The DuckDB TPCH Example

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Re-run an example from DuckDB.

[1] 6001215

This example comes from DuckDB, see the original 2021-05-14 article here.

The example is adapted from a TPC-H benchmark. It's not that big or complex, consisting of basic grouped statistics computed from a join of row-filtered tables. The larger table has about 6 million rows (16 columns), the smaller about 1.5 million rows and 9 columns. It's the kind of stuff SQL databases should excel at. It easily fits in the memory of my laptop. Only the final and most computationally expensive query in the DuckDB example is used here.

This piece explores a few R approaches to the problem, comparing style and, for what it's worth on such a simple problem, performance. Let's start with the DuckDB SQL approach.

Set up and a DuckDB Query The following code block downloads the two example data files (in Parquet format), loads them into DuckDB and runs the example query 50 times, capturing the timing results.

```
dbExecute(con, "CREATE TABLE orders AS SELECT * FROM 'orders.parquet'")
```

[1] 1500000

The query is pretty straightforward. I wonder just a little about how the <= in WHERE 1_shipdate <= DATE '1998-09-02' is evaluated because 1_shipdate in the Parquet file stores character-valued data. DuckDB's rules for implicit type casting are slightly mysterious (https://duckdb.org/docs/sql/expressions/cast). In this example using character or date types probably does not matter, but there might be a small performance gain by avoiding an unnecessary type conversion in the query.

0.1 A straight-up vectorized R approach

First, we need to transfer the DuckDB tables into plain old R data frames, and let's deal with that date type ambiguity mentioned above as well:

```
lineitem <- dbGetQuery(con, "SELECT * FROM lineitem")
orders <- dbGetQuery(con, "SELECT * FROM orders")
lineitem[["l_shipdate"]] <- as.Date(lineitem[["l_shipdate"]])</pre>
```

For me at least, a natural base R approach to problems like this relies on mostly on vectorized operations. The variable h indicates which rows of the orders data frame match the condition. Similarly, i filters the lineitem table rows on the date and join conditions. The statistics on l_extendedprice are mapped over the l_returnflag and l_linestatus groups by Map().

One minor thing to notice, the computed results are slightly different from DuckDB's:

```
vec[[1]][["sum"]] - duck[[3]]
[1] -0.003189087
```

That's because 1_extended_price is represented by double-precision floating point values and R's sum() function uses (platform-specific) extended-precision precision double arithmetic under the hood for accuracy. In this example, the R result is slightly more accurate (you can see this, for instance, using the Rmpfr package). Also note that floating point results can vary depending on the order in which they are computed. R attempts to mitigate some floating point problems like this, at least for summation.

0.2 dplyr

The dplyr data manipulation grammar hews to Codd's relational algebra but, in my opinion, is much more expressive, composable, and readable than SQL.

```
library(dplyr)
t3 <- replicate(50, system.time({
  o <- orders %>%
    select(o_orderkey, o_orderstatus) %>%
    filter(o_orderstatus == "0")
dpl <<- lineitem %>%
    select(l_orderkey, l_shipdate, l_returnflag, l_linestatus, l_extendedprice) %>%
    filter(l_shipdate <= as.Date("1998-09-02")) %>%
    inner_join(o, by = c("l_orderkey" = "o_orderkey")) %>%
```

```
group_by(l_returnflag, l_linestatus) %>%
summarize(sum = sum(l_extendedprice, na.rm = TRUE),
    min = min(l_extendedprice, na.rm = TRUE),
    max = max(l_extendedprice, na.rm = TRUE),
    avg = mean(l_extendedprice, na.rm = TRUE), .groups = "drop")
}))
```

0.3 dplyr + DuckDB

A beautiful thing about dplyr and R's lazy evaluation is that dplyr can act as a kind of query builder for back end database systems (most of the time). This layers the expressive syntax of dpylr over any kind of back-end database, taking advantage of the database query optimization and other optimization tricks.

Dplyr using a DuckDB back-end looks almost exactly like the previous example, but thanks to optimization by DuckDB runs a bit faster.

```
t4 <- replicate(50, system.time({
  o <- tbl(con, "orders") %>%
  select(o_orderkey, o_orderstatus) %>%
  filter(o_orderstatus == "0")
  dplyr_duck <<-
    tbl(con, "lineitem") %>%
    select(l_orderkey, l_shipdate, l_returnflag, l_linestatus, l_extendedprice) %>%
    filter(l_shipdate <= as.Date("1998-09-02")) %>%
    inner_join(o, by = c("l_orderkey" = "o_orderkey")) %>%
    group_by(l_returnflag, l_linestatus) %>%
    summarize(sum = sum(l_extendedprice, na.rm = TRUE),
             min = min(l_extendedprice, na.rm = TRUE),
             max = max(l_extendedprice, na.rm = TRUE),
               avg = mean(l_extendedprice, na.rm = TRUE), .groups = "drop") %>%
    collect()
}))
```

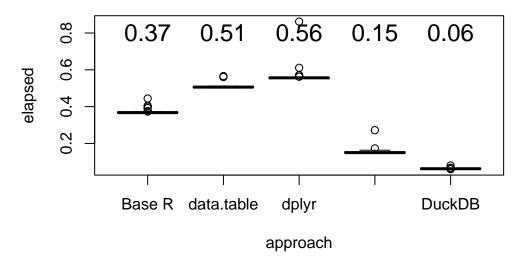
0.4 Data.table

R's data.table package can almost always exceed the performance of any other approach. Aside from speed, data.table is known for a very terse syntax, but it's also very well documented. (And more recently, dplyr partially supports data.table as a back end too.)

0.5 Performance and comments

Stylistically, I prefer either the vectorized base R way or the dplyr approach. Dplyr has the advantage of easily generalizing to more complicated tasks and the ability to work as a front end to database (like DuckDB) and other systems.

Elapsed time (seconds), mean values shown below



Performance-wise, it's a bit of a wash perhaps because this is a fairly trivial example. All the approaches perform well. data.table, as usual, and DuckDB give nearly identical performance and are fastest.

Dplyr + DuckDB gives you all the advantages of dplyr and the speed of DuckDB for this problem, a good combination!