

# databases & dplyr

## Lecture 17

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# The why of databases

# Numbers every programmer should know

Task	Timing (ns)	Timing ( $\mu$ s)
L1 cache reference	0.5	0.0005
L2 cache reference	7	0.007
Main memory reference	100	0.1
Random seek SSD	150,000	150
Read 1 MB sequentially from memory	250,000	250
Read 1 MB sequentially from SSD	1,000,000	1,000
Disk seek	10,000,000	10,000
Read 1 MB sequentially from disk	20,000,000	20,000
Send packet CA->Netherlands->CA	150,000,000	150,000

# Implications for big data

Lets imagine we have a *10 GB* flat data file and that we want to select certain rows based on a particular criteria. This requires a sequential read across the entire data set.

File Location	Performance	Time
in memory	$10\text{ GB} \times (250\text{ }\mu\text{s}/1\text{ MB})$	2.5 seconds
on disk (SSD)	$10\text{ GB} \times (1\text{ ms}/1\text{ MB})$	10 seconds
on disk (HD)	$10\text{ GB} \times (20\text{ ms}/1\text{ MB})$	200 seconds

This is just for *reading* sequential data, if we make any modifications (*writing*) or the data is fragmented things are much worse.

# Blocks

## Cost:

Disk << SSD <<< Memory

## Speed:

Disk <<< SSD << Memory

So usually possible to grow our disk storage to accommodate our data.  
However, memory is usually the limiting resource, and if we can't fit everything into memory?

Create *blocks* - group related data (i.e. rows) and read in multiple rows at a time. Optimal size will depend on the task and the properties of the disk.

# Linear vs Binary Search

Even with blocks, any kind of querying / subsetting of rows requires a linear search, which requires  $\mathcal{O}(N)$  reads.

We can do better if we are careful about how we structure our data, specifically sorting' some (or all) of the columns.

- Sorting is expensive,  $\mathcal{O}(N \log N)$ , but it only needs to be done once.
- After sorting, we can use a binary search for any subsetting tasks -  $\mathcal{O}(\log N)$
- In a databases these “sorted” columns are referred to as *indexes*.
- Indexes require additional storage, but usually small enough to be kept in memory even if blocks need to stay on disk.

# and then?

This is just barely scratching the surface,

- Efficiency gains are not just for disk, access is access
- In general, trade off between storage and efficiency
- Reality is a lot more complicated for everything mentioned so far, lots of very smart people have spent a lot of time thinking about and implementing tools
- Different tasks with different requirements require different implementations and have different criteria for optimization

# Databases



# R & databases - the DBI package

Low level package for interfacing R with Database management systems (DBMS) that provides a common interface to achieve the following functionality:

- connect/disconnect from DB
- create and execute statements in the DB
- extract results/output from statements
- error/exception handling
- information (meta-data) from database objects
- transaction management (optional)

# RSQLite

Provides the implementation necessary to use DBI to interface with an SQLite database.

```
1 library(RSQLite)
```

this package also loads the necessary DBI functions as well (via re-exporting).  
Once loaded we can create a connection to our database,

```
1 con = dbConnect(RSQLite::SQLite(), ":memory:")
2 str(con)
```

Formal class 'SQLiteConnection' [package "RSQLite"] with 8 slots

```
..@ ptr          :<externalptr>
..@ dbname        : chr ":memory:"
..@ loadable.extensions: logi TRUE
..@ flags         : int 70
..@ vfs           : chr ""
..@ ref           :<environment: 0x12b51c800>
..@ bigint        : chr "integer64"
..@ extended_types : logi FALSE
```

# Example Table

```
1 employees = tibble(  
2   name     = c("Alice", "Bob", "Carol", "Dave", "Eve", "Frank"),  
3   email    = c("alice@company.com", "bob@company.com",  
4               "carol@company.com", "dave@company.com",  
5               "eve@company.com",   "frank@company.com"),  
6   salary   = c(52000, 40000, 30000, 33000, 44000, 37000),  
7   dept     = c("Accounting", "Accounting", "Sales",  
8               "Accounting", "Sales", "Sales"),  
9 )
```

```
1 dbListTables(con)
```

```
character(0)
```

```
1 dbWriteTable(con, name = "employees", value = employees)  
2 dbListTables(con)
```

```
[1] "employees"
```

# Removing Tables

```
1 dbWriteTable(con, "employs", employees)
2 dbListTables(con)
```

```
[1] "employees" "employs"
```

```
1 dbRemoveTable(con, "employs")
2 dbListTables(con)
```

```
[1] "employees"
```

# Querying Tables

Databases queries are transactional (see [ACID](#)) and are broken up into 3 steps:

```
1 (res = dbSendQuery(con, "SELECT * FROM employees"))
```

<SQLiteResult>

SQL SELECT \* FROM employees

ROWS Fetched: 0 [incomplete]

Changed: 0

```
1 dbFetch(res)
```

	name	email	salary	dept
1	Alice	alice@company.com	52000	Accounting
2	Bob	bob@company.com	40000	Accounting
3	Carol	carol@company.com	30000	Sales
4	Dave	dave@company.com	33000	Accounting
5	Eve	eve@company.com	44000	Sales
6	Frank	frank@comany.com	37000	Sales

```
1 dbClearResult(res)
```

# For convenience

There is also `dbGetQuery()` which combines all three steps,

```
1 (res = dbGetQuery(con, "SELECT * FROM employees"))
```

	name	email	salary	dept
1	Alice	alice@company.com	52000	Accounting
2	Bob	bob@company.com	40000	Accounting
3	Carol	carol@company.com	30000	Sales
4	Dave	dave@company.com	33000	Accounting
5	Eve	eve@company.com	44000	Sales
6	Frank	frank@comany.com	37000	Sales

# Creating tables

`dbCreateTable()` will create a new table with a schema based on an existing data.frame / tibble, but it does not populate that table with data.

```
1 dbCreateTable(con, "iris", iris)
2 (res = dbGetQuery(con, "select * from iris"))
```

```
[1] Sepal.Length Sepal.Width Petal.Length Petal.Width Species
<0 rows> (or 0-length row.names)
```

# Adding to tables

Data can be added to an existing table via `dbAppendTable()`.

```
1 dbAppendTable(con, name = "iris", value = iris)
```

```
[1] 150
```

```
1 dbGetQuery(con, "select * from iris") |>
2   as_tibble()
```

```
# A tibble: 150 × 5
```

	Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Species
	<dbl>	<dbl>	<dbl>	<dbl>	<chr>
1	5.1	3.5	1.4	0.2	setosa
2	4.9	3	1.4	0.2	setosa
3	4.7	3.2	1.3	0.2	setosa
4	4.6	3.1	1.5	0.2	setosa
5	5	3.6	1.4	0.2	setosa
6	5.4	3.9	1.7	0.4	setosa
7	4.6	3.4	1.4	0.3	setosa
8	5	3.4	1.5	0.2	setosa
9	4.4	2.9	1.4	0.2	setosa
10	4.9	3.1	1.5	0.1	setosa

```
# i 140 more rows
```



# Closing the connection

```
1 con
```

```
<SQLiteConnection>
```

```
Path: :memory:
```

```
Extensions: TRUE
```

```
1 dbDisconnect(con)
```

```
1 con
```

```
<SQLiteConnection>
```

```
DISCONNECTED
```

# **dplyr & databases**

# Creating a database

```
1 db = DBI::dbConnect(RSQLite::SQLite(), "flights.sqlite")
2 ( flight_tbl = dplyr::copy_to(
3     db, nycflights13::flights, name = "flights", temporary = FALSE) )
```

```
# Source:   table<flights> [?? x 19]
```

```
# Database: sqlite 3.45.0 [flights.sqlite]
```

	year	month	day	dep_time	sched_dep_time	dep_delay	arr_time
	<int>	<int>	<int>	<int>	<int>	<dbl>	<int>
1	2013	1	1	517	515	2	830
2	2013	1	1	533	529	4	850
3	2013	1	1	542	540	2	923
4	2013	1	1	544	545	-1	1004
5	2013	1	1	554	600	-6	812
6	2013	1	1	554	558	-4	740
7	2013	1	1	555	600	-5	913
8	2013	1	1	557	600	-3	709
9	2013	1	1	557	600	-3	838
10	2013	1	1	558	600	-2	753

# What have we created?

All of this data now lives in the database on the *filesystem* not in *memory*,

```
1 pryr::object_size(db)
```

2.46 kB

```
1 pryr::object_size(flight_tbl)
```

7.38 kB

```
1 pryr::object_size(nycflights13::flights)
```

40.65 MB

# File size

```
1 fs::dir_info(glob = "*.sqlite") |>  
2   select(path, type, size)
```

```
# A tibble: 1 × 3
```

	path	type	size
	<fs::path>	<fct>	<fs::bytes>
1	flights.sqlite	file	21.1M

# What is `flight_tbl`?

```
1 class(nycflights13::flights)
```

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

```
1 class(flight_tbl)
```

```
[1] "tbl_SQLiteConnection" "tbl_dbi"  
[3] "tbl_sql"              "tbl_lazy"  
[5] "tbl"
```

```
1 str(flight_tbl)
```

List of 2

```
$ src      :List of 2  
..$ con    :Formal class 'SQLiteConnection' [package "RSQLite"] with 8 slots  
.. .. ..@ ptr              :<externalptr>  
.. .. ..@ dbname           : chr "flights.sqlite"  
.. .. ..@ loadable.extensions: logi TRUE  
.. .. ..@ flags             : int 70  
.. .. ..@ vfs               : chr ""  
.. .. ..@ ref               :<environment: 0x13b5f8d88>  
.. .. ..@ bigint            : chr "integer64"  
.. .. ..@ extended_types    : logi FALSE  
..$ disco: NULL
```

```
..- attr(*, "class")= chr [1:4] "src_SQLiteConnection" "src_dbi" "src_sql" "src"  
$ lazy query:List of 5
```

# Accessing existing tables

```
1 (dplyr::tbl(db, "flights"))
```

```
# Source:   table<flights> [?? x 19]
```

```
# Database: sqlite 3.45.0 [flights.sqlite]
```

	year	month	day	dep_time	sched_dep_time	dep_delay	arr_time
	<int>	<int>	<int>	<int>	<int>	<dbl>	<int>
1	2013	1	1	517	515	2	830
2	2013	1	1	533	529	4	850
3	2013	1	1	542	540	2	923
4	2013	1	1	544	545	-1	1004
5	2013	1	1	554	600	-6	812
6	2013	1	1	554	558	-4	740
7	2013	1	1	555	600	-5	913
8	2013	1	1	557	600	-3	709
9	2013	1	1	557	600	2	830



# Using dplyr with sqlite

```
1 (oct_21 = flight_tbl |>
2   filter(month == 10, day == 2)
3   select(origin, dest, tailnum)
4 )
```

```
# Source:   SQL [?? x 3]
```

```
# Database: sqlite 3.45.0 [flights.sqlite]
```

	origin	dest	tailnum
	<chr>	<chr>	<chr>
1	EWR	CLT	N152UW
2	EWR	IAH	N535UA
3	JFK	MIA	N5BSAA
4	JFK	SJU	N531JB
5	JFK	BQN	N827JB
6	LGA	IAH	N15710
7	JFK	IAD	N825AS
8	EWR	TPA	N802UA
9	LGA	ATL	N996DL
10	JFK	FLL	N627JB

```
1 dplyr::collect(oct_21)
```

```
# A tibble: 991 × 3
```

	origin	dest	tailnum
	<chr>	<chr>	<chr>
1	EWR	CLT	N152UW
2	EWR	IAH	N535UA
3	JFK	MIA	N5BSAA
4	JFK	SJU	N531JB
5	JFK	BQN	N827JB
6	LGA	IAH	N15710
7	JFK	IAD	N825AS
8	EWR	TPA	N802UA
9	LGA	ATL	N996DL
10	JFK	FLL	N627JB

```
# i 981 more rows
```

# Laziness

dplyr / dbplyr uses lazy evaluation as much as possible, particularly when working with non-local backends.

- When building a query, we don't want the entire table, often we want just enough to check if our query is working / makes sense.
- Since we would prefer to run one complex query over many simple queries, laziness allows for verbs to be strung together.
- Therefore, by default `dplyr`
  - won't connect and query the database until absolutely necessary (e.g. show output),
  - and unless explicitly told to, will only query a handful of rows to give a sense of what the result will look like.
  - we can force evaluation via `compute()`, `collect()`, or `collapse()`

# A crude benchmark

```
1 system.time({  
2   (oct_21 = flight_tbl |>  
3     filter(month == 10, day  
4     select(origin, dest, ta  
5   )  
6 })
```

user	system	elapsed
0.003	0.000	0.003

```
1 system.time({  
2   print(oct_21) |>  
3   capture.output() |>  
4   invisible()  
5 })
```

user	system	elapsed
0.016	0.000	0.017

```
1 system.time({  
2   dplyr::collect(oct_21) |>  
3   capture.output() |>  
4   invisible()  
5 })
```

user	system	elapsed
0.038	0.003	0.042

# dplyr -> SQL - `show_query()`

```
1 class(oct_21)
```

```
[1] "tbl_SQLiteConnection" "tbl_dbi"  
[3] "tbl_sql"              "tbl_lazy"  
[5] "tbl"
```

```
1 show_query(oct_21)
```

<SQL>

```
SELECT `origin`, `dest`, `tailnum`  
FROM `flights`  
WHERE (`month` = 10.0) AND (`day` = 21.0)
```

# More complex queries

```
1 oct_21 |>
2   summarize(
3     n=n(), .by = c(origin, dest
4   )
```

# Source: SQL [?? x 3]

# Database: sqlite 3.45.0 [flights.sqlite]

	origin	dest	n
	<chr>	<chr>	<int>
1	EWR	ATL	15
2	EWR	AUS	3
3	EWR	AVL	1
4	EWR	BNA	7
5	EWR	BOS	17
6	EWR	BTW	3
7	EWR	BUF	2
8	EWR	BWI	1
9	EWR	CHS	4
10	EWR	CLE	4

```
1 oct_21 |>
2   summarize(
3     n=n(), .by = c(origin, dest
4   ) |>
5   show_query()
```

<SQL>

```
SELECT `origin`, `dest`, COUNT(*) AS `n`
FROM (
  SELECT `origin`, `dest`, `tailnum`
  FROM `flights`
  WHERE (`month` = 10.0) AND (`day` = 21.0)
) AS `q01`
GROUP BY `origin`, `dest`
```

```
1 oct_21 |>
2   count(origin, dest) |>
3   show_query()
```

<SQL>

```
SELECT `origin`, `dest`, COUNT(*) AS `n`
FROM (
  SELECT `origin`, `dest`, `tailnum`
  FROM `flights`
  WHERE (`month` = 10.0) AND (`day` = 21.0)
) AS `q01`
GROUP BY `origin`, `dest`
```

# SQL Translation

In general, dplyr / dbplyr knows how to translate basic math, logical, and summary functions from R to SQL. dbplyr has a function, `translate_sql()`, that lets you experiment with how R functions are translated to SQL.

```
1 dbplyr::translate_sql(x == 1 & (y < 2 | z > 3))
```

Error in dbplyr::translate\_sql(x == 1 & (y < 2 | z > 3)): argument "con" is missing, with no default

```
1 dbplyr::translate_sql(x ^ 2 < 10)
```

Error in dbplyr::translate\_sql(x^2 < 10): argument "con" is missing, with no default

```
1 dbplyr::translate_sql(x %% 2 == 10)
```

Error in dbplyr::translate\_sql(x%%2 == 10): argument "con" is missing, with no default

```
1 con = dbplyr::simulate_dbi()
2 dbplyr::translate_sql(mean(x), con=con)
```

<SQL> AVG(`x`) OVER ( )

```
1 dbplyr::translate_sql(mean(x, na.rm=TRUE), con=con)
```

<SQL> AVG(`x`) OVER ( )

```
1 dbplyr::translate_sql(sd(x), con=con)
```

Error in `sd()`:

! `sd()` is not available in this SQL variant.

```
1 dbplyr::translate_sql(paste(x,y), con=con)
```

<SQL> CONCAT\_WS(' ', `x`, `y`)

```
1 dbplyr::translate_sql(cumsum(x), con=con)
```

<SQL> SUM(`x`) OVER (ROWS UNBOUNDED PRECEDING)

```
1 dbplyr::translate_sql(lag(x), con=con)
```

<SQL> LAG(`x`, 1, NULL) OVER ()



# Dialectic variations?

By default `dbplyr::translate_sql()` will translate R / dplyr code into ANSI SQL, if we want to see results specific to a certain database we can pass in a connection object,

```
1 dbplyr::translate_sql(sd(x), con = db)
```

```
<SQL> STDEV(`x`) OVER ()
```

```
1 dbplyr::translate_sql(paste(x,y), con = db)
```

```
<SQL> `x` || ' ' || `y`
```

```
1 dbplyr::translate_sql(cumsum(x), con = db)
```

```
<SQL> SUM(`x`) OVER (ROWS UNBOUNDED PRECEDING)
```

```
1 dbplyr::translate_sql(lag(x), con = db)
```

```
<SQL> LAG(`x`, 1, NULL) OVER ()
```

# Complications?

```
1 oct_21 |> mutate(tailnum_n_prefix = grepl("^N", tailnum))
```

Error in `collect()`:

! Failed to collect lazy table.

Caused by error:

! no such function: grepl

```
1 oct_21 |> mutate(tailnum_n_prefix = grepl("^N", tailnum)) |> show_qu
```

<SQL>

```
SELECT `origin`, `dest`, `tailnum`, grepl('^N', `tailnum`) AS `tailnum_n_prefix`  
FROM `flights`  
WHERE (`month` = 10.0) AND (`day` = 21.0)
```

**SQL -> R / dplyr**

# Running SQL queries against R objects

There are two packages that implement this in R which take very different approaches,

- `tidyquery` - this package parses your SQL code using the `queryparser` package and then translates the result into R / dplyr code.
- `sqldf` - transparently creates a database with the data and then runs the query using that database. Defaults to SQLite but other backends are available.

# tidyquery

```
1 data(flights, package = "nycflights13")
2
3 tidyquery::query(
4   "SELECT origin, dest, COUNT(*) AS n
5     FROM flights
6     WHERE month = 10 AND day = 21
7     GROUP BY origin, dest"
8 )
```

# A tibble: 181 × 3

	origin	dest	n
	<chr>	<chr>	<int>
1	EWR	ATL	15
2	EWR	AUS	3
3	EWR	AVL	1
4	EWR	BNA	7
5	EWR	BOS	17
6	EWR	BTX	3
7	EWR	BUF	2
8	EWR	BWI	1
9	EWR	CHS	4
10	EWR	CLE	4

# i 171 more rows

```
1 flights |>
2   tidyquery::query(
3     "SELECT origin, dest, COUNT(*) AS n
4       WHERE month = 10 AND day = 21
5       GROUP BY origin, dest"
6   ) |>
7   arrange(desc(n))
```

# A tibble: 181 × 3

	origin	dest	n
	<chr>	<chr>	<int>
1	JFK	LAX	32
2	LGA	ORD	31
3	LGA	ATL	30
4	JFK	SFO	24
5	LGA	CLT	22
6	EWR	ORD	18
7	EWR	SFO	18
8	EWR	BOS	17
9	LGA	MIA	17
10	EWR	LAX	16

# i 171 more rows

# Translating to dplyr

```
1 tidyquery::show_dplyr(  
2   "SELECT origin, dest, COUNT(*) AS n  
3   FROM flights  
4   WHERE month = 10 AND day = 21  
5   GROUP BY origin, dest"  
6 )
```

```
flights %>%  
  filter(month == 10 & day == 21) %>%  
  group_by(origin, dest) %>%  
  summarise(n = dplyr::n()) %>%  
  ungroup()
```

# sqldf

```
1 sqldf::sqldf(  
2   "SELECT origin, dest, COUNT(*) AS n  
3     FROM flights  
4     WHERE month = 10 AND day = 21  
5     GROUP BY origin, dest"  
6 )
```

	origin	dest	n
1	EWR	ATL	15
2	EWR	AUS	3
3	EWR	AVL	1
4	EWR	BNA	7
5	EWR	BOS	17
6	EWR	BTV	3
7	EWR	BUF	2
8	EWR	BWI	1
9	EWR	CHS	4
10	EWR	CLE	4
11	EWR	CLT	15
12	EWR	CMH	3
13	EWR	CVG	9
14	EWR	DAY	4
15	EWR	DCA	3
16	EWR	DFW	8

```
1 sqldf::sqldf(  
2   "SELECT origin, dest, COUNT(*) AS n  
3     FROM flights  
4     WHERE month = 10 AND day = 21  
5     GROUP BY origin, dest"  
6 ) |>  
7   as_tibble() |>  
8   arrange(desc(n))
```

# A tibble: 181 × 3

	origin	dest	n
	<chr>	<chr>	<int>
1	JFK	LAX	32
2	LGA	ORD	31
3	LGA	ATL	30
4	JFK	SFO	24
5	LGA	CLT	22
6	EWR	ORD	18
7	EWR	SFO	18
8	EWR	BOS	17
9	LGA	MIA	17
10	EWR	LAX	16

# i 171 more rows

# Closing thoughts

The ability of dplyr to translate from R expression to SQL is an incredibly powerful tool making your data processing workflows portable across a wide variety of data backends.

Some tools and ecosystems that are worth learning about:

- Spark - [sparkR](#), [spark SQL](#), [sparklyr](#)
- [DuckDB](#)
- Apache [Arrow](#)