> real-time query：实时查询；（强调的是：延迟小）
> ad-hoc：即席查询；强调的是查询的内容是即兴的，所以多种多样

实时更新：经常被提到，是说上层产生一条数据，就能够写入。其实也就是说要求数据库支持“单条导入或更新”的能力。
另外因为我们一般的直觉是：数据只要被写入后，就应该能够被立即查询到。

AnalyticDB: Real-time OLAP Database System at Alibaba Cloud

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OLAP的基本需求：
支持“实时分析”，低延迟（几百毫秒）；

额外需求：
1. 高并发、高吞吐；
2. 支持“结构化数据类型”和“符合数据类型”

ABSTRACT

With data explosion (爆炸；爆发) in scale and variety, OLAP databases play an increasingly important role in serving real-time analysis with low latency (e.g., hundreds of milliseconds), especially when incoming queries are complex and ad hoc in nature. Moreover, these systems are expected to provide 1. high query concurrency and write throughput, and 2. support queries over structured and complex data types (e.g., JSON, vector and texts).

In this paper, we introduce AnalyticDB, a real-time OLAP database system developed at Alibaba. AnalyticDB maintains all-column indexes in an asynchronous manner with acceptable overhead, which provides low latency for complex ad-hoc queries. Its storage engine extends hybrid row-column layout for fast retrieval of both structured data and data of complex types. To handle large-scale data with high query concurrency and write throughput, AnalyticDB decouples read and write access paths. To further reduce query latency, novel (新奇的) storage-aware SQL optimizer and execution engine are developed to fully utilize the advantages of the underlying storage and indexes. AnalyticDB has been successfully deployed on Alibaba Cloud to serve numerous customers (both large and small). It is capable of holding 100 trillion (万亿，10^12) rows of records, i.e., 10PB+ in size. At the same time, it is able to serve 10m+ writes and 100k+ queries per second, while completing complex queries within hundreds of milliseconds.

ADB的主要特点：
1. 所有列都会异步的建立索引；
2. 扩展了“混合行列式”存储；--为了能够快速的同时检索“结构化数据”和“复合类型”的数据。
3. 将“读路径”和“写路径”分开。-- 为了支持‘高并发’和‘高吞吐’；
4. 感知存储的‘SQL优化器’和‘执行引擎’ -- 更好的利用‘底层存储格式’和‘索引’；

为所有列都建立索引是一定会有额外开销的，但是在ADB中，做到这个开销是可以接受的。

100 trillion = 10PB（注意这只是条数）。

如果每条是1KB，那么总的数据量就是 10PB * 1KB = 10^5 PB

ADB的性能数据：
1. 10PB 条数据；
2. 写入：10^7/s（1千万）
   读取：100k/s（10万）
3. 延迟：复杂查询 几百毫秒

PVLDB Reference Format:
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1. INTRODUCTION

AnalyticDB is an OLAP database system designed for high-concurrency, low-latency, and real-time analytical queries on PB scale, and has been running on 2000+ physical machines on Alibaba Cloud [1]. It serves external clients on Alibaba Cloud from a wide range of business sectors, including e-commerce, finance, logistics (物流), public transit (公共交通系统：大众运输), meteorological (气象的) analysis, entertainment (娱乐), etc., as well as internal business operations within Alibaba Group.

在阿里云上，已经部署超过2000台

Recent works [35, 28, 29, 36, 25] have summarized the main challenges of designing an OLAP system as achieving low query latency, data freshness (数据新鲜度), flexibility, low cost, high scalability, and availability. Compared to these works, analytical workloads from our clients elevate (提升；举起) AnalyticDB to an even larger scale: 10PB+ data, hundred thousands of tables and trillions of rows, which presents significant challenges to the design and implementation of AnalyticDB. 挑战1：用户希望‘低延迟’

The first challenge is that today's users face more complicated analytics scenarios than before, but still have high expectation for low query latency. Users often do not tolerate queries that spend a long time. However, as users of AnalyticDB come from various domains, their analytical demands differ significantly and may change frequently, which make their diverse (不同的；多种多样的) and complex queries hard to optimize. The queries range from full scan, point lookup to multi-table join, and involve conditions on many combinations of columns. Although indexing is a straightforward way to improve query performance, building indexes on pre-specified columns is often no longer effective.

The second challenge is that emerging complex analysis tends to involve different types of queries and data at the same time, which requires the system to have a friendly and unified data layout at the storage layer. Traditional OLAP queries and point-lookup queries require different layouts, i.e., column-stores and row-stores respectively [34, 12]. Furthermore, more than half of our users' data has a complex data type, such as text, JSON string, vector, and other multi-media resources. A practical (实用性的) storage layout should be able to provide fast retrieval for many data types, in order to efficiently support queries involving both structured data and data of complex types.

The third challenge is that while the system is processing real-time queries with low latency, it also needs to handle tens of millions of online write requests per second. Traditional designs [6, 8, 10, 29, 5] process reads and writes in the same process path, so that reads could see newly written data once it is committed. However, such designs are no longer well-suited for our case, as consuming a large portion of resources to guarantee query performance will hurt write performance, and vice versa. Careful designs to balance among query latency, write throughput and data visibility should be taken into consideration.

其它OLAP系统总结的难点：
1. 达到低延迟；
2. 数据新鲜度（指是否可以 实时更新、以及数据写入后是否可以立即查询）；
3. 弹性；
4. 低开销；
5. 高扩展性；
6. 高可用性；

ADB点额外挑战：面临的场景中 数据量非常大：
1. 10PB+ 的数据大小；
2. 十万级别 表数量；
3. 万亿级别的行数；

下面的3个挑战，都是因为数据量非常大的情况下，需要解决的。

查询的多样性：
1. 全表扫描、点查询；
2. 多表join；
3. 多种组合的过滤；

虽然通过‘建索引’来提升查询性能是比较直接的，但“预先在指定列上建立索引”是不可行的。

挑战2：存储格式要能同时支持不同类型的‘查询方式’和‘数据格式’

支持查询方式：
1. OLAP查询：列存；
2. 点查询：行存；

不仅要支持存储“复合类型”，而且要能够进行快速检索。

挑战3：同时支持低延迟的实时查询，和高吞吐的写入（千万级 QPS）

<传统的实现方案>

目的：为了方便的实现能够在写入之后立即能被读取。

实现方法：都是将“读”和“写”放在同一个路径。

缺点：读写之间相互影响；

在ADB中，需要在下面三个方便进行权衡：
1. 查询的延迟；
2. 写入的吞吐；
3. 数据的可见性；

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ADB的解决方法：
1. 高效的索引管理（索引引擎）： — 挑战1
2. “混合行列式”存储： — 挑战2
3. “读路径”和“写路径”解耦： — 挑战3
4. 增强的“优化器”和“执行引擎： — 基础挑战

其它OLAP数据库：
1. Vertica：使用projection。不能在column上构建索引（而是只维护了min/max信息）；
2. Teradata DB和Greenplum：使用列存，也可以构建二级索引。缺点是：
   2.1 因为是在索引和数据是一起写入的，所以为了性能，无法在所有列上构建索引；
   2.2 单纯的“列存”，在处理点查询时，需要的“随机IO”比较多。

其它大数据库系统：
1. Hive 和 Spark-SQL：延迟较高（耗时长，通常被认为是“离线”的），不是“实时分析”。
2. Impala：虽然能够在秒级处理分析。但是它不支持“二级索引”（只支持min/max信息）。

其它实时OLAP系统：Druid 和 Pinot：
1. 仅支持基于bitmap的反向索引；不同点是：
   1）Pinot可以在所有column上建立bitmap索引；
   2）Druid只能在“维度列”上建立bitmap索引；
      （所以当过滤条件不是在维度列上，那么查询效率会很差）
2. 索引都是在写入的同时构建的，影响写入性能；
3. 它们支持的查询能力有限：缺少 JOIN,UPDATE/DELETE
4. 因为是存列存，所以“点查询”的性能不高

To address above challenges, we propose and implement several novel designs in AnalyticDB and have made the following contributions:

索引引擎的两个方式：
1. 在所有列上建索引，在运行时基于“过滤系数”来选择索引。
2. 索引的构建是在‘非高峰’时间，并且是‘异步’的。

对于增量数据，使用“排序索引”。

Efficient Index Management. AnalyticDB embeds an efficient and effective index engine, which leverages two key approaches for achieving low latency with acceptable overhead. First, indexes are built on all columns in each table for significant performance gain on ad-hoc complex queries. We further propose a runtime filter-ratio-based index path selection mechanism to avoid performance slow-down from index abuse. Second, since it is prohibitive to update large indexes in the critical path, indexes are asynchronously built during off-peak periods. We also maintain a lightweight sorted-index to minimize the impact of asynchronous index building on queries involving incremental (i.e., newly-written after index building has started) data.

滥用
禁止的

方法：
1. 使用“混合行列式”存储格式；
2. 充分利用“顺序IO”；
3. 支持复合类型；

Storage layout for structured data and data of complex types. We design the underlying storage to support hybrid row-column layout. In particular, we utilize fast sequential disk IOs so that its overhead is acceptable under either OLAP-style or point-lookup workloads. We further incorporate complex data types in the storage (including indexes) to provide the capability of searching resources (i.e., JSON, vector, text) together with structured data.

合并；混合

“读写分离”的好处：将“读路径”和“写路径”分开后，它们就可以独立的进行扩展。

通过另外一个可靠的分布式存储系统（“盘古”），来提供更高的数据可靠性。

为了保证“数据新鲜度”，在“read node”上使用一个“版本检查机制”来做到“写过的数据立即可读”。

Decoupling Read/write. In order to support both high-throughput writes and low-latency queries, our system follows an architecture that decouples reads and writes, i.e., they are served by write nodes and read nodes respectively. These two types of nodes are isolated from each other and hence can scale independently. In particular, write nodes persist write requests to a reliable distributed storage called Pangu [7]. To ensure data freshness when serving queries, a version verification mechanism is applied on read nodes, so that previous writes processed on write nodes are visible.

1. “优化器”：感知存储格式的、高效的实时采样机制（在‘代价分析’中进行基数预测）；
2. 执行引擎：向量化执行（分析类型的查询是计算密集的）

基数预测

Enhanced optimizer and execution engine. To further improve query latency and concurrency, we enhance the optimizer and execution engine in AnalyticDB to fully utilize the advantages of our storage and indexes. Specifically, we propose a storage-aware SQL optimization mechanism that generates optimal execution plans according to the storage characteristics, and an efficient real-time sampling technique for cardinality estimation in cost based optimizer. Besides, we design a high-performance vectorized execution engine for the hybrid storage that improves the efficiency of computation-intensive analytical queries.

计算密集的

The rest of the paper is organized as follows. Section 2 discusses related work and Section 3 presents read/write decoupling architecture. The data structures and indexes for structured data and complex data types are described in Section 4, and optimizations on optimizer and execution engine are described in Section 5. Section 6 evaluates AnalyticDB and Section 7 concludes the paper.

2. RELATED WORK

AnalyticDB is built from scratch for large-scale and real-time analysis on cloud platform. In this section, we compare AnalyticDB with other systems.

OLTP databases. OLTP databases such as MySQL [6] and PostgreSQL [8] are designed to support transactional queries, which can be considered as point lookups that involve one or several rows. Hence, storage engines in OLTP databases are row-oriented and build B+tree index [16] to speed up query performance. However, row-store does not fit for analytical queries as these queries only require a subset of columns, where row-store significantly amplifies I/Os. Moreover, OLTP databases usually actively update indexes in the write path, which is so expensive that affects both write throughput and query latency.

对比：
1. 事务查询的特点：包含很少数量的行（而且一般需要所有列）。
2. 分析型查询：
   1）较多行；
   2）只需要一行中的部分列

在写路径上，更新数据的同时更新‘索引’，会影响吞吐，延迟也较大。

OLAP databases. To improve the efficiency of analytical queries, many OLAP databases like Vertica [29], Teradata DB [10] and Greenplum [5] have been developed. Vertica [29] uses projection to improve query performance. Instead of building conventional indexes on columns, it only keeps information about Min/Max values, leading to high latency from less effective pruning. Teradata DB [10] and Greenplum [5] adopt column-store and allow users to specify indexed columns. However, they have two main limitations: first, they modify column indexes in the write path, which is prohibitive for all-column indexes; second, column-store requires many random I/Os for point-lookup queries.

传统的，惯例的

无法在所有列上构建索引

Big Data systems. With the emergence of Map-Reduce model [18], batch processing engines, such as Hive [35] and Spark-SQL [37, 13], become popular to process large-scale data on many machines. However, the executed queries are considered “offline”. The whole execution could last for minutes or hours, and thus is not well-suited for real-time queries. Impala [28] converts “offline” queries to interactive queries using pipeline processing model and column-store, reducing latency of common queries to seconds. However, Impala does not have column indexes (with Min/Max statistics only), so that it can not handle complex queries well.

Real-time OLAP systems. Recent real-time OLAP systems include Druid [36] and Pinot [25], both adopting column store. They all build bitmap-based inverted indexes, i.e., Pinot on all columns and Druid on Dimension Columns. A query on Druid may suffer high latency, if it involves columns not in Dimension Columns. All their indexes are updated in the write path, which affects the write performance. Besides, they lack support for some important query types such as JOIN, UPDATE, and DELETE, and are inefficient for point-lookup queries as they are column-oriented.

Cloud Analytical Services. A number of cloud analytical services such as Amazon Redshift [21] and Google BigQuery [33] have recently emerged. Amazon Redshift is a fully managed cloud database service. It uses columnar storage and massively parallel processing (MPP) to distribute queries across multiple nodes. A typical Redshift cluster has two or more Compute Nodes which are coordinated through a Leader Node. Compared to it, AnalyticDB introduces a read/write decoupling architecture with independent read nodes and write nodes, as well as a set of coordinators to communicate with. Google BigQuery is the external implementation of one of Google's core technologies called Dremel [31], which includes columnar storage for high storage efficiency and a tree topology for dispatching queries and aggregating results across thousands of machines in seconds. This is different from AnalyticDB, which leverages an efficient index engine and a DAG execution framework.

Redshift:
1. 列存；
2. MPP执行逻辑；

Redshift中只有一个Leader Node来协调读写请求，发送到多个Compute Node上。

而ADB采用的是：读写分离 的架构，有多个Coordinator节点。

拓扑学

BigQuery:
1. 列存；
2. ‘查询分发’和‘聚合聚合’策略是“基于树的拓扑”。

而ADB使用了高效的“索引引擎”和“基于DAG的执行引擎”。

3. SYSTEM DESIGN

As a cloud database, AnalyticDB runs on top of Apsara, a large-scale, general-purpose and highly-reliable computing infrastructure developed at Alibaba Cloud since 2009. Apsara manages all resources among hundreds of thousands of physical machines, and sustains many Alibaba Cloud services, such as searching, computing and storage. AnalyticD-

阿里的“飞天”系统

飞天的组件：
夸父：主要负责网络；
女娲：主要负责协同；
伏羲：主要负责调度；
盘古：主要负责存储；
神农，主要负责监控。

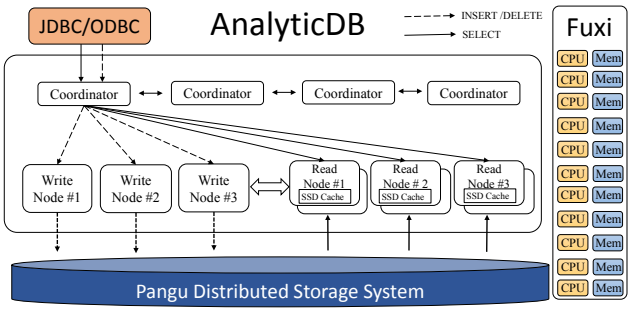


Figure 1: Architecture of AnalyticDB

```
CREATE TABLE db_name.table_name (
    id int,
    city varchar,
    dob date,
    primary key (id)
)
PARTITION BY HASH KEY(id)
PARTITION NUM 50
SUBPARTITION BY LIST (dob)
SUBPARTITION OPTIONS (available_partition_num = 12);
```

使用了“飞天”的两个组件：“盘古”和“伏羲”。

Figure 2: DDL for creation of partitioned table.

B leverages two core components in Apsara, i.e., Pangu [7] (a reliable distributed storage system) and Fuxi [38] (a resource manager and job scheduler), as shown in Figure 1. In this section, we present the vital 至关重要的 design choices made in AnalyticDB, including data model and system architecture.

3.1 Data Model and Query Language

AnalyticDB follows a standard relational data model, i.e., records in tables with fixed schema. In addition, many popular complex data types, e.g., full-text, JSON and vector, are also supported to fulfill increasing analytical demands from real-world applications (detailed in Section 4.1.1 and 4.2.2). AnalyticDB supports ANSI SQL:2003 [19] and enhances it with additional features, such as partition specifications and complex-typed data manipulations.

3.2 Table Partitioning

支持 两级分区

In AnalyticDB, each table is subjective to 倾向于；从属于； two levels of partition, i.e., primary and secondary. Figure 2 illustrates a sample DDL that creates a table with two-level partition, i.e., a primary partition on column *id* with 50 partitions and a secondary partition on *dob* with 12 partitions. The primary partition is based on the hash of a user-specified column, and hence rows are distributed among all primary partitions to maximize concurrency. In practice, any column with high cardinality 基数 could be chosen as this partition column, which makes each partition balanced. Besides, users can optionally specify a secondary partition (called *subpartition*). The secondary partition is a list partition with a threshold defining the maximum partition number, for automatic data 保留 保持 retention and recycling. Usually, a column representing time intervals (e.g., day, week or month) is chosen as the secondary partition column, and hence rows within the same interval are grouped as a partition. Once the number of partitions exceeds the threshold, the oldest partition is discarded automatically.

基数大，（比如整形），也就意味着区分度比较大，这种列适合用hash的方式进行分区。

在第2级分区，通过限制range partition的总数，来达到设置TTL的目的（超期的partition会被自动删除）

3.3 Architecture Overview

Figure 1 shows the system architecture. In overall, there are mainly three types of nodes in AnalyticDB, i.e., Coordinator, Write Node and Read Node. Coordinators collect requests (both writes and queries) from clients through JDBC/ODBC connections, and dispatches them to corresponding write nodes and read nodes. Write nodes are responsible for processing writes (such as `INSERT`, `DELETE`, `UPDATE`), and flush SQL statements into Pangu for persistence. Read nodes are responsible for handling queries (such as `SELECT`). In this manner, Write nodes and read nodes are decoupled from each other (detailed in Section 3.4). Fuxi utilizes available resources in all these nodes to provide computing workers for asynchronous task execution. In addition, AnalyticDB provides a general-purpose and pipeline-mode execution engine (shown in Figure 3) that runs on computing workers. Data flows through the system in units of column blocks (called *Pages*) from the storage to the client. All data processes are in memory and are pipelined between different stages across the network. This pipeline workflow enables AnalyticDB to serve users' complex queries with high throughput and low latency.

3种节点类型：
1. Coordinator Node：接受用户的读写请求；
2. Write Node：处理写请求（insert/update/delete），并将数据 持久化到“盘古”中；
3. Read Node：处理读请求（select）

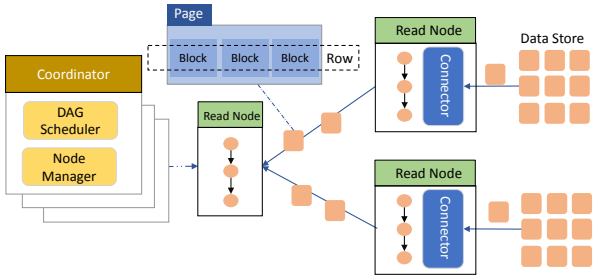


Figure 3: Pipeline-mode execution engine.

注意：读和写是在两种node上进行的，所以它们天然是相互独立的。

“伏羲”调度资源，来满足这些节点上要做的‘异步’工作。

返回给客户端的数据，是以 column blocks（称为page）为单位进行组织的。

所有的数据处理都是在‘内存’中进行的，并且是‘流水化’的。

3.4 Read/Write Decoupling

Traditional OLAP databases couple reads and writes, i.e., a database instance executes any arrived request in the same execution path, without considering whether it is a read or write. Therefore, all concurrent requests share a resource pool and hence affect each other. In the scenario where both query and write concurrency is high, this design leads to poor performance from resource contention. To address this issue, we propose a read/write decoupling architecture. Write nodes are only responsible for write requests while read nodes are for queries. These two types of nodes are isolated from each other, so that writes and queries are handled in completely different execution paths.

3.4.1 High-throughput Write

write node分为master和worker两种。通过ZooKeeper来提供分布式锁服务。

One of write nodes is selected as master and others as workers, and they coordinate with each other through lock service built on ZooKeeper [24]. When write nodes are first launched, the master configures table partitioning (Section 3.2) on workers. Coordinators can then distribute write requests to corresponding workers based on this configuration. When a write request arrives, the coordinator first parses SQL and recognizes it as a write, and then dispatches it to the corresponding write node. Each write node works as an in-memory buffer for received SQL statements and periodically flushes them as a log to Pangu (similar to log writer threads in traditional databases). Once the buffer is completely flushed, the node returns a version (i.e., log sequence number) to coordinators, which then return users a success message for each committed write.

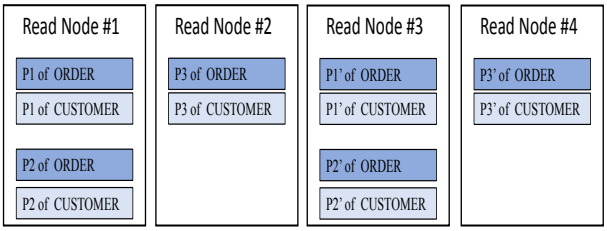
Write Node会在内存中缓存，然后定期的向‘盘古’刷日志。

写入请求，只有在刷入到‘盘古’以后，才会向客户端返回。

When the number of log files on Pangu reaches a certain scale, AnalyticDB will launch multiple MapReduce [18] jobs

当日志积累到一定量级，会使用‘伏羲’来启动MapReduce来进行合并：会生成新的基准数据和索引。

说明：数据的写入策略，追求的是吞吐量，而单个写入的延迟可能会比较高（只有刷入到‘盘古’以后，才会向用户返回）。
有两点：
1）数据是先在Write Node的内存中缓存；
2）这些缓存定期的刷到‘盘古’（即批量刷）；



每个read node都会对应一组partition。因为partition是按照hash方式，所以具有相同hash值的partition都会落在同一个节点上。
也就是说：一个Hash Partition的所有List Partition默认存放于同一个Read Node上

Figure 4: Data placement among read nodes.

on Fuxi to convert log commits into actual data files, i.e., baseline data and indexes (detailed in Section 4).

3.4.2 *Real-time Read*

这种 read node和partition之间的固定映射关系，能够大大减少数据重新分布的需求（减少超过80%）。

Each read node is assigned a number of partitions by coordinators, where partitions with the same hash value are placed in one node. Figure 4 shows this partition placement among read nodes, With the storage-aware optimizer (Section 5.1), this placement helps to save the cost of data redistribution by more than 80%, measured from our production service. Moreover, read nodes are replicated for concurrency and reliability (detailed in Section 3.4.3). Each node loads initial partitions from Pangu, and pulls subsequent updates from corresponding write nodes periodically. It applies updates to its local data copies, which are not written back to Pangu. We choose to continuously pull data from write nodes instead of Pangu, in order to reduce synchronization latency. Therefore, The write node performs as a cache to serve concurrent pulls from different read node replicas.

read node是有多个副本的。

对于增量数据，为了减少数据同步的延迟，让read node是从write node获取数据，而不是从‘盘古’获取。

也就是说，在拉取增量数据过程中，write node相当于一个cache。

Since recent writes need be remotely fetched, read nodes provide two visibility levels to users: *real-time* read where data can be immediately read after written; and *bounded-staleness* read where data is visible within a bounded delay. To sustain (维持；支持，承担) low query latency, AnalyticDB uses bounded-staleness read by default, which is acceptable in most OLAP scenarios. For users demanding high visibility, real-time read can be enabled, which however exposes a data synchronization issue between read nodes and write nodes.

两中可见性级别：
1）实时读取；
2）有限的可过时读取。

注意：这里“可过时”的时间是有上限的。

To solve this issue, we use a version verification mechanism. Specifically, each primary partition is associated with its own version on write node. After a number of write requests on a partition are flushed, the write node will increase this partition's version and attach this value to the response message. Let's look at Figure 5 and take a write-read request sequence as an example. A user writes a record into a table (step 1 & 2), and then immediately sends a query to retrieve it. When coordinator receives this query, it sends both the query and versions (denoted as V_1) cached from previous flush responses (for bounded-staleness read, or pulled from write nodes for real-time read, i.e., step 3) to the corresponding read nodes (step 4). For each partition, the read node compares its local version (denoted as V_2) with V_1. If V_1 is not larger than V_2, the node can directly execute the query. Otherwise, it has to pull the latest data from write nodes (step 5) and updates its local copy first.

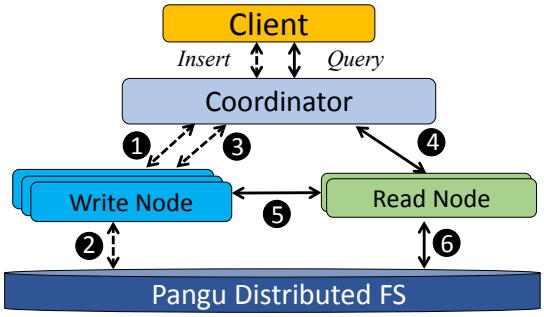
使用“版本检验系统”：每个primary partition（一级的hash分区）都会有一个对应的版本号。

在向partition写入一组数据后，write node会增加这个partition的版本，并将这个 版本号返回给Coordinator。

Following above actions, we can ensure data visibility between read nodes and write nodes for real-time queries. However, if read nodes issue pull requests to write nodes and wait for the required data, the latency would be prohibitively high. We optimize this by replacing read node pulls with write node pushes. When write nodes observe newly written data, they push it along with the versions to corresponding read nodes actively.

如果“read node”在读取的时候，再从“write node”拉取数据，那么延迟必然会比较大。

ADB中，实际采用的是：让“write node”把修改推送给“read node”。



写节点：
1. worker宕机：master会将该worker上的partition均匀的分摊到其它机器上；
2. master宕机：会自动选出一个新的master。

Figure 5: Real-time read workflow.

3.4.3 *Reliability and Scalability*

Reliability. AnalyticDB provides high reliability for both write nodes and read nodes. For write nodes, when a worker fails, the master will evenly (均匀地) distribute partitions that worker serves to other available write nodes. When the master fails, a new master will be elected from active workers.

注意：这里的多副本是“read node”整体的多副本，而不是某个partition的多副本。即，read node的多个部分上，数据是完全一样的。见Figure 4，node1和node3上的数据完全一样；node2和node4上的数据完全一样。

For read nodes, users can specify a replication factor (e.g., 2 by default), and different replicas of the same node are deployed on different physical machines (detailed in Section 3.5). When a read node fails while serving a query, the coordinator will re-send that query to other replicas automatically, which is transparent to users. Note that read nodes will not be blocked by failures of write nodes when pulling new data from them. If read nodes fail to contact a write node, they can directly read data from Pangu (though resulting in higher latency) and continue their executions (step 6 in Figure 5).

‘read node’ 不会因为无法从‘write node’读取到数据而阻塞。read node如果无法连接到‘write node’，就会直接从‘盘古’中读取数据，从而可以继续执行查询。

Scalability. AnalyticDB also guarantees high scalability for write nodes and read nodes. When a new write node is added, the master will adjust table partition placement in order to ensure load balance. The new placement is updated to ZooKeeper, and coordinators can issue subsequent write requests based on the new information. The scalability of read nodes works in a similar way, except that table partition placement is adjusted by coordinators.

扩展性：
1. 写节点：每次调整，会把新的映射关系保存到 ZooKeeper中，Coordinator会读取这个值。
2. 读节点：Coordinator会直接调整 映射关系。

3.5 Cluster Management

支持多租户

The cluster management for AnalyticDB is designed for multi-tenant purposes. That is to say, there could be many AnalyticDB instances existing within one cluster. We design and implement a cluster management component called Gallardo, which utilizes Control Group technology to isolate resources (CPU cores, memory, network bandwidth) among different AnalyticDB instances and guarantee their stability. When a new AnalyticDB is created, Gallardo allocates required resources for it. During allocation, Gallardo carefully places different roles (Coordinator, Write Node, Read Node) and replicas of Read Node into different physical machines, so as to obey the reliability requirement. Note that Gallardo has no confliction with Fuxi. Gallardo is responsible for allocating and isolating resources among different AnalyticDB instances, while Fuxi utilizes available resources from all AnalyticDB instances for computation tasks.

就是c-group

4. STORAGE

The storage model of AnalyticDB supports structured data and other complex data types, such as JSON and vectors. We first discuss our hybrid row-column storage layout, followed by its fast and powerful index engine.

支持复合类型

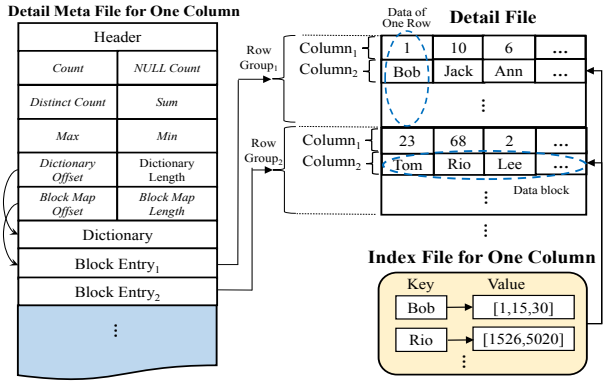


Figure 6: Data format in hybrid row-column store, including meta data and index format.

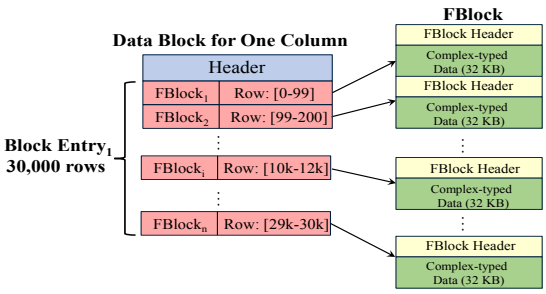


Figure 7: The complex-typed data format.

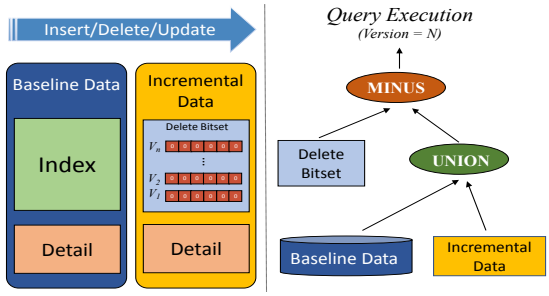


Figure 8: Manipulation and query execution over storage.

4.1 Physical Data Layout

This section first presents the data layout and meta data in AnalyticDB, and then explains how data is manipulated.

4.1.1 Hybrid Row-Column Store

OLAP-style query: 只查询一个宽表中的部分列。

One design goal of AnalyticDB is to support both OLAP-style and point-lookup queries. OLAP-style queries often involve a small set of columns in a wide table. Column-store [34] is well-suited for these queries due to its effective data compression and I/O reduction, but 艰难地行进；挣扎 struggles for point-lookup queries that need to access one or several entire rows. Row-store 胜过；做得比……好 outperforms in point-lookup cases, however, it amplifies access cost for OLAP-style queries [12].

To address this 困境；进退两难 dilemma, we propose a hybrid row-column storage layout, as shown in Figure 6. In our design, data in each table partition is maintained in a single file (called *detail file*), which is divided into multiple *row groups*. Each row group contains a fixed number[1] of rows. Within a row group, all values from the same column are 连续地 contiguously grouped as a data block, and all data blocks are stored in sequence. The data block is the basic operational unit (e.g., for fetch and cache) in AnalyticDB, and it helps achieve high compression ratio to save storage space. Such a hybrid design is able to balance OLAP-style and point-lookup queries with acceptable overhead [12, 20, 34]. Similar to column-store, hybrid-store still clusters data by columns, benefiting OLAP-style queries. Though an entire column resides in multiple data blocks within different row groups, only a small number of sequential seeks are required to fetch all data. As we observe in our real-world AnalyticDB service, this overhead contributes to less than 5% of the overall query latency. For point-lookup queries, it also preserves good performance, as all columns of a specific row are stored in the same row group. Row assembling only involves short-distance sequential seeks [23], instead of cross-segment seeks in column-store.

存储特点：
1. 每30000行组成一个 row group；
2. 在一个row group内，每列是一个data block；

注意：每个data block中行数是相同的；但是数据大小是不一样的。

Complex-typed Data. The hybrid row-column store suits for short columns, e.g., numeric and short string types, but is not for complex-typed data (e.g., JSON and vectors), as this data is of variable sizes and usually much larger. Grouping these rows into fixed-count row groups could result in unexpectedly huge blocks. To address this issue, a fixed-size storage model is designed for complex-typed data. It leverages another level of blocks, namely FBlock, each with a fixed size of 32KB. In particular, a data block (with 30,000 rows) further distributes its rows into multiple FBlocks and stores pointers to these FBlocks instead. In this manner, the data block is still with fixed row count, and all FBlocks are stored in a separate file, as shown in Figure 7. However, the number of rows contained in a FBlock can vary from less than one (i.e., a partial row) to many. To support fast search, we maintain in the data block a block entry for each FBlock, as shown in the left part of Figure 7. Each entry contains two identifiers, i.e., start row and end row of the corresponding FBlock. A row can be split into multiple contiguous FBlocks. For example in Figure 7, FBlock1 and FBlock2 stores rows [0, 99] and [99, 200] respectively, indicating that row 99 is divided into two FBlocks. To access it, we first scan block entries from the data block to locate involved FBlocks (e.g., FBlock1 and FBlock2), and then fetch and 连接 concatenate partial rows.

因为数据有大有小，所有在不同的FBlock中，所对应的数据行数是不同的：可能小于一行（当数据大于32KB时），也可能包含多行。

在data block中保存每个FBlock的指针（称为block entry）。这个指针的value内容包含两部分：起始行号和结束行号。

[1]This number is configurable, set as 30,000 by default according to our production practice.

对于复合类型：
1. 使用“固定大小”的存储模型；
2. 对于复合类型那一列，所对应的data block内部，再分为多个 FBlock（每个FBlock大小固定，为32KB）。
3. 会被拆分为FBlock，将所有FBlock保存在独立的文件中。在data block中保存对于这些FBlock的指针；（该data block仍然是包含30000行数据）；

4.1.2 Meta Data

Each column in the detail file has its own meta data that 使……加快 accelerates retrieval over huge amounts of data in that column. This meta data is stored as a separate file for each column, called *detail meta file* as illustrated in Figure 6. It is small in size (i.e., below 1MB) and is cached in memory for frequent access. Meta data of each column consists of four sections: a *header* that contains a version number and the total length of this detail meta file; a *summary* that contains important statistics required by query optimizer (Section 5.1), such as number of rows, number of NULLs, value cardinality, sum (SUM) and maximum/minimum (MAX/MIN); a *dictionary* that is automatically enabled for columns with low cardinality for space saving; and a *block map* that keeps one entry for each data block, containing its offset/length in the detail file for fast access.

4.1.3 Data Manipulation

操纵；操作；处理

Lamda架构中，数据分为两部分：1）基线数据（历史数据）；2）增量数据。

AnalyticDB uses Lamda architecture for underlying storage (see Figure 8), which contains baseline data and incre-

任何一部分都是包含两部分：数据和索引

注意：两者的“数据”使用的存储格式是相同的；但是两者的索引是不同的：
1. 基线部分：包含“全列索引”；
2. 增量部分：不包含“全列索引”，只有一个基本的“排序索引”。

Algorithm 1: INSERT(SQL, version)

Input: SQL statement and version number
/* parse multiple column values from SQL */
values = parse(SQL);
/* append values to tail of incremental data */
row_id = incremental_data.append(values);
/* add a new bit to the delete bitset */
delete_bitset[row_id] = 0;
/* create a snapshot of delete_bitset */
delete_bitset_snap = create_snapshot(delete_bitset);
/* put a version-snapshot pair into the map */
snap_map.put(version, delete_bitset_snap);

Algorithm 2: DELETE(SQL, version)

Input: SQL statement and version number
/* search according to WHERE conditions */
row_ids = search(baseline_data, incremental_data, SQL.where);
/* delete records satisfying conditions */
for *each row_id in row_ids* **do**
  delete_bitset[row_id] = 1;
delete_bitset_snap = create_snapshot(delete_bitset);
snap_map.put(version, delete_bitset_snap);

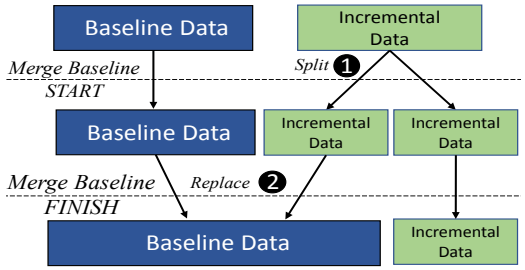


Figure 9: The process of merging baseline data and incremental data.

mental data. The baseline data stores historical data including both index and row-column data. The incremental data keeps the newly written data, and does not contain full-index but a simple sorted index (detailed in Section 4.2.5). Incremental data occurs only on read nodes when they pull and replay logs from write nodes. Baseline and incremental data follow the identical data and meta formats above.

Query Execution. In order to support UPDATE[2] we use bit-set to record the row ids of deleted data. Copy-on-write technology is used to support MVCC (Multi-version concurrency control) [15]. When a row is updated or deleted, a bit-set snapshot along with a version number is stored in an in-memory map for serving subsequent queries. This delete bit-set is divided into small compressed segments, so that snapshots can share unchanged segments to make them space-efficient. Furthermore, when a new version of the snapshot is created, the oldest version will be eliminated once there is no query running on it. Algorithms 1, 2 and 3 explain how INSERT, DELETE and FILTER queries are executed on both baseline and incremental data, following steps in Figure 8. To execute a query, a version number is given firstly, and then corresponding delete bit-set snapshots of

[2]Currently, we only support primary-key-based update to avoid changing too much data in one operation. An update is treated as the combination of a delete and an insert.

Algorithm 3: FILTER(conditions, version)

Input: filter conditions and version number
Output: row ids satisfying conditions
/* get delete bitset according to version */
delete_bitset_snap = snap_map.get(version);
/* get row-ids by searching index with conditions */
row_ids = search(baseline_data, incremental_data, conditions);
/* remove deleted row-ids from the results */
return minus(row_ids, delete_bitset_snap);

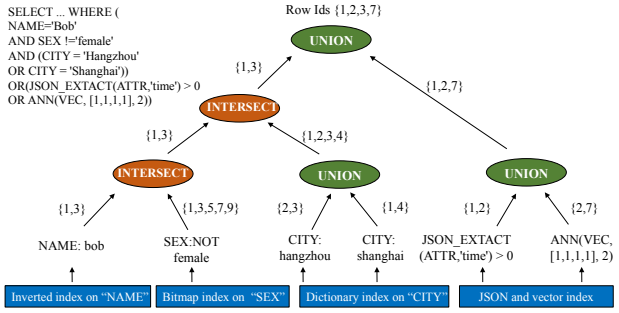


Figure 10: Query over indexes on all columns.

both baseline and incremental data are referenced. Qualified row-ids are obtained from full-index (on baseline data) and sorted index (on incremental data) respectively. After that, we filter out deleted rows from referenced delete bitsets to get the final results.

Merge Baseline Data with Incremental Data. As new data is continuously written, searching on incremental data is significantly slowed down. Therefore, a build process is started asynchronously to merge incremental data into baseline data. During this process, the deleted records will be ignored and a new index will be created correspondingly. As illustrated in Figure 9, the merge procedure is as follows: When the build process starts, we make current incremental data immutable and create another incremental data instance to handle new arrivals. Before the build process finishes, all queries are executed on the baseline data, stale incremental data and new incremental data. Once the new version of baseline data is merged, the old baseline data and stale incremental data can be safely removed. At this time, the new baseline data, along with new incremental data, serves subsequent queries.

4.2 Index Management

Indexes are a key component in almost all databases to improve query performance. However, existing indexing approaches are not able to fully satisfy requirements in OLAP applications. For example, B$^+$-trees are costly to update due to node splitting, and hence are only affordable on carefully selected columns. Systems like Druid [36] choose bitmap-based inverted indexes to build on more columns, but only suitable for some specific data types (e.g., String). Recently, with the increasing need to query on complex-typed data (e.g., JSON, vector and texts), indexes on these types should also be supported. Moreover, most systems build indexes in the write path [8, 6, 5, 10], which significantly limits write performance.

We therefore design and implement an index engine that builds indexes for structured and complex-typed data without affecting write throughput. This engine builds indexes

on all columns to fully support ad-hoc queries, and completely removes index construction from the write path. Several sophisticated designs are made to minimize the storage overhead and maximize the performance.

4.2.1 Index Filtering

Each column in a partition is built with an inverted index, which is stored in a separate file. In the inverted index, the index key is the value from the original column, while the value is the list of corresponding row ids (i.e., row numbers). According to Section 4.1.1, we can easily locate a row via its id, since each row group has a fixed number of rows.

With indexes on all columns, AnalyticDB is able to support high-performance ad-hoc queries. Figure 10 gives a SQL filtering example that contains conditions on both structured data and complex-typed data. For each condition, the index engine filters on its corresponding index and obtains partial results, i.e., a set of qualified row ids. After that, all partial results are merged into the final results through intersection, union, minus, etc. To merge these results, 2-way merging is commonly used in most databases, but it incurs huge memory usage and suffers low concurrency. To mitigate this impact, we apply K-way merging [17] instead, which ensures sub-second query latency on large datasets.

Index Path Selection. However, the overuse of index filtering on all columns may sometimes deteriorate query performance. For example, for two conditions A and B, if the partial results of A is much smaller than that of B, it is more cost-effective to obtain results of A first and further filter them with B, rather than getting both partial results and merging them. To address this issue, we propose a runtime filter-ratio-based index path selection mechanism, which evaluates the *filter ratio* of each condition to decide whether to use the corresponding index at runtime. The filter ratio is defined as the number of qualified rows (retrieved from index) divided by the total number of rows (retrieved from meta data). AnalyticDB uses indexes to filter conditions in ascending order based on their filter ratios. After one condition filtering is finished, if the joint filter ratio of all processed conditions (i.e., calculated by ratio multiplication) is small enough (e.g., less than one percent of total rows), this process termninates and all previously obtained partial results are K-way merged. Subsequent conditions are directly filtered on these row ids instead of on indexes.

4.2.2 Index for Complex-Typed Data

JSON. When a JSON object is inserted, we flatten hierarchical JSON attributes into multiple columns and then build inverted index for each column. For example, given a JSON object {`id, product_name, properties {color, size}`}, it is flattened into columns `id`, `product_name`, `product_properties.color` and `product_properties.size`, each of which is built an index. We apply PForDelta algorithm [39] to compress the row-ids under each index key. Furthermore, a JSON object may contain thousands of attributes (i.e., thousands of indexes). We pack all indexes of one object in a single file to limit the number of files. With the index, AnalyticDB can directly fetch the object according to the predicates in JSON format, which is more efficient than reading and parsing blocks of JSON data from disk.

Full-text. For full-text data, AnalyticDB extends the inverted indexes by storing more information, including term frequency and mapping from document to terms. We then use the popular TF(Term Frequency)/IDF(Inverse Document Frequency) score to calculate the similarity between the query and texts in the database. Only those objects with scores above a threshold are returned to users.

Table 1: Comparison between AnalyticDB (ADB) and Greenplum (GP) on building all-column index of 1TB data.

	ADB	GP
Index Space	0.66TB	2.71TB
Index Building Time	1 hour	0.5 hour
Asynchronous?	Yes	No
Data Insertion Time	4,015s	20,910s

Vector Data. Feature vectors are a common component of many computer vision tasks, such as object/scene recognition and machine learning, where a high-dimensional vector can be extracted from an image via a trained AI model. The similarity of two objects can be measured by the distance of their feature vectors. In queries for vector data, users always require nearest neighbour search (NNS), aiming to find objects that are the closest to the query point in the database. Formally, NNS can be defined as finding the object $NN(q)$ in a finite set $\mathcal{Y} \subset \mathbb{R}^D$ of vectors stored in the same column in the database, who minimizes the distance to the query vector $q \in \mathbb{R}^D$, as Equation 1. AnalyticDB supports different similarity metrics d like Euclidean distance and Cosine distance, which can be specified in SQL language.

$$NN(q) = \arg\min_{y \in \mathcal{Y}} d(q, y) \tag{1}$$

The most brute-force way for NNS is to scan all vectors linearly in the database, compute the distances with the query vector and finally return the top-k results. To avoid such exhaustive search, we implement and combine Product Quantization (PQ) [26] and Proximity Graph (k-NNG) [22]. PQ and k-NNG are experimentally-proven efficient approximate NNS approaches [4] that fetch NN (or k-NN) with high probability. PQ has a smaller index size by decomposing the vector space, while k-NNG holds better search performance and accuracy through its efficient well-connected graphical index. AnalyticDB adaptively chooses the most appropriate one for vector data, depending on the memory resources as well as accuracy and efficiency requirements of users.

4.2.3 Index Space Saving

We apply an adaptive method to reduce index sizes. For each key-value pair in the index, AnalyticDB automatically chooses bitmap or integer array to hold the value based on their space consumption. For example, if the index value is [1,2,8,12], bitmap (2 bytes) is cheaper than integer array (4 bytes). But if the index value is [1,12,35,67], integer array (4 bytes) is a better choice than bitmap (9 bytes). By adopting this method, the overall index size can be reduced by 50%. We also allow users to disable indexes on specific columns to trade latency for space.

4.2.4 Asynchronous Index Building

AnalyticDB serves tens of millions of write requests per second, and thus is not affordable to build all-column indexes in the write path. Alternatively, the index engine builds index asynchronously. Recall that in AnalyticDB the write path ends when write nodes flush write logs to Pangu (Section 3.4.1). The index engine periodically builds inverted indexes on these new writes (i.e., incremental data), and merges them with existing full indexes at background.

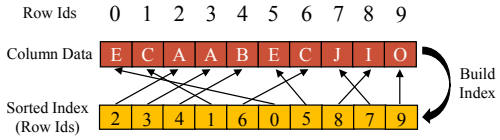


Figure 11: Sorted Index for Incremental Data

ADB中异步构建索引的过程：
1. 使用了 “伏羲”组件的调度功能；
2. 使用 “map-reduce” 作业的形式；
3. 在当前ADB集群内部；
4. 是在 “非高峰”时间执行；

Such asynchronous approach completely hides the overhead of building from users, and preserves both query efficiency and write throughput. The process for building and merging indexes is translated into many Map-Reduce tasks. With the help of Fuxi [38], these tasks run concurrently and automatically during off-peak periods within AnalyticDB cluster, introducing acceptable overhead.

Table 1 compares building all-column index for 1TB data on AnalyticDB and Greenplum [5], a column-store-based OLAP database system. We see that AnalyticDB only uses 0.66TB extra space for indexes, which is much smaller than 2.71TB in Greenplum. Although AnalyticDB doubles the index building time, this asynchronous process does not impact performance of online reads and writes. As shown in Table 1, the time for real-time ingestion (INSERT) of 1TB data in Greenplum is about four times longer than in AnalyticDB. Thus, AnalyticDB yields acceptable overhead in exchange for significant performance improvement for ad-hoc queries, which is evaluated in Section 6.

4.2.5 *Index For Incremental Data*

这个 “排序索引” 只在read node上构建。

The adoption of asynchronous indexes brings in a performance gap: before the new index is online, incremental data lack the support of indexes, and thus they need be scanned to serve a query with high latency. To close this gap, the index engine independently (独立地；独自地) builds *sorted indexes* in read nodes for incremental data. The sorted index is actually an array of row ids in the data block. As illustrated in Figure 11, for an ascending sorted index, the i-th element T_i represents that the i-th smallest value in the data block is at row T_i. A search in incremental data is then converted to a binary search, reducing the complexity from $O(n)$ to $O(\log n)$. To store the sorted index, we allocate an additional header in each data block. As there are 30k rows in a block and each row id is a short integer, the size of the header, i.e., the sorted index, is just about 60KB. Before flushing a data block, the index engine builds the sorted index and dumps it to the head of the file. This building process is executed locally in read nodes and is quite lightweight.

1. 数组元素的下标：表示大小递增关系；
2. 数组元素的值：对应的行号；

因为每个data block的数据行为30000，而short类型(int16_t)最大值为 65535，所以使用short类型即可。每个元素为2个字节。

4.2.6 *Index Cache for Conditions*

ADB对于索引有两层cache：
1. 查询条件的cache；
2. 索引数据的cache(以page为粒度)

Traditional databases cache indexes (at the granularity of index page) in the memory to reduce costly disk I/Os. AnalyticDB applies not only an index-page cache, but a more aggressive query-condition cache. This query-condition cache treats query conditions (e.g. `id < 123`) as keys, and query results (i.e., row ids) as values. In consequence, repeated filtering over index pages can be completely avoided. When the query-condition cache misses, we can access indexes in index-page cache to compute query results.

One challenge in our two-level cache policy is that user conditions change continuously and dramatically, resulting in frequent cache eviction. However, we observe that this will not affect overall cache effectiveness much: 1) the conditions with large-size results are rare and do not change frequently (e.g., `WHERE city='Beijing'`), so that their caches can last for a long time; 2) the conditions with small-size

如果查询条件变化，那么 “查询条件的cache” 就不会起作用。那为什么ADB中观察到不会影响很大：
1. 结果集较大的：比较少，并且不会频繁变化；
2. 结果集较小的：比较多，会经常变化；但是因为结果集较小，重新计算的代价也不大。

也就是说，需要比较费的计算资源的（结果集较大的）条件，一般都会被cache住。
而小查询，即使在cache中被淘汰了，重新计算的开销也很小。

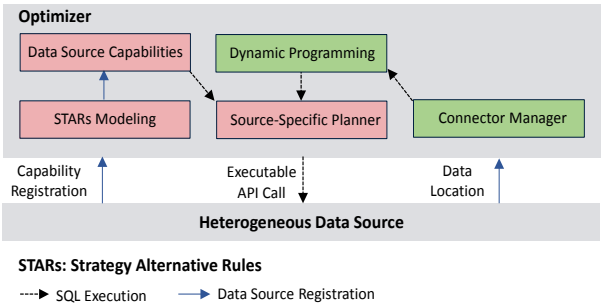


Figure 12: The STARs framework of AnalyticDB.

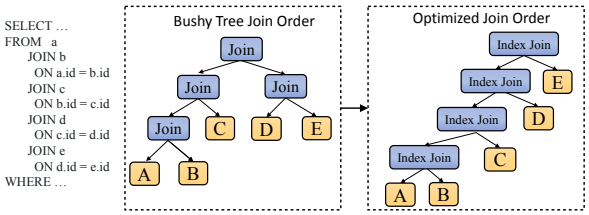


Figure 13: Storage-aware join optimization.

results are massive and change dramatically (e.g., `WHERE user_id=XXX`), but their results can be re-computed with low cost. In summary, costly computations are usually well cached to save resources, while light queries are re-computed without much extra overhead. This observation ensures the effectiveness of our index cache.

5. OPTIMIZER AND EXECUTION ENGINE

In this section, we discuss the novel optimizations adopted by optimizer and execution engine respectively, which further improve query latency and concurrency.

ADB同时使用 CBO 和 RBO

5.1 Optimizer

The AnalyticDB optimizer provides both CBO (cost-based optimization) and RBO (rule-based optimization), and targets the real-time online analytics that require extremely low response time and high concurrency. It contains a rich set of relational algebra conversion rules (关系代数转化规则) to ensure that the optimal plan can be always selected. These rules include:[1] basic optimization rules (e.g., cropping (修剪；剪辑), pushdown/merge, deduplication (去重), constant folding/predicate derivation (谓词推导));[2] probe optimization rules for different Joins (e.g., BroadcastHashJoin, RedistributedHashJoin, NestLoopIndexJoin), Aggregate, JoinReorder, GroupBy pushdown, Exchange pushdown, Sort pushdown, etc.; and[3] advanced optimization rules (e.g., Common Table Expression). Other than the generic CBO/RBO above, two key features are developed, i.e.,[4] storage-aware optimization and[5] efficient real-time sampling.

5.1.1 *Storage-Aware Plan Optimization*

Predicate Push-down. Predicate (i.e., condition) push-down is to extract the relational algebraic calculations in SQL that can take advantage of the underlying storage, and to convert this query plan into two equivalent parts (i.e., for the compute layer and the storage layer respectively). Since there is no clear boundary in the original query plan to support this separation, it completely relies on the optimizer. Predicate push-down has already been implemented in many distributed databases, but mainly focusing on AND operators of single-column conditions. They do not consider

大多数的数据库，通常只支持在 单列上的过滤条件，并且只支持 “AND” 操作符。

other common operators, such as functions and joins, which are usually implemented in the compute layer. This is because many existing databases do not provide the interface for the storage layer to register its advanced capability. As a result, the storage layer can only do a single column or a combination of condition filtering.

AnalyticDB introduces a STARs (STrategy Alternative Rules) [30, 14] framework to make the optimizer extensible for predicate push-down, as illustrated by Figure 12. STARs provide a high-level, declarative, implementation-independent specification of legal 合法的；法定的 strategies for query execution. Each STAR defines a set of high-level constructs from low-level database operators or other STARs. With the STARs framework, AnalyticDB abstracts the capability of heterogeneous 混杂的；各种各样的 data sources according to the dimensions of relational algebra, and characterizes the capability of storage as relational algebra that can be utilized. In addition, the STARs framework also provides cost calculation. That is, performing a push-down is not simply dependent on the capability of storage, but also on the cost of its relational algebra ability. During the dynamic planning, both the cost and execution capability are used as reference factors at the same time, so as to avoid blindly pushing down and causing performance deterioration. This is important in low latency and high concurrency environment. After the optimizer completes the initial distributed execution plan, the relational algebraic operators applicable 可应用的；合适的 for target data sources are encapsulated by means of dynamic programming, and transformed into corresponding storage API calls.

Join Push-down. Data redistribution is another important aspect of distributed database execution plan. It is different from those in traditional databases, mainly due to the mismatch between the physical distribution characteristics of data and the logical semantics of relational algebra. For example, in SQL statement "`SELECT T.tid, count(*) FROM T JOIN S ON T.sid = S.sid GROUP BY T.tid`", based on whether table T and S are hashed by the same field and with partitions placed at the same read node (Section 3.4.2), AnalyticDB is able to select the best join push down strategy. The avoidance of data redistribution is very important, since the cost of physical data redistribution is prohibitive 代价过高的、禁止的, which involves serialization, de-serialization, network overhead, etc. In the case that table T and S are not hashed by the same field, AnalyticDB clearly knows shuffling which table is more efficient, by obtaining the sizes of T and S from the underlying storage. As mentioned previously, the optimizer expands and calculates the cost of all possible execution plans. It is in this way that AnalyticDB achieves an execution plan that is optimal for data characteristics at different data sizes.

Index-based Join and Aggregation. Index-on-all-columns further eliminate the overhead on building hash indexes, by[1] doing lookup on existing indexes instead. When adjusting the order of join, the optimizer avoids generating BushyTree and prefers LeftDeepTree, when most of join columns are partition columns and have indexes. With the LeftDeepTree, AnalyticDB utilizes existing indexes better (see Figure 13). Additionally, we also[2] push down predicates and aggregations. For example, aggregations like `count` can be returned directly from indexes; and filtering can be evaluated solely on indexes. All these optimizations reduce the query latency while improving the cluster utilization, which enables AnalyticDB to support high concurrency easily.

如果需要join的列是partition column，并且都有索引，那么使用 LeftDeepTree，而不是 BushyTree

5.1.2 *Efficient Real-time Sampling*

Cost estimation is the foundation for cost-based optimization and is determined by the cardinality estimation 基数估计 that heavily relies on the available statistics. In modern databases, statistics are collected and utilized in a limited way where data skewness 歪斜 and correlation 相关；关联 are not well handled, resulting in sub-optimal query plans. Besides, since one of our system design goals is the short response time of queries that are either simple or complex, conventional approaches (such as real-time statistics, predicate selectivity 谓词选择性 profiling, and execution results feedback) are impractical due to their overheads and complexities. Instead, we design and implement an efficient sampling-based cardinality estimation framework. Our framework takes advantages of the AnalyticDB's high-performance storage engine that provides efficient data access and evaluation through abundant types of indexes, caches, and optimized computation. At optimization time, the optimizer sends request on the sampling predicates (individual or compound decided by optimization rules) to the storage engine through the framework APIs. Storage engine then accesses the sampled data via appropriate indexes/caches, evaluates the predicates via optimized computation paths, and returns the cardinality results. The optimizer utilizes the sampled cardinality to estimate candidate plans and choose the optimal one.

Although our sampling framework estimates the cardinality efficiently, further optimizations are carried out to further reduce the overhead, especially for those critical business scenarios where queries run in sub-seconds. Such optimizations include caching previously sampled results (and cardinality estimates), optimized sampling algorithm, and improved derived cardinality, etc. By applying all these, our sampling-based cardinality framework is able to estimate the cardinality at extremely low overhead in milliseconds while providing high estimation accuracy.

1. 通用的、流式的执行引擎；
2. 在该 执行引擎 上运行 DAG框架；

5.2 Execution Engine

AnalyticDB provides a general-purpose, pipeline-mode execution engine, as well as a DAG [27] (Directed Acyclic Graph) running framework on top of this engine. It is suitable for both small (with low latency) and large-scale (with high throughput) workloads. AnalyticDB execution engine is column-oriented, which takes advantages of the underlying hybrid store clustering data on columns. Compared to row-oriented execution engine, this vectorized engine is cache-friendly and avoids loading unnecessary data into memory.

执行引擎：
1. 列式的；
2. 向量化的；
（cache友好、避免加载不需要的列）

Like many OLAP systems, runtime code generator [32] (CodeGen) is used to improve the efficiency of CPU-intensive operations. AnalyticDB CodeGen is based on ANTLR ASM [2] that dynamically generates code for the expression trees. This CodeGen engine also takes runtime factors into consideration, allowing us to leverage the power of heterogeneous hardware in a task-level granularity. For example, most types of data (such as `int` and `double`) in vectorized engine are aligned. In a heterogeneous cluster with CPUs supporting AVX-512 instruction set, we can generate bytecodes using SIMD instructions to improve performance. In addition, by consolidating 合并 the internal data representation between storage layer and execution engine, AnalyticDB is able to operate directly on serialized binary data rather than Java objects. This helps eliminate the overhead of serialization and de-serialization, which accounts for more than 20% of time when shuffling a large amount of data.

在ADB中，在‘存储引擎’和‘执行引擎’中的数据表示方法是相同的。

ADB是用java实现的

Table 2: Three kinds of queries for evaluation.

Query type	Query
Full Scan (Q1)	`SELECT * FROM orders ORDER BY o_trade_time LIMIT 10`

Point Lookup (Q2)	`SELECT * FROM orders`
	`WHERE o_trade_time BETWEEN '2018-11-13 15:15:21' AND '2018-11-13 16:15:21'`
	`AND o_trade_prize BETWEEN 50 AND 60 AND o_seller_id=9999 LIMIT 1000`

Multi-table Join (Q3)	`SELECT o_seller_id, SUM(o_trade_prize) AS c FROM orders`
	`JOIN user ON orders.o_user_id = user.u_id`
	`WHERE u_age=10 AND o_trade_time BETWEEN '2018-11-13 15:15:21' AND '2018-11-13 16:15:21'`
	`GROUP BY o_seller_id ORDER BY c DESC LIMIT 10;`

6. EVALUATION

In this section, we evaluate AnalyticDB in both real workloads and TPC-H benchmark [11] to demonstrate AnalyticDB's performance under different types of queries and its write capability.

6.1 Experimental Setup

The experiments are conducted on a cluster of eight physical machines, each with an Intel Xeon Platinum 8163 CPU (@2.50GHz), 300GB memory and 3TB SSD. All these machines are connected through 10Gbps Ethernet network. We create one AnalyticDB instance with 4 coordinators, 4 write nodes, and 32 read nodes within this cluster.

Real Workloads. We use two real tables in our production for the evaluation. The first table is called Users Table, which uses `user_id` as its primary key, and has 64 primary partitions (no secondary partition). The second table is called Orders Table, which uses `order_id` as its primary key, and has 64 primary partitions and 10 secondary partitions. These two tables are associated with each other through `user_id`. We use three types of queries generated from our users (as shown in Table 2), ranging from scan, point lookup to multi-table join. Note that all three queries contain `o_trade_time`, which is a timestamp column. It is because Druid MUST have a timestamp column as the partition key, and queries without specifying the timestamp column are much slower [36].

Systems to compare against. We compare AnalyticDB with four OLAP systems: PrestoDB [9], Spark-SQL [13], Druid [36], and Greenplum [5]. Greenplum has index on all columns; Druid does not support index on numeric columns; PrestoDB and Spark-SQL keep data in Apache ORC (Optimized Record Columnar) File [3] and do not have index on any column. All systems are run in their default configurations. Note that Druid does not support complex queries like JOIN, so that most of TPC-H queries and Q3 in Table 2 can not be executed. Hence, we omit it in corresponding experiments. In all experiments, the term *concurrency number* refers to the number of concurrently running queries.

6.2 Real Workloads

This section first presents query performance on 1TB data and 10TB data, and then shows the write throughput.

6.2.1 Query on 1TB Data

We generate a dataset of 1TB to run the three queries in Table 2. Figure 14 and Figure 15 show the 50-percentile and 95-percentile query latency of AnalyticDB, PrestoDB, Druid, Spark-SQL, and Greenplum respectively. As can be seen, AnalyticDB achieves a lower latency by at least an order of magnitude compared to other systems.

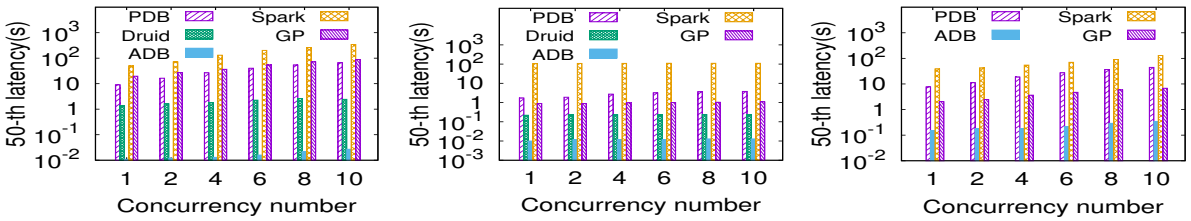
Q1. With the help of the index engine, AnalyticDB avoids expensive scan and sort over the entire table, which is different from PrestoDB and Spark-SQL. In particular, AnalyticDB distributes the operators of `ORDER BY` and `LIMIT` to each secondary partition, which holds the index for column `o_trade_time`. Since the index is ordered, each partition just traverses the index to obtain qualified row ids, involving only dozens of index entries. Although Greenplum also builds index on all columns, it fails to utilize them for `ORDER BY` operators and executes a full scan, thus is much slower than AnalyticDB. Druid uses `o_trade_time` as the column for range partitioning [36]. When doing `ORDER BY` on this column, Druid filters from the largest range partition. It achieves better performance than Greenplum, but is still slower than AnalyticDB as it still scans all rows in that partition.

Q2. In our dataset, the number of rows satisfying conditions on `o_trade_time`, `o_trade_prize` and `o_seller_id` are 306,340,963, 209,994,127, and 210,408 respectively. Without index support, PrestoDB and Spark-SQL has to scan all rows for filtering. Druid and Greenplum achieve better performance as they can benefit from fast searches on indexed columns. However, Druid only builds indexes on string columns. Greenplum's indexes are available for all columns, but it has to filter multiple conditions sequentially, and does not have cache for unchanged conditions. Compared to them, AnalyticDB directly scans indexes on three columns in parallel, and caches qualified row ids respectively (Section 4.2.6). Hence, the subsequent queries with same conditions could benefit from the index cache.

Q3. As shown in Figure 14 and Figure 15, the 50/95-percentile latency of Q3 is higher than that of Q1 and Q2 under different concurrency levels. This is because Q3 is a much more complicated query, i.e., a multi-table join scan combined with `GROUP BY` and `ORDER BY` operators. Though the latency is slightly high due to the query complexity, AnalyticDB still ensures that the optimal execution can be achieved. In particular, AnalyticDB translates the join operator into equality sub-queries and makes use of indexes to complete these sub-queries. It further leverages indexes to execute `GROUP BY` and `ORDER BY` operators and avoids the overhead of building a hashmap. Greenplum is slower than AnalyticDB, because it bears the hashmap overhead from hash join. To make it fair, we also evaluate AnalyticDB in hash join mode and are able to achieve comparable performance with Greenplum.

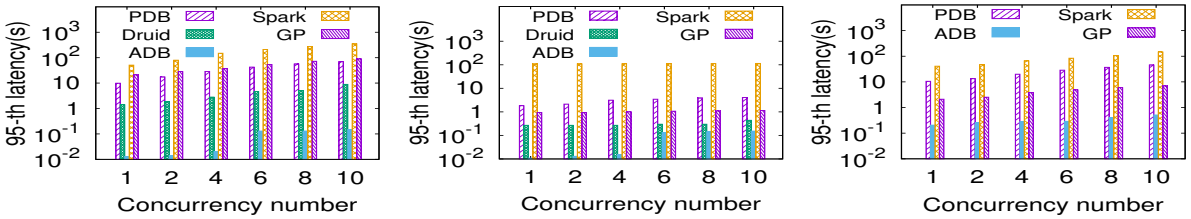
6.2.2 Query on 10TB Data

We further generate a larger dataset of 10TB data and increase the level of concurrency. As the comparison systems are much slower than AnalyticDB in large datasets and higher concurrency, we omit them from this analysis.



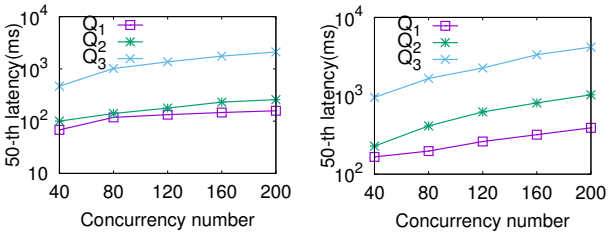
(a) Q1 (b) Q2 (c) Q3

Figure 14: 50-percentile latency, 1TB data (PDB for PrestoDB, ADB for AnalyticDB, GP for Greenplum).



(a) Q1 (b) Q2 (c) Q3

Figure 15: 95-percentile latency, 1TB data (PDB for PrestoDB, ADB for AnalyticDB, GP for Greenplum).



(a) 1TB (b) 10TB

Figure 16: 50-percentile latency of AnalyticDB on 1TB and 10TB data.

Figure 16 illustrates the 50-percentile latency of three queries on both 1TB and 10TB data. We can see that, for Q1 and Q2, the latency is within hundreds of milliseconds under different concurrency levels. For Q3, the latency with 200 concurrency is much higher than that with 40 concurrency. The reason is that the computing capacity under 8 machines has been saturated. Specifically, with 64 primary and 10 secondary partitions, the real concurrent threads could reach 128,000 under 200 concurrency. There are in total $48 \times 8 = 384$ CPU cores on these eight machines. As Q3 is computing-intensive, the performance is deteriorated due to frequent context switch, suffering from high latency.

From Figure 16 we can see that the variation trend on 10TB data under different concurrency levels is similar to that on 1TB data. That is, the performance is not affected dramatically in spite of the increase in data size. The query latency on 10TB just doubles that on 1TB, because AnalyticDB searches indexes for row ids first and only needs to fetch qualified rows. With the help of index cache, index lookup is cost-effective and brings down the overall overhead. In summary, the performance of AnalyticDB is slightly impacted by the table size, but is more dominated by the computation on indexes as well as the number of qualified rows.

6.2.3 *Write Throughput*

To evaluate the write performance of AnalyticDB, we insert records, each with 500 bytes, into Orders Table. Table 3 illustrates the write throughput (write requests per second). Thanks to the read/write decoupling architecture and asynchronous index building, the write throughput grows nearly linearly with the increasing number of write nodes, until Pangu is saturated. When the number of write nodes reaches 10, the write throughput is 625,000 and the bandwidth corresponds to about 300 MB/s. Note that index building tasks are distributed over the entire AnalyticDB cluster with affordable overhead (as evaluated in Table 1 in Section 4.2.4), which will not affect both query efficiency and write throughput.

Table 3: Write throughput under different numbers of write nodes.

write node number	2	4	6	8	10
write throughput	130k	250k	381k	498k	625k

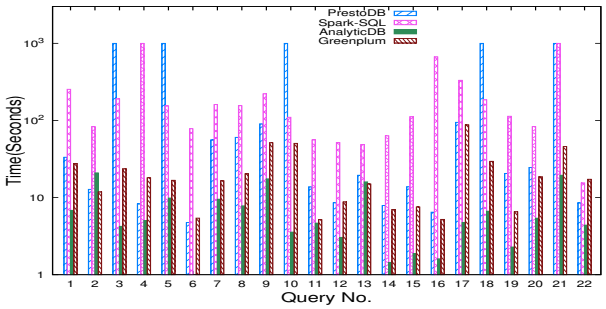


Figure 17: TPC-H performance comparison.

6.3 TPC-H Benchmark

We generate 1TB data for TPC-H evaluation. Figure 17 illustrates the performance comparison among AnalyticDB, PrestoDB, Spark-SQL, and Greenplum [3]. AnalyticDB achieves the smallest running time for 20 out of 22 queries, and outperforms the second best, i.e., Greenplum, by 2x. Compared to Spark-SQL, AnalyticDB adopts pipeline process model and indexes, which is faster than stage-based process. PrestoDB also adopts pipeline process, but it lacks indexes on columns. Although Greenplum also has both

[3]In Figure 17, if the time of a query is 1000s, it means the system encountered an exception when running the query and we did not get a result, e.g., query No.3 of PrestoDB and query No.21 of Spark-SQL.

pipeline process and all-column index, AnalyticDB preserves four additional advantages. First, AnalyticDB uses hybrid row-column storage, while Greenplum uses column-store. About half of columns are involved in a common TPC-H query, and hence AnalyticDB can fetch multiple columns of a row with a single I/O. Second, AnalyticDB's runtime cost-based index path selection (using real intermediate results) leads to better table access plans, compared to statistics-based planning in Greenplum. Third, AnalyticDB combines K-ways merging with composite predicates pushdown. Fourth, AnalyticDB incorporates vectorized execution engine and applies optimized CodeGen to all operators and expressions. For query No.2, AnalyticDB is slower than PrestoDB and Greenplum, because it chooses a different join order for multi-table join.

7. CONCLUSION

This paper presents AnalyticDB, a high-concurrent, low-latency, and real-time OLAP database at Alibaba. AnalyticDB has an efficient index engine to build index for all columns asynchronously, which helps improve query performance and hide index building overhead. With careful designs, the all-column index just consumes 66% more storage. AnalyticDB extends hybrid row-column layout to support both structured and other complex-typed data that may be involved in complex queries. To provide both high-throughput write and high-concurrent query, AnalyticDB follows a read/write decoupling architecture. Moreover, we enhance the optimizer and execution engine in AnalyticDB to fully utilize the advantages of our storage and indexes. Our experiments have showed that all these designs help AnalyticDB achieve better performance compared to state-of-art OLAP systems.

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