Apache Arrow Based Workflows for Large Data Analytics

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Outline

- Motivating remarks
- Performance working with single files
 - Delimited text
 - Serialized object
 - Fast formats for rectangular data
- Parquet data format
- Apache arrow
 - Single file API
 - Data set API
- Arrow examples in R

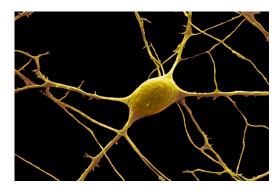
Resources

- Big Data in R with Arrow
 - 1-Day Posit::Conf (2023) Workshop
 - https://posit-conf-2023.github.io/arrow/
- Larger-Than-Memory Data Workflows with Apache Arrow
 - 2022 UseR! Conference
 - https://arrow-user2022.netlify.app/
- Apache Arrow documentation
 - https://arrow.apache.org/docs/
 - https://arrow.apache.org/docs/r/
- Feather V2 with Compression Support in Apache Arrow 0.17.0
 - https://ursalabs.org/blog/2020-feather-v2/
- Arrow Cheatsheet
 - https://github.com/apache/arrow/blob/main/r/cheatsheet/arrow-cheatsheet.pdf
- Materials for this talk
 - o https://github.com/kylebaron/data-2024

Resources

- Apache Arrow Overview
 - https://arrow.apache.org/overview/
- François Michonneau Blog
 - https://francoismichonneau.net/2022/08/arrow-dataset-creation/
 - https://francoismichonneau.net/2022/09/arrow-dataset-part-2/
 - https://francoismichonneau.net/2022/10/import-big-csv/

Where I've been



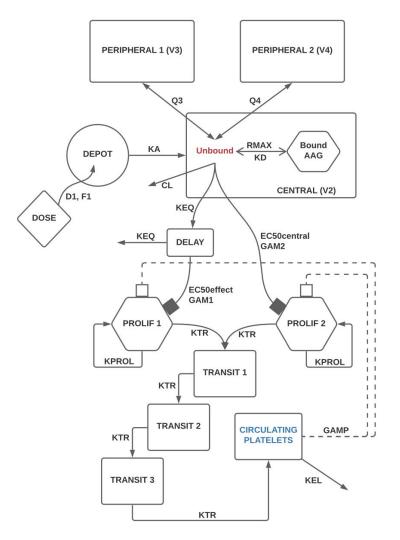




College of Pharmacy

Experimental and Clinical Pharmacology





So, what do you mean by "Big Data"?



UnitedHealth Group Minnetonka, MN

Fortune Global 500 list of 2023

Rank +	Company +	Country +	Industry \$	Revenue in USD +
1	Walmart	United States	Retail	\$611.3 billion
2	Saudi Aramco	Saudi Arabia	Energy	\$603.7 billion
3	State Grid	China	Energy	\$530.0 billion
4	Amazon	United States	Internet services and retailing	\$514.0 billion
5	China National Petroleum	China	Petroleum	\$483.1 billion
6	Sinopec Group	China	Petroleum	\$471.2 billion
7	ExxonMobil	United States	Petroleum	\$413.7 billion
8	Apple	United States	Technology	\$394.3 billion
9	Shell	United Kingdom	Petroleum	\$386.2 billion
10	UnitedHealth Group	United States	Health care	\$324.2 billion

I don't usually work with billions of records

```
> library(data.table)
> data <- fread("pk-data.csv")</pre>
   user system elapsed
 0.343 0.000 0.100
                          Really?
> dim(data)
[1] 59,845 76
> file.size("pk-data.csv")/1e6 # MB
[1] 24.86339
```

Simulation output from a recent project

902M pd-sim-out-1-tn1.parquet 902M pd-sim-out-1-tn2.parquet 902M pd-sim-out-1-tn3.parquet 902M pd-sim-out-1-tn4.parquet

```
> data <- lapply(files, arrow::read
  user system elapsed
  3.496  4.468  1.619</pre>
```

pd-sim-out-1-tn5.parquet

```
> sum(sapply(data, nrow))
[1] 195,000,000
```

902M

"Big Data" can factor into your analyses in a variety of ways

Finding the right approach to handling bulky data can greatly streamline your analyses

- Read efficiency
- Write efficiency
- Storage efficiency
- Analysis efficiency

Working with single files

data.ext → R data frame

Delimited text		
utils	read.csv(), write.csv()	What you used when you learned R
readr	read_csv(), write_csv()	Lots of use; "tidy"
vroom	<pre>vroom(), vroom_write()</pre>	Lazy load via ALT REP; R 3.5+ only
data.table	<pre>fread(), fwrite()</pre>	Known as the speed champ
arrow	read_csv_arrow(), write_csv_arrow()	Is it faster than fread()?
Serialized obje	ct	
base	readRDS(), saveRDS()	Comes with R; slow; handles any object
qs	<pre>qread(), qwrite()</pre>	My favorite; doesn't deal with stan objects well
Rectangular, fa	est	
fst	read_fst(), write_fst()	Replaced by qs; part of the "fastverse"
arrow	read_parquet(), write_parquet()	Wide use
arrow	read_feather(), write_feather()	New and fast

NYC Taxi Data (tiny)



- 1,672,513 rows
- 24 columns
- Multiple data types
 - Integer
 - Numeric
 - Character
 - Datetime

library(arrow)
bucket <- s3_bucket("voltrondata-labs-datasets/nyc-taxi-tiny")
copy_files(from = bucket, to = "nyc-taxi")</pre>

Read times (ms) - NYC taxi data set

	Function <fct></fct>	Time <dbl></dbl>	Relative <dbl></dbl>	Min <dbl></dbl>	Max <dbl></dbl>	Data <chr></chr>	n <int></int>
1	utils::read.csv()	9169	5.18	8240	10840	taxi	10
2	readr::read_csv()	1771	1	1596	2247	taxi	10
3	<pre>data.table::fread()</pre>	732	0.413	655	847	taxi	10
4	<pre>vroom::vroom()</pre>	541	0.305	458	1045	taxi	10
5	<pre>arrow::read_csv_arrow()</pre>	280	0.158	248	355	taxi	10
6	base::readRDS()	1703	0.962	1525	2752	taxi	10
7	qs::qread()	387	0.218	351	430	taxi	10
8	fst::read_fst()	466	0.263	322	1099	taxi	10
9	arrow::read_feather()	132	0.0748	32	656	taxi	10
10	arrow::read_parquet()	98	0.0553	41	180	taxi	10

Write times (ms) - NYC taxi data set

Function	Time	Relative	Min	Max	Data	n
<fct></fct>	<dbl></dbl>	<dbl></dbl>	<dbl></dbl>	<dbl></dbl>	<chr></chr>	<int></int>
1 utils::write.csv()	16568	3.45	15072	17903	taxi	10
<pre>2 readr::write_csv()</pre>	4797	1	3980	6145	taxi	10
<pre>3 data.table::fwrite()</pre>	984	0.205	975	1007	taxi	10
4 vroom::vroom_write()	4760	0.992	3847	6859	taxi	10
<pre>5 arrow::write_csv_arrow()</pre>	5958	1.24	5908	5996	taxi	10
6 base::saveRDS()	9458	1.97	9409	9555	taxi	10
7 qs::qsave()	505	0.105	477	639	taxi	10
<pre>8 fst::write_fst()</pre>	311	0.0648	290	356	taxi	10
<pre>9 arrow::write_feather()</pre>	201	0.0419	191	212	taxi	10
10 arrow::write_parquet()	652	0.136	634	686	taxi	10

File size - NYC taxi data set

	Format <chr></chr>		Unit <chr></chr>	Relative <dbl></dbl>	Data <chr></chr>
1	CSV	236.	MB	1	taxi
2	rds	51.3	MB	0.218	taxi
3	qs	60.1	MB	0.255	taxi
4	fst	114.	MB	0.484	taxi
5	parquet	54.4	MB	0.231	taxi
6	feather	111.	MB	0.470	taxi

Data compression - NYC taxi data set

	Format <chr></chr>	-	Size <dbl></dbl>		Relative <dbl></dbl>	
1	CSV		236.		1	
2	feather	yes	111.	MB	0.470	taxi
3	parquet	yes	54.4	MB	0.231	taxi
4	feather	no	296.	MB	1.25	taxi
5	parquet	no	59.6	MB	0.253	taxi

Parquet format

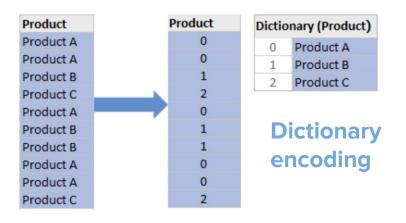
- Columnar storage
- Compression by column
- Bit packing
- Store row group stats
- Dictionary encoding
- Run-length encoding

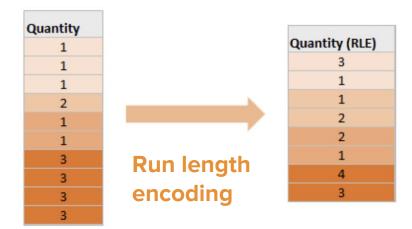


https://www.upsolver.com/blog/apache-parquet-why-use

Parquet Encodings

Product	Quantity	OrderDate
Product A	1	06/12/2021 19:01:15.000
Product A	1	07/12/2021 19:01:16.000
Product B	1	08/12/2021 19:01:16.231
Product C	2	09/12/2021 19:01:17.000
Product A	1	10/12/2021 19:01:18.000
Product B	1	11/12/2021 19:01:19.565
Product B	2	12/12/2021 19:01:20.000
Product A	2	13/12/2021 19:01:20.876
Product A	2	14/12/2021 19:01:21.500
Product C	1	15/12/2021 19:01:22.000





Data compression and encoding - NYC taxi data set

	Format	Comp	Dict	Size	Unit	Relative	Data
	<chr></chr>	<chr></chr>	<chr></chr>	<dbl></dbl>	<chr></chr>	<dbl></dbl>	<chr></chr>
1	parquet	yes	yes	54.4	MB	1	taxi
2	parquet	no	yes	59.6	MB	1.10	taxi
3	parquet	yes	no	88.4	MB	1.63	taxi
4	parquet	no	no	242.	MB	4.46	taxi

- Several performant options for reading csv
- fwrite() was fastest csv writer
- qread() / qwrite() good all around
- Arrow
 - feather and parquet are both very fast
 - parquet has great storage
 - parquet is special

What is Apache Arrow?



What is Arrow?

Format

Apache Arrow defines a language-independent columnar memory format for flat and includin analytic operations on modern hardware like CPUs and GPUs. The Arrow memory format data ediso supports zero-copy reads for lightning-fast data access without serialization overhead.

Learn more about the design or read the specification.

Libraries

Arrow's libraries implement the format and provide building blocks for a range of use cases, including high performance analytics. Many popular projects use Arrow to ship columnar data efficiently or as the basis for analytic engines.

Libraries are available for C, C++, C#, Go, Java, JavaScript, Julia, MATLAB, Python, R, Ruby, and Rust. See how to install and get started.

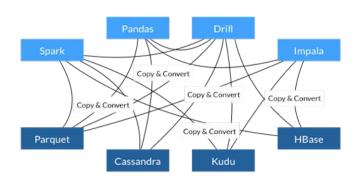
Ecosystem

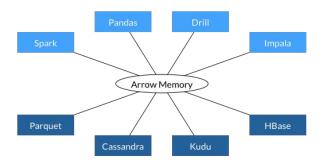
Apache Arrow is software created by and for the developer community. We are dedicated to open, kind communication and consensus decisionmaking. Our committers come from a range of organizations and backgrounds, and we welcome all to participate with us.

Learn more about how you can ask questions and get involved in the Arrow project.

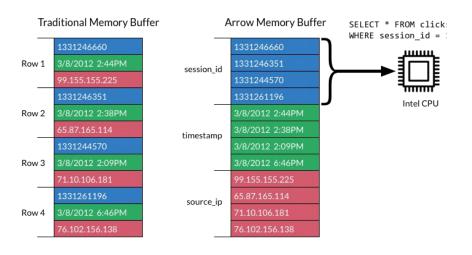
- Cross-language
- Development platform
- In-memory analytics
- Not (just) a file format

Standardized, language-agnostic in-memory format





	session_id	timestamp	source_ip
Row 1	1331246660	3/8/2012 2:44PM	99.155.155.225
Row 2	1331246351	3/8/2012 2:38PM	65.87.165.114
Row 3	1331244570	3/8/2012 2:09PM	71.10.106.181
Row 4	1331261196	3/8/2012 6:46PM	76.102.156.138

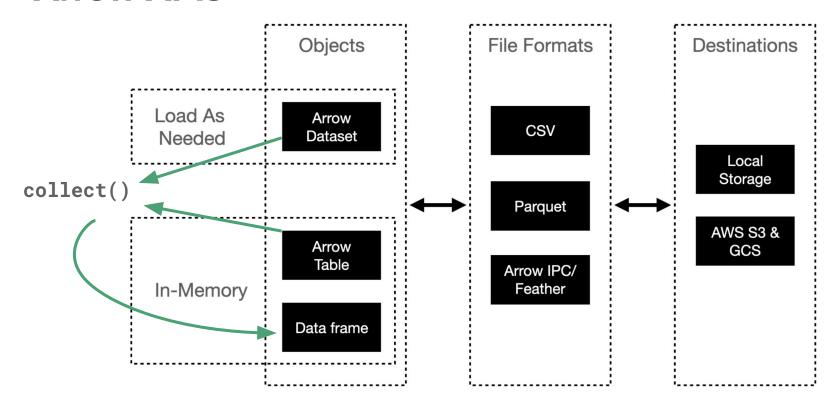


https://arrow.apache.org/overview/

Arrow APIs

- Single-file API
 - o arrow::read_parquet(), arrow::write_parquet()
 - Data is stored in a (single) file
 - Read can return data.frame or arrow table
 - Data is in memory
- Dataset API
 - arrow::open_dataset(), arrow::write_dataset()
 - Data is stored a directory
 - One or more files
 - Directory can be partitioned in subdirectories
 - Data engineering
 - Data is loaded only when needed

Arrow APIs



Single-file and data set API

Read a single file, returns data frame in memory

```
df <- read_parquet("big-data.parquet")</pre>
```

Read a single file, returns arrow table in memory

```
at <- read_parquet("big-data.parquet", as_data_frame = FALSE)
at <- arrow_table(df)</pre>
```

Read directory, returns data set object, instant

```
ds <- open_dataset("data-dir/")
class(ds)
[1] "FileSystemDataset" "Dataset" "ArrowObject" "R6"</pre>
```

"tidy" workflow for arrow data sets and tables

Arrow table (at): in memory
Arrow data set (ds): on disk (memory-mapped)
Both: return R data frame via collect()

```
at %>%
   group_by(var1, var2) %>%
   summarise(Mean = mean(value)) %>%
   collect()

ds %>%
   group_by(var1, var2) %>%
   summarise(Mean = mean(value)) %>%
   collect()
```

Apache Arrow Demo

- Simulate from compartmental PK model
 - 4 dose levels
 - o 300 subjects per dose
 - 26 output records per subject
 - o 3000 replicates
- Output
 - o 3.6 million subjects
 - Random variability
 - o 9.36 million rows, 12 columns
 - o 3.3 GB (parquet); 7 GB (feather)
- All simulation and analysis done on Apple
 M1 Pro (2021) 16 GB

