Optimizing Data Access with Compute Offloading, Fast Hardware-Accelerated Data Transport, and Modern Query Languages

[Jayjeet Chakraborty](), [Carlos Maltzahn]()
UC Santa Cruz

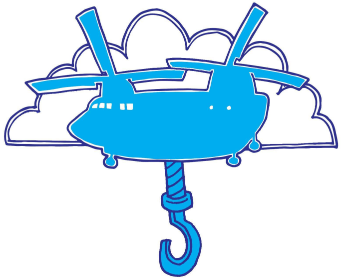
cross.ucsc.edu

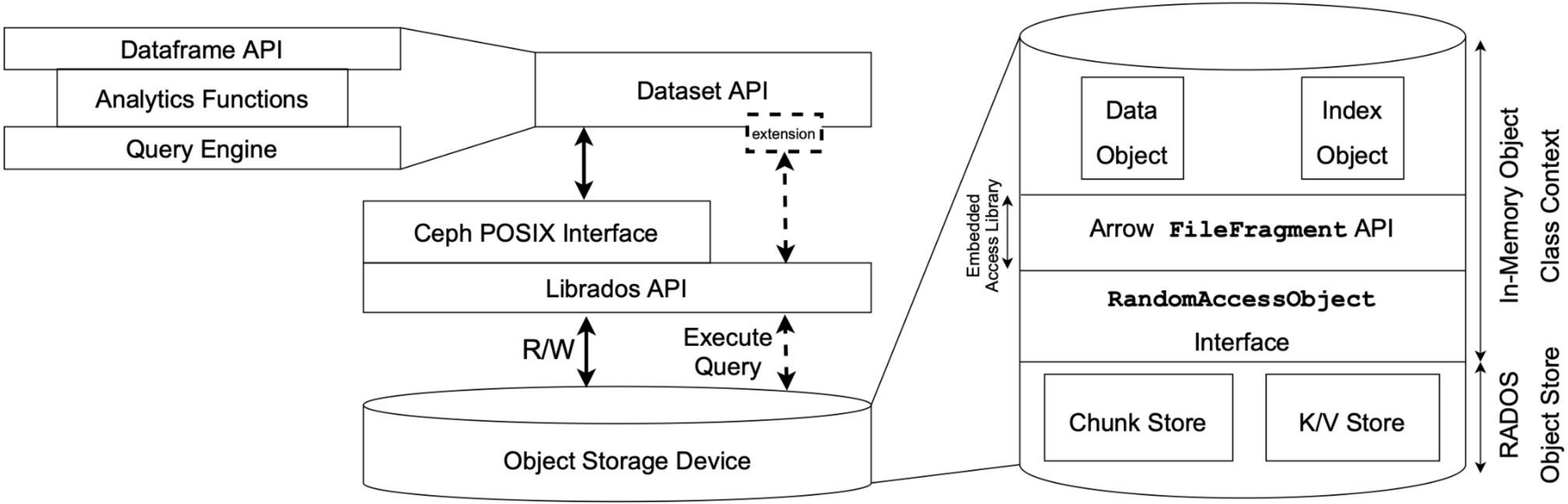
About Me

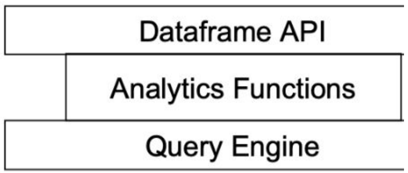
- PhD Student @ UC Santa Cruz
  - Going to 3rd yr.
  - **Advisor**: Carlos Maltzahn
  - Systems Research Lab, UCSC
- Summer Intern at InfluxData Inc.
- Former IRIS-HEP Fellow (2020/2021)
- Former GSoC student (2019)
- Co-Creator of SkyhookDM
- Researching Data management, Databases, and Storage systems

My Interests/Ongoing Work

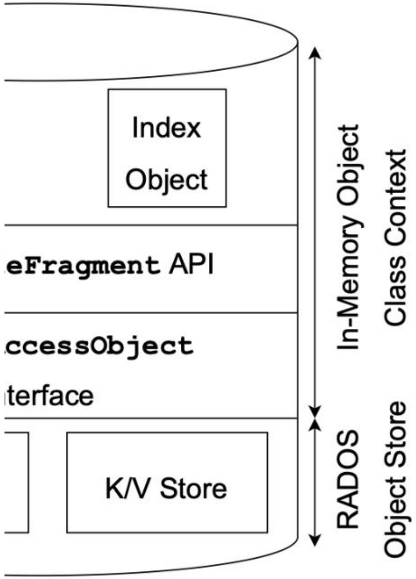
- Exploring ways to accelerate queries in data management systems
  - Computational storage:
    - Offload query execution logic to storage servers/devices
      - **Skyhook**: Apache Arrow in Ceph Object Store
        - Reduce data movement
        - Reduce metadata overload on the client
        - Low barrier to computational storage
        - Contributed to Apache Arrow open-source project last year
        - Published in CCGrid'22
    - Embedding (de)compression, (de)serialization inside Smart NICs
      - NVIDIA BlueField 2

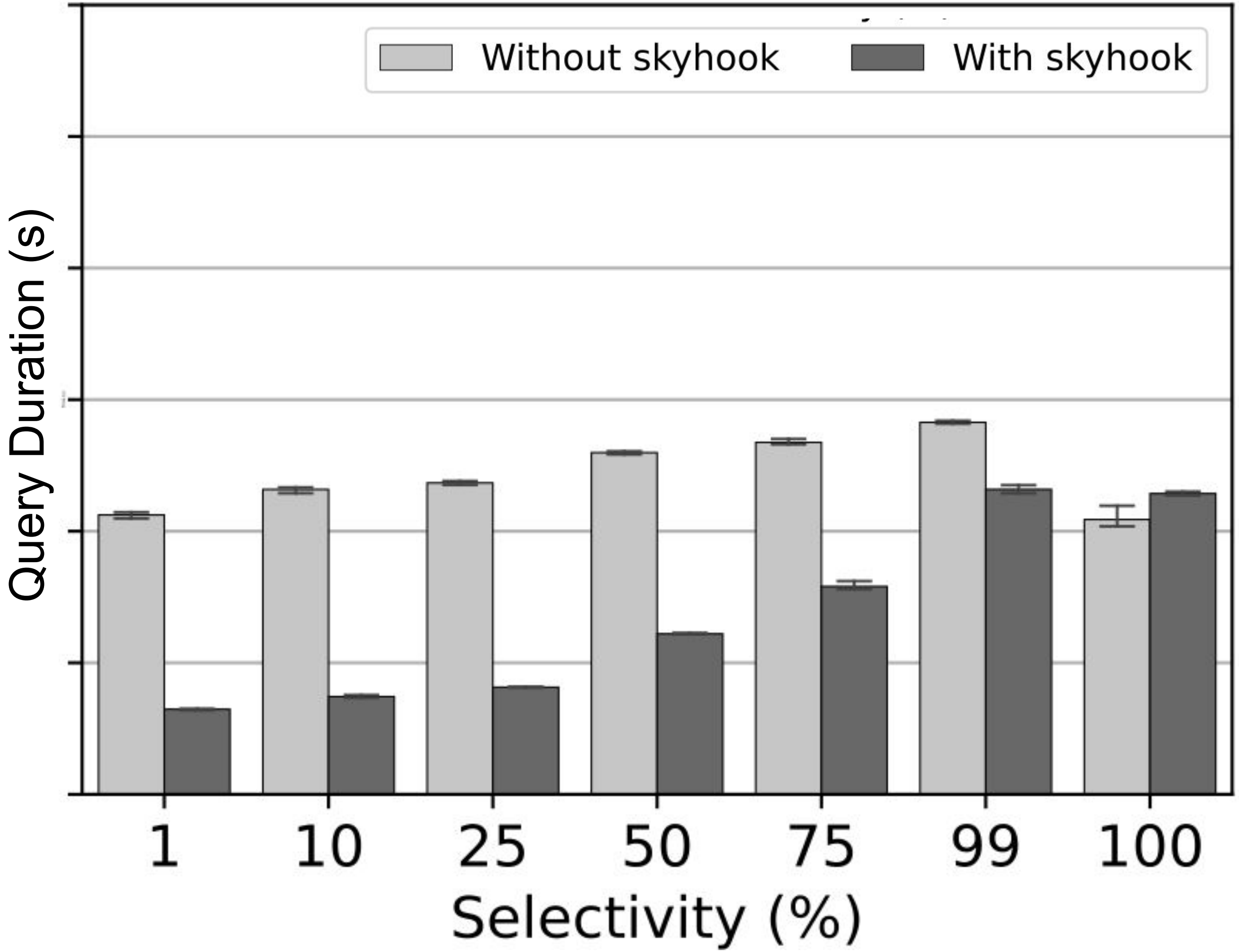



Dataframe API
Analytics Functions
Query Engine
Dataset API
extension
Ceph POSIX Interface
Librados API
R/W
Execute
Query
Object Storage Device
Data
Object
Index
Object
Embedded
Access Library
Arrow FileFragment API
RandomAccessObject
Interface
Chunk Store
K/V Store
In-Memory Object
Class Context
RADOS
Object Store



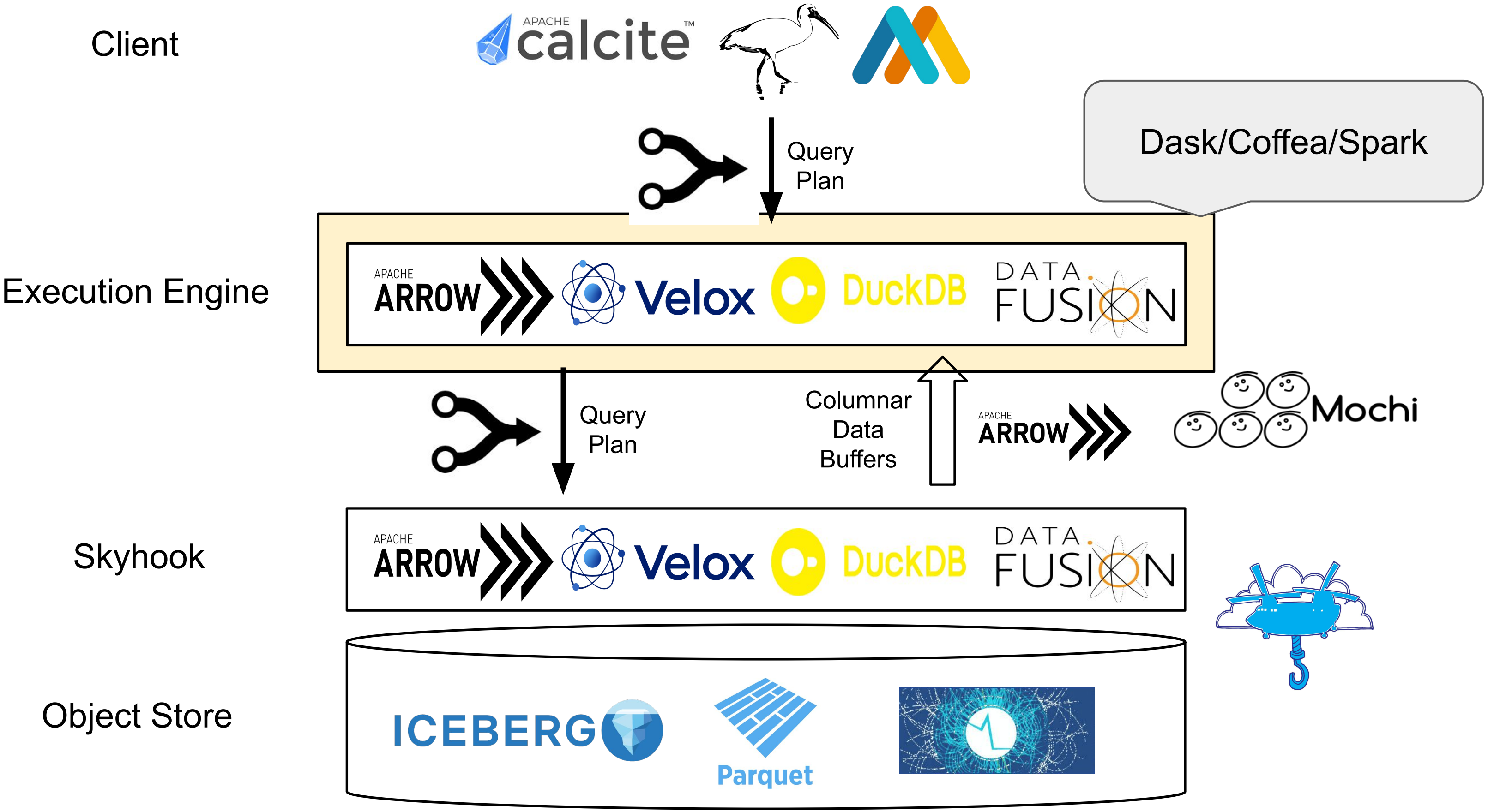

```
# Reading from Parquet
import pyarrow.dataset as ds
format_ = "parquet"
dataset = ds.dataset(
    "/dataset", format=format_
)
dataset.to_table()

# Reading from Parquet using Skyhook
import pyarrow.dataset as ds
format_ = ds.SkyhookFileFormat(
    "parquet", "/ceph.conf"
)
dataset = ds.dataset(
    "/dataset", format=format_
)
dataset.to_table()
```




Without skyhook
With skyhook
Query Duration (s)
1
10
25
50
75
99
100
Selectivity (%)

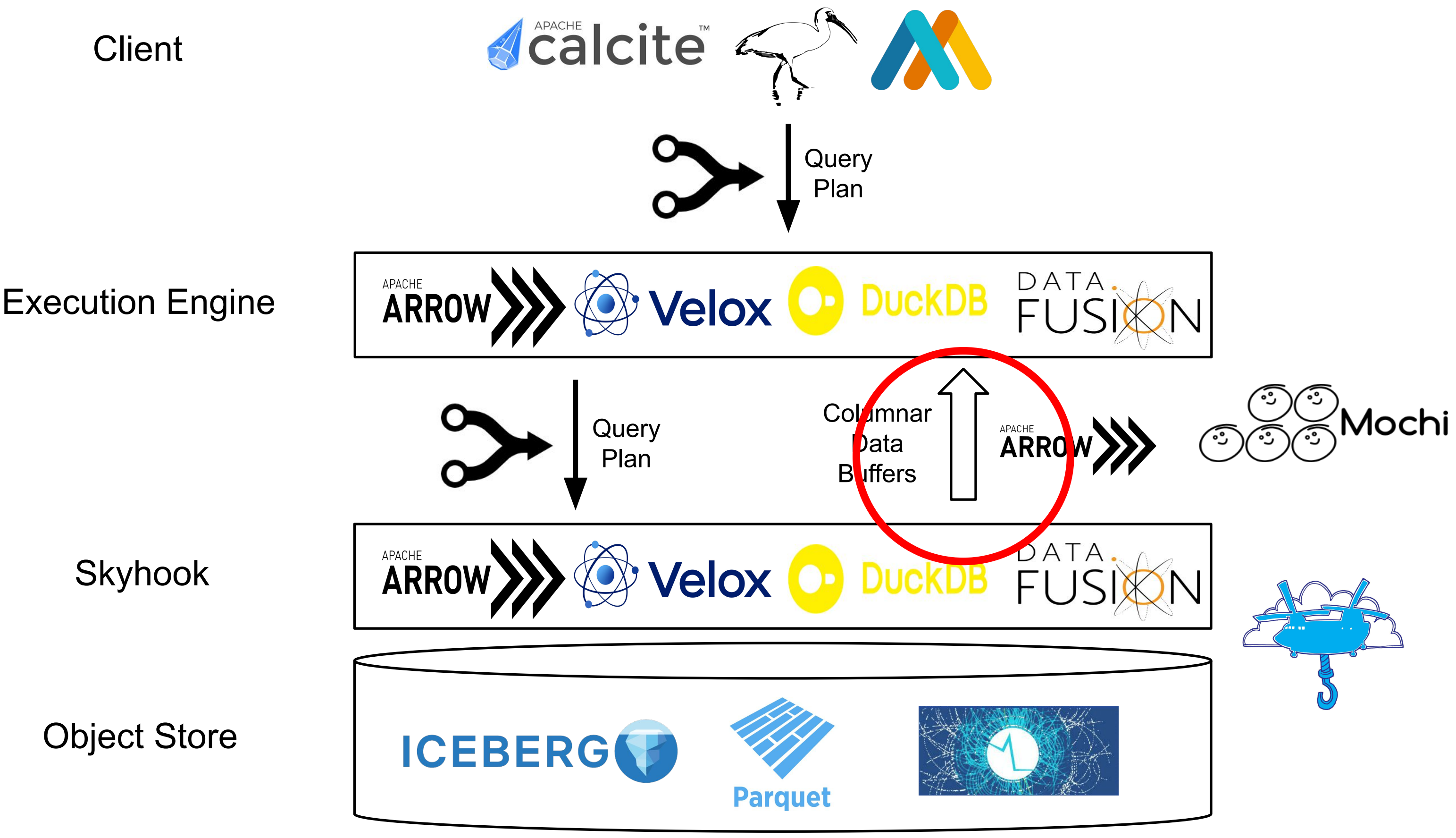
My Interests/Ongoing Work

- Deconstructed "Data Management"
    - Pick and choose your own stack
    - No more redundant data management systems
    - Enable standardization
    - **Build your custom data system with modular interoperable frameworks**
        - Query languages
        - Query Interfaces and Compiler
        - Task schedulers
        - Query execution engines
        - Storage systems
        - File formats
    - We aim to prototype a initial version of such a system using the Python SDKs in each layer


Client
APACHE calcite
Query Plan
Dask/Coffea/Spark
Execution Engine
APACHE ARROW
Velox
DuckDB
DATA FUSION
Query Plan
Columnar Data Buffers
APACHE ARROW
Mochi
Skyhook
APACHE ARROW
Velox
DuckDB
DATA FUSION
Object Store
ICEBERG
Parquet

My Interests/Ongoing Work

- Leveraging modern networking devices
  - RDMA-enabled NICs common in Data centers
    - ConnectX-3/5/6
    - Upto 100 Gbps
  - Move from TCP/IP to RDMA for fast data transfers
    - Avoid copying and serialization overhead of TCP/IP
    - Use data transport frameworks used in HPC
      - Mochi Thallium from Argonne National Labs
    - **Thallus: Faster Columnar (Apache Arrow) Data Transport using RDMA**
      - Arrow Flight (gRPC-based) as our baseline
      - Preparing for submission


Client
APACHE calcite
Query Plan
Execution Engine
APACHE ARROW
Velox
DuckDB
DATA FUSION
Query Plan
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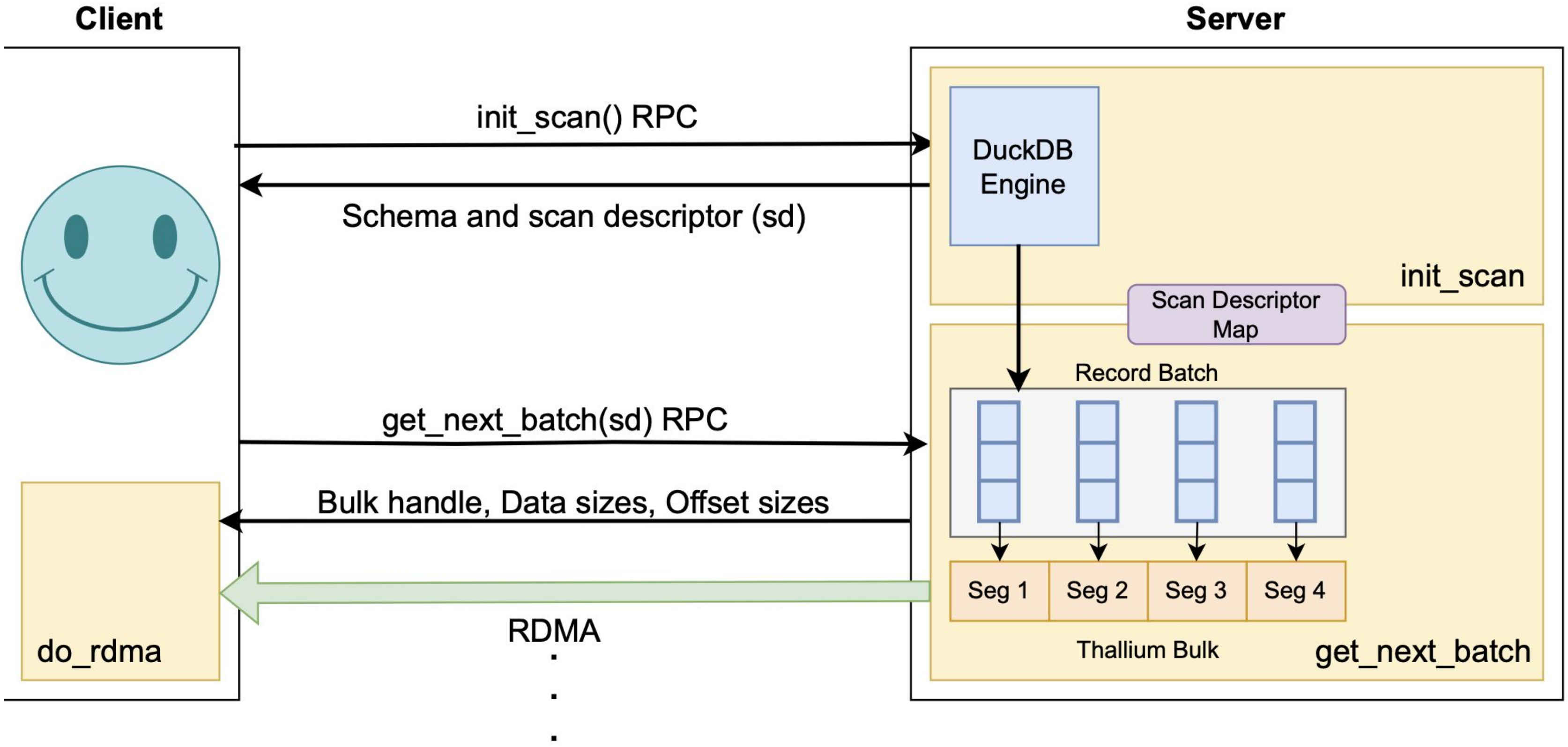
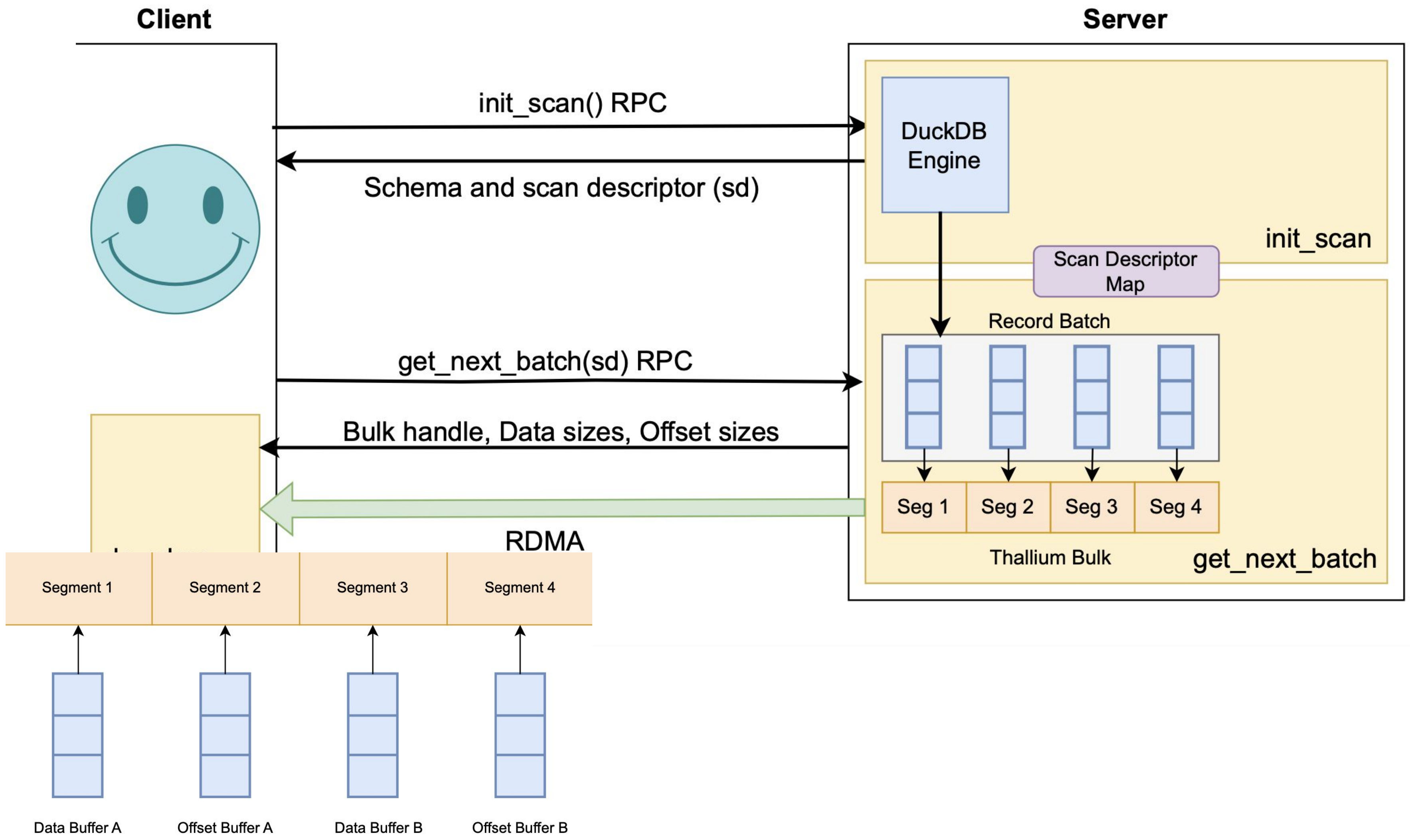

Client
Server
init_scan() RPC
Schema and scan descriptor (sd)
DuckDB Engine
init_scan
Scan Descriptor Map
Record Batch
get_next_batch(sd) RPC
Bulk handle, Data sizes, Offset sizes
Seg 1
Seg 2
Seg 3
Seg 4
RDMA
do_rdma
Thallium Bulk
get_next_batch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Schema and scan descriptor (sd)
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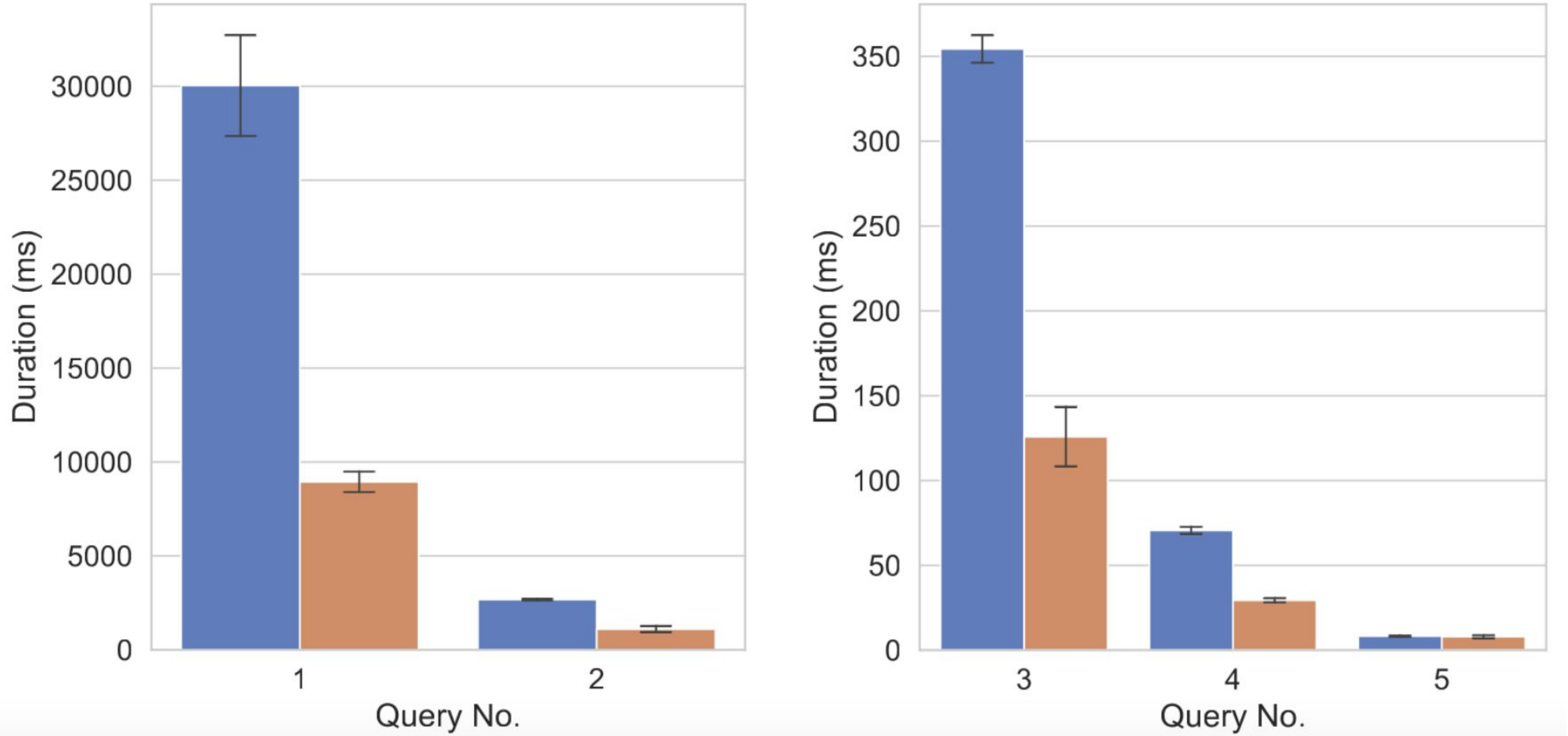
get_next_batch(sd) RPC
Bulk handle, Data sizes, Offset sizes
Seg 1
Seg 2
Seg 3
Seg 4
RDMA
Thallium Bulk
get_next_batch
Segment 1
Segment 2
Segment 3
Segment 4
Data Buffer A
Offset Buffer A
Data Buffer B
Offset Buffer B


Duration (ms)
30000
25000
20000
15000
10000
5000
0
1
2
Query No.
Duration (ms)
350
300
250
200
150
100
50
0
3
4
5
Query No.

My Interests/Ongoing Work

- Alternative query languages for HEP data
  - Malloy QL, project by Google
    - **Designed for handling hyper-dimensional data**
    - Generates the most optimized SQL possible
    - Much simpler syntax than SQL, better UX
    - Plugins for BigQuery, DuckDB, PostGres
    - 2 parts to every query:
      - Source: A table or computation result set
      - Query: Pipelined set of stages defining a query operation
    - Python package for Malloy: malloy-py

Evaluating Query Languages and Systems for High-Energy Physics Data

[Extended Version]

Dan Graur
Department of Computer Science
ETH Zurich
dan.graur@inf.ethz.ch

Ingo Müller
Department of Computer Science
ETH Zurich
ingo.mueller@inf.ethz.ch

Mason Proffitt
Department of Physics
University of Washington
masonLp@uw.edu

Ghislain Fourny
Department of Computer Science
ETH Zurich
ghislain.fourny@inf.ethz.ch

Gordon T. Watts
Department of Physics
University of Washington
gwatts@uw.edu

Gustavo Alonso
Department of Computer Science
ETH Zurich
alonso@inf.ethz.ch

ABSTRACT

In the domain of high-energy physics (HEP), query languages in general and SQL in particular have found limited acceptance. This is surprising since HEP data analysis matches the SQL model well: the data is fully structured and queried using mostly standard operators. To gain insights on why this is the case, we perform a comprehensive analysis of six diverse, general-purpose data processing platforms using an HEP benchmark. The result of the evaluation is an interesting and rather complex picture of existing solutions: Their query languages vary greatly in how natural and concise HEP query patterns can be expressed. Furthermore, most of them

only a small subset of the available attributes, derivation of additional measures (potentially by joining and reducing the sequences *within the same event*), and selection of an interesting subset of events, which are then summarized using a reduction. HEP data is thus stored and analyzed in non-first normal form (NF^2)—a feature that early database systems did not support and thus the main reason why relational engines were rejected by physicists historically (along with the lack of support for used-defined code [39]).

Nowadays, most particle physicists work with a domain-specific system called the ROOT framework [4, 12], and increasingly so with its new RDataFrame interface [27]. In ROOT, queries are writ-

Handwritten SQL to Malloy for **Q4**

```sql
SELECT
    FLOOR((
        CASE
        WHEN MET.pt < 0 THEN -1
        WHEN MET.pt > 2000 THEN 2001
        ELSE MET.pt
        END) / 20) * 20 + 10 AS x,
    COUNT(*) AS y
FROM '{dataset_path}'
WHERE (
    SELECT
        COUNT(*)
    FROM UNNEST(Jet)
    WHERE Jet.pt > 40
) > 1
GROUP BY FLOOR((
CASE
    WHEN MET.pt < 0 THEN -1
    WHEN MET.pt > 2000 THEN 2001
    ELSE MET.pt
END) / 20) * 20 + 10
ORDER BY x;
```

Preview

```
source: hep is table('duckdb:../hep.parquet') {
 declare: x is
          floor((pick -1  when MET.pt < 0
          pick 2001 when MET.pt > 2000
          else MET.pt) / 20) * 20 + 10
}
```

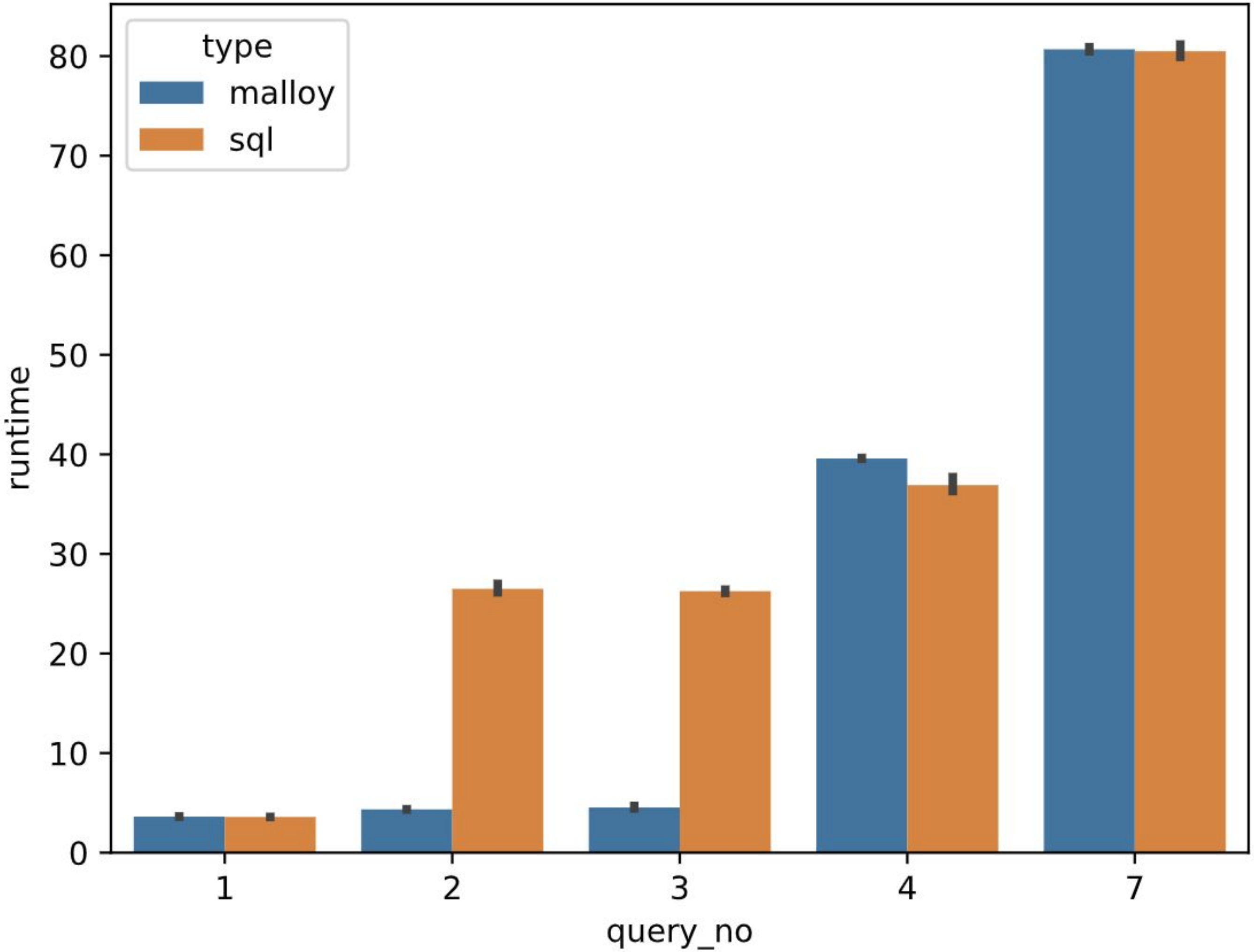
Run

```
query: hep -> {
  declare: t is Jet.count() {? Jet.pt > 40} > 1
  group_by: x, event
  where: t
}
-> {
  group_by: x
  aggregate: y is count()
  order_by: x
}
```

Equivalent Malloy gen. SQL for **Q4**

```
WITH __stage0 AS (
  SELECT
    ((floor((
      CASE WHEN hep.MET."pt"<0 THEN -1
      WHEN hep.MET."pt">2000 THEN 2001
      ELSE hep.MET."pt" END)*1.0/20))*20)+10
    as "x",
     hep."uid" as "uid"
  FROM (SELECT gen_random_uuid() uid, * FROM '{dataset_path}') as hep
  LEFT JOIN (select UNNEST(generate_series(1,
          100000, --
          -- (SELECT genres_length FROM movies limit 1),
          1)) as __row_id) as Jet_0 ON  Jet_0.__row_id <= array_length(hep."Jet")
  GROUP BY 2, 1
  HAVING (COUNT( CASE WHEN hep.Jet[Jet_0.__row_id]."pt">40 THEN 1 END)>1)
)

SELECT
   base."x" as "x",
   COUNT( 1) as "y"
FROM __stage0 as base
GROUP BY 1
ORDER BY 1 asc NULLS LAST
```


type
malloy
sql
runtime
0
10
20
30
40
50
60
70
80
1
2
3
4
7
query_no

Goals

- Leverage modern hardware and protocols in data management
- Expose complex functionality using simple interfaces and APIs
- World is moving towards composable data management, stay ahead !
- Prepare for the **Analysis Grand Challenge**