

Lec 20 - databases & dplyr

Statistical Programming

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The why of databases

Numbers every programmer should know

Task	Timing (ns)	Timing (μs)
L1 cache reference	0.5	
L2 cache reference	7	
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

From [jboner/latency.txt](#) & [sirupsen/napkin-math](#)

Jeff Dean's original talk

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.

If we can store the file in memory:

- $10 \text{ GB} \times (250 \mu\text{s}/1 \text{ MB}) = 2.5 \text{ seconds}$

If we have to access the file from SSD:

- $10 \text{ GB} \times (1 \text{ ms}/1 \text{ MB}) = 10 \text{ seconds}$

If we have to access the file from disk:

- $10 \text{ GB} \times (20 \text{ ms}/1 \text{ MB}) = 200 \text{ seconds}$

This is just for reading sequential data, if we make any modifications (writing) or the data is

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 $O(N)$ accesses where N is the number of blocks.

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

- Sorting is expensive, $O(N \log N)$, but it only needs to be done once.
- After sorting, we can use a binary search for any subsetting tasks ($O(\log N)$).
- These "sorted" columns are known as indexes.
- Indexes require additional storage, but usually small enough to be kept in memory while blocks 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.

```
library(RSQLite)
```

this package also loads the necessary DBI functions as well.

Once loaded we can create a connection to our database,

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

## Formal class 'SQLiteConnection' [package "RSQLite"] with 5 slots
##  ..@ Id                  :<externalptr>
##  ..@ dbname               : chr ":memory:"
##  ..@ loadable.extensions: logi TRUE
##  ..@ flags                : int 6
##  ..@ vfs                 : chr ""
```

Example Table

```
employees = data.frame(  
  name = c("Alice", "Bob", "Carol", "Dave", "Eve", "Frank"),  
  email = c("alice@company.com", "bob@company.com",  
           "carol@company.com", "dave@company.com",  
           "eve@company.com", "frank@comany.com"),  
  salary = c(52000, 40000, 30000, 33000, 44000, 37000),  
  dept = c("Accounting", "Accounting", "Sales",  
          "Accounting", "Sales", "Sales"),  
)
```

```
dbWriteTable(con, name = "employees", value = employees)  
## [1] TRUE  
  
dbListTables(con)  
## [1] "employees"
```

Removing Tables

```
dbWriteTable(con, "employs", employees)
## [1] TRUE

dbListTables(con)
## [1] "employees" "employs"

dbRemoveTable(con, "employs")
## [1] TRUE

dbListTables(con)
## [1] "employees"
```

Querying Tables

```
(res = dbSendQuery(con, "SELECT * FROM employees"))
## <SQLiteResult>
##   SQL  SELECT * FROM employees
##   ROWS Fetched: 0 [incomplete]
##           Changed: 0

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

dbClearResult(res)
## [1] TRUE
```

Creating empty tables

```
dbCreateTable(con, "iris", iris)

(res = dbSendQuery(con, "select * from iris"))
## <SQLiteResult>
##   SQL  select * from iris
##   ROWS Fetched: 0 [complete]
##       Changed: 0

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

```
dbFetch(res) %>% as_tibble()
## # A tibble: 0 × 5
## # ... with 5 variables: Sepal.Length <dbl>, Sepal.Width <dbl>, Petal.Length <dbl>,
## #   Petal.Width <dbl>, Species <chr>

dbClearResult(res)
```

Adding to tables

```
dbAppendTable(con, name = "iris", value = iris)
## [1] 150
## Warning message:
## Factors converted to character

(res = dbSendQuery(con, "select * from iris"))
## <SQLiteResult>
##   SQL select * from iris
##   ROWS Fetched: 0 [incomplete]
##       Changed: 0

dbFetch(res) %>% as_tibble()
## # A tibble: 150 x 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        3.0        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         5.0        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         5.0        3.4        1.5        0.2  setosa
```

Ephemeral results

```
res
## <SQLiteResult>
##   SQL  select * from iris
##   ROWS Fetched: 150 [complete]
##           Changed: 0

dbFetch(res) %>% as_tibble()
## # A tibble: 0 x 5
## # ... with 5 variables: Sepal.Length <dbl>, Sepal.Width <dbl>, Petal.Length <dbl>,
## #   Species <chr>

dbClearResult(res)
```

Closing the connection

```
con
## <SQLiteConnection>
##   Path: :memory:
##   Extensions: TRUE

dbDisconnect(con)
## [1] TRUE

con
## <SQLiteConnection>
##   DISCONNECTED
```

dplyr & databases

Creating a database

```
(db = DBI::dbConnect(RSQLite::SQLite(), "flights.sqlite"))

## <SQLiteConnection>
##   Path: flights.sqlite
##   Extensions: TRUE

flight_tbl = dplyr::copy_to(db, nycflights13::flights, name = "flights", temporary = FALSE)
flight_tbl

## # Source:  table<flights> [?? x 19]
## # Database: sqlite 3.37.2 [flights.sqlite]
##   year month   day dep_time sched_dep_time dep_delay arr_time sched_arr_time
##   <int> <int> <int>   <int>           <int>    <dbl>   <int>           <int>
## 1 2013     1     1      517             515       2     830           819
## 2 2013     1     1      533             529       4     850           830
## 3 2013     1     1      542             540       2     923           850
## 4 2013     1     1      544             545      -1    1004          1022
## 5 2013     1     1      554             600      -6    812           837
## 6 2013     1     1      554             558      -4    740           728
## 7 2013     1     1      555             600      -5    913           854
## 8 2013     1     1      557             600      -3    709           723
## 9 2013     1     1      557             600      -3    838           846
## 10 2013    1     1      558             600      -2    753           745
## # ... with more rows, and 11 more variables: arr_delay <dbl>, carrier <chr>,
```

What have we created?

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

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

```
## 2,456 B
```

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

```
## 6,192 B
```

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

```
## 40,650,048 B
```

```
ls -lah *.sqlite
```

```
## -rw-r--r-- 1 rundel staff 21M Mar 23 10:36 flights.sqlite
```

What is flight_tbl?

```
class(nycflights13::flights)

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

class(flight_tbl)

## [1] "tbl_SQLiteConnection" "tbl_db"      "tbl_sql"
## [4] "tbl_lazy"      "tbl"

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: 0x1254dc5d8>
##     ... .@ bigint       : chr "integer64"
##     ... .@ extended_types: logi FALSE
##   ..$ disco: NULL
##   -. attr(*, "class")= chr [1:4] "src_SQLiteConnection" "src_db" "src_sql" "src"
```

Accessing existing tables

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

```
## # Source:  table<flights> [?? x 19]
## # Database: sqlite 3.37.2 [flights.sqlite]
##   year month   day dep_time sched_dep_time dep_delay arr_time sched_arr_time
##   <int> <int> <int>   <int>           <int>    <dbl>   <int>       <int>
## 1 2013     1     1      517            515        2     830        819
## 2 2013     1     1      533            529        4     850        830
## 3 2013     1     1      542            540        2     923        850
## 4 2013     1     1      544            545       -1    1004       1022
## 5 2013     1     1      554            600       -6     812        837
## 6 2013     1     1      554            558       -4     740        728
## 7 2013     1     1      555            600       -5     913        854
## 8 2013     1     1      557            600       -3     709        723
## 9 2013     1     1      557            600       -3     838        846
## 10 2013    1     1      558            600       -2     753        745
## # ... with more rows, and 11 more variables: arr_delay <dbl>, carrier <chr>,
## #   flight <int>, tailnum <chr>, origin <chr>, dest <chr>, air_time <dbl>,
## #   distance <dbl>, hour <dbl>, minute <dbl>, time_hour <dbl>
```

Using dplyr with sqlite

```
(oct_21 = flight_tbl %>%
  filter(month == 10, day == 21) %>%
  select(origin, dest, tailnum)
)

## # Source:  lazy query [?? x 3]
## # Database: sqlite 3.37.2 [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
## # ... with more rows
```

```
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
## # ... with 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

```
system.time({
  oct_21 = flight_tbl %>%
    filter(month == 10, day == 21) %>%
    select(origin, dest, tailnum)
  )
})

##      user  system elapsed
##  0.002   0.000   0.002
```

```
system.time({
  print(oct_21) %>%
    capture.output() %>%
    invisible()
})

##      user  system elapsed
##  0.015   0.000   0.015
```

```
system.time({
  dplyr::collect(oct_21) %>%
    capture.output() %>%
    invisible()
})

##      user  system elapsed
##  0.038   0.003   0.041
```

dplyr -> SQL - dplyr::show_query()

```
class(oct_21)
```

```
## [1] "tbl_SQLiteConnection" "tbl_db"           "tbl_sql"  
## [4] "tbl_lazy"             "tbl"
```

```
show_query(oct_21)
```

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

More complex queries

```
oct_21 %>%  
  group_by(origin, dest) %>%  
  summarize(n=n(), .groups = "drop")
```

```
## # Source:  lazy query [?? x 3]  
## # Database: sqlite 3.37.2 [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     BTV      3  
## 7 EWR     BUF      2  
## 8 EWR     BWI      1  
## 9 EWR     CHS      4  
## 10 EWR    CLE      4  
## # ... with more rows
```

```
oct_21 %>%  
  group_by(origin, dest) %>%  
  summarize(n=n(), .groups = "drop") %>%  
  show_query()
```

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

```
oct_21 %>% count(origin, dest) %>% show_query()
```

```
## <SQL>
## SELECT `origin`, `dest`, COUNT(*) AS `n`
## FROM (SELECT `origin`, `dest`, `tailnum`
## FROM `flights`
## WHERE ((`month` = 10.0) AND (`day` = 21.0)))
## 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.

```
dbplyr::translate_sql(x == 1 & (y < 2 | z > 3))  
## <SQL> `x` = 1.0 AND (`y` < 2.0 OR `z` > 3.0)  
  
dbplyr::translate_sql(x ^ 2 < 10)  
## <SQL> POWER(`x`, 2.0) < 10.0  
  
dbplyr::translate_sql(x %% 2 == 10)  
## <SQL> `x` % 2.0 = 10.0  
  
dbplyr::translate_sql(mean(x))  
## Warning: Missing values are always removed in SQL.  
## Use `AVG(x, na.rm = TRUE)` to silence this warning  
## This warning is displayed only once per session.  
## <SQL> AVG(`x`) OVER ()
```

```
dbplyr::translate_sql(sd(x))

## <SQL> sd(`x`)

dbplyr::translate_sql(paste(x,y))

## <SQL> CONCAT_WS(' ', `x`, `y`)

dbplyr::translate_sql(cumsum(x))

## Warning: Windowed expression 'SUM(`x`)' does not have explicit order.
## Please use arrange() or window_order() to make deterministic.

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

dbplyr::translate_sql(lag(x))

## <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,

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

## Warning: Missing values are always removed in SQL.
## Use `STDEV(x, na.rm = TRUE)` to silence this warning
## This warning is displayed only once per session.

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

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

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

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

## Warning: Windowed expression 'SUM(`x`)' does not have explicit order.
## Please use arrange() or window_order() to make deterministic.

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

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

Complications?

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

## Error: no such function: grepl

oct_21 %>% mutate(tailnum_n_prefix = grepl("^N", tailnum)) %>% show_query()

## <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 teh data and then runs the query using that database. Defaults to SQLite but other backends are available.

tidyquery

```
data(flights, package = "nycflights13")

tidyquery::query(
  "SELECT origin, dest, COUNT(*) AS n
   FROM flights
  WHERE month = 10 AND day = 21
  GROUP BY origin, dest"
)
```

```
## # 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    BTV      3
## 7 EWR    BUF      2
## 8 EWR    BWI      1
## 9 EWR    CHS      4
## 10 EWR   CLE      4
## # ... with 171 more rows
```

```
flights %>%
  tidyquery::query(
    "SELECT origin, dest, COUNT(*) AS n
     WHERE month = 10 AND day = 21
     GROUP BY origin, dest"
  ) %>%
  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
## # ... with 171 more rows
```

Translating to dplyr

```
tidyquery::show_dplyr(  
  "SELECT origin, dest, COUNT(*) AS n  
   FROM flights  
  WHERE month = 10 AND day = 21  
 GROUP BY origin, dest"  
)  
  
## flights %>%  
##   filter(month == 10 & day == 21) %>%  
##   group_by(origin, dest) %>%  
##   summarise(n = dplyr::n()) %>%  
##   ungroup()
```

sqldf

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

```
##      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
```

```
sqldf::sqldf(  
  "SELECT origin, dest, COUNT(*) AS n  
   FROM flights  
  WHERE month = 10 AND day = 21  
 GROUP BY origin, dest"  
) %>%  
  as_tibble() %>%  
  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  
## ... with 171 more rows
```