql
-- Get column names for the planes table
SELECT column_name
FROM information_schema.columns
WHERE table_name = 'planes';
```

Table 21: 9 records

column_name
tailnum
year
type
manufacturer
model
engines
seats
speed
engine

<mark style="background-color: lightblue">R</mark>

```r
dbListFields(conn, "planes")
```

```
[1] "tailnum"      "year"         "type"         "manufacturer" "model"
[6] "engines"      "seats"        "speed"        "engine"
```

<mark style="background-color: #e24e2f">SQL</mark>

```sql
-- Get column names for the flights table
SELECT column_name
FROM information_schema.columns
WHERE table_name = 'flights';
```

Table 22: Displaying records 1 - 10

column_name
year
month
day
dep_time
sched_dep_time
dep_delay
arr_time
sched_arr_time
arr_delay
carrier

`<mark style="background-color: lightblue">R</mark>`

```r
dbListFields(conn, "flights")
```

```
 [1] "year"           "month"          "day"            "dep_time"
 [5] "sched_dep_time" "dep_delay"      "arr_time"       "sched_arr_time"
 [9] "arr_delay"      "carrier"        "flight"         "tailnum"
[13] "origin"         "dest"           "air_time"       "distance"
[17] "hour"           "minute"         "time_hour"
```

- Let us Join them with the key `tailnum`

LEFT JOIN

`<mark style="background-color: #e24e2f">SQL</mark>`

```
-- flight is from the flights table
-- type is from the planes table
-- both tables have a tailnum column, so we need to tell them apart
-- if you list both tailnums in SELECT, you'll get two tailnum columns
SELECT "flight", flights."tailnum", "type"
FROM flights
LEFT JOIN planes
ON flights."tailnum" = planes."tailnum";
```

Table 23: Displaying records 1 - 10

flight	tailnum	type
67	N16713	Fixed wing multi engine
373	N659JB	Fixed wing multi engine
764	N665UA	Fixed wing multi engine
2171	N747UW	Fixed wing multi engine
366	N414WN	Fixed wing multi engine
1550	N14228	Fixed wing multi engine
4694	N14993	Fixed wing multi engine
1647	N689DL	Fixed wing multi engine
24	N197JB	Fixed wing multi engine
4485	N711MQ	Fixed wing multi engine

RIGHT JOIN

`<mark style="background-color: #e24e2f">SQL</mark>`

```
SELECT "flight", flights."tailnum", "type"
FROM flights
RIGHT JOIN planes
ON flights."tailnum" = planes."tailnum";
```

Table 24: Displaying records 1 - 10

flight	tailnum	type
461	N693DL	Fixed wing multi engine
4424	N19966	Fixed wing multi engine
6177	N34111	Fixed wing multi engine

flight	tailnum	type
731	N319NB	Fixed wing multi engine
684	N809UA	Fixed wing multi engine
1279	N328NB	Fixed wing multi engine
1691	N34137	Fixed wing multi engine
1447	N117UW	Fixed wing multi engine
3574	N790SW	Fixed wing multi engine
3351	N711MQ	Fixed wing multi engine

FULL JOIN

<mark style="background-color: #e24e2f">SQL</mark>

```
SELECT "flight", flights."tailnum", "type"
FROM flights
JOIN planes
ON flights."tailnum" = planes."tailnum";
```

Table 25: Displaying records 1 - 10

flight	tailnum	type
461	N693DL	Fixed wing multi engine
4424	N19966	Fixed wing multi engine
6177	N34111	Fixed wing multi engine
731	N319NB	Fixed wing multi engine
684	N809UA	Fixed wing multi engine
1279	N328NB	Fixed wing multi engine
1691	N34137	Fixed wing multi engine
1447	N117UW	Fixed wing multi engine
3574	N790SW	Fixed wing multi engine
3351	N711MQ	Fixed wing multi engine

<mark style="background-color: #e24e2f">SQL</mark>

```
SELECT "flight", flights."tailnum", "type"
FROM flights
FULL JOIN planes
ON flights."tailnum" = planes."tailnum";
```

Table 26: Displaying records 1 - 10

flight	tailnum	type
67	N16713	Fixed wing multi engine
373	N659JB	Fixed wing multi engine
764	N665UA	Fixed wing multi engine
2171	N747UW	Fixed wing multi engine
366	N414WN	Fixed wing multi engine
1550	N14228	Fixed wing multi engine
4694	N14993	Fixed wing multi engine
1647	N689DL	Fixed wing multi engine
24	N197JB	Fixed wing multi engine
4485	N711MQ	Fixed wing multi engine

COUNT

Example: Count the number of time zones from `airports` table.

We want to count the number of individual flights associated with time zones.

1. Select the `tzone` column

2. count each row (`*`) associated with `tzone`

3. We get this from the `airports` table
4. We need to group them by `tzone`

Everything must be inside of the quotation marks.

`<mark style="background-color: lightblue">R</mark>`

```
count_airports <- "SELECT tzone,
                  COUNT(*)
                  From airports
                  GROUP BY tzone"
```

There are three ways to run this query

1. Use the function `dbGetQuery()` from {DBI} package.

- Now let us run `dbGetQuery()` function

count_tzone

<mark style="background-color: lightblue">R</mark>

```r
dbGetQuery(conn, count_airports)
```

```
                 tzone count_star()
1       Asia/Chongqing            2
2                 <NA>            3
3     Pacific/Honolulu           18
4      America/Chicago          342
5  America/Los_Angeles          176
6     America/New_York          519
7    America/Vancouver            2
8    America/Anchorage          239
9       America/Denver          119
10     America/Phoenix           38
```

It will get run in database, the count for each time zone are totaled and it will get returned to R as a dataframe. So this is actually a dataframe that was passed back to R and if we store it , then it will be ready when we need it.

- Or directly

  R

```r
"SELECT tzone,
                 COUNT(*)
                 From airports
                 GROUP BY tzone" %>%
  dbGetQuery(conn, .)
```

```
                 tzone count_star()
1    America/Vancouver            2
2    America/Anchorage          239
3       America/Denver          119
4       Asia/Chongqing            2
5                 <NA>            3
6  America/Los_Angeles          176
7      America/Phoenix           38
8     Pacific/Honolulu           18
9     America/New_York          519
10     America/Chicago          342
```

2a. We can use `tbl()` from `{dplyr}` with `sql()`

<mark style="background-color: lightblue">R</mark>

```r
tbl(conn, sql(count_airports))
```

```
# Source:   SQL [10 x 2]
# Database: DuckDB v1.1.3-dev165 [semiyari@Windows 10 x64:R 4.4.2/C:\Users\semiyari\Desktop\
   tzone               `count_star()`
   <chr>                        <dbl>
 1 America/Phoenix                 38
 2 Asia/Chongqing                   2
 3 <NA>                             3
 4 Pacific/Honolulu                18
 5 America/Los_Angeles            176
 6 America/Vancouver                2
 7 America/Anchorage              239
 8 America/Denver                 119
 9 America/Chicago                342
10 America/New_York               519
```

This will create a table similar to one we had in method 1. The difference is the `dbGetQuery()` returns a dataframe back to R. `tbl()` function actually leaves the result table still in the database. And we can see it R does not know how many rows there. on the top of the table you will see something similar to

Source:SQL [?? x 2]

If we want to get the resul of that query back to R we need to use `collect()` function

<mark style="background-color: lightblue">R</mark>

```r
tbl(conn, sql(count_airports)) %>%
  collect()
```

```
# A tibble: 10 x 2
   tzone               `count_star()`
   <chr>                        <dbl>
 1 Asia/Chongqing                   2
 2 <NA>                             3
 3 America/Vancouver                2
```

```
 4 America/Anchorage              239
 5 America/Denver                 119
 6 Pacific/Honolulu                18
 7 America/New_York               519
 8 America/Chicago                342
 9 America/Los_Angeles            176
10 America/Phoenix                 38
```

Now it will return the data as a datafram into R.

- We also can get it directly by

```
"SELECT tzone,
                COUNT(*)
                From airports
                GROUP BY tzone" %>%
  sql() %>%
  tbl(conn, .) %>%
  collect()
```

```
# A tibble: 10 x 2
   tzone                `count_star()`
   <chr>                         <dbl>
 1 America/Phoenix                  38
 2 America/Los_Angeles             176
 3 America/New_York                519
 4 America/Vancouver                 2
 5 America/Anchorage               239
 6 America/Denver                  119
 7 Asia/Chongqing                    2
 8 <NA>                              3
 9 Pacific/Honolulu                 18
10 America/Chicago                 342
```

2b. We can use `tbl()` from `{dplyr}` with its functions

If you are familiar with dplyr and not very comfortable with SQL, you may want using database connection with dplyr commands inside of the database.

Let us we want to count the time zone in flights data frame.

- We start with creating a connection to an individual table (or multiple tables) using `tbl()`

- We create a linked version of table in R. The first argument is the connection we made and the second is the name of the table we want to connect to.

```
airports_table <- tbl(conn, "airports")
```

- Now we have the connection we can do exactly what we did in {dplyr}
- Remember in {dplyr} we gorup by things first

```
airports_table %>%
  group_by(tzone) %>%
  summarise(count = n())
```

```
# Source:   SQL [10 x 2]
# Database: DuckDB v1.1.3-dev165 [semiyari@Windows 10 x64:R 4.4.2/C:\Users\semiyari\Desktop\I
   tzone               count
   <chr>               <dbl>
 1 America/Phoenix        38
 2 Pacific/Honolulu       18
 3 America/Vancouver       2
 4 America/Anchorage     239
 5 America/Denver        119
 6 Asia/Chongqing          2
 7 <NA>                    3
 8 America/Los_Angeles   176
 9 America/New_York      519
10 America/Chicago       342
```

- We see the same output that we had before. If you look closely at the table, you will see the number of rows are not known.
- Once **{dplyr}** detects the connection (`conn`), it automatically knows you're working with a database and will translate the `filter()`, `group_by()`, and `summarise()` operations into the appropriate **SQL** commands instead of running them in R.
- The benefit of working in the database caused the faster performance (without using R memory) Also without knowing SQL, we just use {dplyr} functions.
- As you can see the number of rows is unknown. The reason is, R just has the first few observations and it does not know how many is there. To bring back data to R we need to do one additional step , which was applying the `collect()` function

```r
airports_table %>%
  group_by(tzone) %>%
  summarise(count = n()) %>%
  collect() -> count_tzone
count_tzone %>%
  print()
```

```
# A tibble: 10 x 2
   tzone               count
   <chr>               <dbl>
 1 America/Phoenix        38
 2 America/Vancouver       2
 3 America/Anchorage     239
 4 America/Denver        119
 5 America/Chicago       342
 6 Asia/Chongqing          2
 7 <NA>                    3
 8 Pacific/Honolulu       18
 9 America/Los_Angeles   176
10 America/New_York      519
```

Copying data from R to the database

So far we have been reade,create data, retrieve data from database. Now we want the table that we created and add it to database. We can do this by using `copy_to()` function.

- Suppose we want to store the table `count_tzone` from R back to database as a permanent table.
- Let us look at the tables in our database just to make sure that table isn't there.

  R

```r
dbListTables(conn)
```

```
[1] "airlines" "airports" "flights"  "planes"   "weather"
```

- Let's give a name to table that we have created by SQLin R.

To store the table we use `copy_to()` function, where the first argument is the connection we made, the second argument is the table that we want to copy to database and the third argument is the name of the table on the database. By default table will be added temporary if you want it permanent you need to type `temporary = FALSE`, to store data permanently.

- Now let us add the `count_tzone` which we were created by {dbplyr} to database

  R

```
copy_to(conn, count_tzone, name = "zone_count", overwrite = TRUE)
```

check to see if the table was added to database

<mark style="background-color: lightblue">R</mark>

```
dbListTables(conn)
```

```
[1] "airlines"   "airports"   "flights"    "planes"     "weather"
[6] "zone_count"
```

- `tzone_c`

  R

```
airports_table %>%
  group_by(tzone) %>%
  summarise(count = n()) %>%
  collect() ->
  tzone_c
```

- Now let us add the `tzone_c` which we were created by {dbplyr} to database

  R

```
copy_to(conn, tzone_c, name = "zone_t", overwrite = TRUE)
```

check to see if the table was added to database

<mark style="background-color: lightblue">R</mark>

```
dbListTables(conn)
```

```
[1] "airlines"   "airports"   "flights"    "planes"     "weather"
[6] "zone_count" "zone_t"
```

Remove a table from database

We can Delete table by `dbRemoveTable()` function from {DBI} package.

- Let us remove the file we just added

  R

```
dbRemoveTable(conn, "zone_t")
```

check to see if the table was removed from database

```
<mark style="background-color: lightblue">R</mark>
```

```
dbListTables(conn)
```

```
[1] "airlines"   "airports"   "flights"    "planes"     "weather"
[6] "zone_count"
```

- Now we want to remove `count_tzone` from database

  R

```
dbRemoveTable(conn, "zone_count")
```

- Let us to check if it was deleted

  R

```
dbListTables(conn)
```

```
[1] "airlines" "airports" "flights"  "planes"   "weather"
```

```
<mark style="background-color: lightblue">R</mark>
```

```
dbListFields(conn, "flights")
```

```
 [1] "year"           "month"          "day"            "dep_time"
 [5] "sched_dep_time" "dep_delay"      "arr_time"       "sched_arr_time"
 [9] "arr_delay"      "carrier"        "flight"         "tailnum"
[13] "origin"         "dest"           "air_time"       "distance"
[17] "hour"           "minute"         "time_hour"
```

Close the connection

<mark style="background-color: lightblue">R</mark>

```
dbDisconnect(conn)
```

- To check if the connection is closed use the `dbIsValid()` function in R. This function returns TRUE if the connection is valid (open) and FALSE if it is closed.

  R

```
dbIsValid(conn)
```

```
[1] FALSE
```

- Or

  R

```
# Close the previous connection if it is open
if (dbIsValid(conn)) {
  dbDisconnect(conn)
  cat("Previous connection closed.")
} else {
  cat("No active connection to close.")
}
```

```
No active connection to close.
```

- Or Check it as follow:

  R

```
# Check if the connection is closed
if (!dbIsValid(conn)) {
  print("Connection is closed.")
} else {
  print("Connection is open.")
}
```

```
[1] "Connection is closed."
```

How about if we want to Use {RSQLite} instead of {duckdb}

<mark style="background-color: lightblue">R</mark>

```
library(RSQLite)
```

- To collect the file go to SQLITE TUTORIAL
- Scroll down to Download SQLite sample database
- You get a zipfile. Double click to open it and then extract the file. I put the file `chinook.db` in my data folder

  R

```
con_sqlite <- dbConnect(SQLite(), "../data/chinook.db", synchronous = NULL)
```

- We just created the connection

In the following we will get the list of tables in our database

<mark style="background-color: lightblue">R</mark>

```
dbListTables(con_sqlite)
```

```
 [1] "albums"          "artists"         "customers"       "employees"
 [5] "genres"          "invoice_items"   "invoices"        "media_types"
 [9] "playlist_track"  "playlists"       "sqlite_sequence" "sqlite_stat1"
[13] "tracks"
```

Here is the detail of table that called `artists`

<mark style="background-color: lightblue">R</mark>

```
dbListFields(con_sqlite, "artists")
```

```
[1] "ArtistId" "Name"
```

<mark style="background-color: lightblue">R</mark>

```
dbListFields(con_sqlite, "customers")
```

```
 [1] "CustomerId"   "FirstName"    "LastName"     "Company"      "Address"
 [6] "City"         "State"        "Country"      "PostalCode"   "Phone"
[11] "Fax"          "Email"        "SupportRepId"
```

<mark style="background-color: lightblue">R</mark>

```
dbDisconnect(con_sqlite)
```

<mark style="background-color: lightblue">R</mark>

```
dbIsValid(con_sqlite)
```

```
[1] FALSE
```

Close the connection

<mark style="background-color: lightblue">R</mark>

```
# Check if the connection is closed
if (!dbIsValid(con_sqlite)) {
  print("Connection is closed.")
} else {
  print("Connection is open.")
}
```

```
[1] "Connection is closed."
```

- **Note:**
  - It's best to have SQL written in a separate file (that ends in ".sql").
  - If you want to load the results of a SQL query in R, saved in "query.sql", do

```
mydf <- DBI::dbGetQuery(conn, statement = read_file(here("query.sql")))}
```

Source

Source