Adaptive and Robust Query Execution for Lakehouses at Scale

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ABSTRACT

Many organizations have embraced the "Lakehouse" data management paradigm, which involves constructing structured data warehouses on top of open, unstructured data lakes. This approach stands in stark contrast to traditional, closed, relational databases and introduces challenges for performance and stability of distributed query processors. Firstly, in large-scale, open Lakehouses with uncurated data, high ingestion rates, external tables, or deeply nested schemas, it is often costly or wasteful to maintain perfect and up-to-date table and column statistics. Secondly, inherently imperfect cardinality estimates with conjunctive predicates, joins and user-defined functions can lead to bad query plans. Thirdly, for the sheer magnitude of data involved, strictly relying on static query plan decisions can result in performance and stability issues such as excessive data movement, substantial disk spillage, or high memory pressure. To address these challenges, this paper presents our design, implementation, evaluation and practice of the Adaptive Query Execution (AQE) framework, which exploits natural execution pipeline breakers in query plans to collect accurate statistics and re-optimize them at runtime for both performance and robustness. In the TPC-DS benchmark, the technique demonstrates up to 25× per query speedup. At Databricks, AQE has been successfully deployed in production for multiple years. It powers billions of queries and ETL jobs to process exabytes of data per day, through key enterprise products such as Databricks Runtime, Databricks SQL, and Delta Live Tables.

PVLDB Reference Format:
Maryann Xue, Yingyi Bu, Abhishek Somani, Wenchen Fan, Ziqi Liu, Steven Chen, Herman van Hovell, Bart Samwel, Mostafa Mokhtar, RK Korlapati, Andy Lam, Yunxiao Ma, Vuk Ercegovac, Jiexing Li, Alexander Behm, Yuanjian Li, Xiao Li, Sriram Krishnamurthy, Amit Shukla, Michalis Petropoulos, Sameer Paranjpye, Reynold Xin, and Matei Zaharia. Adaptive and Robust Query Execution for Lakehouses at Scale. PVLDB, 17(12): 3947 - 3959, 2024.
doi:10.14778/3685800.3685818

1 INTRODUCTION

Modern enterprises store the majority of their vast amounts of raw, structured, semi-structured, and unstructured data in scalable and elastic **data lakes** like Amazon S3, Azure Data Lake Storage, and Google Cloud Storage. These data lakes have raw, usually uncurated datasets stored in open file formats such as Apache Parquet. They can be processed using various engines, including Apache Spark [46] and Presto [41]. However, data lakes can face challenges related to data quality, transactional properties, governance, and the ability to support complex analytics. In contrast, a **data warehouse** is a structured storage system that is optimized for query and analysis. It usually stores structured and processed data, making it suitable for BI (business intelligence) and reporting. Data warehouses are designed for high-performance queries but may struggle to handle large volumes of raw or unstructured data efficiently.

The concept of a **Data Lakehouse** [7] emerged to combine the strengths of both data lakes and data warehouses, including open storage formats and raw data support from data lakes, as well as transaction support and data governance from data warehouses. Databricks supports major, open-source, industrial Lakehouse storage implementations including Linux Foundation Delta Lake [6, 31], Apache Iceberg [4], and Delta UniForm [21]. In a Lakehouse, a distributed query engine such as the one in Figure 1 needs to support a range of analytics workloads, including BI, data exploration, advanced analytics, and ETL (extract, transform, load) jobs. In this setting, statistics are often unavailable, or not as accurate or up-to-date as in closed systems such as data warehouses. This necessitates a more dynamic approach to query optimization and execution, such as the solution that we propose in this paper. But first, let us discuss the challenges that query optimizers face in a Lakehouse.

Supporting raw, uncurated data (lacking statistics). When organizations move data from their data lakes to their warehouses, the data is typically first cleaned via ETL jobs. This step normalizes column values, flatten semi-structured data like JSON, discards faulty values, and so forth. The result is a structured dataset that is amenable to fast BI processing. In contrast, raw data tends to be uncurated. It contains little to no statistics. As a result, in a Lakehouse query engine, properties of the data have to be discovered during execution to obtain the performance benefits usually achieved by pre-processing.

Supporting external tables (lacking statistics). In the Lakehouse paradigm, organizations have the flexibility to utilize their own storage space in the cloud for tabular data and employ their own catalogs or third-party catalog services for table metadata. This approach allows them to incorporate various query engines tailored to different workloads while accessing the same data. However, in such scenarios, there is no straightforward method to ensure the presence of statistics in table metadata.

Proceedings of the VLDB Endowment, Vol. 17, No. 12 ISSN 2150-8097.
doi:10.14778/3685800.3685818

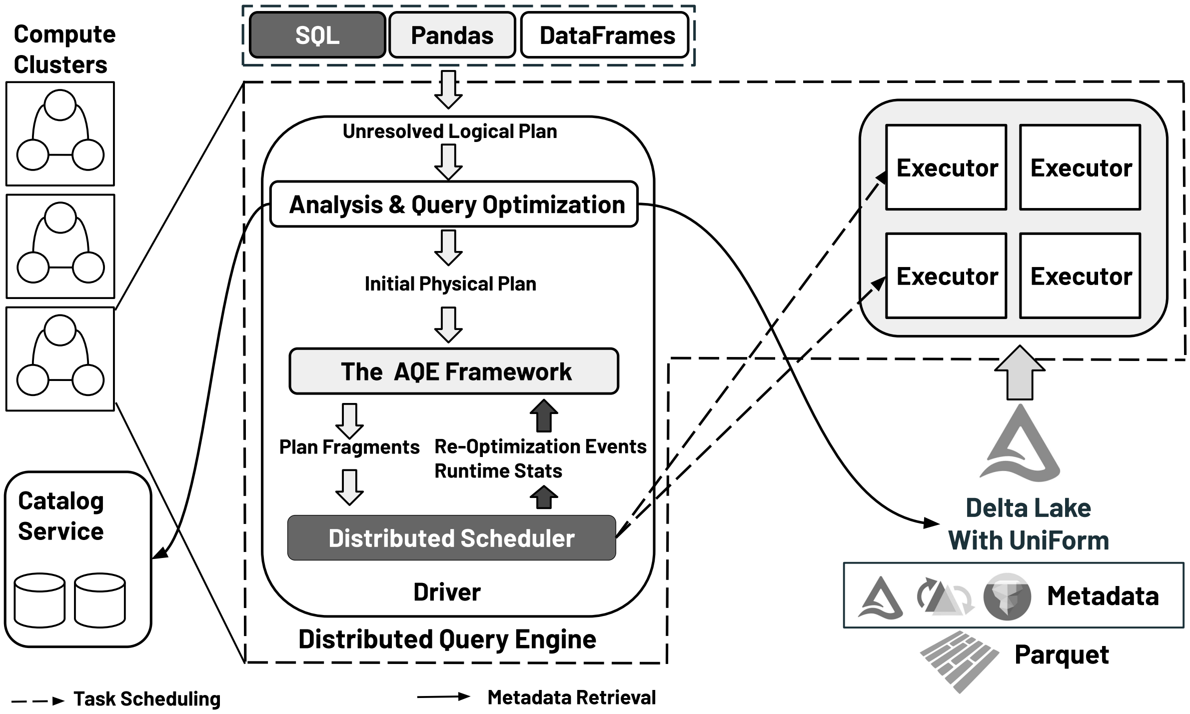


Figure 1: Databricks' Lakehouse architecture. The AQE layer sits between Query Optimizer and Distributed Scheduler, runs as part of the Photon distributed query engine. The query engine executes queries on a distributed cluster of public cloud instances, while AQE drives the execution of decomposed fragments of a query plan.

Supporting deeply nested data (lacking statistics). Nested, de-normalized schemas are becoming increasingly popular in both raw and curated datasets because of the enhanced readability by reducing complex joins. Data types like arrays, maps, and structs, as well as their arbitrary recursive combinations, are extensively employed by organizations. Such deeply nested fields are typically accessed after unnesting operations and can be referenced in operators like Filter, Join and Aggregation. Gathering statistics for hundreds to thousands of deeply nested fields within arrays, structs, and maps, and subsequently representing them in a catalog, is often expensive and unpractical.

Supporting rapidly evolving data and workloads (stale statistics and volatile histories). In many organizations, data from their products are ingested at an astonishing speed into the Lakehouse. Thus, maintaining up-to-date statistics like histograms of individual table columns is resource consuming. Furthermore, workloads can burst or dip from time to time without a clear repetitive pattern. Therefore, learning statistics from historical queries is not always feasible.

Supporting UDFs (lacking information for cardinality estimation). The widespread adoption of user-defined functions (UDFs), including user-defined scalar functions, user-defined aggregation functions (UDAFs) and user-defined table-valued functions (TVFs) within our platform, underscores their importance in customer workloads. However, UDFs present a challenge for accurate cardinality estimation and cost modeling, because they operate as black boxes to the query optimizer.

Supporting diverse workloads (amplifying bad plans). In a Lakehouse, table sizes range from Megabytes to Petabytes. Thus, an optimizer overestimate may cause a miss of a key optimization so that a query can runs into a timeout, e.g., when shuffling a massive amount of data; an underestimate may result in an aggressive query plan which may lead to unnecessary, high memory pressure or disk spillage.

To address these challenges, we built an adaptive query execution (AQE) framework. The key idea is to collect statistics during query execution from task metrics of completed and ongoing query plan fragments, and subsequently re-optimize unfinished execution plan fragments into better ones based on these runtime statistics. The AQE layer, depicted in Figure 1, is placed between static query optimizer and distributed scheduler. It incorporates key innovations in plan representation (Section 4.1), event-driven architecture (Section 4.2), a cancellation primitive (Section 4.3), and leveraged performance and robustness opportunities in distributed query processing (Section 5 and 6). As a result, AQE delivers up to 25× individual query speedup for standard TPC benchmark queries as well as up to 1.7× total speedup per benchmark (see Section 7), on top of our vectorized Photon execution engine [11]. Today, AQE has been enabled by default in all Databricks production environments, supporting billions of diverse Lakehouse queries and ETL jobs per day with latencies ranging from tens of milliseconds to a few hours. While the idea of dynamic query optimization has been explored in earlier research prototypes [28, 33, 36, 43, 44], we believe this paper describes one of the largest successful, industrial deployments at scale.

In the rest of this paper, we describe the background of Lakehouse and Photon in Section 2, and detail our motivations for AQE in Section 3; Section 4 presents the AQE framework; Section 5 explains a few important performance optimizations while Section 6 elaborates how AQE makes the query execution robust; we then present quantitative performance evaluations as well as our operational practices with AQE in Section 7; finally, we discuss related work in Section 8 and conclude the paper in Section 9.

2 BACKGROUND

This section briefly introduces the background that AQE fits into, including an overview of the Lakehouse and the Photon query engine.

2.1 Data Lakehouse

By combining the strengths of data lakes and data warehouses, a Data Lakehouse [7] aims to provide a more flexible, scalable, and cost-effective solution for managing and analyzing diverse data sets in modern data-driven environments. This concept has gained popularity as organizations seek ways to harness the full potential of their data assets with one simple platform. As a result, the majority of Databricks customers have been using Delta or Delta UniForm for their data. Key advantages of a data Lakehouse include:

- **Unified, open storage.** A Lakehouse typically uses a unified storage system with an open data format that can accommodate both raw, unprocessed data (similar to a data lake) and structured, processed data (similar to a data warehouse). In an industrial Lakehouse, the open-source Parquet format is used for both data and metadata. This way, organizations can use any compute engines to query or run machine learning models over their existing data rather than loading the data into a warehouse.
- **Automatic data management.** Like data warehouses, a Lakehouse typically offers an ACID table storage layer over cloud object stores. In our case, both Delta Lake and Delta UniForm enable warehouse-style features such as ACID transactions, time travel, audit logging, and fast metadata operations over tabular datasets.
- **Data governance.** Unlike an ad-hoc data lake, a Lakehouse incorporates data governance and metadata management, through a catalog service, to ensure the quality, security, and compliance of the data. The catalog service could be run at any third party outside of the core storage and compute.
- **Elastic and efficient query processing.** In a Lakehouse with diverse workloads, an instance of a distributed query engine (a.k.a. computer cluster) can be created based as-needed to execute those workloads so as to save costs. The adaptive and robust query execution described in this paper fits into this layer in the Lakehouse stack.

Figure 1 gives a high-level view of query engine, catalog service, and the Lakehouse storage.

2.2 The Databricks Photon Query Engine

Photon [11], which started as a vectorized, single-thread query execution library, has evolved into a full-fledged, new-generation, distributed query engine powering Databricks' major products including Databricks Runtime, Databricks SQL, and Delta Live Tables. As illustrated in Figure 1, inputs to the Photon query engine consist of unresolved logical plans generated from SQL texts, Python/Scala DataFrame programs, or Pandas programs. The analyzer retrieves table metadata from catalog services, performs semantic analysis, and converts an unresolved logical plan into a resolved logical plan. Next, the static optimizer rewrites the resolved logical plan into an optimized logical plan and converts it into an initial physical plan. The scheduler assigns execution tasks, which are parallel instances of a physical plan fragment, to run on executors. Within each task, vectorized execution operators and expression evaluators are invoked to process data. Unlike most other query engines, the Photon engine incorporates an AQE (adaptive query execution) framework positioned between the static optimizer and scheduler. Upon receiving an initial physical plan from the optimizer, AQE divides the plan into fragments, orchestrates their execution with dependencies, monitors their progress, and continuously adjusts uncompleted plan fragments based on runtime metrics from the execution tasks.

3 PROBLEMS AND ALTERNATIVES

In this section, we go over critical query plan decisions in a distributed, Lakehouse query engine (Section 3.1), a running example with AQE (Section 3.2), and a detailed comparison with alternative approaches (Section 3.3).

3.1 Key Query Plan Decisions

In a distributed query engine, the query optimizer typically makes the following decisions, which are critical to individual query's performance as well as the engine's stability.

- **Physical operator selections**. Broadcast Join and Shuffled Join are two typical distributed Join algorithms. They have very different performance characteristics. A misplacement could cause severe performance or even stability issues, e.g., either unnecessarily shuffling huge amounts of data or mistakenly broadcasting a huge amount of data to all executors.
- **Degrees of parallelism**. Determining the optimal degree of parallelism, including both Scan and Shuffle parallelism, remains challenging in distributed query processing. Poorly chosen parallelism can lead to severe issues; for example, excessive parallelism can overload and throttle the task scheduler.
- **Trade-offs based on data volume**. In our Photon engine, we have developed several Semi-Join reduction filter variants, such as dynamic partition/file pruning filters [23] and Bloom filters [14] to not only speedup individual joins but also remedy imperfect join orders. However, due to filter creation costs, the choice of these filters is often a data-dependent decision.
- **Optimizations based on dynamic data properties.** A set of query optimizations are subject to data properties such as empty intermediate relations, single-row relations, partitioning properties, and interesting orders. Oftentimes, such data properties can only be discovered during query execution.

- **Graceful degradation strategies**. Situations due to unanticipated data, e.g., skew or intermediate data bloat, might cause queries to either run into a timeout (e.g., hours, days) or result in memory pressure in executors. Therefore, the optimizer may need to balance performance and stability.

3.2 Example Query

In the rest of this paper, we will use the example SQL query with the TPC-H schema in Listing 1 (Q0) as a running example to elaborate problems, concepts, ideas and optimizations. For Q0, key problems adaptive query execution (AQE) tries to tackle include the following.

```
SELECT c.c_name,
       o.o_orderdate,
       SUM(o.o_totalprice) AS revenue
FROM customer AS c, orders AS o
WHERE c.c_mktsegment = 'BUILDING'
      AND c.c_acctbal > 8000.0
      AND c.c_custkey = o.o_custkey
      AND o.o_orderdate BETWEEN date('2024-03-15')
          AND date('2024-04-15')
GROUP BY c.c_name, o.o_orderdate
ORDER BY revenue DESC
LIMIT 10
```

Listing 1: Q0: an example SQL query.

- What is the number of rows from the `customer` table qualifying the two `WHERE` predicates, and what is the corresponding size-in-bytes? (Section 4.1.)
- Should we apply Semi-Join reduction filter variants, namely, a dynamic file pruning filter or a Bloom filter? (Section 5.1.)
- How can we leverage dynamic data properties discovered during execution time to perform further query optimizations? (Section 5.2.)
- Which join algorithm should be used? (Section 5.3.)
- What should be a proper degree-of-parallelism to run the query? (Section 5.4.)
- How should cases like skew and memory pressure be mitigated, for unanticipated, extreme data? (Section 6.)

3.3 Alternatives to AQE

Static query optimizers rely on stored catalog statistics (e.g., obtained from the Analyze Table command), cardinality estimation, and a cost model (a.k.a., a function of cardinality and plan), to make aforementioned planning decisions. A viable alternative to adaptive query execution is to enhance the accuracy of statistics, cardinality estimation, and cost modeling. However, despite decades of efforts within the database community, cardinality estimations remain challenging in traditional database systems [32].

Cardinality estimation. Column-level statistics such as the number of distinct values and histograms can provide good estimates for a local, binary comparison predicate directly over a table column, yet estimation errors may arise in the case of conjunctive predicates, predicates with UDFs, and join predicates. Further, errors may amplify on complex query plans with multiple such predicates. A "famous" cardinality estimation heuristic in System R [38] is that any equality filter predicate over an un-indexed table column by default reduces input cardinality to 1/10. Modern optimizers still have similar heuristics when they lack information. For instance, the open-source Catalyst optimizer [8] uses the worst-case cardinality as an estimate when information is unavailable.

Physical plan cost models. A traditional Cascades-style planner [25] usually requires a numeric physical plan cost to do search space prioritization, alternative plan comparison, branch-and-bound, and pruning. As mentioned in literature [32], cost models tend to have smaller errors than cardinality estimates. However, a "perfect" cost model still has to be kept in sync with the evolution of query execution and hardware characteristics over time.

Below, we delve into several alternative approaches along the lines of improving static optimizer cardinality estimates for the Lakehouse challenges mentioned in Section 1.

- **Sampling**. There has been a flurry of research literature [1, 17, 18] attempting to leverage sampling, including random samples, online samples, block samples, materialized samples, and stratified samples to make cardinality estimation better. In practice, they could be effective for specific scenarios, e.g., random samples for uniformly distributed data, and stratified samples [1] for predicates over strata columns. Nevertheless, there is an inherent trade-off between the expense of sample collection and its effectiveness.
- **History-based cardinality estimation** like the LEO prototype [40] may work for repetitive query workloads in a relatively closed environment that compute and history-store are bundled together in a single cluster instance. However, the Lakehouse architecture operates at a larger scale with higher elasticity, which requires a dis-aggregation of compute, storage and catalog. Thus, building a separate history-store service in the control plane might pose non-trivial engineering challenges such as binary compatibility and RPC latency.
- **Machine learning** could be a promising direction to make estimates more accurate. However, in order to deploy it in production, there is still substantial engineering work to tune models, in addition to challenges like debuggability and interpretability.

Note that the adaptive query execution described in this paper requires the existence of synchronous pipeline breakers during the distributed execution of a query, such that re-optimizations can kick in and be effective. Some query engines have such breakers in the way they implement DAG (directed acyclic graph) Scheduler, Task Scheduler, Shuffle, Join, Aggregation, and Sort; others may lack it by design. In our Photon engine, the Shuffle implementation has such a breaker, originally for the simplicity of task scheduling and fault-tolerance. Thus, AQE is a natural fit. At a high level, AQE and advancements in its alternatives are largely complementary in their evolutions. Better static query plans may eventually relax constraints on the query execution substrate, while AQE provides the ultimate safeguard to experiment with its alternatives. Based on these observations several years ago, we prioritized and executed an adaptive query processing strategy.

4 THE AQE FRAMEWORK

In this section, we present the AQE framework by introducing the representation of plan fragments (Section 4.1), the re-optimization event loop (Section 4.2), and the cancellation and idempotence of plan fragments (Section 4.3).

4.1 Plan Representation

Adjusting execution plan fragments dynamically while the plan is running may introduce significant complexity to the execution engine. To maintain system simplicity, AQE integrates special operators into both logical and physical plans to represent plan fragments. These operators enable on-the-fly plan modifications through logical/physical rewrite rules or planner rules. Similar to our static optimizer as well as a couple of other optimizers [8, 37], plans are immutable in AQE and rewrite rules return new plan instances. Key concepts in the plan representation are outlined below.

- **QueryStage**: A QueryStage operator denotes a plan fragment submitted to the distributed scheduler. The corresponding logical and physical plan fragments are wrapped inside a QueryStage, which functions as a leaf operator, akin to table scans. This ensures that the enclosed plan fragments do not accidentally get modified by any subsequent plan rewrites that only intend to re-optimize the remaining part of the query plan. In the current system, QueryStages are cut at Shuffle boundaries.
- **LogicalLink**: A LogicalLink serves as a backward mapping pointer from a physical operator to its corresponding logical operator. These links are populated for each physical operator by the physical planner at the time of initial planning and at each occurrence of AQE re-planning. This mapping allows the AQE framework to bring the ongoing logical plan in sync with the current physical plan in order to perform re-optimization from the logical plan with the latest statistics inferred from runtime task metrics.
- **Runtime Statistics**: Each QueryStage can either estimate statistics from running tasks' metrics or collect statistics from completed tasks' metrics. These runtime statistics, such as size-in-bytes and row counts, offer more accurate insights than those obtained from traditional static cardinality estimation. With LogicalLinks, the statistics can be fed into logical plans as well.

Figure 2 visualizes QueryStages and LogicalLinks in the initial physical plan for `Q0` (Listing 1). Runtime statistics are obtained in physical QueryStages and populated back to the logical plan as per LogicalLinks.

4.2 AQE Re-Optimization Event Loop

As described in the code snippet in Listing 2, for a given query, the core of AQE is a while-loop wherein the loop body listens to re-optimization events, re-optimizes the uncompleted logical plan, re-generates the physical plan for a re-optimized logical plan, breaks down the physical plan into QueryStages, and submits new runnable QueryStages to the scheduler. Note that line 16 in Listing 2 invokes the same static physical planner, where both planner rules (choosing physical operators for logical operators) and physical rewrite rules (rewriting physical plans to better ones) can be called. Several rules applied at lines 14 and 16 in Listing 2 make their decisions based on costs derived from runtime statistics. Typical re-optimization events include:

- **QueryStage completion**: When a QueryStage completes successfully, its dependent QueryStages may be able to start, and accurate runtime statistics of the completed QueryStage become available in remaining logical plans for AQE to make new optimization decisions.
- **QueryStage failure**: When a QueryStage fails (or times out), actions need to be taken to either fail the query entirely or attempt recovery from failure by adjusting the query plan.
- **Heuristics with task metrics**: In addition to metrics from completed or failed QueryStages, metrics from ongoing QueryStages can also be valuable to AQE. AQE includes a metric evaluation framework that monitors metrics reported for running QueryStages and decides whether or when re-optimization is needed. Once a change in such metrics is deemed promising for optimizations to apply, a new re-optimization event will be offered to `reOptEventQueue`.

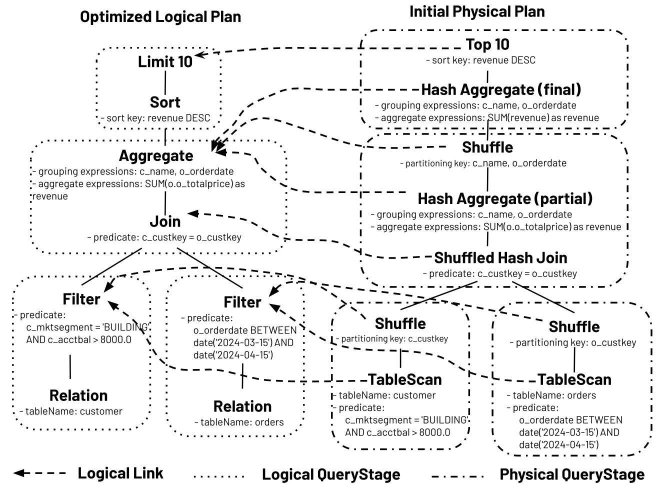


Figure 2: QueryStages and LogicalLinks

The key in the event loop is the utilization of either **actual statistics observed from completed QueryStages** or **estimated statistics from running QueryStages' metrics**. These statistics serve as the foundation for refining critical decisions pertaining to unfinished query plan fragments.

Let us use Q0 (Listing 1) to elaborate on the QueryStage completion event. For plans described in Figure 2, in Listing 2, lines 3-4 first submit the two bottom physical QueryStages to the scheduler; when one of them completes, a re-optimization event is taken at line 10 and `currentLogicalPlan` is updated with accurate, runtime statistics at line 12 and re-optimized at line 14; finally, new, runnable QueryStages are submitted to the scheduler, and the loop continues to wait for new re-optimization events.

4.3 QueryStage Cancellation and Idempotence

In the AQE event loop (Listing 2), line 21 cancels running QueryStages that are no longer needed. This situation can occur either when the corresponding logical plan is completely optimized away, or when a running QueryStage has a semantically equivalent replacement in the rewritten plan that is considered superior. This approach abstracts the cancellation implementation from the logical and physical re-optimizations invoked from lines 13 to 16, which simplifies rewriting logics. For instance, all the logical rewrites and

```
1 // Kick off initial QueryStages.
2 LogicalPlan currentPlan = initialPhysicalPlan.logicalLink;
3 List<QueryStage> initialRunnableStages = breakDown(
      initialPhysicalPlan);
4 initialRunnableStages.foreach(stage => Scheduler.submit(
      stage));
5 runningStages.addAll(initialRunnableStages);
6 do {
7   // Blocking wait until new re-optimization event
8   // being added into `reOptEventQueue` by producer
9   // threads.
10  Event reOptEvent = reOptEventQueue.take();
11  // Update `runningStages` and `currentPlan`.
12  currentPlan = update(reOptEvent, runningStages,
        currentPlan);
13  // Call logical rewrite rules to optimize `currentPlan`.
14  LogicalPlan reOptPlan = reOptimize(currentPlan);
15  // Convert `reOptPlan` to a physical plan.
16  PhyiscalPlan currentPhysicalPlan = plan(reOptPlan);
17  // Break down `currentPhysicalPlan` into runnable
18  // QueryStages.
19  List<QueryStage> runnableStages = breakDown(
        currentPhysicalPlan);
20  // Cancel running QueryStages that are no longer needed.
21  runningStages.diff(runnableStages).foreach(stage =>
        Scheduler.cancel(stage))
22  // Submit new runnable QueryStages to the scheduler.
23  List<QueryStage> runnableNewStages = runnableStages.diff(
        runningStages)
24  newStagesToRun.foreach(stage => Scheduler.submit(stage));
25  runningStages.addAll(newStagesToRun);
26 } while (hasUncompletedStages());
```

Listing 2: A Sketch of the AQE Re-Optimization Event Loop.

planner rules outlined in Section 5 and Section 6 take advantage of this mechanism to stop ongoing large scans, shuffles, or disk spills. For idempotence, a completed QueryStage would not be rerun because it becomes a leaf node in the new logical and physical plans from lines 13 to 16, while line 23 ensures that an identical, running QueryStage would not be repetitively submitted.

5 PERFORMANCE OPTIMIZATIONS

In this section, we go over several important performance optimizations applied in AQE, including

- **logical rewrites** that inject Semi-Join reduction filter variants such like dynamic partition/file pruning filters (DPPs, DFPs) [23] and Bloom filters [14] (Section 5.1), and optimize away plan fragments that are no longer needed (Section 5.2);
- **a planner rule** that revisits and changes the static planning decision on which join algorithm to use for a logical Join operator (Section 5.3);
- **a physical rewrite** that dynamically adjusts the Shuffle parallelism (Section 5.4).

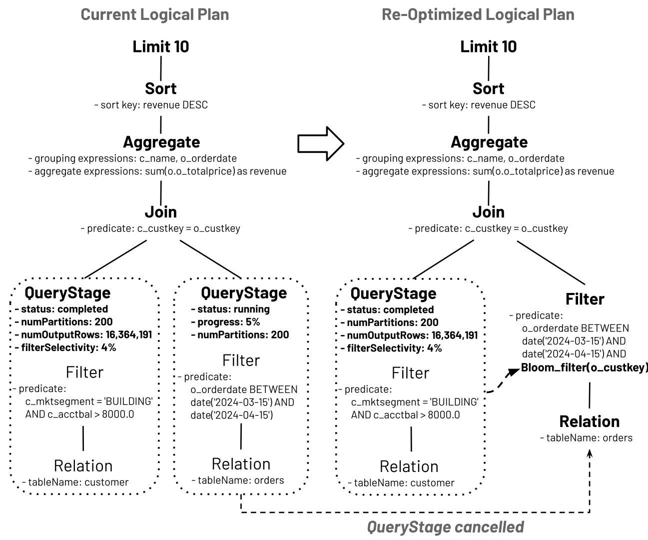


Figure 3: The Bloom Filter Rewrite Example

5.1 Logical Rewrite: Dynamic Join Filters

We have implemented a logical rewrite rule to inject dynamic Semi-Join reduction filter variants, including DPPs, DFPs, and Bloom filters. This rule has been added to a rule batch in the definition of `reOptimize`, which is called at line 14 of Listing 2. It is well known that these filters are not free – there are overheads associated with creating, aggregating, distributing, and applying them. Therefore, to place a filter, the reduced disk I/O or CPU usage must outweigh its creation overhead. With runtime statistics in AQE, the benefit-to-overhead analysis becomes more accurate, leading to better decision-making than the static optimizer. Let us consider `Q0` (Listing 1) to exemplify the rewrite rule. In Figure 3, suppose the QueryStage originating from the `customer` table completes first during execution, with the actual selectivity for `c_mktsegment = 'BUILDING' AND c_acctbal > 8000.0` being 4%, and the actual output row number from the filter being 16,364,191. Meanwhile, the QueryStage from the `orders` table progressed 5%. Utilizing the runtime statistics, the rewrite rule acknowledges that (a) a Bloom filter requires only tens of megabytes to achieve a false-positive rate of 1%, and (b) applying the Bloom filter on the `orders` side can potentially drop numerous rows early on before the Shuffle. Then, by comparing with the estimated statistics on the other side of the Join, the rule determines that canceling the QueryStage from `orders` and injecting a Bloom filter is relatively cheap yet likely worthy. Consequently, in the rewritten plan, it constructs a Bloom filter from the completed QueryStage and applies it to the scan of the `orders` table. The actual cancellation is done at line 21 in Listing 2 after a different QueryStage from `orders` is generated.

5.2 Logical Rewrite: Dynamic Data Properties

Runtime statistics collected from completed QueryStages are accurate in deriving actual data properties, including scenarios with empty relations and single-row relations. Consequently, we have implemented a rewrite rule to propagate empty relations bottom-up within a remaining logical plan. For instance, in scenarios where

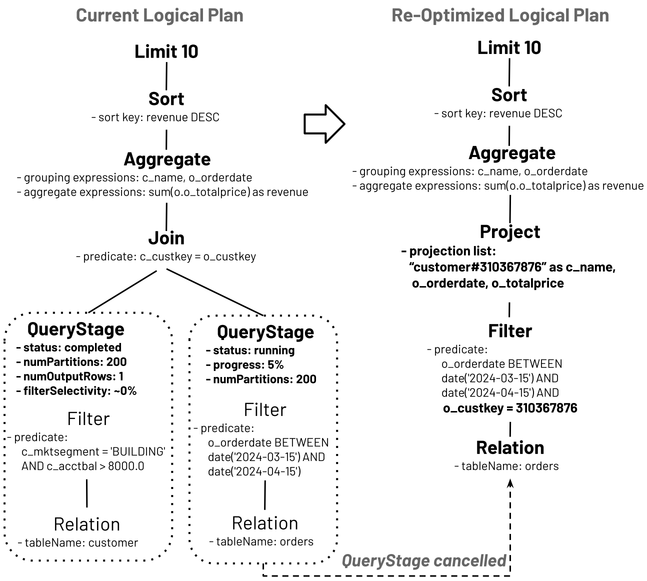


Figure 4: The Dynamic Data Property Rewrite Example

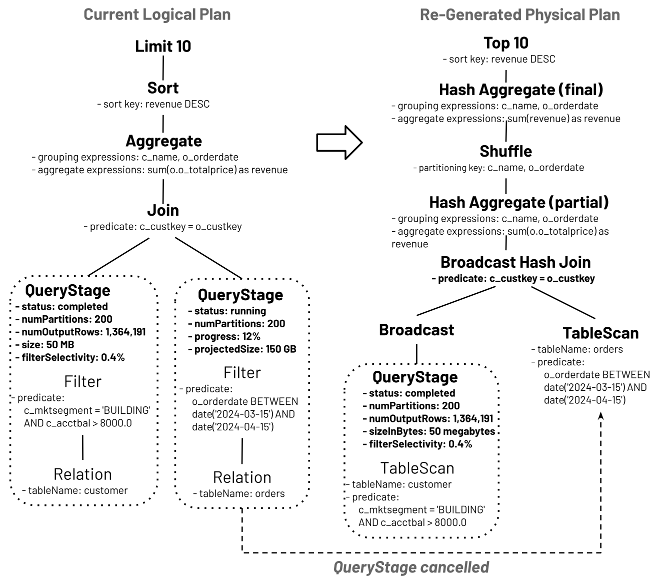


Figure 5: Join Algorithm Re-Selection Example

one side of an inner Join yields no rows, the rule intelligently eliminates the need for further join execution and replaces it with an empty relation, optimizing query performance. The same transformation is applied during post-order plan traversal, ensuring that all unnecessary operators can be optimized away.

Similarly, we have another rule that applies when completed QueryStages contain only a single row. For instance, if the underlying intermediate data comprises only one row, unnecessary operations such as Join, Aggregation, and Sort can be omitted from the plan. Figure 4 uses `Q0` (Listing 1) as a running example. Suppose the QueryStage from the `customer` table has only one output row. This rule folds the join condition with a constant, eliminates the Join operator, cancels the running QueryStage from `orders`, and pushes down the extra predicate `o_custkey = 310367876`. The extra predicate pushed down to the table scan can be used to prune files to speed up the query.

5.3 Planner Rule: Join Algorithm Re-Selection

In the Photon query engine, there are two primary, distributed join algorithms: Broadcast Hash Join and Shuffled Hash Join.

- **Broadcast Hash Join**. When one side of a Join is small enough to fit into the memory of an individual executor, a Broadcast Hash Join is often preferred for its performance benefits. In this approach, the smaller side (known as the build side) is broadcast to all participating executor nodes, eliminating the need for repartitioning of the other side (the probe side). It is important to note that different joiner threads on the same executor node share the same build side hash table and data, residing in memory.
- **Shuffled Hash Join**. In contrast to the Broadcast Hash Join, in a Shuffled Join, both sides undergo shuffling before being joined. On an individual executor, the local join algorithm is a vectorized implementation of Hybrid Hash Join [11, 39], which can gracefully spill to disk if necessary.

The static decision regarding which join algorithm to pick is based on estimates, which can sometimes lead to suboptimal outcomes. Situations may arise where a Join initially planned as a Shuffled Hash Join, due to estimates suggesting both sides are too large, might actually reveal one side to be small enough for broadcasting during execution. In such cases, AQE intervenes to dynamically alter the execution plan, converting it to a Broadcast Hash Join. This adjustment circumvents the costly shuffle of the large side, thereby significantly enhancing performance.

Using `Q0` (Listing 1) as an example, suppose the initial physical plan uses Shuffled Hash Join (as shown in Figure 2) due a static selectivity overestimate of predicates over the `customer` table, while the QueryStage originating from the table completes first during execution, with the actual output row number from the filter being 1,364,191 and the output size in bytes being 50 megabytes. At this point, the current logical plan is illustrated on the left-hand side of Figure 5. Because of updated runtime statistics and the progress of the running QueryStage, the join algorithm selection rule in the physical planner re-chooses to use a Broadcast Hash Join, as visualized on the right-hand side of Figure 5. Consequently, the new QueryStage from `orders` does not have a Shuffle, leading to the cancellation of the corresponding running QueryStage with a Shuffle, as per line 21 in Listing 2.

Symmetrically, a Broadcast Hash Join may be selected by the static planner due to an underestimation, potentially leading to high memory pressure as well as high network bandwidth consumption during execution. In this case, AQE re-planning can switch it to a Shuffled Hash Join, which improves query performance too by avoiding sending a large build side to all executors and loading it into memory.

5.4 Physical Rewrite: Elastic Shuffle Parallelism

In a distributed query engine, determining the number of Shuffle partitions poses a significant challenge. Some systems begin with a

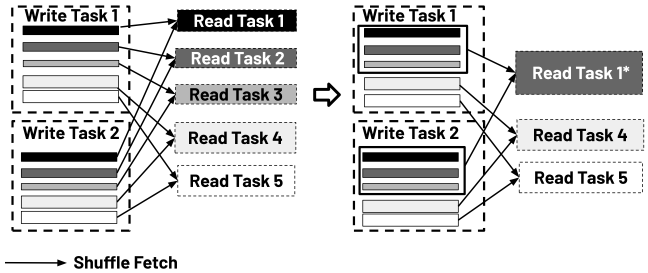


Figure 6: Coalesce Shuffle Partitions

fixed degree of Shuffle parallelism, while others rely on complex heuristics. However, identifying the optimal number of partitions is data-dependent, and accurate data sizes, especially those of intermediate stages, are often unavailable during static query optimizations, making it particularly challenging. The decision has a critical impact to query performance:

- **Under-parallelism**. In this scenario, each Shuffle consumer task handles a large volume of data, which can result in unnecessary CPU cache misses or disk spillages (e.g., for operators like Join, Aggregation, and Sort), consequently slowing down queries.
- **Over-parallelism**. Conversely, in this case, there may be numerous small network data fetches, leading to inefficient network I/O patterns. On top of that, over parallelism also causes excessive scheduling overhead, which can be another significant contributor to performance slowdowns.

To address this issue, AQE calculates a relatively large number of Shuffle partitions based on the input data size for the ShuffleWrite operator. Then, once the ShuffleWrite completes, the actual sizes of each initial partition become available, and based on this information AQE is able to merge adjacent small Shuffle partitions into larger partitions via a physical rewrite rule. The rule modifies the partitioning specification in the ShuffleRead operator. In our query engine, Shuffle partitions are physically contiguous in partition numbers, allowing the "merge" operation to be logical without additional reads or writes of the Shuffle data. Consequently, Shuffle consumer tasks operate on "coalesced" partitions, reducing both concurrent network fetches and task scheduling overhead, thereby improving overall performance. Figure 6 illustrates an example where Shuffle consumer tasks are reduced from 5 to 3 and concurrent Shuffle fetches are reduced from 10 (5×2) to 6 (3×2).

6 ROBUSTNESS

Aside from performance improvements, AQE also serves as the last line of defense to ensure the query engine's robustness. While stability issues are infrequent in production environments, the capability of graceful degradation without query failures or system crashes is paramount for enterprise products. This section introduces three adaptive plan remediations: Broadcast Hash Join fallback (Section 6.1), Shuffle elimination fallback (Section 6.2), and data skew handling (Section 6.3). In these situations, the crucial step is to identify signs of distress early and frame them as re-optimization events, allowing AQE to intervene and mitigate potential issues.

6.1 Logical Rewrites: Broadcast Hash Join Fallback

Despite the dynamic join algorithm re-selection based on actual data sizes, edge cases may still arise where an executor may exhaust memory resources during the execution of a Broadcast Hash Join, in the following two cases.

```
-- Input query:
SELECT *
FROM customer AS c
WHERE c.c_custkey NOT IN (SELECT o_custkey FROM orders)

-- Rewritten query when orders is not empty:
-- If orders has a NULL o_custkey:
--   no customer row qualifies the NOT IN predicate;
-- otherwise:
--   a normal LEFT ANTI JOIN can work, except that
--   customer rows with c_custkey being NULL do not
--   qualify the NOT IN predicate.
SELECT * FROM (
  SELECT * FROM customer AS c
  WHERE NOT EXISTS (
          SELECT * FROM orders WHERE o_custkey IS NULL)
        AND c.c_custkey IS NOT NULL
) AS c
LEFT ANTI JOIN orders AS o ON c.c_custkey = o.o_custkey
```

Listing 3: A Robust Rewrite for Null-Aware Anti Join.

- **Case 1**: a logical Join can use a Shuffled Hash Join implementation, but the query attempts to enforce a Broadcast Hash Join implementation through a SQL hint. When SQL queries are tool-generated (typically, by BI tools), users themselves can hardly fix such hints.
- **Case 2**: the logical Join is a Null-aware Anti Join [12], which is used to implement `NOT IN` subqueries. This can be implemented using a Broadcast Hash Join but not by a Shuffled Hash Join, because the latter does not always produce correct results as per standard SQL semantics. In addition, the build side and probe side cannot be switched. When the right-hand side of `NOT IN` is not empty, there is an expensive yet robust plan as described in Listing 3, but the engine would prefer to optimistically use the typically-faster Broadcast Hash Join implementation.

In both cases, the AQE metric framework can detect that the build side of the Broadcast Hash Join is too large, and proactively raises a re-optimization event, before executors actually run out of memory. This event encapsulates the resource issue about to happen. Subsequently, line 12 of Listing 2 updates `currentLogicalPlan` accordingly, by rewriting the logical Join operator linked from the vulnerable Broadcast Hash Join, to a more robust plan.

- For Case 1, the rewritten logical plan drops the Join hint, and then the planner will opt for a Shuffled Hash Join at line 16 of Listing 2.
- For Case 2, similarly, `currentLogicalPlan` is modified according to Listing 3, as the right-hand side of `NOT IN` has been confirmed to be non-empty.

When new QueryStages are generated for a rewritten plan, as outlined in Section 4.3, the existing QueryStage containing the susceptible Broadcast Hash Join gets canceled. This ensures that user queries can successfully execute instead of encountering failures. An alternative is to resort to disk spilling in the Broadcast Hash Join operator, however, it still is not fully robust, because it requires broadcasting the entire Join build side to each executor and subsequently spilling it. For instance, a query with a very large `NOT IN` right-hand side can lead to network and disk stability issues for the entire system beyond the query itself.

6.2 Planner Rule: Shuffle Elimination Fallback

Akin to the Shuffle elimination optimizations in SCOPE [47], our static optimizer performs cost-based Shuffle elimination too. In most situations, fewer Shuffles tend to make a query run faster. However, when there is an overestimate on the number of distinct values of a partitioning column, a potential risk of this optimization is the reduced effective task parallelism. One symptom of under-parallelism is excessive disk spillage. In rare and extreme cases, it may run out of disk quota.

```
SELECT R.a, R.h, S.c, SUM(R.d * S.e) AS v
FROM R, S
WHERE R.a = S.a AND R.b=S.b AND p(R.g)
GROUP BY R.a, R.h, S.c
ORDER BY v DESC
LIMIT 10
```

Listing 4: Q1: Example for Shuffle Elimination.

We reference Q1 from Listing 4 to illustrate this scenario. Suppose there is an overestimation of the number of distinct values on `R.a` after filter predicate `p(R.g)`. As the plan shown Figure 7(a), this overestimation leads the static optimizer to choose to partition by `R.a` and `S.a` for the Shuffled Hash Join, effectively eliminating the Shuffle for the subsequent Hash Aggregation by <`R.a`, `R.h`, `S.c`>. However, during execution, it turns out that there are only 2 distinct values of `R.a`, and thus the Hash Aggregation after Join only has two effective, parallel tasks across all executors, regardless of the number of Shuffle partitions. This can cause over spillage when the number of groups by <`R.a`, `R.h`, `S.c`> is excessively large, especially if the join predicate leads to a many-to-many join. In this case, similar to Section 6.1, the metric framework triggers an AQE re-optimization event when it detects the under parallelism, such that AQE re-planning disables the Shuffle elimination optimization and produces a fallback plan like Figure 7(b). For normal cases, the fallback plan runs slower than the initial physical plan, as it has more Shuffles, but it saves `Q1` by increasing the effective parallelism from 2 to 200.

6.3 Physical Rewrite: Skew Join Handling

We have also implemented a physical rule to handle skewed join keys. The rule is able to discover data skew on a set of join keys in a Shuffled Hashed Join, which manifests as a few partitions containing significantly more data than others. In such cases, the rule can eliminate the skewness by logically splitting those large, consumer-side partitions into smaller, more balanced partitions, optimizing task sizes for improved performance. The core of this rewrite is similar to literature [45] except that it is done at runtime rather than static planning time.

Let us still use Q0 (Listing 1) to explain the rule. As visualized in Figure 8, suppose the `orders` table is skewed on a specific `o_custkey`, meaning one customer having placed significantly more orders than other average customers. Instead of performing the join operation for all the data containing this skewed `o_custkey` in a single task (i.e., Join Task 1 in Figure 8), the rule rewrites the partitioning specification in the two ShuffleRead operators so as to create new consumer tasks (Join Task 1.1 to 1.3) to run the same per-task Hash Join implementation, which joins a slice of the skewed partition from `orders` with the replicated (in 3-ways), corresponding `customer` partition.

7 EVALUATIONS AND PRACTICES

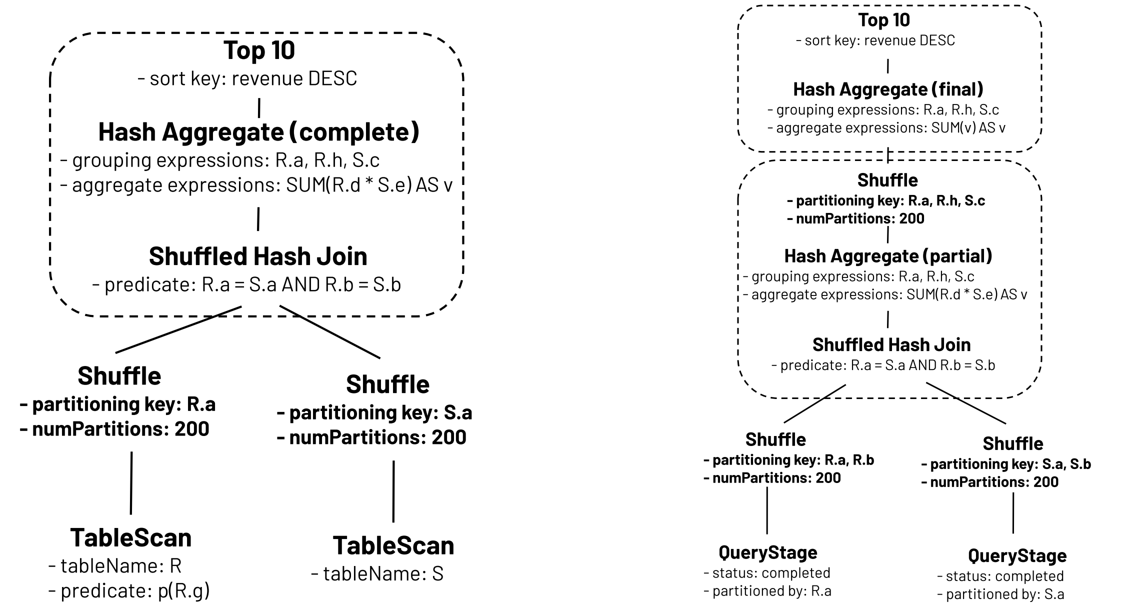
In this section, we present TPC benchmark results (Section 7.1), AQE re-optimization overhead (Section 7.2), and our operational practices (Section 7.3)

7.1 Performance Improvements

We evaluate AQE performance improvements on a 16-node AWS cluster with one driver node. Each node is an i3.2xlarge instance with 64GB of memory and 8 vCPUs (Intel Xeon E5 2686 v4). We ran benchmarks of TPC-H and TPC-DS, stored with the Delta format in Amazon S3, on different scale factors (1000 and 3000), with and without pre-collected table and column statistics via the `Analyze Table` command. All benchmarking runs, whether AQE-disabled or AQE-enabled, were performed with the Photon query engine. Figure 9 plots queries with 15%+ wall clock time reductions in all benchmarks, in relative wall clock time numbers where the baseline is always 1.0. Table 1 presents a summary of benchmark results regarding individual query speedup, total speedup, and the number of queries experiencing a reduction in latency of 15% or more. As both TPC benchmarks feature uniformly distributed data, the observed performance enhancements are largely attributed to dynamic Join filters (see Section 5.1), join algorithm re-selection (refer to Section 5.3), and elastic degree-of-parallelism adjustments (outlined in Section 5.4). Since all benchmarks were conducted on clusters of the same size, it is expected that the speedup with a scale factor of 1000 is less than with a scale factor of 3000. For example, the difference in performance between a Shuffled Join and a Broadcast Join is typically smaller on a smaller data set.

7.2 Re-Optimization Overhead

It is important to recognize that lines 11 to 25 in Listing 2 might not directly contribute to a query's wall clock time. This is because the AQE event loop operates concurrently with the actual query execution, and there could be ongoing QueryStages while the re-optimization steps are running. Thus, in our evaluation, we record the wall clock time spent on these lines as "re-optimization time" when there is no running QueryStage. The last two columns in Table 1 illustrate the P50 (median) and P95 (95 percentile) re-optimization time percentage in query latency, across all assessed benchmarks. In Table 1, the AQE overhead in TPC-H is lower than



(a) Initial Physical Plan: effective parallelism = 2

(b) Robust, Fallback Plan: effective parallelism = 200

Figure 7: Shuffle Elimination Fallback Example Q1. We compare the effective parallelism for boxes with dashed lines.

Table 1: Benchmark Result Summary for Photon + AQE-enabled v.s. Photon + AQE-disabled.

Benchmark	**Max per query speedup**	**Total speedup**	**Num queries with 15%+ latency reductions**	**AQE overhead (P50)**	**AQE overhead (P95)**
TPC-H SF=1000 (with stats)	9×	1.56×	8	0.4%	1.4%
TPC-H SF=3000 (with stats)	12×	1.72×	11	0.1%	0.5%
TPC-DS SF=3000 (with stats)	4×	1.21×	28	1.0%	4.4%
TPC-DS SF=3000 (without stats)	25×	1.33×	29	0.9%	3.2%

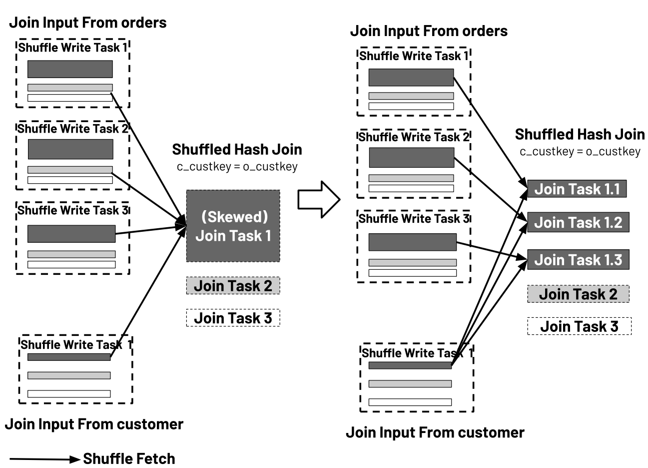


Figure 8: The Skew Join Rewrite Example

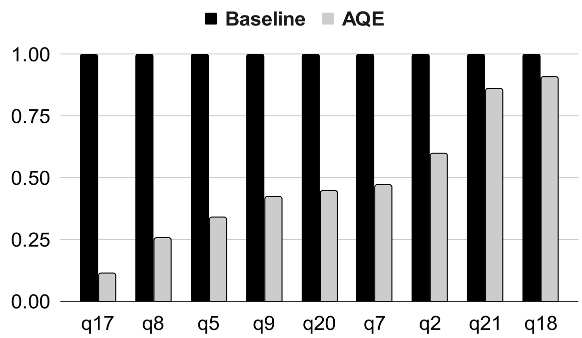
in TPC-DS. It is because TPC-DS queries typically have more selective `WHERE` predicates for file pruning and scan less data than TPC-H queries.

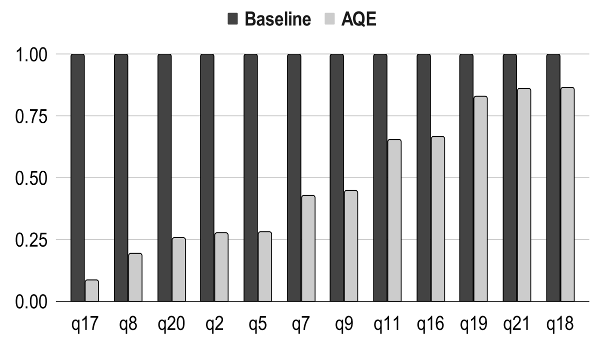
7.3 Operational Practices

To support production operations, AQE offers two levels of debuggability and observability. First, customers can access the query plan evolution history via the query UI, allowing them to track intermediate query plans and understand how their queries are executed. Second, for internal teams, we log QueryStage statistics and rule decisions during AQE, which helps to identify why an expected optimization did not occur and highlights missed opportunities. These logs are compliant with privacy standards and do not contain any customer data or query information. New AQE features are introduced gradually in phases into production, allowing for signal collection and validation at each step. Notably, the improved engine robustness (Section 6) has significantly increased customer satisfaction with our products, and hence reduced our operational load.

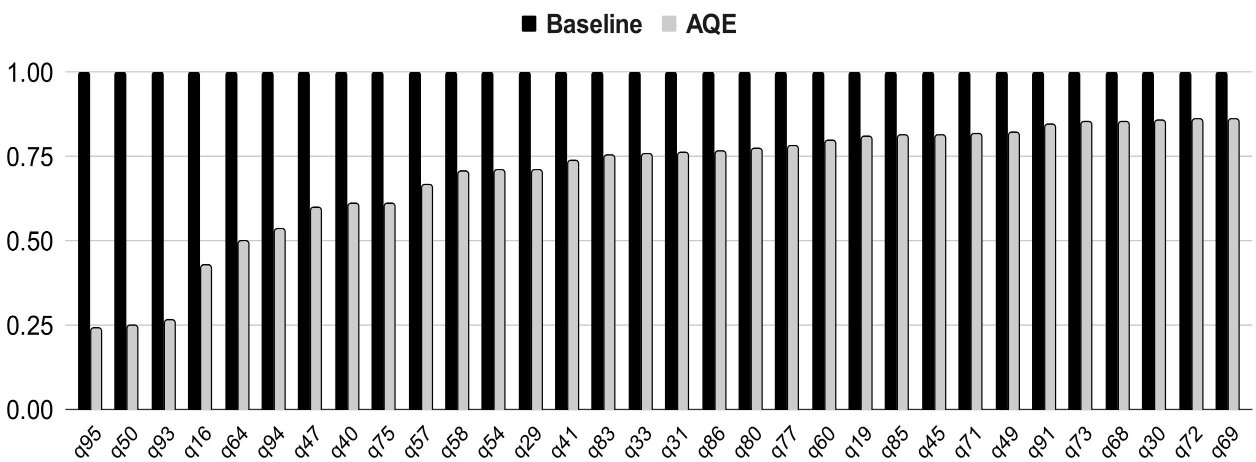
8 RELATED WORK

Drawbacks of a few alternatives to AQE have been elaborated in Section 3.3. In this section, we compare the role of our AQE layer with related work from three angles, i.e., (a) distributed query

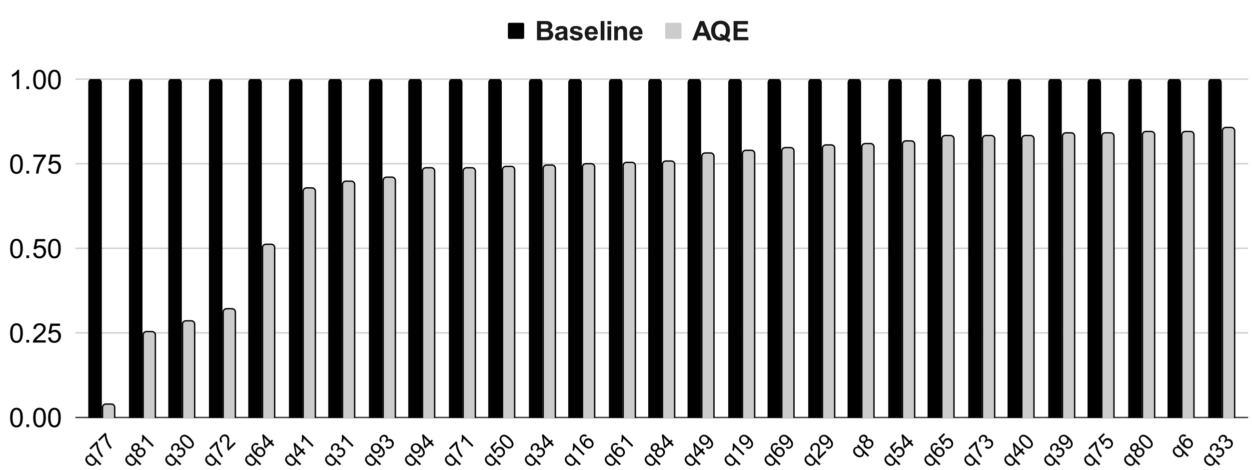




(a) TPC-H (ScaleFactor=1000) with Delta with Analyze Table stats (b) TPC-H (ScaleFactor=3000) with Delta with Analyze Table stats



(c) TPC-DS (ScaleFactor=3000) with Delta with Analyze Table statistics



(d) TPC-DS (ScaleFactor=3000), with Delta without Analyze Table statistics

Figure 9: Performance Evaluations. "Baseline" is Photon with AQE-disabled, while "AQE" is Photon with AQE-enabled. For both Baseline and AQE, an experimental cluster has 1 i3.2xlarge driver with 16 i3.2xlarge executors. All queries run sequentially. All numbers are relative between Baseline and AQE. All numbers are the average from three replicated runs on dedicated clusters.

engines, (b) static query optimization techniques, and (c) dynamic query re-optimization techniques.

Distributed Query Engines. Traditional, shared-nothing data warehouses (or databases) like GRACE [24], Gamma [22], Teradata [16], Vertica [30] and Redshift [27] tightly couple metadata, storage, and compute in a single cluster. The shared-nothing architecture was optimized for query latency, but lacks elasticity for changing workloads and has a high software complexity due to proprietary implementations of storage format, concurrency control, and data replication. From 2000s to 2010s, MapReduce [20], and subsequently its successor Spark [5, 46], were invented to make large-scale data processing over data lakes simple, elastic, and scalable. After the rise of MapReduce and its corresponding open-source ecosystem Hadoop [3], a flurry of new "shared-disk" query engines have been developed in the industry, such as SparkSQL [8], Impala [29], F1 Query [37], BigQuery [13], Redshift Spectrum [15], Presto [41], and Snowflake [19]. The new "shared-disk" architecture separates storage out from compute, to shared, distributed file systems, which makes the query processing layer simple and elastic. Although these systems were originally built to fit either a data lake or a closed data warehouse, by addressing the challenges presented in Section 1, they can evolve to natively support Lakehouses. For instance, the work described in this paper is a continuation of SparkSQL and brings its performance and stability to the next level.

Static Query Optimization. System R [38] firstly introduced a bottom-up query optimizer with dynamic programming to select the "best" plan for a given query, with respect to access paths, join orders and interesting orders, according to a numeric cost model of physical plans. As a step forward from the System R optimizer, Cascades [25] was an optimizer framework involving top-down dynamic programming, with key components such as a memo structure, physical data properties and requirements, search space prioritization, exploration rules, enforcer rules, and branch-and-bound. Notably, in the late 1990s, SQL Server rebuilt its query optimizer with a Cascades-style architecture [34]. To accommodate the need of processing massive data in a data lake, SCOPE [47] extended SQL Server's optimizer to better exploit partitioning properties so as to reduce unnecessary data shuffles in execution plans. When cardinality estimation is flawless, industrial optimizers usually can find reasonably good physical plans. However, it is well known that cardinality estimation can be orders-of-magnitude off [32], and estimation errors can lead to either missed performance improvement opportunities or system stability issues. Having AQE to complement the static optimizer, our query engine is less sensitive to estimation errors and can robustly converge to a "good enough" execution plan at runtime.

Dynamic Query Re-Optimization. Although dynamic query re-optimization has not been widely adopted in industrial databases and query engines, a number of research prototypes explored this approach, and a couple of commercial systems productionized some ideas. INGRES [43] was the earliest system with dynamic re-optimization. It decomposes a join query into multiple single-table queries, executes them first, stores intermediate results, collects stats, and then optimizes and executes Joins. Several subsequent research prototypes [28, 33, 36] convert remaining execution plans back to SQL queries to parse, analyze and optimize again at either a blocking operator boundary or an artificial materialization point. Compared to those prototypes, our AQE framework models uncompleted plans in a more natural way to avoid unnecessary overhead for short-running queries, and supports a new primitive to cancel running plan fragments. The Shark prototype [44] proposed the idea of PDE (partial DAG execution), which collects runtime statistics at stage boundaries to select better join algorithms and handle data skews. AQE can be viewed as a continuation, expansion and productionization of PDE, with emphasis on system simplicity, optimization opportunities, and robustness. Teradata IPE (incremental planning and execution) [42] and AQE share some similarities, yet the optimizations described in the IPE documentation are less extensive than what AQE covers. BigQuery leverages an in-memory, blocking Shuffle implementation [2] to dynamically adjust the degree-of-parallelism and the partitioning function for the receiver side of a Shuffle. In contrast, the techniques described Section 5.4 and Section 6.3 are logical "merge" and "split" operations without reading or writing the shuffled data again and hence do not require an in-memory Shuffle implementation. Instead of re-running optimizations, literature [9, 10, 26] proposed to deploy alternative execution plans simultaneously and route tuples into proper operators based on information collected at runtime. The Oracle adaptive plan [35] productionized the research direction and the routing decision is made based on the first few tuple batches. However, our re-optimizations discussed in Section 5 and Section 6 are more sophisticated than simple switches such that require holistically rewriting logical plans and re-generating physical plans. In addition, deploying alternative execution plans at runtime may result in overheads and complexities in a distributed query engine involving task scheduling. In the initial stages of the AQE project, we took the initiative to develop and contribute our work with several AQE primitives to the open-source Spark [5]. The system described in this paper represents an advancement beyond the scope of previous efforts in the Spark community, specifically tailored for the Photon [11] distributed query engine.

9 CONCLUSION

In this paper, we introduce AQE, an adaptive and robust query execution framework featuring a suite of dynamic optimizations that underpin Databricks Runtime, Databricks SQL, and Delta Live Tables. The framework effectively tackles key challenges faced by a static query optimizer in a Data Lakehouse environment, including issues such as missing catalog statistics, imperfect cardinality estimation, and an inaccurate cost model. We have integrated AQE into our production environment, where it routinely processes exabytes of data across billions of queries each day. This default deployment has not only significantly elevated the performance of our products but has also enhanced their overall stability. To our knowledge, AQE marks a pioneering achievement as the first industrial system running full-fledged dynamic query optimizations at scale.

ACKNOWLEDGMENTS

We would like to thank Intel Corporation for funding the initial exploration of the adaptive query execution idea and prototype with Apache Spark, as well as Spark committers who contributed to the AQE module in open-source Spark.

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REFERENCES

[1] Sameer Agarwal, Barzan Mozafari, Aurojit Panda, Henry Milner, Samuel Madden, and Ion Stoica. 2013. BlinkDB: queries with bounded errors and bounded response times on very large data. In *Proc. ACM EuroSys*. 29–42.
[2] Hossein Ahmadi. 2016. In-memory query execution in Google BigQuery. https://cloud.google.com/blog/products/bigquery/in-memory-query-execution-in-google-bigquery. Last accessed: July 18, 2024.
[3] Apache Hadoop. 2008. https://hadoop.apache.org/. Last accessed: July 18, 2024.
[4] Apache Iceberg. 2020. https://iceberg.apache.org/. Last accessed: July 18, 2024.
[5] Apache Spark. 2010. https://spark.apache.org/. Last accessed: July 18, 2024.
[6] Michael Armbrust, Tathagata Das, Sameer Paranjpye, Reynold Xin, Shixiong Zhu, Ali Ghodsi, Burak Yavuz, Mukul Murthy, Joseph Torres, Liwen Sun, Peter A. Boncz, Mostafa Mokhtar, Herman Van Hovell, Adrian Ionescu, Alicja Luszczak, Michal Switakowski, Takuya Ueshin, Xiao Li, Michal Szafranski, Pieter Senster, and Matei Zaharia. 2020. Delta Lake: High-Performance ACID Table Storage over Cloud Object Stores. *Proc. VLDB Endow* 13, 12 (2020), 3411–3424.
[7] Michael Armbrust, Ali Ghodsi, Reynold Xin, and Matei Zaharia. 2021. Lakehouse: A New Generation of Open Platforms that Unify Data Warehousing and Advanced Analytics. In *CIDR*.
[8] Michael Armbrust, Reynold S. Xin, Cheng Lian, Yin Huai, Davies Liu, Joseph K. Bradley, Xiangrui Meng, Tomer Kaftan, Michael J. Franklin, Ali Ghodsi, and Matei Zaharia. 2015. Spark SQL: Relational Data Processing in Spark. In *Proc. ACM SIGMOD*. 1383–1394.
[9] Ron Avnur and Joseph M. Hellerstein. 2000. Eddies: Continuously Adaptive Query Processing. In *Proc. ACM SIGMOD*. 261–272.
[10] Shivnath Babu, Pedro Bizarro, and David J. DeWitt. 2005. Proactive re-optimization with Rio. In *Proc. ACM SIGMOD*. 936–938.
[11] Alexander Behm, Shoumik Palkar, Utkarsh Agarwal, Timothy Armstrong, David Cashman, Ankur Dave, Todd Greenstein, Shant Hovsepian, Ryan Johnson, Arvind Sai Krishnan, Paul Leventis, Ala Luszczak, Prashanth Menon, Mostafa Mokhtar, Gene Pang, Sameer Paranjpye, Greg Rahn, Bart Samwel, Tom van Bussel, Herman Van Hovell, Maryann Xue, Reynold Xin, and Matei Zaharia. 2022. Photon: A Fast Query Engine for Lakehouse Systems. In *Proc. ACM SIGMOD*. 2326–2339.
[12] Srikanth Bellamkonda, Rafi Ahmed, Andrew Witkowski, Angela Amor, Mohamed Zait, and Chun-Chieh Lin. 2009. Enhanced subquery optimizations in oracle. *Proc. VLDB Endow.* 2, 2 (2009), 1366–1377.
[13] BigQuery. 2015. https://cloud.google.com/bigquery/docs. Last accessed: July 18, 2024.
[14] Burton H. Bloom. 1970. Space/time trade-offs in hash coding with allowable errors. *Commun. ACM* 13, 7 (1970), 422–426.
[15] Mengchu Cai, Martin Grund, Anurag Gupta, Fabian Nagel, Ippokratis Pandis, Yannis Papakonstantinou, and Michalis Petropoulos. 2018. Integrated Querying of SQL database data and S3 data in Amazon Redshift. *IEEE Data Eng. Bull.* 41, 2, 82–90.
[16] John Catozzi and Sorana Rabinovici. 2001. Operating System Extensions for the Teradata Parallel VLDB. In *Proc. VLDB Endow.* 679–682.
[17] Surajit Chaudhuri, Gautam Das, and Utkarsh Srivastava. 2004. Effective use of block-level sampling in statistics estimation. In *Proc. ACM SIGMOD*. 287–298.
[18] Surajit Chaudhuri, Bolin Ding, and Srikanth Kandula. 2017. Approximate query processing: No silver bullet. In *Proc. ACM SIGMOD*. 511–519.
[19] Benoit Dageville, Thierry Cruanes, Marcin Zukowski, Vadim Antonov, Artin Avanes, Jon Bock, Jonathan Claybaugh, Daniel Engovatov, Martin Hentschel, Jiansheng Huang, Allison W. Lee, Ashish Motivala, Abdul Q. Munir, Steven Pelley, Peter Povinec, Greg Rahn, Spyridon Triantafyllis, and Philipp Unterbrunner. 2016. The Snowflake Elastic Data Warehouse. In *Proc. ACM SIGMOD*. 215–226.
[20] Jeffrey Dean and Sanjay Ghemawat. 2004. MapReduce: Simplified Data Processing on Large Clusters. In *Proc. USENIX OSDI*. 137–150.
[21] Delta UniForm. 2023. https://www.databricks.com/blog/delta-uniform-universal-format-lakehouse-interoperability. Last accessed: July 18, 2024.
[22] David J. DeWitt, Shahram Ghandeharizadeh, Donovan A. Schneider, Allan Bricker, Hui-I Hsiao, and Rick Rasmussen. 1990. The Gamma Database Machine Project. *IEEE Trans. Knowl. Data Eng.* 2, 1 (1990), 44–62.
[23] DFP. 2020. Faster SQL Queries on Delta Lake with Dynamic File Pruning. https://www.databricks.com/blog/2020/04/30/faster-sql-queries-on-delta-lake-with-dynamic-file-pruning.html. Last accessed: July 18, 2024.
[24] Shinya Fushimi, Masaru Kitsuregawa, and Hidehiko Tanaka. 1986. An Overview of The System Software of A Parallel Relational Database Machine GRACE. In *Proc. VLDB Endow.* 209–219.
[25] Goetz Graefe. 1995. The Cascades Framework for Query Optimization. *IEEE Data Eng. Bull.* 18, 3 (1995), 19–29.
[26] Goetz Graefe and Karen Ward. 1989. Dynamic Query Evaluation Plans. In *Proc. ACM SIGMOD*. 358–366.
[27] Anurag Gupta, Deepak Agarwal, Derek Tan, Jakub Kulesza, Rahul Pathak, Stefano Stefani, and Vidhya Srinivasan. 2015. Amazon Redshift and the Case for Simpler Data Warehouses. In *Proc. ACM SIGMOD*. 1917–1923.
[28] Navin Kabra and David J. DeWitt. 1998. Efficient Mid-Query Re-Optimization of Sub-Optimal Query Execution Plans. In *Proc. ACM SIGMOD*. 106–117.
[29] Marcel Kornacker, Alexander Behm, Victor Bittorf, Taras Bobrovytsky, Casey Ching, Alan Choi, Justin Erickson, Martin Grund, Daniel Hecht, Matthew Jacobs, Ishaan Joshi, Lenni Kuff, Dileep Kumar, Alex Leblang, Nong Li, Ippokratis Pandis, Henry Robinson, David Rorke, Silvius Rus, John Russell, Dimitris Tsirogiannis, Skye Wanderman-Milne, and Michael Yoder. 2015. Impala: A Modern, Open-Source SQL Engine for Hadoop. In *Proc. CIDR*.
[30] Andrew Lamb, Matt Fuller, Ramakrishna Varadarajan, Nga Tran, Ben Vandiver, Lyric Doshi, and Chuck Bear. 2012. The Vertica Analytic Database: C-Store 7 Years Later. *Proc. VLDB Endow.* 5, 12 (2012), 1790–1801.
[31] Linux Foundation Delta Lake. 2020. https://delta.io. Last accessed: July 18, 2024.
[32] Guy Lohman. 2014. Is Query Optimization a "Solved" Problem?. In *ACM SIGMOD Blog*.
[33] Volker Markl, Vijayshankar Raman, David E. Simmen, Guy M. Lohman, and Hamid Pirahesh. 2004. Robust Query Processing through Progressive Optimization. In *Proc. ACM SIGMOD*. 659–670.
[34] Benjamin Nevarez. 2011. *Inside the SQL Server Query Optimizer*. Simple Talk Publishing.
[35] Oracle Adaptive Plan. 2013. Adaptive Plans in Oracle Database 12c. https://oracle-base.com/articles/12c/adaptive-plans-12cr1. Last accessed: July 18, 2024.
[36] Christina Pavlopoulou, Michael J. Carey, and Vassilis J. Tsotras. 2022. Revisiting Runtime Dynamic Optimization for Join Queries in Big Data Management Systems. In *Proc. EDBT*. 1:1–1:12.
[37] Bart Samwel, John Cieslewicz, Ben Handy, Jason Govig, Petros Venetis, Chanjun Yang, Keith Peters, Jeff Shute, Daniel Tenedorio, Himani Apte, Felix Weigel, David Wilhite, Jiacheng Yang, Jun Xu, Jiexing Li, Zhan Yuan, Craig Chasseur, Qiang Zeng, Ian Rae, Anurag Biyani, Andrew Harn, Yang Xia, Andrey Gubichev, Amr El-Helw, Orri Erling, Zhepeng Yan, Mohan Yang, Yiqun Wei, Thanh Do, Colin Zheng, Goetz Graefe, Somayeh Sardashti, Ahmed M. Aly, Divy Agrawal, Ashish Gupta, and Shivakumar Venkataraman. 2018. F1 Query: Declarative Querying at Scale. *Proc. VLDB Endow.* 11, 12 (2018), 1835–1848.
[38] Patricia G. Selinger, Morton M. Astrahan, Donald D. Chamberlin, Raymond A. Lorie, and Thomas G. Price. 1979. Access Path Selection in a Relational Database Management System. In *Proc. ACM SIGMOD*. 23–34.
[39] Leonard D Shapiro. 1986. Join processing in database systems with large main memories. *ACM Transactions on Database Systems (TODS)* 11, 3 (1986), 239–264.
[40] Michael Stillger, Guy M. Lohman, Volker Markl, and Mokhtar Kandil. 2001. LEO - DB2's LEarning Optimizer. In *Proc. VLDB Endow*. 19–28.
[41] Yutian Sun, Tim Meehan, Rebecca Schlussel, Wenlei Xie, Masha Basmanova, Orri Erling, Andrii Rosa, Shixuan Fan, Rongrong Zhong, Arun Thirupathi, Nikhil Collooru, Ke Wang, Sameer Agarwal, Arjun Gupta, Dionysios Logothetis, Kostas Xirogiannopoulos, Amit Dutta, Varun Gajjala, Rohit Jain, Ajay Palakuzhy, Prithvi Pandian, Sergey Pershin, Abhisek Saikia, Pranjal Shankhdhar, Neerad Somanchi, Swapnil Tailor, Jialiang Tan, Sreeni Viswanadha, Zac Wen, Biswapesh Chattopadhyay, Bin Fan, Deepak Majeti, and Aditi Pandit. 2023. Presto: A Decade of SQL Analytics at Meta. *Proc. ACM SIGMOD* 1, 2 (2023), 189:1–189:25.
[42] Teradata IPE. 2024. Incremental Planning and Execution. https://docs.teradata.com/r/Enterprise_IntelliFlex_VMware/SQL-Request-and-Transaction-Processing/Query-Rewrite-Statistics-and-Optimization/Teradata-Optimizer-Processes. Last accessed: July 18, 2024.
[43] Eugene Wong and Karel Youssefi. 1976. Decomposition - A Strategy for Query Processing. *ACM Transactions on Database Systems (TODS)* 1, 3 (1976), 223–241.
[44] Reynold Xin, Josh Rosen, Matei Zaharia, Michael J Franklin, Scott Shenker, and Ion Stoica. 2013. Shark: SQL and rich analytics at scale. In *Proc. ACM SIGMOD*. 13–24.
[45] Yu Xu, Pekka Kostamaa, Xin Zhou, and Liang Chen. 2008. Handling data skew in parallel joins in shared-nothing systems. In *Proc. ACM SIGMOD*. 1043–1052.
[46] Matei Zaharia, Mosharaf Chowdhury, Tathagata Das, Ankur Dave, Justin Ma, Murphy McCauley, Michael J. Franklin, Scott Shenker, and Ion Stoica. 2012. Resilient Distributed Datasets: A Fault-tolerant Abstraction for In-memory Cluster Computing. In *Proc. USENIX NSDI*. 15–28.
[47] Jingren Zhou, Per-Åke Larson, and Ronnie Chaiken. 2010. Incorporating partitioning and parallel plans into the SCOPE optimizer. In *Proc. IEEE ICDE*. 1060–1071.