

LakeSoul's NativeIO Layer Implementation Principle and Practice

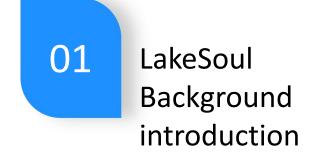
Chen Xu Beijing Shuyuan Ling Technology Co., LTD

Outline



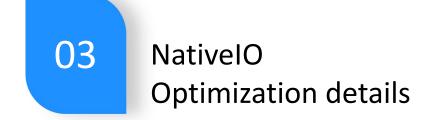


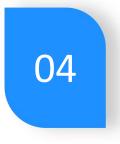






NativelO Layer design and implementation





NativeIO Application and prospects







LakeSoul Open source lake warehouse framework introduction

TLF AI & DATA

- Website: https://lakesoul-io.github.io/
- GitHub: https://github.com/lakesoul-io/LakeSoul

Originated in the realtime data flow scenario of large recommendation and advertising businesses

2021.12

LakeSoul Domestic selfresearch flow batch integrated lake warehouse framework open

2022.07

Refactoring metadata to improve concurrent update and transaction capabilities

2022.10

Release Flink CDC multi-table automatically into the lake, support the whole library. synchronization, automatic DDL change

2023.05

Release of Native IO to expand performance leadership. LakeSoul Project was donated to Linux, Foundation Incubation

2023.06~Now

Release the full link flow lincremental calculation, automatic merge and other functions. Súpport for PyTorch, Ray, and Pandas reads

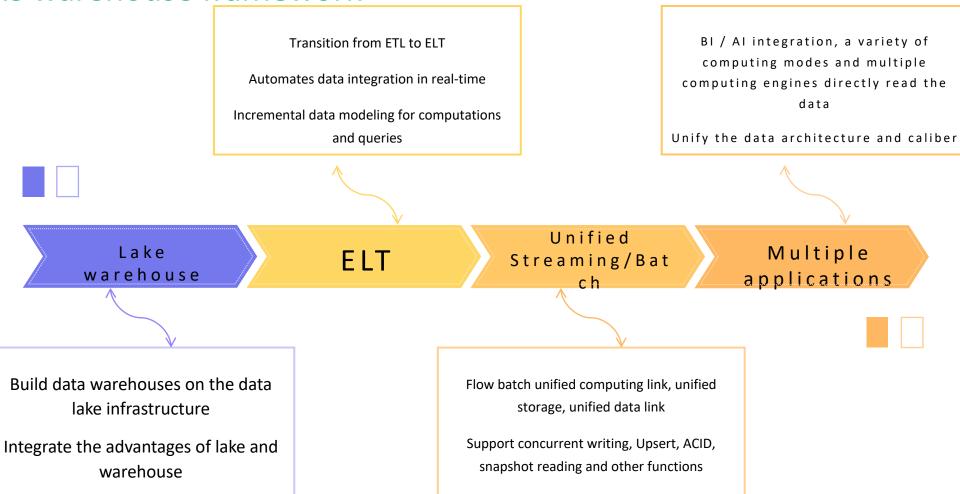




LakeSoul Open source lake warehouse framework introduction

Open source project positioning: one-stop Data +

Al Lake warehouse framework









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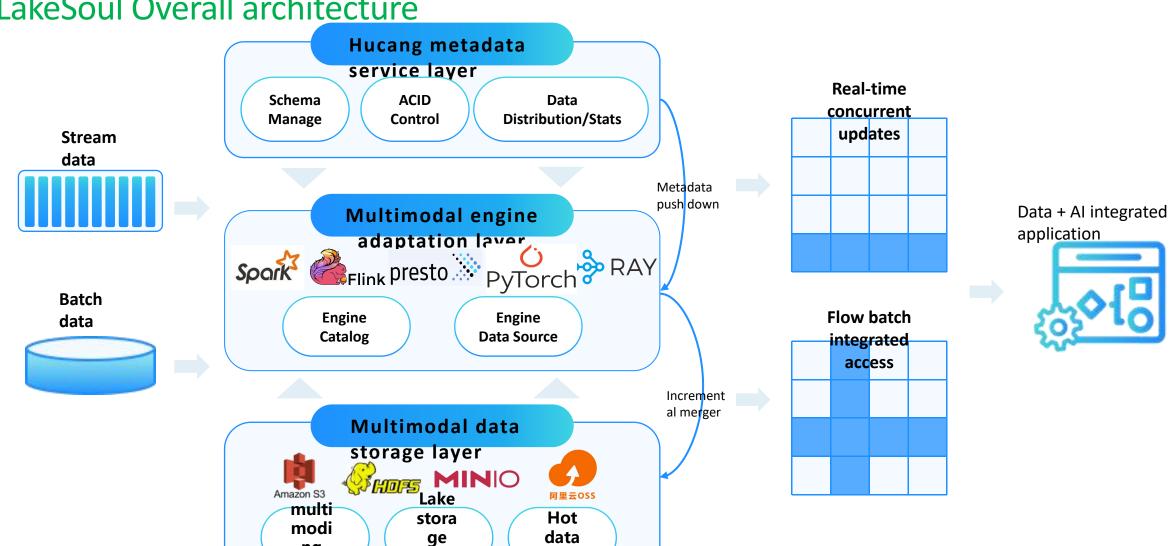
LakeSoul Overall architecture

ng

data

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cache





lake architecture

data Integration Need to support a variety of data source collection, CDC flow update, improve the real-time performance

data storage

 Cloud native architecture, computing and storage separation, and cloud storage performance optimization

data handling

 Need to support high performance, low latency flow, batch computing

Data application

Need to support big data, AI multiple scenarios, computing ecology

LakeSoul, Open source lake warehouse framework introduction LakeSoul Framework solution: Native 10



layer

data Integration Support multi-source heterogeneous data source and data acquisition tools, support real-time CDC writing, Upsert update

real-time

data storage

 Separation of storage and calculation, elastic capacity expansion, and highly optimized for cloud object storage

Cloud native

high-

performance



NativelO

data handling Support high performance batch computing, low delay real-time incremental computing

Open

Ecosystem

Data application

Data application requires data consumption to support a variety of application scenarios (AI, BI)



design goal



Unified packaging

- Unified IO implementation, encapsulate Upsert and MOR logic
- Independent of the computational engine implementation
- Package the Java / Python interface



Multi-engine ecology

- Vectorized memory format, zero-copy across languages
- Vectorization computing framework, AI framework docking

high-performance

- For high-throughput batch reading and writing design
- Separated elastic Compaction, reduced write magnification
- Use fully the asynchronous parallel means to improve the storage system access performance



Technical selection

- Implementation language: Rust
- data format:
 - Apache Parquet (disk) + Apache Arrow (memory)
 - There are main key table, no primary key table
- Physical implementation
 - Apache DataFusion
 - Apache Arrow-RS
 - Tokio

- NativeIO SDK:
 - Arrow C data interface
 - Java: com.github.jnr:jnr-ffi
 - Rust: std::ffi, arrow::ffi
 - Python: cython, ctypes, pyo3
- Engine Connectors
 - Spark/Flink/Presto
 - PyTorch/Pandas/Ray



NativeIO Overall architecture

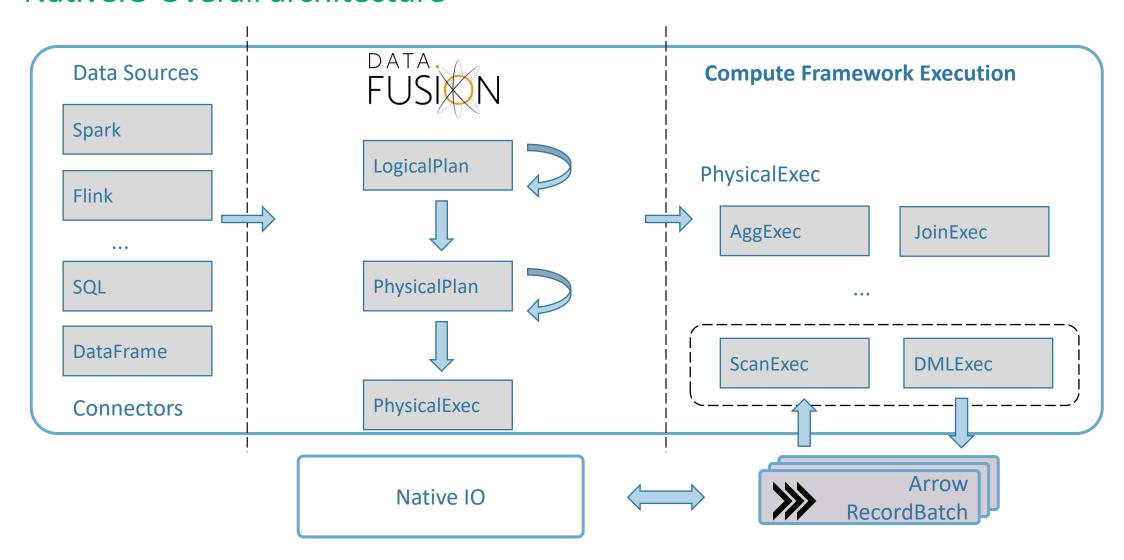




Table file organization format

- partition table
 - Supports multilevel range partitions, with one subdirectory per level
 - table_path/'date=20240110'/
- Main key table

1100000

- Monolayer of LSM-Tree
- Upsert When the file is divided according to the main key hash, and the main key is sorted within the shard
- Support for reading and writing in CDC format
 - With a rowkind hidden column: I / U / D
- Support for concurrent partial field updates (Partial

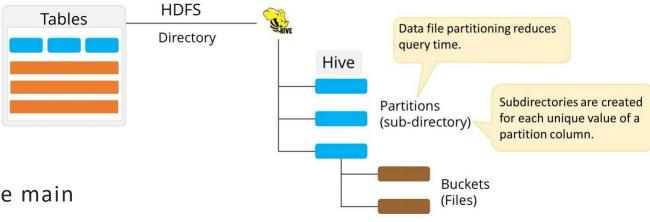


Photo credit: https://www.simplilearn.com/tutorials/hadoop-tutorial/data-file-partitioning



Primary Key table write process

Plan Tree **Insert Into:** FilePath = TablePath/Partition/prefix-{version id } {bucket id}.parquet **Native Interface** Repartition: Partitioning = HashPartitioning(HashKey, HashBucketNum) **Native Interface** Sort: SortKey=[HashKey] Native Interface Native Parquet Writer

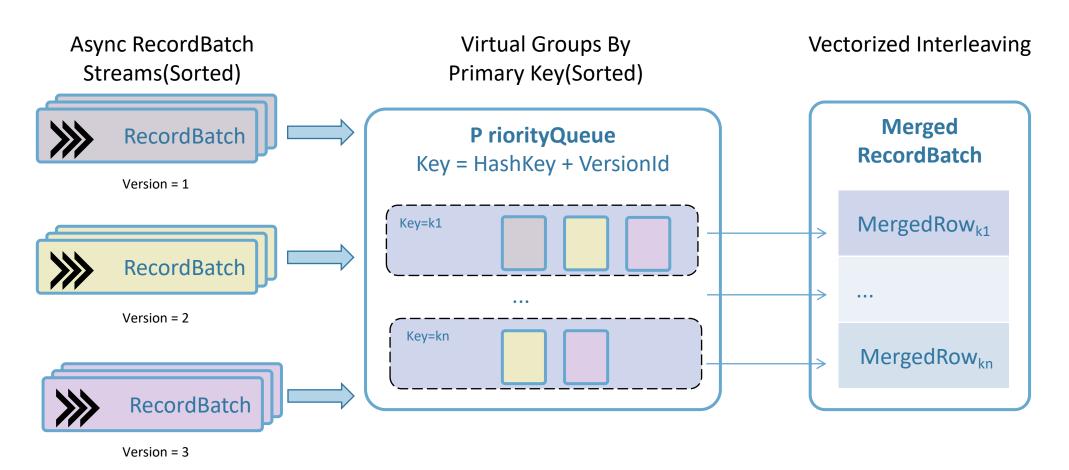
- The execution position of hash slice

 (Repartition) and sorting can be adjusted flexibly
 - Spark: Sding and sorting are performed in Spark
 - Flink: Sding is performed in Flink and sorting is performed in NativeIO layer
- Engine global fragmentation to reduce the number of small files
- Native Level sorting uses Spill Sort to save memory
- Write path without Compaction

 (additional automatic Compaction service)



Primary key table read process





Primary key table read process

[RecordBatch], batch_size=2

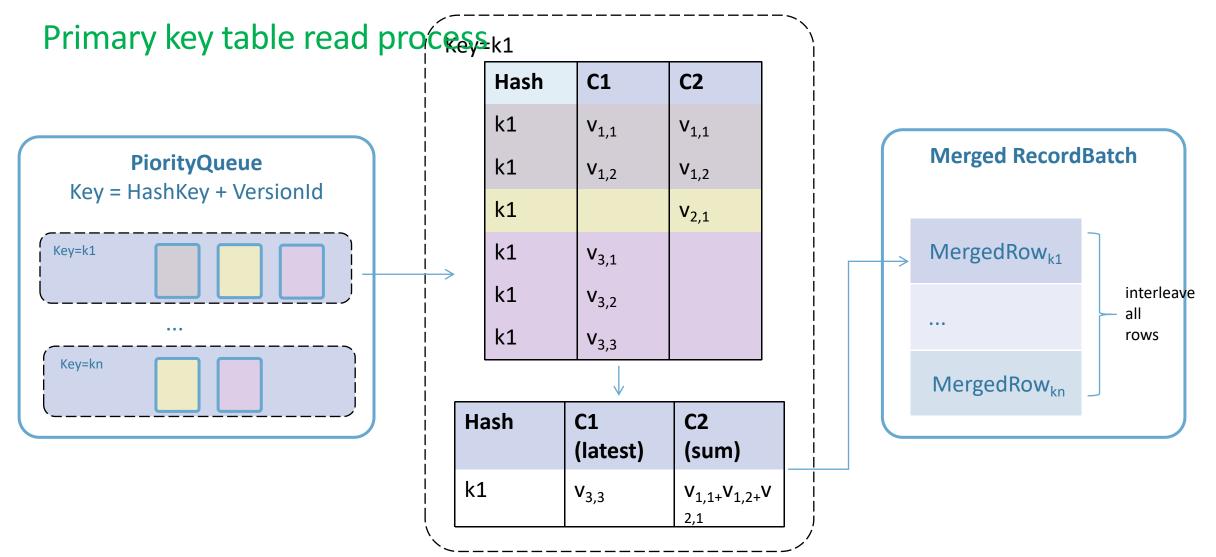
Hash	Value
01	а
01	b
11	а
21	a
21	b
21	С
21	d
31	a
31	b

BatchRange

Hash	Value
01	а
01	b
11	а
21	а
21	b
21	С
21	d
31	а
31	b

- The same primary key may come from the same batch, multiple batch per file, and a batch of different files
- Organize the same primary key together using the priority queue (record stream id, batch id, row id, no data copy)





- Each group selects the line number corresponding to the latest primary key to form the {stream_id, batch_id, begin / end_row_id} quple
- Batch final output using the Arrow Interleave operator



CDC (Change Data Capture) native support

Automatically add the RowKind hidden columns

PK	Value	RowKind
01	а	1
01	b	U
11	а	1
21	а	1
21	b	U
21	null	D

The deleted row is automatically filtered during the batch read (Spark/Flink/Presto/PyTorch)

PK	Value
01	b
11	а

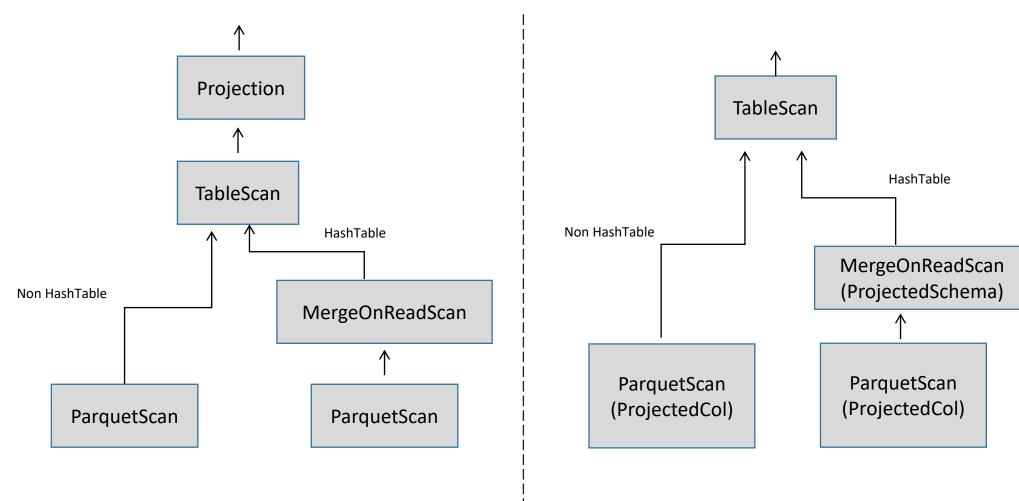
Flow read automatically fill Flink RowData.rowKind Field

PK	Value	RowKind
01	а	1
01	b	U
11	а	1
21	а	1
21	b	U
21	null	D

LakeSoul NativelO Performance Optimization LakeSoul



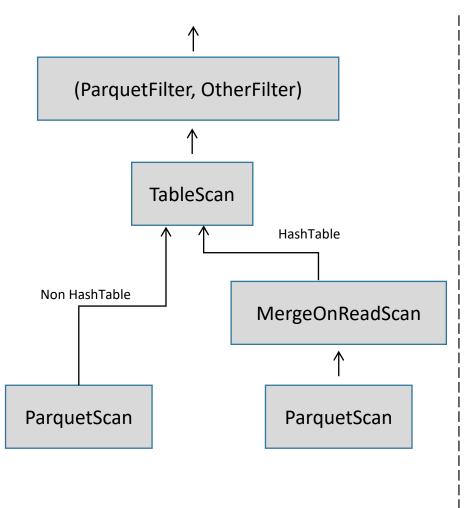
Column cutting push down

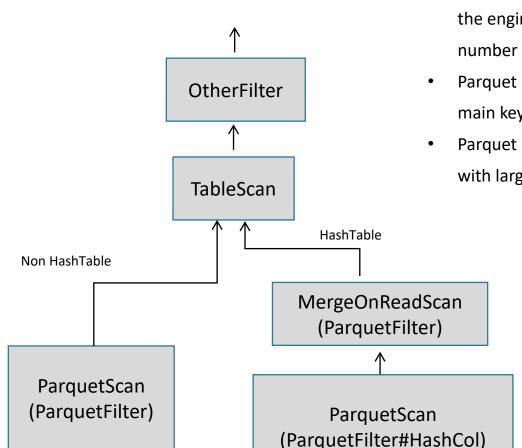


LakeSoul NativelO Performance Optimization LakeSoul









- Partition cropping is done in advance at the engine layer to reduce the Plan Task
- Parquet RowGroup Stats Cropping (the main key point check effect is obvious)
- Parquet Reader Filter: Off off (effective with large proportion filtering)

LakeSoul NativelO Performance Optimization LakeSoul





Object storage performance optimization

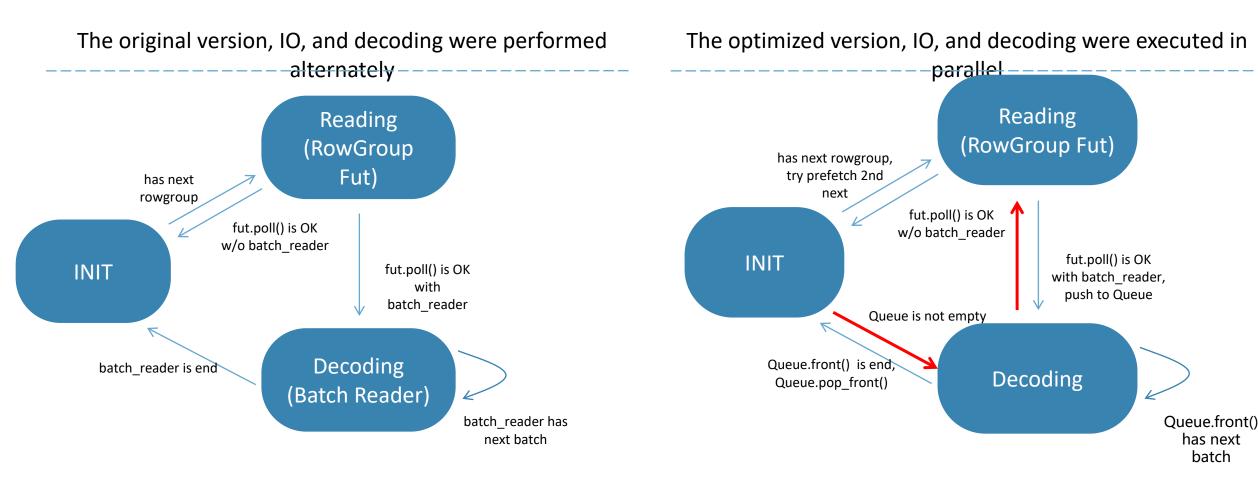
- Cloud Object Storage Features:
 - High bandwidth, high concurrency, and high latency
 - Single-threaded synchronization: read 30 MB/s, write 20 MB / s
- Object storage performance optimization:
 - Read the request split: ~8MB / req
 - Write the request split (Multipart Upload):> 5MB
 - Read does not cross the Part boundary: RowGroup- -Part corresponding
- Parquet File read and write optimization on the object storage
 - RowGroup Size: ~30MB
 - Aynchronously prefetch RowGroup when reading
 - Write when asynchronous concurrent upload RowGroup

LakeSoul NativelO Performance Optimization





Object storage and read optimization: Parquet RowGroup Prefetch

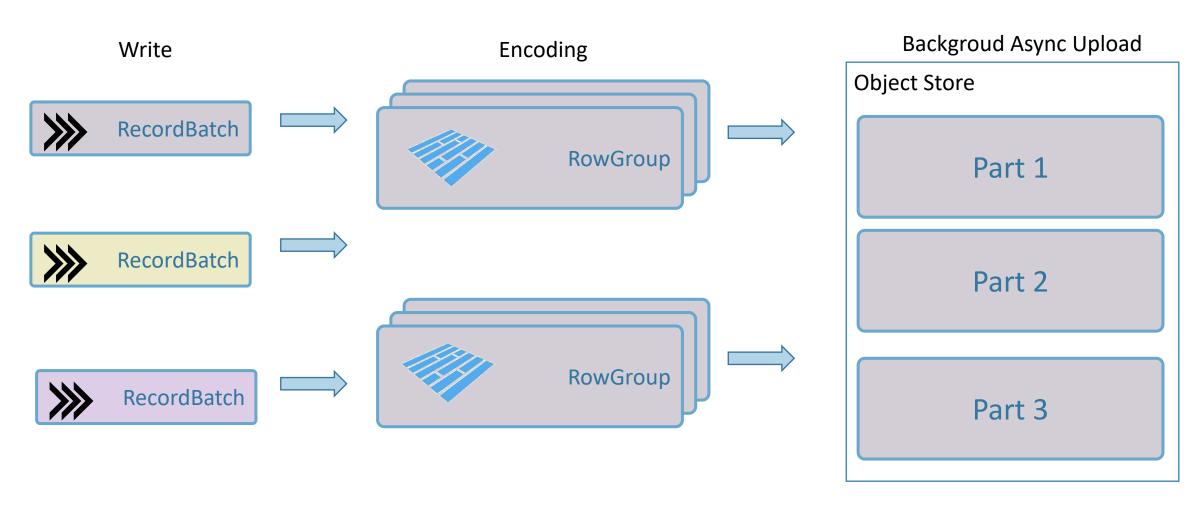


S3 takes 200Mbps 800Mbps

LakeSoul NativeIO Performance Optimization: Parquet RowGroup Parallel Multipart



Upload



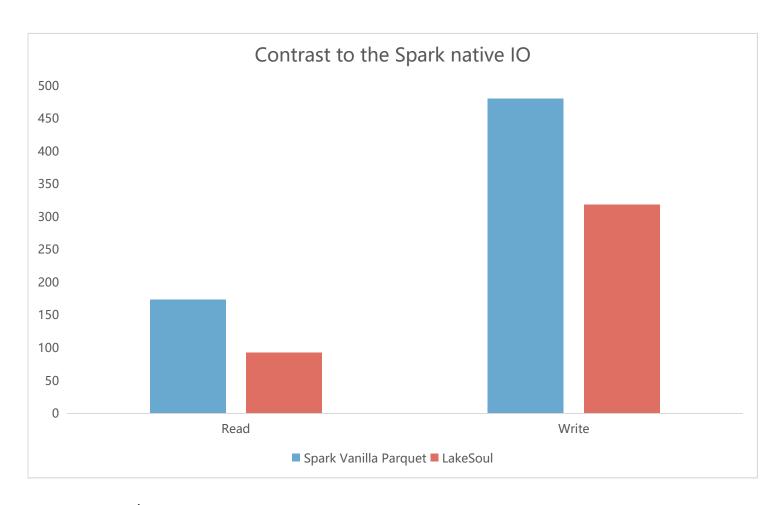
100Mbps 300Mbps bandwidth for single core write S3

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IO Benchmark



test mode:

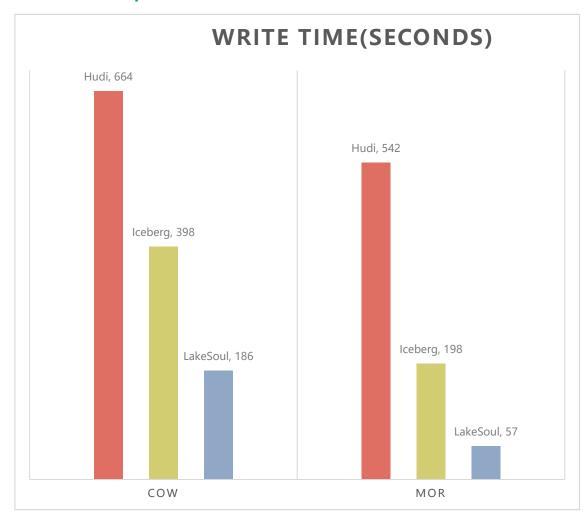
- TPCH-SF100 Orders table, 150 million rows, read after writing to S3
- Spark 1c8q

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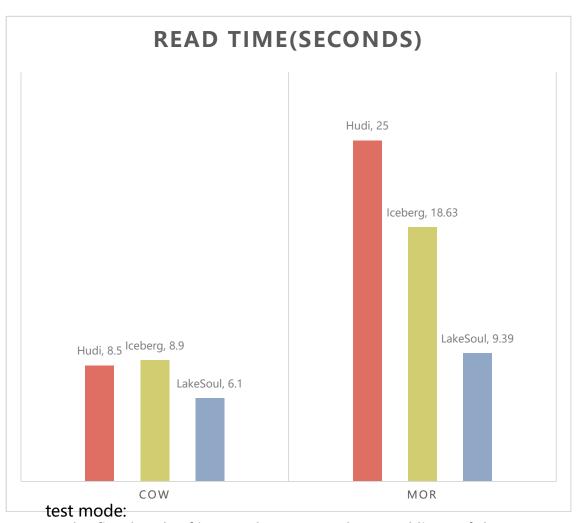




COW / MOR read and write Benchmark



https://github.com/meta-soul/ccf-bdci2022-datalake-contest-examples/tree/mor https://github.com/meta-soul/ccf-bdci2022-datalake-contest-examples/tree/cow



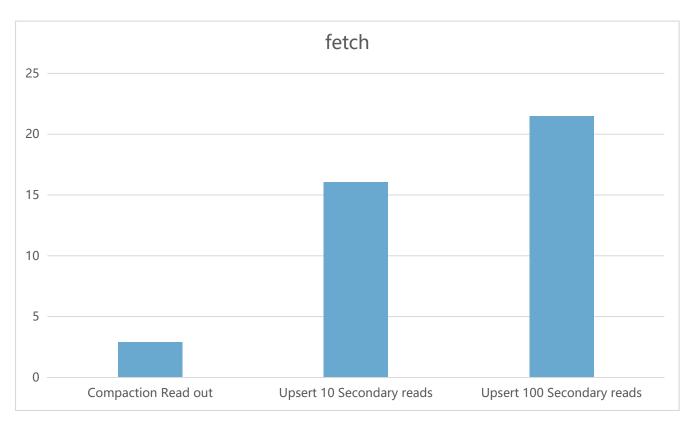
- The first batch of inserted 1000, ten thousand lines of data
- 10 Upsert 100 million lines of data
- No Compaction was performed with the MOR read

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The MOR small file reads the Benchmark



- Document size: 43MB (10 times), 4.8MB (100 times)
- Read to merge 10 files: 16s
- Read to merge 100 files: 21.5s
- Combining 100 files takes time to increase by 30%

test mode:

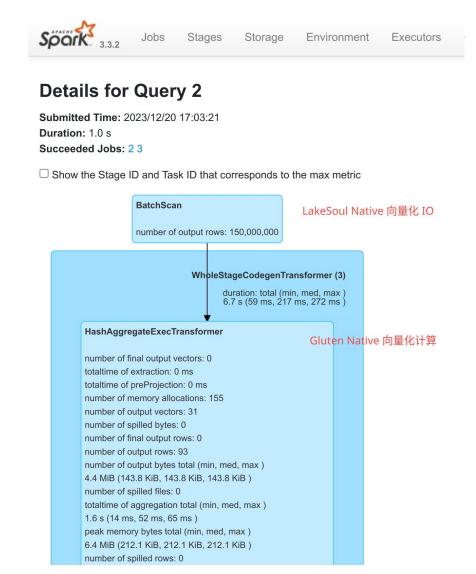
- The first batch of inserted 1000, ten thousand lines of data
- 10 times and 100 times Upsert 100 million lines of data
- No Compaction was performed with the MOR read

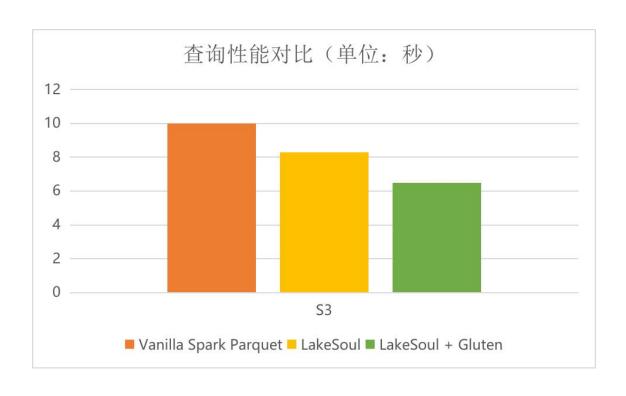
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Vectorization engine: Spark Gluten



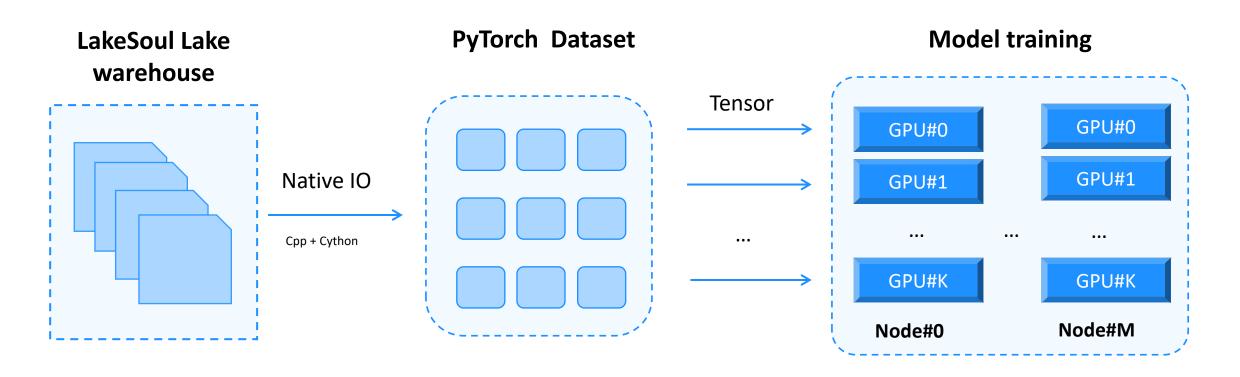


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The AI training reads from the LakeSoul table



LakeSoul Table data

RecordBatch based on PyArrow

Docking of PyTorch and HuggingFace ecology

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Al and Data Science computing ecology: PyTorch, HuggingFace, Ray, Pandas, PyArrow

```
from lakesoul.arrow import lakesoul dataset
ds = lakesoul dataset("table name", partitions={'split': 'train'})
# iterate batches in dataset
# this will not load entire table to memory
for batch in ds.to batches():
     . . .
# convert to pandas table
# this will load entire table into memory
df = ds.to table().to pandas()
```

```
import datasets
import lakesoul.huggingface
dataset =
datasets.IterableDataset.from lakesoul("lakesou
l table", partitions={'split': 'train'})
```

```
import ray.data
import lakesoul.ray
ds = ray.data.read lakesoul("table name",
partitions={'split': 'train'})
```

Support for a distributed training environment

LakeSoul NativeIO Application practice. LakeSoul to with





Al large model training//github.com/lakesoul-io/LakeSoul/tree/main/python/examples

```
dataset table = "imdb"
def read_text_table(datasource, split):
   dataset = datasets.IterableDataset.from_lakesoul(datasource, partitions={"split": split})
   for i, sample in enumerate(dataset):
       yield {"text": sample["text"], "label":sample["label"]}
 # Tokenize the IMDb dataset
 train_tokenized_imdb = IterableDataset\
     .from_generator(read_text_table, gen_kwargs={"datasource":dataset_table, "split":"train"})\
     .map(preprocess function, batched=True)\
     .shuffle(seed=1337, buffer_size=25000)
 test_tokenized_imdb = IterableDataset\
     .from_generator(read_text_table, gen_kwargs={"datasource":dataset_table, "split":"test"})\
     .map(preprocess_function, batched=True)
```

LakeSoul Recent development plan DakeSoul





function

- Pluggable WAL support Sub-second-level real-time visibility
- Real-time data quality verification
- Hadoop / K8s automated deployment
- Front-end of the data

organism's habits

- Support for more database entry into the lake
- Kafka Connect Sink
- LogStash Sink

function

- Minor compaction
- Spark Columnar Writer
- Presto Velox Connector
- Apache Doris Connector
- Clickhouse Connector

development platformub: https://github.com/lakesoul-io/LakeSoul



thanks

Quick experience:

https://lakesoul-io.github.io/zh-Hans/docs/Getting%20Started/setup-local-env