Near Data Processing in Taurus Database

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***Abstract*—Huawei's cloud-native database system GaussDB for MySQL (also known as Taurus) stores data in a separate storage layer consisting of a pool of storage servers. Each server has considerable compute power making it possible to push data reduction operations (selection, projection, and aggregation) close to storage. This paper describes the design and implementation of near data processing (NDP) in Taurus. NDP has several benefits: it reduces the amount of data shipped over the network; frees up CPU capacity in the compute layer; and reduces query run time, thereby enabling higher system throughput. Experiments with the TPC-H benchmark (100 GB) showed that 18 out of 22 queries benefited from NDP; data shipped was reduced by 63%; and CPU time by 50%. On Q15 the impact was even higher: data shipped was reduced by 98%; CPU time by 91%; and run time by 80%.**

***Index Terms*—cloud DBMS systems, query processing, storage virtualization, selection pushdown, early data reduction, online analytical processing, database engine architecture**

I. Introduction

Applications are increasingly migrating to cloud platforms offered by vendors including Amazon, Microsoft, Google, Alibaba, and Huawei. Many applications store their data in a relational database, making relational database services a crucial part of a cloud platform.

Huawei's cloud platform includes several database offerings under the unifying brand 'GaussDB'. GaussDB for MySQL is a cloud-native database service, fully compatible with MySQL. The underlying technology is called Taurus, and we will use this term here.

Taurus separates compute and storage. Data is divided into slices that are distributed among a number of multi-tenant Page Stores. The DBMS frontend, where all query processing occurs, is a slightly modified version of MySQL 8.0. A summary description of the architecture is provided in Section II. A detailed description can be found in [1].

Query processing in MySQL is designed for transactional workloads, dominated by simple queries and short transactions. MySQL performs poorly on queries that sift through large amounts of data [2]. In a cloud environment where compute and storage are decoupled, the network is a shared resource that may become overloaded, so it is important to minimize network load. Early data filtering can reduce data volume and network utilization simultaneously. As a result, CPU load on the frontend server also reduces, thus enabling higher system throughput.

Relational query processors try to reduce the amount of data to process by executing data reduction operators—selection (filtering), projection, and aggregation—as early as possible. Near data processing (NDP) goes a step further, and pushes down selection, projection, and aggregation to storage nodes. This reduces CPU load on the frontend server, and spreads it over multiple storage nodes. It also reduces the amount of data shipped from storage over the network—sometimes dramatically—which may reduce query run time substantially. For example, on TPC-H [3] Q6, network data volume and run time were reduced by 99% and 89%, respectively. The experimental results appear in Section VII of this paper. NDP is an idea that can be and has been applied at many levels of the memory hierarchy, and in different software systems—for example, cloud storage services (Amazon S3 Select); database storage servers (Oracle Exadata); and SSD controllers (SmartSSD). More detail about prior work is provided in Section VIII on related work.

This paper is about engineering NDP into an existing code base in an effective, yet minimally disruptive manner. Our NDP design and implementation have the following noteworthy features.

- NDP processing is completely encapsulated within and below the InnoDB storage engine—in fact, almost entirely within index scan cursors. The MySQL query execution layers above the storage engine are unaware of NDP processing.
- MySQL query execution depends on index scans returning rows in sorted order, and row versions consistent with the scan's read-view (multi-versioning). Our implementation ensures that NDP-enhanced scans still satisfy these properties.
- An NDP scan reads batches of pages, and parallelizes reads across Page Stores. By contrast, a regular InnoDB scan does not perform batch reads.
- Selection predicates are converted into LLVM [4] intermediate representation (IR) on the compute node. The IR is compiled into architecture-specific native code on storage nodes.
- Page Stores treat NDP processing as a best-effort activity to minimize the impact on other Page Store tenants. A Page Store is free to ignore an NDP processing request,

and return unprocessed database pages. Any remaining NDP processing is completed by InnoDB on the compute node.
- Only a subset of the queries undergo NDP processing, and our design ensures that non-NDP queries do not suffer any performance penalties due to the new 'NDP' code path.

The rest of this paper is organized as follows. A brief overview of the Taurus architecture appears in Section II. A high-level overview of the NDP solution appears in Section III. The NDP system design is presented in Section IV, and includes the NDP-related changes in the query optimizer, InnoDB storage engine, and Page Stores. Details of how NDP accomplishes column projection, predicate evaluation, and aggregation are presented in Section V.

Taurus combines NDP with the ability to execute query plans in parallel, and the resulting synergy enables three levels of parallelism as described in Section VI. Experimental results are captured in Section VII. The related work is described in Section VIII, and conclusions and some future work are mentioned in Section IX.

II. Taurus Overview

Taurus is a relational database architecture designed by Huawei for multi-tenant cloud environments. This section contains a brief overview of the design; a more detailed description can be found in [1].

Taurus separates compute and storage, and relies only on append-only storage. Its architecture and replication algorithms result in higher availability than the traditional quorum-based replication without sacrificing performance or increasing hardware costs. The replication algorithms use separate persistence mechanisms for database logs and pages, and ensure strong consistency for logs and eventual consistency for pages to optimize performance and availability.

As illustrated in Fig. 1, a Taurus DBMS consists of four major logical components: database frontends (DB master and replica nodes); a Storage Abstraction Layer (SAL); Log Stores; and Page Stores. These components are distributed between two physical layers: a compute layer and a storage layer, shown on the two sides of the network layer in Fig. 1. The database is divided into fixed-size (10 GB) segments called *slices* that are distributed among multiple Page Stores. Log Stores and Page Stores are multi-tenant services shared by many database servers.

Taurus storage is designed to work with different database frontends: MySQL, PostgreSQL, and openGauss. The frontend layer consists of one master that can serve both read and write queries, and up to 15 read replicas that execute read queries only. A frontend server is responsible for accepting incoming connections; optimizing and executing queries; and managing transactions. All of the updates are handled by the master, whose job is to make modifications to database pages persistent by synchronously writing log records, in triplicate, to durable storage in Log Stores. The master also periodically communicates the locations of the latest log records to all of the read-only replicas so that they can read the latest log entries, and update any affected pages in their buffer pools.

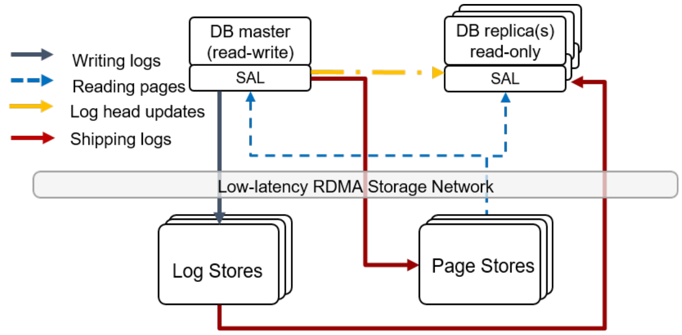

Fig. 1. Taurus architecture.

The Storage Abstraction Layer (SAL) is an independent component running on the database server. The SAL isolates the database frontend from the underlying complexity of remote storage; slicing of the database; recovery; and read replica synchronization. The SAL writes log records to Log Stores; distributes them to Page Stores; and reads pages from Page Stores. The SAL is also responsible for creating, managing, and destroying slices in Page Stores; and routing page read requests to Page Stores.

A Log Store is a service executing in the storage layer responsible for storing log records durably. Once all of the log records belonging to a transaction have been made durable, transaction completion can be acknowledged to the client. Log Stores serve two purposes. First and foremost, they ensure the durability of log records. Second, they also serve log records to read replicas so that the replicas can apply the log records to the pages in their buffer pools.

Page Store servers are also located in the storage layer. A Page Store server hosts slices from multiple database frontends (tenants). However, a slice contains table and index data from only one database, thereby achieving tenant-level data separation. Each slice is replicated to three Page Stores for durability and availability. The main function of a Page Store is to keep pages up-to-date, and serve read requests from the masters and replicas. A Page Store receives log records from multiple masters for the pages it hosts, and applies the log records to bring pages up-to-date so they are ready to be served.

III. Life of a query with NDP

This section provides an overview of how an example query undergoes NDP processing. The NDP design and implementation are described in detail in sections IV and V, respectively. The sample query in Listing 1 that computes the average salary of workers younger than 40 who joined the company in 2010, is used as an example.

```
SELECT AVG(salary)
FROM Worker
WHERE age < 40 AND
  join_date >= DATE '2010-01-01' AND
  join_date < DATE '2010-01-01' + INTERVAL '1' YEAR;
```

Listing 1. A sample query to demonstrate the effects of NDP.

A part of the query's EXPLAIN output describing MySQL's execution plan with NDP-related information is shown in Listing 2. For brevity, only the relevant information—appearing in the 'Extra' column—is shown.

```
Using pushed NDP condition
(((testdb.worker.join_date >= DATE'2010-01-01') AND
  (testdb.worker.join_date < <cache>((DATE'
     2010-01-01' + INTERVAL '1' YEAR))) AND
  (testdb.worker.age < 40)));
Using pushed NDP columns; Using pushed NDP aggregate
```

Listing 2. NDP-related information in MySQL's EXPLAIN output.

In this example, the entire `WHERE` clause is pushed into Page Stores, but this is not always the case. Residual predicates may remain, to be evaluated by the MySQL query executor in the compute node. Because the query only projects one column out of many in the *Worker* table, NDP column projection is also chosen. The calculation of `AVG` is pushed down as well. In short, the query benefited from NDP fully because all three types of pushdowns happened, but in general, the three decisions are taken independently.

NDP processing begins closest to where the data lives: inside Page Stores. After applying NDP processing to a page, the Page Store returns the result as a special NDP-page. NDP pages may have fewer rows remaining because of predicate filtering; and the rows themselves may be narrower (due to NDP column projections) and aggregated (due to NDP aggregation). NDP pages from one query are unlikely to be of use to other queries. Accordingly, they are stored in a separate buffer, and are accessible only to the query that requested the pages.

Selection predicates that have been pushed down to Page Stores—all of the `WHERE` conditions for the query in Listing 1—are compiled into an LLVM bitcode function [4], and then to native code using just-in-time compilation. When a Page Store receives a read request for a page, it first filters the rows by calling the compiled function. The remaining rows undergo NDP column projection, and only the columns requested by the query are retained. Next, partial aggregation is performed, and the sum of salary and the number of rows associated with the sum—using which `AVG(salary)` can be computed—are retained. The remaining narrowed and aggregated rows are stored in special NDP pages, and returned to MySQL's InnoDB storage engine via the SAL.

Next, any residual predicates—none in the example query—are evaluated by the MySQL query executor, projection expressions computed, and query results produced. The query executor orchestrates execution as before: iterators are initiated top-down in a tree, and data and result rows percolate bottom-up.

The process described is for a particular query. In the general case, it is carried out separately for each query block in a complex query with subqueries. In case of an inner query block, the result produced is consumed by the containing query block. NDP functionality is largely encapsulated within the index scan operator, and that operator can appear in any query block—main or inner—within the query.

The query optimizer in Taurus can produce a parallel query plan, in which multiple workers scan a table concurrently. Each worker scans a portion of the data, and may perform NDP operations in the scan. `AVG` is computed by keeping `SUM` and `COUNT` values per thread, and a separate 'leader' thread then aggregates the partial values.

IV. Design of the NDP System

This section describes the NDP design in more detail, beginning with a summary of design goals and constraints. The changes required to support NDP involve three subsystems: the MySQL query optimizer (Section IV-B), the InnoDB storage engine (Section IV-C), and Page Stores (Section IV-D). Taurus NDP flows and the affected subsystems are shown in Fig. 2.

A. Design goals and constraints

An important design goal was to minimize the effect of NDP-related changes to the software layers above the InnoDB storage engine. This was achieved by encapsulating NDP processing entirely within the index scan operator, and making it invisible to the operators higher up in a query tree.

An InnoDB table is always accessed by scanning an index (primary or secondary) in forward or reverse order. Rows are returned in sorted order on the index key, and other operators may depend, implicitly or explicitly, on receiving rows in sorted order. It was important to retain this property of scans when NDP was enabled.

A Page Store is a multi-tenant service, and may run out of resources (CPU time) required for NDP processing. Instead of waiting for resources and blocking progress, a Page Store can skip NDP processing and just return the requested page. In that case, InnoDB will complete the NDP processing of the page. As a result, the query executor can rely on the requested NDP processing being done—either by Page Stores or by InnoDB.

Because of multi-versioning, the latest version of a row on a page may not be visible to a scan. A Page Store is unable to traverse a row's undo chain and reconstruct older versions because the required undo records may reside in other Page Stores. Such invisible rows must be returned to InnoDB, which *is* able to reconstruct the correct older version, and perform the requested NDP processing on the row.

B. NDP support in the query optimizer

We considered two approaches to integrate NDP support into query optimization.

- During plan enumeration, consider NDP as an alternative, and estimate its cost and benefits. This may influence join order, join types, table access methods, and so on.
- Treat NDP as a query plan post-processing step: finalize a query plan without considering NDP, and then consider enabling NDP for each of the table accesses in the plan.

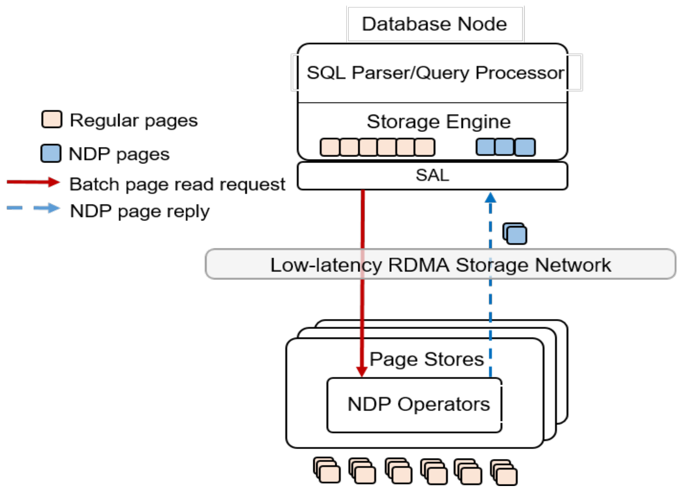

Fig. 2. NDP flow and the affected software components

The first approach can potentially produce a faster plan, but increases the optimizer's search space. For example, a hash-join with NDP pushdown may be better than a nested-loop join without NDP. By not considering NDP during plan enumeration, the optimizer may miss the hash join plan. However, we opted for the second approach for several reasons.

1) It does not require changing the core optimizer, and just requires adding a (less intrusive and less risky) post-processing step.
2) Where possible, the optimizer already pushes down data reduction operators on top of index scans. NDP is essentially a more efficient way of evaluating the operators, so the risk of performance regression is low.
3) NDP processing is not guaranteed; Page Stores may ignore the optimizer's NDP request due to resource constraints.

The post-processing approach works as follows. For each table access in the final plan, the optimizer considers NDP column projection and NDP predicate evaluation. For the last table access in a query block, the optimizer also considers NDP aggregation if a `GROUP BY` clause or aggregation functions are present. If the optimizer enables any of the three NDP features, the table access is marked as an 'NDP scan'.

NDP is only beneficial if an access method reads many rows: for example, a full table scan or range index scan. Accordingly, NDP is not considered for table access methods that access only a few rows—for example, a point lookup.

C. NDP support in InnoDB storage engine

The InnoDB storage engine handles all of the complexities related to NDP scans, and shields the SQL executor from NDP. Indeed, the SQL executor only provides InnoDB the necessary callback functions for predicate evaluation or value accumulation (for aggregations).

1) NDP Descriptor: For an NDP scan, InnoDB encapsulates and builds all of the relevant information in a data structure called an 'NDP descriptor'. A separate NDP descriptor exists for each table in a query block, and contains the following information.

- the number and data types of the index columns and the lengths of the fixed-length columns
- the columns to be projected, if any
- the encoded filtering predicates in the LLVM IR (intermediate representation) format, if any
- the aggregation functions to call and the `GROUP BY` columns, if any
- a transaction ID that represents an MVCC (multi-version concurrency control) read-view low watermark. If the transaction ID of a row is less than this low watermark, the row is visible to the scan; otherwise it may not be. Note that a complete list of active transactions is not included to reduce CPU overhead in Page Stores.

2) 'NDP' Pages: An NDP I/O request reaches a Page Store, and using the accompanying NDP descriptor, the Page Store converts a regular InnoDB page into an 'NDP' page. Unlike a regular fixed-length InnoDB page (usually 16 KB), an NDP page is of variable length. To avoid drastic code changes in InnoDB, and to use the same InnoDB code path to process both regular and NDP pages, we decided that an NDP page should resemble a regular InnoDB page.

- An NDP page contains the same page header as a regular InnoDB page. The records in an NDP page have the same structure as regular InnoDB records. As a result, the existing InnoDB page cursor functions, which iterate over records in a page, remain unchanged. The code that formats a record (to extract fields from a record) can be used on the NDP record with minimal changes.
- The records in an NDP page are also chained in index key order. If a query uses the index to satisfy an ordering requirement, an NDP scan of the index still satisfies the ordering requirement, and a sort is avoided.
- As an optimization, if NDP predicate filtering removes all of the records in a page, the resulting empty page is indicated specially without requiring explicit materialization.

Although an NDP record resembles a regular InnoDB record, there may be two differences. First, the NDP record may be narrower because some columns may have been removed. Second, the NDP record may represent an aggregation of multiple regular records. A mix of regular records and NDP records can co-exist in an NDP page.

The InnoDB record header contains a "record type" field which is reused to tag NDP records as indicated in Listing 3. The two new status values indicate to InnoDB row scan functions whether NDP projection or aggregation has happened on a particular record.[1] For regular InnoDB records, the scan functions follow the existing code path; for NDP records, NDP-specific code is used.

[1]NDP filtering removes records altogether, and therefore, does not require a code.

```
#define REC_STATUS_ORDINARY 0
#define REC_STATUS_NODE_PTR 1
#define REC_STATUS_INFIMUM 2
#define REC_STATUS_SUPREMUM 3
#define REC_STATUS_NDP_PROJECTION 4
#define REC_STATUS_NDP_AGGREGATE 5
```

Listing 3. Two newly added NDP record types in storage/innobase/rem/rec.h

3) Interaction between NDP and the InnoDB buffer pool: The existing InnoDB buffer pool is used to store NDP pages. Using the buffer pool to store both regular pages and NDP pages has the advantage of memory sharing. When there are no NDP scans, the entire buffer pool is still available to regular scans. Because NDP pages are custom made for a particular table access, although the NDP pages reside in the buffer pool, they should only be visible to the thread that performs the NDP scan and not to the other concurrent queries and transactions.[2] To achieve this invisibility, NDP pages are not inserted into such buffer pool management data structures as hash map, LRU list, flush list, etc. NDP pages are managed by InnoDB persistent cursors——InnoDB's regular mechanism for driving table access. The InnoDB persistent cursor is responsible for allocating NDP pages from the buffer pool free list, and releasing the NDP pages. The number of NDP pages allocated is controlled so that regular scans are not deprived of memory.

4) NDP scans and batch reads: Like a regular scan, an NDP scan also traverses a B+ tree to locate leaf pages. When the traversal reaches a level-1 page (the level immediately above the leaf level), the NDP scan extracts the child leaf page ID's from the level-1 page, and packs the leaf page ID's into a single I/O request, called a 'batch read.' A batch read's memory footprint is known (controlled using a newly introduced MySQL parameter called $innodb\_ndp\_max\_pages\_look\_ahead$), and an NDP scan's memory footprint is set to be the same value: after an NDP scan finishes processing an NDP page in the batch, the page is immediately released back to buffer pool free list.

An NDP batch read uses page locking *and* LSN versioning for concurrency control as follows. Traditionally, page locking is used to solve concurrent read-write conflicts in a B-tree traversal. However, given an NDP batch read's large size (typically around a thousand pages), it impractical to lock and block modifications to individual pages. During a B-tree traversal, shared page locks are obtained starting from the root page until a level-1 page. Since the sub-tree is share-locked, no transaction can modify the sub-tree structure (e.g., insert or delete a page). Then an LSN (Log Sequence Number) corresponding to the locked sub-tree structure is generated.

The LSN accompanies the NDP batch read request to the Page Store. Once an NDP batch read request is submitted, the the B-tree locks can be released, and the sub-tree may be modified. The Page Store only returns those page versions matching the LSN value, and thus, the batch read is shielded from the concurrent B-tree modifications.

[2]The converse is not true. Regular non-NDP pages *are* available to NDP threads: they are simply copied to the NDP area of the buffer pool, and do not require I/O's.

Before a leaf page ID is added to a batch read request, a check is made whether the page already exists in the buffer pool. If so, an I/O is avoided by copying the cached (non-NDP) page to the NDP page area. A copy is required instead of using the non-NDP page directly because the page may be modified by concurrent transactions once we release the page locks, and we need to ensure the NDP scan observes a consistent sub-tree structure. Only those page ID's not found in the buffer pool get inserted into a batch read request.

A batch read is aware of scan boundaries. For example, in an index range scan of $c1 \leq 1000$, where $c1$ is the index key, the batch read will not read leaf pages beyond the range because level-1 pages store 'boundary' $c1$ values.

In addition to reducing the number of I/O requests, batch reads offer two other benefits.

- They facilitate parallelism in the Page Stores. A Page Store can assign a thread to work on a page, and multiple threads can process the batched pages in parallel. Large batch read sizes (around a thousand pages) also means that multiple Page Stores are likely to engage in servicing the request.
- They facilitate cross-page aggregation in Page Stores, details of which are provided in Section V-C.

NDP can be enabled in parallel index scans, as described in Section VI.

D. NDP support in Page Stores

Because Page Stores are intended to support several frontend systems, including MySQL, PostgreSQL, and openGauss, the NDP framework for Page Stores is DBMS-independent. DBMS-specific shared libraries can be loaded as plugins into the Page Stores. The Page Store NDP framework accepts an NDP descriptor as a type-less byte stream, which an NDP plugin interprets. An NDP I/O begins as a regular page read returning a regular page that the NDP plugin then converts into an NDP page. Multiple threads undertake NDP processing of pages concurrently, independently, and in any order enabling flexibility and parallelism in the Page Store. The logical page ordering is enforced in the frontend storage engine, not in the Page Stores.

Once a regular page has been read, an NDP plugin iterates through the records in the page, and checks whether a record is visible by comparing the record's transaction ID with the transaction ID in the NDP descriptor. If the former is lower, the record is visible to the transaction requesting the page; otherwise, the record is *ambiguous* in that the Page Store cannot determine if it is visible. Visible delete-marked records are skipped. Such NDP operations as column projections, predicate evaluations, and aggregations are then applied to the visible records.

A Page Store is a multi-tenant service that simultaneously supports multiple frontend instances, processing a mix of NDP and non-NDP read requests. When there are many concurrent NDP requests, a Page Store CPU may become a bottleneck, and negatively affect the overall client response time. To alleviate, two optimizations—NDP descriptor cache and resource control—are introduced.

1) NDP descriptor cache: Initial performance tests revealed that NDP descriptor decoding caused a bottleneck in Page Store CPU—a few milliseconds per decoding on average—and slowed down queries. Significant CPU time was also spent compiling LLVM bitcode into native code and obtaining the function pointer. A typical query scanning a large table generates many waves of NDP page read requests with the same NDP descriptor to a Page Store. This access pattern was leveraged by introducing an NDP descriptor cache. Instead of decoding descriptors and converting LLVM bitcode for each NDP request, the first request caches the result which is reused subsequently. (The cache key is computed by applying a hash function to the NDP descriptor fields.) This optimization dramatically reduced the average decoding time to less than 5 microseconds, and improved performance on some benchmarks by up to 50%.

2) NDP resource control: A Page Store keeps pages up to date by applying log records, and serves page read requests. It also performs several secondary tasks: compaction; creating snapshots; and doing backups. Hence, it must be able to limit the resources used for NDP requests. A dedicated thread pool was introduced to control the number of NDP pages processed concurrently. New NDP page read requests are added to a queue, and wait for their turn. NDP processing does not block regular page reads/writes, and is treated as a best-effort activity. If the Page Store has enough resources to complete an NDP request without undue waiting, the NDP processing of a page is done; otherwise, it is skipped, and the frontend node completes it. NDP resource control works closely with other Page Store flow control mechanisms to provide balance and fairness among different Page Store tenants. Interestingly, because NDP resource control is page-scoped, NDP benefit to a query is not all-or-nothing: some pages might undergo NDP processing before resource throttling kicks in, and NDP processing is left to the InnoDB layer.

V. NDP IMPLEMENTATION

NDP reduces data by retaining only the necessary rows and columns required in a query, and by aggregating the retained rows. This section describes the implementation details of how the NDP system performs column projection (Section V-A); row filtering using predicate evaluation (Section V-B); and row aggregation (Section V-C).

A. NDP column projection

For each table, the query optimizer estimates the total width of the columns required in a query, and compares it to the total width of all of the columns. When the width reduction is high enough, the query optimizer enables NDP column projection for the table access. For fixed-sized columns, the column widths can be easily obtained from the system dictionary. For variable-sized columns, average sizes—calculated using table statistics—are used.

In addition to the columns required by a query, some fields needed by InnoDB's internal processing are always included. For example, the primary key columns are always included even if the query does not require them because InnoDB needs them for persistent cursor re-positioning. The transaction ID is also included for MVCC handling.

Only visible records are projected. Ambiguous records are returned unchanged because InnoDB requires the entire record to construct the old record version using its 'undo' log. Sending a 'narrower' ambiguous record could cause InnoDB to malfunction if the record is actually not visible, and InnoDB needs to construct an older version.

B. NDP predicate evaluation

1) NDP predicate evaluation workflow: Even without NDP, MySQL's query optimizer always pushes down predicates into a table access when possible (the 'classical' predicate pushdown). Only such pushed predicates are eligible for NDP evaluation; cross-table predicates are not.

Not all data types and operators are supported by the LLVM engine in Page Stores (Section V-B2), and expressions with user-defined functions cannot be NDP-pushed because they might pose security risks. The optimizer takes a conservative approach, and maintains explicit lists of allowed data types, operators, and functions. The optimizer then calculates the filter factors of the predicates, and enables NDP only if the predicates are sufficiently selective. The query optimizer then separates NDP predicates from the original ones: the residual non-NDP predicates are evaluated by the SQL executor.

Although the SQL executor never evaluates NDP predicates, InnoDB may do so (by calling SQL executor functions) in the following four cases.

1) InnoDB handles ambiguous records—records that cannot be handled by Page Stores.
2) A Page Store may not evaluate NDP predicates because of resource constraints, and InnoDB finishes the job.
3) InnoDB may not even push NDP predicates to Page Stores because of its own resource constraints (buffer-pool pressure).
4) An NDP page is copied from an existing (non-NDP) page in the buffer pool.

A Page Store's NDP plugin invokes the LLVM engine to evaluate NDP predicates on the records—as explained in Section V-B2. A Page Store can only safely discard 'false' visible (unambiguous) records: for the rest, decision must be deferred to InnoDB.

Records disqualified by the NDP predicates are removed from the page, and column projection is performed on the surviving records, if applicable.

2) The role of LLVM in predicate evaluation: Prior research has shown that interpretive expression evaluation, as done by traditional relational systems, can be slow [5]–[8]. Therefore, Taurus compiles expressions into bitcode—wrapped in a function—and then calls the function once for each row. In some of the prior research, LLVM query engines were built from scratch [9]–[12]. In contrast, Taurus LLVM bitcode compilation is non-invasive; requires no changes to the existing Volcano-style SQL executor; combines LLVM interpretation and execution; and uses a shared library of pre-compiled complex functions. Bitcode for predicates is generated just before query execution.

Classical (non-LLVM) MySQL predicate evaluation proceeds by traversing a tree of various expression nodes, and calling the necessary functions such as '>' and '≤'. This approach is slow because of the frequent function calls and cache misses. LLVM, in contrast, traverses an expression tree bottom-up; emits bitcode along the way; and creates a composite function that encodes the entire expression tree. This process is illustrated using the `WHERE` condition "($a > 1$ `AND` $b > 2$) `OR` $c >= 3$". The resulting IR (intermediate representation) code appears in Listing 4. In the code, a label with the prefix '%' represents an LLVM register.

`AND` $b >= 2$) `OR` $c >= 3$.

```
define i32 @f() #0 {
entry:
  %0 = load i32, i32* %a, align 4
  %cmp = icmp sgt i32 %0, 1 ; a > 1?
  br i1 %cmp, label %b_and_cont, label %b_or_cont ;
       shortcut may happen

b_and_cont:
  %1 = load i32, i32* %b, align 4
  %cmp1 = icmp sgt i32 %1, 2 ; b > 2?
  br i1 %cmp1, label %b_and_true, label %b_or_cont

b_and_true:
  store i32 1, i32* %retval
  br b_ret;

b_or_cont:
  %2 = load i32, i32* %c, align 4
  %cmp3 = icmp sge i32 %2, 3 ; c >= 3?
  store i32 %cmp3, i32* %retval
  br b_ret;

b_ret:
  ret i32 %retval
}
```

Listing 4. LLVM intermediate representation (IR) code for the predicate "($a > 1$ AND $b > 2$) OR $c >= 3$".

LLVM execution requires several common utility functions—for example, *bin2decimal* that converts a decimal number's binary representation into a format used by MySQL. Such utility functions are pre-compiled, and collected into a shared library that is installed on all of the Pages Stores. This design choice eliminated the need to convert large complex functions into LLVM bitcode.

LLVM compilation itself consists of several steps depicted in Fig. 3 and described below.

1) Predicates for each table in the query are identified and translated using the LLVM C/C++ API so that code generation can begin. As already indicated in Section V-B1, predicate identification is done by the query optimizer based on the predicate's estimated selectivity. In Fig. 3, table-scoped conditions marked as the triangles '1' and '2' are chosen, but cross-table conditions are left alone because they will not participate in NDP processing.
2) Rewritten predicates are compiled into IR by the LLVM frontend Clang [13]. To facilitate debugging and to identify mistakes, in-memory IR can be optionally persisted on disk. In Fig. 3, the expressions corresponding to the triangles '1' and '2' are traversed bottom-up, and the IR code is emitted along the way as illustrated in Listing 4.
3) The resulting in-memory IR code is packed into the NDP descriptor and sent to each Page Store. There is a separate NDP descriptor per table. The IR codes for '1' and '2' are put in the NDP descriptors of the *Supplier* and *Lineitem* tables, respectively.
4) A Page Store extracts the IR bitcode from the NDP descriptor and sends it to the LLVM execution engine. The engine returns the address of a function f that encodes the predicates. The Page Store uses f—which may call some utility functions present in the shared library—to perform record filtering. To further speed-up f, it is just-in-time compiled into native machine code before the first call. Just-in-time compilation permits architecture-specific native code generation—for example, ARM or X86—depending on the Page Store hardware. In Fig. 3, the IR codes for '1' and '2' are just-in-time compiled to native functions f_1 and f_2, which then filter *Supplier* and *Lineitem* rows, respectively.

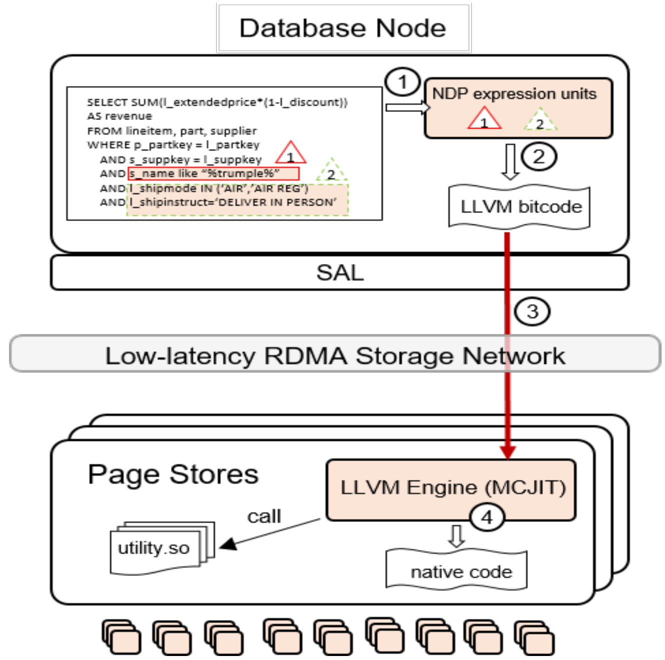

Fig. 3. The four steps in the LLVM compilation workflow.

Care must be taken to ensure that filtering and expression evaluation on Page Stores produce the same result as that produced by the hypothetical non-NDP evaluation on the SQL node; otherwise, the query may produce incorrect results because of arithmetic overflow, underflow, and floating-point arithmetic issues.

C. NDP aggregation computation

MySQL query optimizer enables NDP aggregation on a table T based on the following logic.

- MySQL query execution proceeds block-by-block, and therefore, T must be the last table accessed in a query block. Furthermore, there must be no residual predicates that need still need evaluation by the SQL executor during or after the table access.
- If the aggregation is for a `GROUP BY` clause, then the index access chosen for T must satisfy the grouping column requirement. This restriction exists because sort- or hash- `GROUP BY` is not implemented in Page Stores.

Page Stores perform aggregations on per-page basis, and the work is best explained using an example.[3]

- Suppose that an aggregation group on the page P_1 has 5 records, and the aggregation function itself is `SUM`. Let $P_1 = \{(1,2),(2,10)?,(3,7),(4,8)?,(5,2)\}$ in which the first tuple value indicates record ID, and the second tuple value indicates the column value to be summed up. Two of the records are ambiguous in the sense described in Section IV-D, and are denoted by '?'. Recall that the Page Stores cannot process ambiguous records.
- A Page Store computes $\text{NDP}(P_1)$—the NDP-processed version of P_1—as follows. Visible (non-ambiguous) records—except the last record in a group—are summed up, and discarded; and the summation is attached to the last record. Thus, $\text{NDP}(P_1) = \{(2,10)?,(4,8)?,((5,2),9)\}$ in which 9 resulted from $2+7$, and the resulting longer record $((5,2),9)$ is an 'NDP' aggregation record indicated with the value 5 in Listing 3.
- In general, P_1 will have records with many grouping values, and each grouping value is handled similarly.

Page Stores can also aggregate across pages, and there are two cases to consider.

1) If `GROUP BY` clause is present, only logically adjacent pages can be aggregated. Page Stores generally do not know the logical order of pages, and therefore, cross-page aggregation does not happen.
2) If `GROUP BY` clause is absent (scalar aggregation), even logically non-adjacent pages can be aggregated, and cross-page aggregation happens.

For cross-page aggregation, the Page Stores have to recognize which pages belong to the same table access from the SQL node. It is difficult (and may not be feasible) to collect such pages from different I/O requests. Therefore, a simpler approach was chosen: cross-page aggregation happens only to the pages of the same I/O request. InnoDB's batch reads play an important role here because they enable cross-page aggregations.

[3]In this section, we assume that NDP predicate filtering—which precedes NDP aggregation—has already happened inside a Page Store.

Continuing with the previous example, suppose that `GROUP BY` clause is absent, and the scalar `SUM` aggregation spans across another page P_2.

- Let $P_2 = \{(11,10),(12,2)?,(13,5),(14,9)\}$.
- $\text{NDP}(P_2) = \{(12,2)?,((14,9),15)\}$.
- Cross-page aggregation across P_1 and P_2, denoted by $\text{NDP}(P_1,P_2)$ is computed as follows. Ambiguous records are left alone; non-ambiguous records are summed up; and the value is attached to the latter of the two pages in the batch I/O request ordering. Assuming P_2 is that latter page, $\text{NDP}(P_1,P_2) = \{(2,10)?,(4,8)?,(12,2)?,((14,9),26)\}$ in which 26 results from 2 (P_1) + 9 (P_1) + 15 (P_2).

InnoDB performs the residual aggregation work on the ambiguous records, and shields the SQL executor from NDP aggregations in the following sense. Consider the 'NDP' aggregation record $((14,9),26)$. Its prefix $(14,9)$ is a regular (non-NDP) record, and it sent to SQL executor. InnoDB then calls the SQL executor's appropriate aggregation function ('sum' in this case), and provides the special value 26.

VI. Three Levels of Parallelism

Query processing in the MySQL 8.0 community version is single threaded, but a different group at Huawei has added parallel query (PQ) capabilities. The initial implementation is limited in scope: a table or range scan can be range-partitioned into many sub-scans that are processed in parallel by a pool of worker threads. A sub-scan can be converted into an NDP scan as described in Section IV-C.

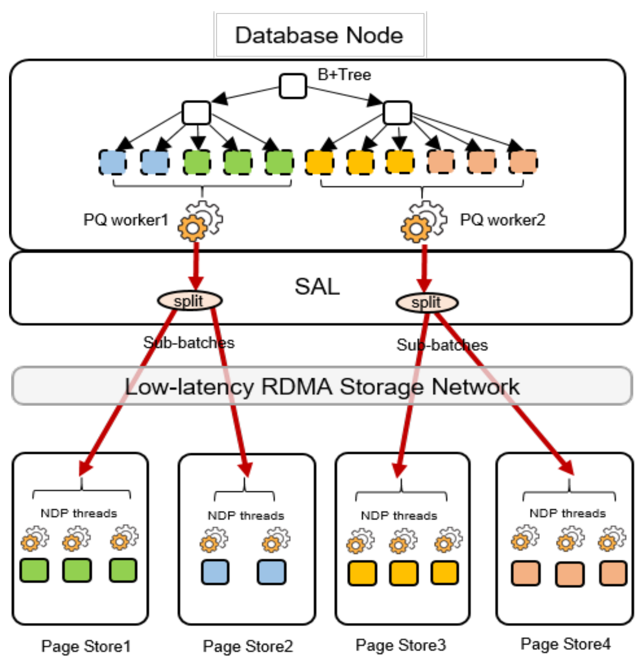

Fig. 4. Three-level parallelism enabled by combining PQ and NDP.

By combining PQ and NDP, Taurus achieves three levels of parallelism as illustrated in Fig. 4: in the SQL node, across Page Stores, and within a Page Store. These three levels of parallelism work together to reduce processing time significantly.

1) SQL node parallelism: PQ drives the SQL node parallelism; it partitions a table and uses multiple PQ worker threads to scan the partitions concurrently. The other two levels of parallelism are driven by the NDP batch read capability.

2) Parallelism across Page Stores: When a PQ worker thread scans its assigned partition, the thread can activate NDP, which sends batch reads to the Page Stores. The pages in a batch are usually scattered across multiple slices, and the slices are usually hosted by multiple Page Stores. Specifically, the Storage Abstraction Layer (SAL) splits a batch read into multiple sub-batches, based on where the pages are located. Pages that belong to the same slice are assigned to the same sub-batch. SAL concurrently sends the sub-batches to Page Stores, with the effect that multiple Page Stores are engaged in parallel to serve the original batch read.

3) Parallelism within a Page Store: When a Page Store receives a batch read request (which may be a sub-set of the original batch read), the Page Store can use multiple concurrent threads to serve the batch read, with each thread performing NDP operations (column projections, predicate evaluations, and aggregations) on its pages in the batch.

VII. Experimental Results

A. Initial micro-benchmarks

The most direct benefit of NDP is a reduction in network traffic: data filtered out in Page Stores never travels over the wire to InnoDB and beyond. This effect can be clearly demonstrated using queries that simply count the number of rows. The performance of `COUNT(*)` queries is a perennial problem in MySQL, and NDP provides immediate customer benefits. We illustrate the gains on a 1 TB TPC-H database with a workload consisting of the three `COUNT(*)` variants shown in Listing 5, plus Q1 and Q6 from TPC-H.

```
Q0: SELECT COUNT(*) FROM lineitem;
Q001: SELECT COUNT(*) FROM lineitem
      WHERE l_shipdate < DATE '1998-07-01';   #table
        scan
Q002: SELECT COUNT(*) FROM lineitem
   WHERE l_suppkey <= 10000;  # secondary index scan
```

Listing 5. The `COUNT(*)` variants in the micro-benchmark.

The queries were run on a small test cluster with four Page Store nodes. Each node was running on Intel® Xeon® Gold 6161 CPU @ 2.20 GHz with 44 cores, 250 GB memory, and had a Huawei Hi1822 network card rated at 25 Gbps. The SQL node had 360 GB of memory, but was otherwise identical to the Page Store nodes. Parallel query used 32 threads.

The plans for Q0 and Q001 use a table (primary index) scan, and Q002 plan uses a secondary index scan. Q1 scans the *Lineitem* table and performs a `GROUP BY` with multiple aggregates. Q6 computes one aggregate on the *Lineitem* table, but has several conjunctive predicates. As can be seen in Fig. 5, with NDP, network reads are reduced to negligible amounts for the `COUNT(*)` queries and Q6. The reduction is less for Q1 but is still considerable.

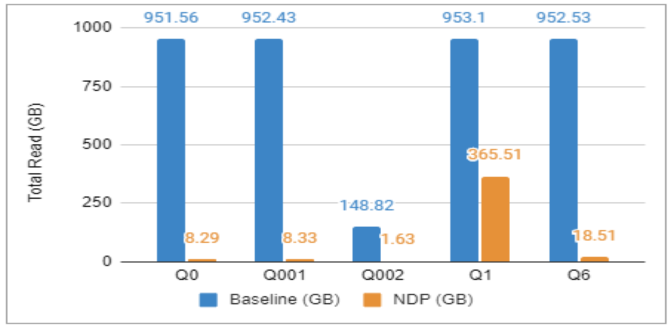

Fig. 5. Network read reduction with NDP.

Figure 6 shows the relative reduction in run time compared with single-threaded execution without NDP or PQ, and illustrates how NDP complements PQ.

With a PQ degree of 32, the theoretical run time reduction is: $1 - \frac{1}{32} = 96.875\%$. However, with PQ only and no NDP, queries Q0, Q001, and Q6 achieve less than 86% reductions because they must each transfer about 950 GB of data over the network, and bottleneck on I/O. Q002 and Q1 achieve relatively higher reductions with PQ-only because they scan much smaller secondary indexes, and are less I/O intensive. Q1 is more CPU intensive than the other queries because of its expensive aggregation expressions.

When NDP is combined with PQ, we see further run time reduction for all five queries. The reductions are all close to or achieve the theoretical maximum because with NDP enabled, the I/O bottleneck is avoided.

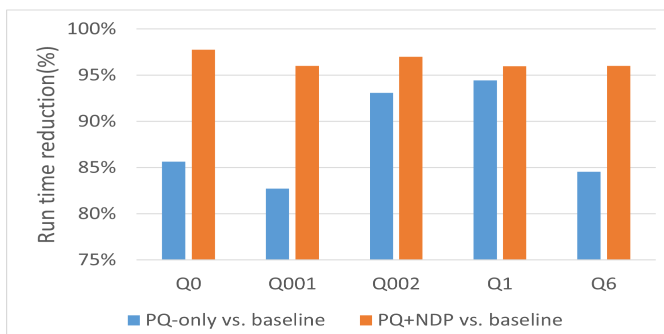

Fig. 6. Run time reduction with NDP and PQ (higher is better).

B. TPC-H: Experimental Setup

We ran the complete set of 22 TPC-H queries with and without NDP enabled on a regular production cluster in Huawei's cloud (Beijing region, instance class 16U64G). The database size was 100 GB. The buffer pool size was set to 20 GB, and the sort and join buffer sizes were both set to 1 GB. We ran the 22 queries in sequence without restarting the server in between.

C. TPC-H: Data and CPU reduction

Fig. 7 plots the reduction in network traffic (resulting in data reduction) and CPU time on the SQL node with NDP enabled.

Overall, network traffic was reduced by 63% and CPU time by 50%, and 18 out of the 22 queries benefited from NDP. In the following, we shall analyze a few queries in more detail to gain insight into the factors influencing NDP's effectiveness.

Queries Q6, Q12, Q14, and Q15 all exhibit over 90% reduction in network traffic and over 85% reduction in CPU time. They all have query plans that include scanning the *Lineitem* table where filtering and column projection can be pushed down to Page Stores. Q6 does nothing but scans the *Lineitem* table and applies filtering and aggregation. NDP achieves 99% reduction of network traffic and 91% CPU reduction. Q12 contains a hash join of *Orders* and *Lineitem* and applies NDP to both inputs. Q14 applies NDP on a scan of the *Lineitem* table, and joins the remaining rows with *Part* using an NL join, achieving data and CPU reductions of 95% and 89%, respectively. Q15 scans *Lineitem*, applies NDP, and achieves 98% reduction in network traffic and 91% CPU reduction.

Two queries, Q10 and Q16, also achieve over 90% reduction in network traffic but a slightly lower CPU reduction, 73% and 63%, respectively.

Queries Q11, Q17, Q19, and Q20 had plans with no NDP applied, and consequently saw no reduction at all. NDP is enabled on a scan only if the scan is estimated to cause at least 10,000 pages of I/O.[4] All four queries had plans where the only opportunities to apply NDP were on scans that were deemed too small. For Q11, the NDP-eligible scan was on the *Nation* table. For the other three queries, the NDP-eligible scans were on the relatively small *Part* table, and many of its pages remained in the buffer pool, so the scans were estimated to read too few pages to qualify for NDP. Out of those three, Q19 is chosen for further illustration. Q19 performs a nested loop join on *Part* (outer table) with *Lineitem* (inner table) using the predicate '$p\_partkey = l\_partkey$'. NDP did not happen on *Part* because of buffer pool caching; it did not happen on *Lineitem* because an index lookup on $l\_partkey$ provides an efficient access path, and on average, only 28 inner rows are estimated to join with an outer row.

It is quite common for a query to require only a few columns from a table. For this reason, it may be beneficial to apply NDP even when there is no filtering condition. Projection-only NDP was used in 8 of the 22 TPC-H queries yielding substantial benefits. On Q18, for example, projection-only NDP is applied on two table scans (*Orders*, *Lineitem*) resulting in a data reduction of 80%, and CPU reduction of 67%. On Q9, it is applied on three scans (*Orders*, *Lineitem*, *Partsupp*) achieving a data reduction of 62%, and CPU reduction of 42%.

MySQL's current version of hash join does not include Bloom filter pushdown—a standard feature of most hash join implementations—which would have allowed even further data reduction on the probe side of hash joins used in the query plans.

[4]Just as an example, a scan size based on table cardinality, row width, and selectivity might be estimated at 14,000 pages, but at query run time, if 5,000 of the table's pages are in the buffer pool, only about 9,000 I/O's can be expected, and the scan would *not* quality for NDP.

D. TPC-H: Run-time reduction

NDP delegates part of query execution to Page Stores, thereby reducing the amount of processing performed on the SQL node. This normally reduces query run time but not always, as we will see. Fig. 8 plots the relative reduction in run time of the 22 TPC-H queries caused by NDP. The total run time of the 22 queries was reduced by 28%. Run time was reduced by 60% or more for seven of the queries, and by as much as 80% for three of the queries.

As expected, run time reduction is highly correlated to data reduction: queries with the most data reduction also tend to have the highest run time reduction. However, Q4 is an apparent exceptions to this trend. Q4 sees a data reduction of 16% from NDP, but run time increases by 12%.

Q4 performs a nested loop join of *Orders* and *Lineitem* with *Lineitem* as the inner. This generates a large number of lookups in the primary index of *Lineitem*, which is where most of the run time is spent. With NDP enabled, more of the lookups will cause a buffer pool miss because the three prior queries (Q1 through Q3) have not brought any *Lineitem* pages into the buffer pool. Q2 does not access the *Lineitem* table at all. Q1 and Q3 do scan the *Lineitem* table, but apply NDP to the scans, so they do not bring any regular *Lineitem* pages into the buffer pool either. So when Q4 runs with NDP enabled, it begins with a buffer pool containing very few *Lineitem* pages, resulting in a flurry of buffer pool misses. If Q1 through Q3 ran with NDP disabled, Q1 and Q3 would have brought *Lineitem* pages into the buffer pool, and Q4 would have started with a 'warm' buffer pool. We verified this hypothesis with the following experiment.

- When Q1 through Q3 ran with NDP disabled, the resulting buffer pool had 1,272,972 *Lineitem* pages.
- When Q1 through Q3 ran with NDP enabled, the resulting buffer pool had only 24,186 *Lineitem* pages.

E. TPC-H: Run-time further reduced by Parallel Query

Parallel query can reduce run time of some but not all queries. We repeated the test of TPC-H queries with both NDP and PQ enabled. PQ reduced the run time further by at least 10% on seven of the 22 queries. Figure 9 plots the additional run time reduction (after NDP) from PQ on the seven queries. The remaining queries saw no further reductions because the optimizer chose fully serial plans. Huawei is currently enhancing PQ functionality to enable parallelism in more queries.

The degree of parallelism was 16, so the maximum reduction is $1-\frac{1}{16} = 93.75\%$. On six queries, the run time reduction from PQ is close to the theoretical maximum. However, for Q15, the reduction is only about half of the maximum. NDP achieves a data reduction of 98%, but the plan contains an NL join that is executed serially, which limits parallelism gains.

Q1 contains an expensive aggregation operation that is performed on the SQL node when run serially. When PQ is enabled, this work is spread over many worker threads, resulting in a substantial run time reduction over NDP alone.

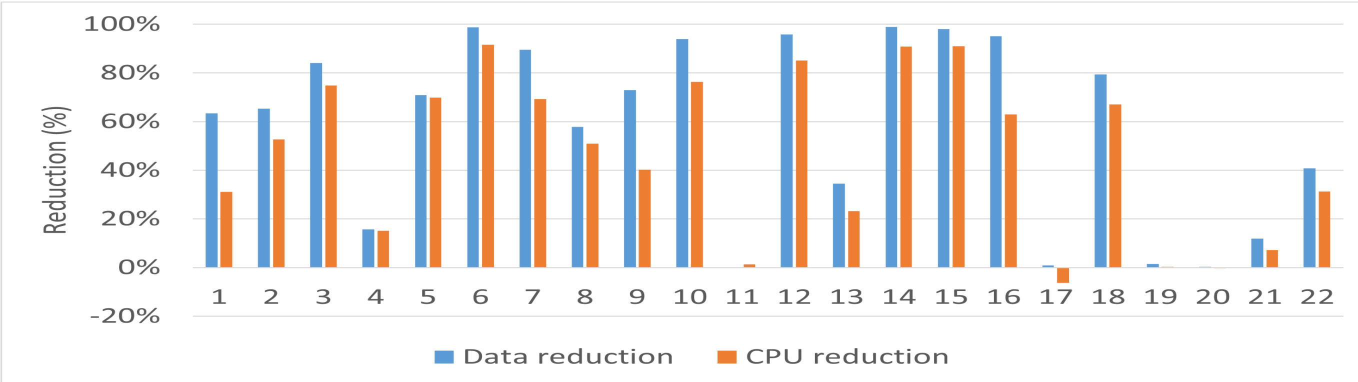

Fig. 7. CPU time and network traffic reduction with NDP TPC-H queries.

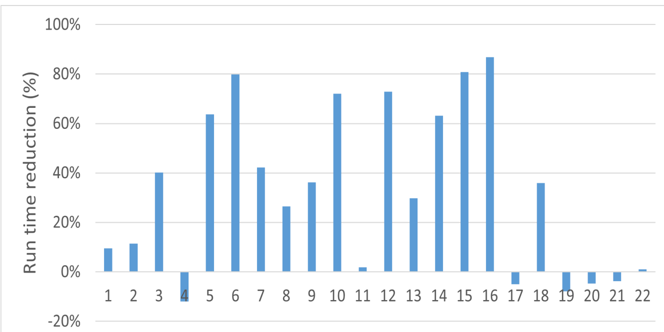

Fig. 8. Run time reduction with NDP.

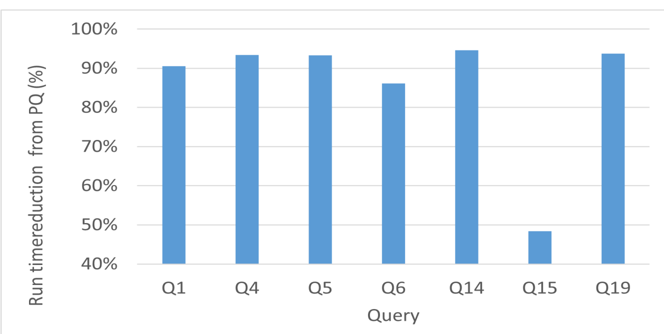

Fig. 9. Further run time reduction from PQ.

Q4, Q5, and Q19 benefited from parallel NL joins: multiple worker threads performing lookups on the inner table(s) concurrently.

VIII. Related work

Processing data near to where it lives is a decades-old idea that has seen increased interest in the last 8-10 years, The research reported in this paper is about near data processing applied to database storage nodes, but as noted in [14], the same idea can be—and has been—applied at other levels of the memory hierarchy too: caches, DRAM, nonvolatile storage-class memory, and so on. For example, the 'active-routing' suggested in [15] pushes computation to a router attached to memory to better exploit parallelism and bandwidth of a memory bank.

A classification provided in [16] divides NDP into three categories based on the locations of the NDP-like operations.

1) In-storage computing (ISC) for SSD-based approaches—sometimes also referred to as 'SmartSSD' (SSD with an on-board FPGA)—for example [17].
2) In-memory computing (IMC) for DRAM-based approaches—for example, the JAFAR accelerator described in [18].
3) Near-storage computing (NSC) for system-on-a-chip (SoC)-based approaches.

The Page Store-based NDP processing of this paper is an ISC approach. Out of those three categories, the FPGA-based ISC approaches seem to have received the most attention as detailed later in this section. Indeed, some researchers are advocating that time has come to create NDP-aware data centre servers based on application needs: compute-intensive, data-intensive, and possibly re-configurable varieties of them [16].

There are two fundamental reasons for the recent surge of interest in NDP. First, big-data applications need to process large data volumes, and information extracted from such applications are often complicated summaries, thereby offering aggregation and filtering opportunities. More important, query optimizers can push down aggregation and filtering—in many cases—to such data containers as tables and indexes residing on disk servers. Second, in the increasingly common cloud-deployed applications, disk servers are remote even to their compute servers, and early filtering saves network bandwidth between the two before subsequently saving CPU cycles on the compute servers.

In this research, the NDP decisions are taken by the MySQL query optimizer, but as suggested in [19], a disk server-resident local optimizer can optimize selected operators, gather data statistics, and cooperate with the global optimizer. A prototype of such a system was demonstrated using the Apache Calcite DBMS framework [20].

For analytical workloads, the benefits of equipping storage nodes with computational power have long been understood, for example, in Oracle Exadata [21] and MySQL's NDB cluster [22]. In cloud-native database systems, separating compute nodes from storage nodes has become standard.

In addition to Taurus [1], two other MySQL-based offerings separate compute and storage: Amazon's Aurora [23], and Alibaba's POLARDB [24]. Although all three systems separate compute and storage, their design and implementation are very different.

In Taurus, NDP exploits parallelism in storage nodes, whereas PQ exploits parallelism in compute nodes. NDP and PQ work seamlessly together.

Aurora's 'parallel query' feature is in fact a limited form of NDP: it pushes predicate evaluation and projection (but not aggregation) down into storage nodes [25]–[27]. Parallelism arises from the fact that there are multiple storage nodes but processing in the compute node apparently remains single threaded. 'Parallel query' requires pushdown of at least one `WHERE` clause (except for join queries), whereas Taurus does not have that restriction.

In Taurus NDP, the compute node receives a single data stream from storage nodes, and NDP processing is fully encapsulated within InnoDB. In Amazon Aurora, the compute node receives two data streams from storage nodes: a "partial result stream" and a "raw stream." The raw stream passes through InnoDB, the SQL execution engine, and finally lands in a PQ-specific component named "Aggregator". The partial result stream bypasses InnoDB and goes to the Aggregator directly. The Aggregator combines the two streams into a single stream for further processing.

Alibaba's POLARDB [28] implements parallel query execution in the SQL node similar to Taurus, but does not push data reduction operations to storage nodes, and hence has no NDP support. Reference [24] describes a joint pilot project aimed at pushing table-scan operators into SSD drives and implement the scans using FPGA. The project does not appear to have gone beyond the pilot stage.

The recently announced AQUA project from Amazon Web Services [29] takes a somewhat similar approach by installing FPGA modules next to the SSD's storing data, and then having the FPGA's do data filtering, aggregation, compression, and encryption. A similar FPGA-based NDP approach for the RocksDB key-value store is demonstrated in [30], and reports NDP benefits on point queries, range scans, and graph analysis queries. The 'intelligent storage engine' described in the Ibex prototype [31] is also an NDP engine, and can push down projections, selections, and grouping operations. Because the implementation is FPGA-based, each row of data read from a SATA disk is annotated with its column metadata.

Exadata [21] 'Smart Scans' perform row filtering and column projection, but not aggregation in storage nodes. It can handle filtering operations on compressed data. Bloom filters computed during the build phase of hash joins can also be pushed down. Exadata storage also maintains index-like structures (storage indexes) that help reduce physical I/O.

In Amazon Web Services' 'S3 Select', selections, projections, and scalar aggregates can be pushed into S3 storage nodes [32]. Data must be in CSV, JSON, or Parquet [33] formats. Two recent prototypes PushdownDB [34] and FlexPushdownDB [35] were developed using 'S3 Select'. The former pushed selections, projections, and aggregates; the latter combined that with data caching.

IX. Conclusion and Future Work

In Taurus, near-data processing (NDP) pushes data reduction operators (selection, projection, and aggregation) from the compute node to storage nodes (Page Stores), and reduces data sizes close to the source. For analytical queries, much less data travels over the wire from Page Stores to the compute node. Less CPU processing on the compute nodes may translate to reduced query run time. Parallel query (PQ) deploys multiple threads to process partitioned data which can further reduce run time. As the experiments on TPC-H queries showed, the effects can be dramatic: on Q15 data shipped was reduced by 98%, CPU time by 91%, and run time by 80%.

NDP reduces CPU load on the compute nodes, and the freed up CPU cycles become available to other queries, enabling higher system throughput. On the TPC-H queries, total CPU time on the compute nodes was reduced by as much as 50%.

The NDP implementation in Taurus affected three system layers: query optimizer, InnoDB storage engine, and page stores. We made conservative design choices that favored simplicity over complexity; avoided cascading code changes; and minimized chances of performance regressions.

Several directions for future work are possible. NDP operations and parallel query execution need to be integrated into the cost-based query optimization. NDP expression evaluation needs to be extended to support more data types and more operators. The current NDP implementation only pushes down local predicates (predicates involving columns from a single table). We plan to push down join predicates in the form of Bloom filters. Another possibility is to rewrite predicates to make more of them NDP-eligible as was done in Amazon Redshift [36] and AQUA [29].

A separate team at Huawei is planning to add NDP functionality to GaussDB for OpenGauss by writing NDP plugins specific to that PostgreSQL-based system.

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