Break Up the Pipeline Structure to Reach a Nearly Optimal End-to-End Latency

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ABSTRACT
Query optimization is still problematic in the commercial database system because database optimizers sometimes choose a bad execution plan with several-fold latency differences. In this paper, we design a new dynamic optimization strategy called query split, which takes advantage of run-time statistics. Integrating query split into PostgreSQL, we have a 2x speedup in total end-to-end latency on Join Order Benchmark and achieve near-optimal latency by comparing with the optimal execution plan. Our finding reveals that breaking up the static pipeline between database optimizer and executor can benefit the query processing and greatly reduce end-to-end latency.

1 INTRODUCTION
Although query optimization is a decades-old topic, current optimizers still sometimes make sub-optimal plans due to cardinality estimation errors. Cardinality estimation is essential for query optimizers because cost calculation relies on the estimation of the relation size. However, due to some coarse assumptions made by the database system, cardinality estimation could have a bad performance in real workloads, resulting in sub-optimal plans.

Many attempts have been made in literature to address the issue of cardinality estimation error. One approach is to record the correlation between attributes, using data structures like multi-dimensional histogram [11]. Another approach is to make a better query plan with the help of the result of the query that have been executed before [9, 13, 20, 24, 30, 33, 34]. However, none of these approaches are completely satisfying [31].

As it is difficult to solve the cardinality estimation problem, re-optimization [3, 18, 31] is proposed to avoid the need for accurate cardinality estimation. Reoptimization first generates an initial execution plan at the beginning, and then detects during runtime whether the actual behavior of a query plan becomes significantly different from what was expected. Reoptimization attempts to correct the execution plan whenever a significant deviation is found.

We use a high-level concept "dynamic query optimization" to summarize the characteristic of reoptimization that its execution plans would change during actual execution. In dynamic query optimization, the query optimization and execution are interleaved. As feedback from the executor comes in, more information becomes available, and the optimizer can make better execution plans accordingly. As reoptimization only triggers the interleaving of database optimizer and executor reactively [2], we believe reoptimization does not fully explore this field, and more attempts can be made in dynamic query optimization, for example, how about interleaving optimizer and executor proactively?

Three reasons make dynamic query optimization be a promising approach for generating the optimal execution plan. First, compared to the traditional static pipeline, dynamic query optimization can improve query optimization by knowing more about run-time status. Second, dynamic query optimization can be implemented easily in the current RDBMS architecture, without significant change of the optimizer and executor, model training or storage overhead. Third, dynamic query optimization and cardinality estimation techniques can benefit each other. Dynamic query optimization decreases the problem size of cardinality estimation. Meanwhile, the cardinality estimation technique improves the plan made by dynamic query optimization.

In this paper, we establish a new dynamic query optimization strategy called query split to improve the cardinality estimation. For selection-projection-join (SPJ) queries, we split the query into several subqueries and execute them sequentially to get the result of the original plan. By materializing the subquery results, we get more precise statistics about the original query, which is used in later subquery optimization to make a better execution plan.

Query split has two characteristics. First, unlike reoptimization that needs to be triggered, query split is a proactive strategy. Second, query split only makes execution plan between the execution of different subqueries. As a result, query split decreases the frequency of calling optimizer, hence reducing the overhead.

Query split is a novel attempt in dynamic query optimization. Different from reoptimization, query split provides a proactive interleaving strategy, which fills with the blank of dynamic query optimization. Under proper designs, our experiment shows that query split outperforms PostgreSQL on Join Order Bench-mark [23] and gets a nearly optimal end-to-end latency.

The rest of the paper is organized as follows. Section 2 motivates the dynamic query optimization and query split. Section 3 formally
describes query split and prove its correctness. Section 4 shows preliminary implementations of query split. Section 5 evaluates the performance of query split. Section 7 gives a case study on query split for a deep insight. Section 8 discusses the related work, and Section 9 concludes the paper. We leave some details about experiment and discussion in our technical report [17].

2 MOTIVATION

In this section, we characterize a fundamental limitation of the traditional query processing pipeline and use it as motivation to introduce a novel query processing framework called query split.

• We first review the problem of cardinality estimation and explain why it is hard to accurately estimate cardinality of complex query result (in Section 2.1).

• Then we review an existing query processing technique called reoptimization, which circumvents the need for accurate cardinality estimation. Reoptimization dynamically adjust the query execution plan based on runtime statistics, thus resulting in an improved overall performance (in Section 2.2).

• Next, we discuss the underlying philosophy of reoptimization, and generalize it to a new concept called dynamic query optimization, in which the steps of query optimization and execution are interleaved and integrated together (in Section 2.3).

• Last, we propose a new dynamic query optimization strategy called query split, and informally describe it and discuss its characteristics (in Section 2.4).

2.1 Intrinsic Difficulty of Cardinality Estimation

Currently, most database systems estimate cardinality as the product of three terms: size of both relations and predicate selectivity, in which the selectivity is estimated via table statistics [32]. For example, in PostgreSQL, the selectivity of a simple predicate on base tables is estimated using gathered statistics such as histograms, most common values and their frequencies, and the number of distinct values. For conjunctive predicates, it is commonly assumed that the component predicates are independent, so the final selectivity is the product of selectivity of each predicate [23]. For complex join queries, independence between join predicates is often assumed, and their selectivities are multiplied together. In MySQL, the cardinality estimation strategy is very similar [27].

There are two major reasons why it is hard to guarantee the accuracy of cardinality estimation [18]. The first reason is that optimizer lacks the statistics of intermediate relations. We use an example to demonstrate why this is a problem that troubles the optimizer.

Example 1. A database contains two relations \( A(a,b) \) and \( B(a,b) \) and some statistics in the system catalog including the cardinality of two relations \( n_a \) and \( n_b \) and the value distribution of attributes \( f_a^A \), \( f_b^A \) and \( f_a^B \). Given a natural join query \( r = A \bowtie B \), the cardinality of \( r \) is given by:

\[
 n_r = n_a \times n_b \times (\text{select}_{A,B} \times n_A \times n_B \times \sum_{i \in \text{dom}(a)} (f_a^A(i) \times f_b^A(j))) 
\]

where \( \text{dom}(a) \) is the domain of attributes \( a \).

However, when we apply a filter to attribute \( b \), cardinality estimation of \( r \) becomes more difficult. Consider the query \( r = A \bowtie \sigma_{b < x} (B) \), and denote the intermediate relation as \( t = \sigma_{b < x} (B) \). So that the query can be rewritten as \( r = A \bowtie t \), and the cardinality of \( t \) is \( n_t = n_B \times f_b^B(x) \). Since any other statistic about \( t \) is unknown, the optimizer must approximate those missing statistics by some assumptions. For example, if we assume independence between attributes \( a \) and \( b \) in table \( B \), we can get \( f_a^B(i) = f_b^B(i)(b = x) = f_b^B(i) \), which can then be used to estimate the selectivity of join predicate. However, those assumptions may not be actually valid, and would introduce error in estimation.

Similar situation happens when the filter \( \sigma_{b < x} (B) \) is replaced by a new join, e.g. \( r = A \bowtie (B \bowtie C) \). Since we only have the statistics of base relations, to estimate the cardinality of the final result \( n_r \), we have to assume independence across joins. Specifically, we use the selectivity of joins between base relations to approximate the selectivity of joins containing intermediate results, which also leads to estimation error.

From the above example, we can see that the optimizer has to make assumptions to make up for the lack of statistics, which inevitably generates estimation error.

The second reason is error propagation. Ioannidis and Christodoulakis mathematically deduce that the cardinality estimation error of an N-way natural join grows exponentially with N, under the assumption that there is some error in estimating the distribution of join attribute in each relation [15]. Hence, except for small queries, cardinality estimation results are often not trustworthy. Although these results are based on theoretical analysis, they are also generally valid in practice based on our empirical observations during experiments.

2.2 Reoptimization

As it is hard to make cardinality estimation always accurate, Kabra and DeWitt proposed reoptimization [18] to circumvent this problem. Reoptimization collects statistics during runtime to monitor query execution. When the collected statistics deviate too much from prediction, the system replans the remainder of the query plan in light of this new information, which can alter join orders and physical operators of the remaining part.

Reoptimization does not make drastic changes to the query execution engine. Instead, it detects during runtime whether the actual behavior of a query plan becomes significantly different from what was expected and attempts to correct the execution plan whenever it happens. In other words, reoptimization admits that the query optimizer can make mistakes in decisions and thus tries to alleviate them. In a recent work, Perron et al. [31] evaluated the performance of reoptimization on the Join Order Benchmark [23], and their result suggests that reoptimization can significantly reduce query execution time.

Reoptimization makes use of the statistic of intermediate results, and in this paper we refer them as runtime statistics, to distinguish them from statically collected statistics. By using runtime statistics, the optimizer improves cardinality estimation from two aspects: first, by replacing estimated statistics with runtime statistics, the optimizer reduces the cardinality estimation error caused by problematic assumptions. For example, the runtime statistics can include the actual distribution of attributes in the intermediate result, which leads to more accurate cardinality estimation. Another aspect is that runtime statistics stop error propagation. Optimizer
With such information, the optimizer can either keep the original plan or produce another plan to be executed. This iteration can happen several times until the final result is ready. Dynamic query optimization emphasizes the interleaved steps of query execution.

2.3 Dynamic Query Optimization

The general idea of changing the plan halfway through execution actually leads us to a broader research space. Reoptimization is a reactive technique as it is triggered only when we find estimation being wrong. Alternatively, we can also proactively change the execution plan, and call the query optimization routine any time to potentially change the plan. Besides, there are other interesting research questions, like when and what statistics should we gather during runtime. For example, whether we should collect statistics at each node in the join tree or only at some of these nodes.

We introduce a high-level concept called dynamic query optimization to characterize this new research space. As shown in Figure 1, in a dynamic query optimization scheme, the optimizer initially provides an execution plan to be executed. Then, either during or after the execution of plan, we switch back to the optimizer, with some intermediate results and runtime statistics. With such information, the optimizer can either keep the original plan or produce another plan to be executed. This iteration can happen several times until the final result is ready. Dynamic query optimization is fundamentally different from the traditional static query optimization, in which the query plan is fixed during the whole procedure.

Dynamic query optimization can be classified as a specific case of the more general concept of adaptive query processing [2], in which query execution strategy changes adaptively based on the actual state during execution. Most existing adaptive query processing techniques keep the strict order between optimizer and executor. For example, parametric query optimization [16] and Rio [3] give a set of possible optimal plans to the executor instead of giving one single optimal plan and the plan can be switched during execution. Eddies [1] generate a basic join tree by a simple pre-optimizer and can dynamically change the tuple pipeline in join operators during execution.

Compared to other adaptive query processing techniques, dynamic query optimization emphasizes the interleaved steps of query optimization and execution. The optimizer only determines the initial few steps of the query plan at beginning and gradually decide the next steps as more information becomes available. This direction so far has not been thoroughly explored by existing works on adaptive query processing.

2.4 Query Split

Calling optimizer again to modify the execution plan leads to non-trivial overhead, especially if done very frequently. In this paper, we propose a new dynamic query optimization strategy called query split which has lower overhead comparatively. In query split, we execute a small part of query each time and materialize its result until the entire query has been executed. We provide an example to demonstrate how query split works in practice.

**Example 2.** As shown in Figure 2(a), we consider a query \( G = R_1 \bowtie R_2 \bowtie R_3 \bowtie R_4 \bowtie R_5 \) on five relations. First, we split query \( G \) into three subqueries, as shown in Figure 2(b): \( S_1 = R_2 \bowtie R_3 \), \( S_2 = R_3 \bowtie R_4 \bowtie R_5 \), and \( S_3 = R_1 \bowtie R_2 \). Then, we execute \( S_1 \) and materialize the result as temporary table \( t_1 \). Next, we replace \( R_2 \) and \( R_3 \) in \( S_2, S_3 \) by \( t_1 \), resulting in \( S_2 = t_1 \bowtie R_4 \bowtie R_5 \), and \( S_3 = R_1 \bowtie t_1 \), as shown in Figure 2(c). Afterwards we execute the modified version of \( S_2 \), and materialize its result as \( t_2 \). Finally, as shown in Figure 2(d), we replace \( t_1 \) in \( S_3 \) by \( t_2 \) to get \( S_3 = R_1 \bowtie t_2 \), and then replan and execute it to obtain the result.
and it is a promising approach that reached near-optimal execution time in the Join Order Benchmark.

3 FORMULATION & DEFINITION

In this section, we formalize query split. We first define the concept of selection-projection-join query and formally describe query split for such queries (in Section 3.1). Then, we design an implementation for reconstruction algorithm, which is one of the components of query split, and prove its correctness (in Section 3.2).

3.1 Framework Overview

In this section, we give an overview of query split framework. For simplicity, we temporarily restrict our attention to selection-projection-join (SPJ) queries in the following three sections (Section 3, 4, and 5), which only involve selection, projection, and join operators. These three operators are chosen because they can be connected together to compose most of the basic SQL SELECT queries, covering all the queries in the Join Order Benchmark [23]. query split can be extended to handle more general queries, which will be discussed in Section 6.

First, let us define a normal form of SPJ queries. Then by relational algebra manipulation, every SPJ queries can be transformed into the following normal form, in which we denote by $R$ a set of relations, $S$ a set of selection predicates over $R$ and $P$ a set of projection attributes, via equivalence rules (details can be found in Appendix A).

$q(R, S, P) = \Pi_P(\sigma_S(r_1 \times r_2 \times ... \times r_m))$, $r_i \in R$

Now, we can formally describe the query split. The framework consists of five components: query splitting algorithm, run-time statistics collector, query optimizer, query executor, and the reconstruction algorithm. The relationship between five components are shown in Figure 3. Query splitting algorithm takes the global query as input and splits it into subqueries, and then we obtain the result via the following steps:

1. In each iteration, the reconstruction algorithm picks a subquery and sends it to the query optimizer.
2. The query optimizer makes an execution plan and delivers it to the query executor.
3. The query executor executes the plan, materializes the results and sends them to statistic collector.
4. The run-time statistic collector obtains new statistics, which can help the optimizer make better plans for the remaining subqueries in the following iterations.
5. After all subqueries have been executed, the reconstruction algorithm reconstructs the final query result relation from subquery results.

Note that statistics collector, query optimizer, and query executor are existing components in RDBMS. In the following, we define query splitting algorithm and reconstruction algorithm, the two new concepts that we propose in this paper.

We first formalize the concept of subquery and query splitting algorithm, in which we stipulate that subqueries do not contain projection operations. The definition of query splitting algorithm here is abstract, and we will discuss possible concrete implementations in Section 4.1.

3.2 Replacement Reconstruction

In this section, we propose a concrete reconstruction algorithm called replacement reconstruction, which is correct with respect to every query splitting algorithm that are guaranteed to cover the original query. The correctness of this algorithm will be proved later.

Figure 3: The framework of query split

**Definition 1.** Given two SPJ queries $q(R, S, P)$ and $q'(R', S')$. If $R' \subseteq R$ and $S' \subseteq S$, then $q'$ is said to be a subquery of query $q$. Query splitting algorithm is an algorithm which takes a SPJ query $q$ as input and returns a set of subqueries of $q$.

Next, we define the concept of reconstruction algorithm.

**Definition 2.** Reconstruction algorithm is an algorithm that takes a set of subqueries $Q$ and a set of projection attributes $P$ as input and returns a reconstructed relation. A reconstruction algorithm $A$ is correct with respect to a query splitting algorithm $B$ if, for every SPJ query $q(R, S, P)$, the reconstructed relation is always equal to the result of the original query, if we feed the output of $B$ on $q$ together with $P$ as input of $A$.

Clearly, not every query splitting algorithm has a corresponding reconstruction algorithm. A crucial question here is under which conditions a correct reconstruction algorithm exists. To answer this question, we first define the concept of subquery cover.

**Definition 3.** Given a SPJ query $q(R, S, P)$, let $Q = \{q_1(R_1, S_1), ..., q_n(R_n, S_n)\}$ be a set of subqueries of $q$. We denoted $R(Q) = \bigcup_{i=1}^{n} R_i$ and $S(Q) = \bigcup_{i=1}^{n} S_i$. $Q$ is said to cover $q$ ($Q \rightarrow q$) if:

1. $R(Q) = R$
2. $S(Q)$ logically implies $S$.  \(^1\)

Intuitively, the reconstruction can succeed only if there is no information loss between the set of subqueries and the original query, and the subquery cover concept formalizes this intuition. To ensure a correct reconstruction algorithm exists, the set of subqueries $Q$ returned by a query splitting algorithm with query $q$ need to satisfy $Q \rightarrow q$. And we give a simple reconstruction algorithm that guarantees correctness under such conditions in the following section.

\(^1\)"A logically implies $B$" means that each predicate from $B$ can be inferred by $A$. 
Algorithm 1 Replacement Reconstruction

Require: \( Q \) a set of subqueries, \( P \) a set of projection attributes

1: function \textsc{ReplaceRecon}(\( Q, P \))
2: \( L \leftarrow \emptyset \)
3: while \( Q \neq \emptyset \) do
4: \( q_i(R_i, S_i) \leftarrow \text{QSELECT}(Q) \)
5: \( q_i(R_i, S_i) \leftarrow \text{QEXEC}(Q) \)
6: \( m_i \leftarrow \text{EXEC}(q_i) \)
7: \( \text{system\_catalog} \leftarrow \text{STAT}(m_i) \)
8: \( Q \leftarrow Q \setminus \{q_i\} \)
9: \( \text{flag} \leftarrow 0 \)
10: for all \( q_j(R_j, S_j) \in Q \) do
11: if \( R_j \cap R_i \neq \emptyset \) then
12: \( \text{replace subset } R_j \cap R_i \text{ in } R_j \text{ with } m_i \) \( q_j \leftarrow \text{replace}(q_j, m_i, R_i) \)
13: \( \text{flag} \leftarrow 1 \)
14: end if
15: end for
16: if \( \text{flag} = 0 \) then
17: \( L \leftarrow L \cup \{m_i\} \)
18: end if
19: end while
20: \( \text{Res} \leftarrow m_1 \times m_2 \times \ldots \times m_n, m_i \in L \)
21: return \( \Pi_P(\text{Res}) \)
22: end function

- **Initial:** initialize the set of subquery results \( L \) as empty set.
- **Loop(execute):** execute a subquery \( q_i(R_i, S_i) \) from \( Q \) and materialize the result as \( m_i \), then collect run-time statistics.
- **Loop(modify):** remove \( q_i(R_i, S_i) \) from \( Q \), then pick out all subqueries \( q_j(R_j, S_j) \) whose set of relations \( R_j \) intersects with \( R_i \), modify these subqueries via a specific protocol that will be described later \( q_j \leftarrow \text{replace}(q_j, m_i, R_i) \). If there is no such \( q_j \), add \( m_i \) to \( L \). After this, check whether \( Q \) is empty and repeat the loop if not.
- **Merge:** when \( Q \) is empty, compute the Cartesian product of all relations in \( L \) and project the result by \( P \), and the end result is the reconstructed relation.

It remains to describe how \( \text{replace}(q_j, m_i, R_i) \) works. It actually modifies the subquery \( q_j(R_j, S_j) \) from two aspects.
- First, replace all relations in \( R_j \cap R_i \) by \( m_i \). In other words, set the set of relations of \( q_j \) as \( R_j \leftarrow R_j \setminus \{m_i\} \).
- After replacing old relations from \( R_j \) with \( m_i \), some predicates in \( S_j \) would be referencing removed relations. Update those predicates by using the corresponding attributes in \( m_i \) instead.

Now we can prove the correctness of replacement reconstruction algorithm.

**THEOREM 1.** Let \( q(R, S, P) \) be an SPJ query, \( Q \) be a set of subqueries of \( q \). If \( Q \rightarrow c_q \), then the output of the replacement reconstruction algorithm is equal to the result of \( q \).

This implies that the replacement reconstruction algorithm is a correct reconstruction algorithm for any query splitting algorithm that guarantees its output to cover the original query. The proof of this theorem can be found in B.

**Remark:** In Definition 1, we assume that there is no projection operation in subqueries for simplicity. In practice, we can push down the projection operation to each subquery to effectively reduce the size of the temporary relation and minimize execution time. In principle, any attribute which doesn’t appear in other subqueries can be safely projected away.

## 4 DETAIL IMPLEMENTATION

Although we formally described the query split in Section 3, there are still some components that are relatively flexible. In this section, we examine these components in more detail, and provide some concrete implementations: the query splitting algorithm (in Section 4.1) and the criterion for selecting which subquery to execute each time (in Section 4.2). However, since our paper aims to verify the general effectiveness of query split, an in-depth research of these components is beyond the scope of this paper. The contents of this section only serve as some preliminary designs for reference.

### 4.1 Query Splitting Algorithm

In this section, we propose three simple query splitting algorithms (MinSubquery, RelationshipCenter, and EntityCenter).

#### 4.1.1 MinSubquery

This is the most straightforward query splitting algorithm, in which we split the query into minimal subqueries. For each selection predicate that spans more than one relation, we use those relations to construct a relation set \( R_i \). Then we construct the set of selection predicates \( S_i \) to contain all the selection predicates over \( R_i \). We use an example query (shown in Figure 5(a)) to demonstrate the procedure of MinSubquery below.

**Example 3 (MinSubquery).** As shown in Figure 5(a), there are five join predicates (denoted by \( \bowtie \)) and two selection predicates (denoted by \( \Rightarrow \)). To create subqueries, first construct the...
following relation sets involved in join predicates: \(R_1 = \{k, mk\}, R_2 = \{ci, mk\}, R_3 = \{ci, n\}, R_4 = \{mk, t\}, R_5 = \{ci, t\}\). Then, for each relation set \(R_6, S_6\) is equal to the union of all selection predicates in the original query over \(R_6\). As shown in Figure 5(b), this results in five subqueries \(q_1 = \sigma_{f_6}(k) \forall mk, q_2 = mk \forall ci, q_3 = \sigma_{f_6}(n) \forall ci, q_4 = \sigma_{f_6}(t) \forall mk\) and \(q_5 = ci \forall \sigma_{f_6}(t)\).

![Figure 5: Join graph split by MinSubquery](image)

4.1.2 RelationshipCenter. Because subqueries in query split are always materialized, it would be beneficial to attempt to constrain the size of subquery result when constructing the subqueries. There are several potential benefits for doing this: first, a small subquery result can speed up the later execution, as the completed subqueries will often be used in other subqueries. Another benefit is that it improves the robustness of the framework by using less memory. In query split, each subquery result must be materialized in memory after execution, and hence subqueries with bounded result sizes lead to more stable memory usage.

In MinSubquery, any join predicate can be use as a foundation for creating subqueries, and subqueries created this way are often translated to general theta-joins. The result size of such subqueries cannot be effectively bounded, and in the worst case the size can be as large as the product of the size of all join relations. In contrast, when one relation contains several foreign keys to other relations, and they are joined together via the foreign keys, the result size doesn’t exceed the size of the first relation. Here we make use of this fact to develop a new query splitting algorithm.

We introduce two new concepts: entity relation and relationship relation, which are inspired by the entity-relationship diagram [4]. If the primary key of a relation is referenced by another relation as foreign key, we denote such relations as entity relation. For relations that do not have a primary key or their primary keys are not referenced by any other relation, we denote them as relationship relation.

With the above definitions, we can see that when a relationship relation joins with several entity relations via foreign-key joins, the cardinality of the join result will not exceed the size of the relationship relation. Based on this, we propose the RelationshipCenter algorithm to control the size of each subquery. The algorithm ensures that most subqueries contain one relationship relation and multiple entity relations. The concrete steps of RelationshipCenter are shown as follows.

- First, we classify all relations into two types: relationship and entity by the above definitions.
- Next, we remove redundant selection predicates, and we prefer to reserve foreign-key joins as much as possible.
- Then, we construct a directed graph for the given query, in which each vertex represents a relation. For each foreign-key join predicate, we create an edge from the relation which contains the foreign key to the relation where primary key comes. For every other selection predicate that spans multiple relations, we consider all possible pairs from the involved relations, and create one or two edges between them, depending on their relation types: if both relations are the same type, we create two edges in both directions. Otherwise, we create an edge from relationship relation to entity relation.
- Last, for each relation that connects to other relations, we create a subquery based on this relation. The relation set of the subquery contains the given relation and all relations it links to. The selection predicate set contains all predicates over the relation set.

Example 4 demonstrates how RelationshipCenter works.

![Figure 6: Join graph split by RelationshipCenter](image)

**Example 4 (RelationshipCenter).** As shown in Figure 6(a), the query consists of one non-foreign key join \((mk \Rightarrow ci)\) and four foreign key joins \((k \Rightarrow mk, t \Rightarrow mk, t \Rightarrow ci\) and \(n \Rightarrow ci)\). Hence, relation \(mk\) and \(ci\) are relationships and relation \(k, n, t\) are entities. Then as shown in Figure 6(b), we first remove \(mk \Rightarrow ci\) because it is redundant, then draw a directed graph with four edges \((E_1 = mk \Rightarrow k, E_2 = mk \Rightarrow t, E_3 = ci \Rightarrow t\) and \(E_4 = ci \Rightarrow n)\), corresponding to join predicates. Next, consider all relations: relation \(k, n\) and \(t\) don’t connect to any other relation, hence we do not create subqueries for them; relation \(mk\) connects to \(k\) and \(t\), resulting in subquery \(S_1 = \sigma_{f_6}(k) \Rightarrow mk \Rightarrow \sigma_{f_6}(t)\); relation \(ci\) connects to \(n\) and \(t\), and we have subquery \(S_2 = \sigma_{f_6}(n) \Rightarrow ci \Rightarrow \sigma_{f_6}(t)\).

4.2 Execution Order Decision

In this section, we propose some feasible criteria to decide which subquery to execute each time. Although we have proved that execution order does not affect the correctness of query split, different execution orders can load to different execution time. Therefore, we give some feasible implementations as the candidates and evaluate their efficiency in Section 5.

4.2.1 Heuristic Rule Based Subquery Selection. One intuitive approach is to use heuristic rules to order the subqueries. We take the
execute plans of subquery as input and assign a numeric value to each of them. Each time, we choose the subquery with the lowest numeric value, and return this subquery and its execution plan to execute.

We have designed some ranking functions for the algorithm in Table 1. We denote \( q \) a subquery, \( \text{plan}(q) \) the execution plan made by optimizer, \( \text{plan}(q).\text{cost} \) the estimated cost of \( \text{plan}(q) \), and \( \text{row}(q) \) the estimated size of its result. The most basic approach is to use the estimated cost of subqueries for ranking. However, this approach fails to consider the future influence, since a large intermediate result will slow down future subqueries. Take this into consideration, we designed other four candidates \( \text{row}(q) \), \( \text{row}_{\text{hybrid}}(q) \), \( \text{hybrid\_sqrt}(q) \) and \( \text{hybrid\_log}(q) \) with detailed expression in Table 1.

Table 1: The expression of different ranking functions

| ranking function | expression |
|------------------|------------|
| \( \text{cost}(q) \) | \( \text{plan}(q).\text{cost} \) |
| \( \text{row}(q) \) | \( \text{row}(q) \) |
| \( \text{row}_{\text{hybrid}}(q) \) | \( \text{plan}(q).\text{cost} \times \text{row}(q) \) |
| \( \text{hybrid\_sqrt}(q) \) | \( \text{plan}(q).\text{cost} \times \sqrt{\text{row}(q)} \) |
| \( \text{hybrid\_log}(q) \) | \( \text{plan}(q).\text{cost} \times \log(\text{row}(q)) \) |

4.2.2 Global View Based Subquery Selection. Looking only at subqueries themselves from a local perspective may not always lead to a good execution order. An alternative approach is to choose subqueries from a global view, and we have designed one such algorithm called \( \text{global\_sel} \).

\( \text{global\_sel} \) starts the selection process with a plan generated from the original query. Then, given an execution tree for the original query, we choose the deepest operator node, find the relations involved in the operator, and select the subquery whose relation set contains those relations. If multiple subqueries can be selected, we choose one of them by an arbitrary tie-breaking rule.

Example 5 illustrates the procedure for the global view based subquery selection.

**Example 5 (GLOBAL\_SEL).** We split the query into three subqueries \( S_1 = \sigma_{f_k}(k) \Join m.k, S_2 = \sigma_{f_k}(n) \Join c.i, \) and \( S_3 = c.i \Join \sigma_{f_k}(t) \Join m.k. \) As shown in Figure 7, at the beginning, the deepest non-leaf node in global plan is \( k \Join m.k \), and the involved relations are \( \{k,m.k\}. \) Hence, subquery \( S_1 \) would be first executed because it is the only subquery whose relation set contains \( k \) and \( m.k \). Then we materialize the subquery result as a temporary table, and call optimizer for the remainder of the original query. In this iteration, the deepest non-leaf node in modified global plan is \( S_1 \Rightarrow t \), so we choose \( S_3 \) because its relation set contains \( S_1 \) and \( t \).

5 EXPERIMENT

As we have motivated query split and introduced all the details, we evaluate its performance on real-world workload in this section. We first describe how our experiments are organized (Section 5.1), and then introduce the baselines that we use (Section 5.2). Next, we evaluate the performance impact of different query splitting algorithms and execution order decisions (Section 5.3), and compare a fine-tuned query split implementation with baselines (Section 5.4). Last, we discuss the potential out of memory issue and its implications (Section 5.5).

5.1 Experiment Setup

Our experiments are performed on a 64-bit Windows 10 computer with an Intel Core i9-10900K CPU (3.70 GHz) and we use the source code of PostgreSQL 12.3 as basis for all of our implementations. We set max parallel workers to 0, so the CPU only uses one core during query processing. Furthermore, the system has 128 GB of RAM, and we set up the PostgreSQL parameters so that the database can store the entire IMDB database and temporary data in memory. This setting ensures that no disk IO will happen during the query execution. We have also modified the default cost model parameters of PostgreSQL to target this in-memory query execution setting. More details of the experimental setup can be found in Appendix C.

We use Join Order Benchmark (JOB) [23] as our experiment workload. JOB is a real-world workload over the IMDB dataset and has a high value for evaluating the performance of RDBMS. JOB has 113 queries, and 91 of them have non-empty results. We run these 91 queries and record their latencies as reported by PostgreSQL.

We have released the source code of query split that we used in experiments on Github.

5.2 Baseline

Aside from the built-in optimizer of PostgreSQL, we introduce another baseline called optimal plan, which intends to capture the latency of the optimal static query execution plan for each query. This plan is obtained by using two tricks: first, in optimal plan, the optimizer remembers the true cardinalities of all past intermediate results for a given query and use them during query optimization. Second, we encourage the optimizer to try the join orders that haven’t been explored yet by artificially decreasing the cost of these join orders. By iterating the same query several times, the optimizer will know the true cardinality of most intermediate relations, and would make a near optimal plan accordingly (we describe the detail of this baseline in Appendix D).

Another baseline that we originally considered is reoptimization [18], which has been previously evaluated on JOB via simulation by Perron et al. [31]. We implemented the reoptimization technique in PostgreSQL (we describe the details in Appendix E). The results of this baseline (denoted as “re-PostgreSQL”) have been shown in Figure 8. Notice that the end-to-end latency of “re-PostgreSQL” is

https://github.com/zhaojy20/break-up-pipeline.
close to the optimal result in most queries. But in query 23, 44, 61, PostgreSQL fails to output results and reports an out of memory error. Upon checking the system log, we find out that out of memory occurs due to temporary table materialization exceeding the limit of the memory buffer. This problem was not reported in the previous simulation result [31], because temporary tables were allowed to be written back to disk in the simulation, which is not a practical behavior in an actual deployment setting.

The performance of "re-PostgreSQL" illustrates that although reoptimization can make better cardinality estimation, the consumption of local memory buffer is a serious problem that is hard to avoid. To decrease memory consumption, it is necessary to control the timing of materialization, and carefully choose which intermediate results to be materialized. All these decisions are highly non-trivial, and as a result we have to give up using "re-PostgreSQL" as a baseline.

![Figure 8: The latency of each query in re-PostgreSQL](image)

### 5.3 Performance Impact of Different Implementations

We first evaluate the performance of different implementations of *query split*. The result is shown in Table 2, in which we report the total end-to-end latency of 91 queries in JOB. As we have mentioned in Section 4.1.2, some implementations of query split strategy can trigger out of memory error (we will explain reasons in Section 5.5). If we exclude all the out-of-memory queries (query 23, 24, 37, 61), we obtain a reduced JOB and the total end-to-end latency of reduced JOB is reported in the brackets for reference.

From Table 2, we can conclude that both query splitting algorithms and execution order decisions influence the end-to-end latency. Among query splitting algorithms, *EntityCenter* uses the longest time for every execution order. This result may be due to the huge subquery results, which apparently slow down the execution speed of the following subqueries. The result suggests that *EntityCenter* is not a good choice for query splitting. *Min-subquery* has the best performance when the execution order is determined by the ranking function *row_hybrid*(q). In other cases, *RelationshipCenter* prevails.

Next, we observe that the end-to-end latency between five execution order decisions also changes significantly. *row*(q) is the worst subquery order selection strategy, as it ignores the cost, which is directly related to the execution time. *cost*(q) has the second-worst performance among all subquery selections, which justifies our previous intuition that execution order decisions should also consider the future influence. *hybrid_sqrt*(q) and *hybrid_log*(q) both perform better than *row_hybrid*(q), which indicates that although we need to consider the size of the subquery to be executed, it’s not proper to give it the same weight as cost.

To our surprise, although *global_sel* provides a global view, it does not outperform the heuristic rule based methods. Actually, the performance of *global_sel* is worse than *hybrid_sqrt*(q) for most query splitting algorithms. We investigated into this and found out that in many cases, the global plan made by the optimizer is far from the actual optimal plan. As a result, the execution order based on the global plan also performs poorly. The underlying cause of the bad global plan is the increased error of cardinality estimation with the larger query due to error propagation [15]. The result indicates that global view based subquery selection is not as effective as we consider.

According to Table 2, we choose *RelationshipCenter* with *hybrid_sqrt*(q) to represent query split strategy in the rest of paper, which has the least total end-to-end latency among all implementations.

### 5.4 Performance of Query Split

We further compare *query split* with the built-in PostgreSQL optimizer and *optimal plan*. Table 3 shows the total latency of PostgreSQL, *query split*, and *optimal plan* in JOB and reduced JOB, and the latency of each query is shown in Figure 9.

![Figure 9: The latency of each query](image)

Two conclusions can be drawn from Table 3 and Figure 9. First, in both JOB and reduced JOB, *query split* has a 1.8× speedup in total latency compared to PostgreSQL, which verifies the effectiveness of *query split*. And as shown in Figure 9, for most long-time queries in PostgreSQL (longer than 10 seconds), the speedup that we achieve is quite significant.

Second, *query split* is very close to the optimal result. Although there is still a gap between *query split* and *optimal plan* in total latency, the gap is mainly caused by query 21, 28 and 61, whereas the latency of other queries in *query split* is close to *optimal plan*. The result suggests that it is promising for *query split* to reach the optimal end-to-end latency by using better query splitting algorithms and execution order decisions.

Another implication of Figure 9 is that the accuracy of cost model would affect the system performance. In Figure 9, we observe that

3 OOM: 3 times out of memory in 91 queries
Table 2: Total latencies for different implementations on JOB and reduced JOB

| Function       | MinSubquery | RelationshipCenter | EntityCenter |
|----------------|-------------|--------------------|--------------|
| cost(q)        | 3 OOM (378.698) | 419.684(344.282)  | 563.618(483.831) |
| row(q)         | 1 OOM (393.300) | 431.257(352.363)  | 458.871(402.320)   |
| row_hybrid(q)  | 1 OOM (304.802) | 400.945(320.305)  | 457.227(399.177)   |
| hybrid_sqrt(q) | 3 OOM (291.282) | 345.793(262.874)  | 444.373(385.500)   |
| hybrid_log(q)  | 3 OOM (309.415) | 363.229(287.250)  | 431.816(372.144)   |
| global_sel     | 1 OOM (313.730) | 367.031(284.895)  | 2 OOM (347.816)    |

Table 3: Total latency comparison

| Implementation | Latency(s) JOB | Latency(s) reduced JOB |
|----------------|---------------|------------------------|
| PostgreSQL     | 647.636       | 488.457                |
| query split    | 345.793       | 262.874                |
| optimal plan   | 278.687       | 223.677                |

Figure 10: Distribution of size of subquery result

in query 50, 51, 52, and 55, the latency of optimal plan is longer than query split. The reason for this counterintuitive phenomenon is that the cost model underestimates the cost of index scan, which leads the optimizer to select a suboptimal physical operator. As the number of configuration parameters that can be tuned in PostgreSQL is limited, it is impossible to tune a perfect cost model. The issue of cost model accuracy is beyond the scope of this paper, and we merely point it out as a potential direction for future research.

5.5 Memory Usage

In this subsection, we investigate into the out of memory issue that happened during our experiments. Although the total memory that PostgreSQL can use is 128 GB, the total capacity of buffer which is used to store temporary tables is limited to 512 MB in our experiments. As we can see in Table 2, whether out of memory (OOM) will occur depends heavily on the choice of query splitting strategy. There are two reasons why OOM arises for MinSubquery and EntityCenter:

1. As we have discussed in Section 4.1, we cannot control the size of intermediate results in MinSubquery and EntityCenter, thus need to materialize a very large temporary table for some queries.
2. We do materialization more often in MinSubquery. This is because each subquery in MinSubquery is only allowed to contain two relations, and more subqueries are needed to cover the original query.

To illustrate our points, we show the distribution of size of subquery result in Figure 10 and the average amount of subqueries induced by different query splitting algorithms in out-of-memory queries (query 23, 24, 37, 61) in Table 4. As shown in Figure 10, subqueries in MinSubquery and EntityCenter are more likely to larger result size (rows > 2M). In Table 4, we can see that MinSubquery splits the original query into more subqueries than others.

Table 4: Average amount of subqueries

| Query splitting strategy | Average number |
|--------------------------|----------------|
| MinSubquery              | 6.25           |
| RelationshipCenter       | 2.5            |
| EntityCenter             | 4.5            |

There are three implications of these results: (a) we should try to control the size of subquery results. (b) we should control the amount of subqueries and release the memory allocated for subquery results as soon as they are no longer needed. (c) we should give a high priority to those subqueries that reference previous subqueries, so that we can release the memory previously allocated.

6 DEAL WITH NON-SPJ QUERY

In this section, we discuss how to extend query split to handle queries that contain other operations (e.g. outer join, semi join, or aggregation functions). We first give an overview of the extended query split in Section 6.1, then introduce the specific processing methods for different kinds of non-SPJ operations in Section 6.2. Although we have not implemented the support for these kinds of queries, the basic underlying ideas are quite straightforward.
6.1 Overview

To deal with non-SPJ queries, the basic idea is to split them into non-SPJ operations that connect several SPJ subqueries and apply query split on each subquery.

The workflow of the extended algorithm is shown in Figure 11. If the query \( Q \) is a SPJ query, we simply run standard query split on it. Otherwise, we process \( Q \) as follows:

1. We parse the query, and select a non-SPJ operator (denote as \( op \)) with maximal depth, such that all its inputs are SPJ queries.
2. We obtain the result of \( op \) by the methods that we will describe in Section 6.2.
3. We generate a new query \( Q' \) from \( Q \) by regarding the result of \( op \) as a base relation.
4. Repeat (1)-(3) on \( Q' \) until it becomes a SPJ query.

Figure 11: The workflow of extended query split

6.2 Execute non-SPJ Operators

To obtain the result of a non-SPJ operator, we first construct the input subqueries and execute them via query split. Then, we deliver the subquery results to the non-SPJ operator and execute it.

As shown in Figure 12, to deliver the subquery results to the non-SPJ operator, we can choose either pipelining one tuple at a time or materializing the entire result. Note that this is different from standard query split, since it is not necessary to gather run-time statistics. Although the run-time statistics can be used for choosing a better physical operator, the benefit of doing this is often very limited.

Figure 12: Subqueries of a non-SPJ operator

7 CASE STUDY

In this section, we choose two example queries (in Section 7.1 and 7.2) from JOB as case study to obtain some insights into query split. We demonstrate the detailed execution plan of query split on these queries by Figure 13 and 14, and explain what makes query split faster than PostgreSQL, then discuss our findings from case studies in Section 7.3 and Section 7.4.

Before analyzing the examples, we introduce the marks that will appear in the figures. In Figure 13 and 14, the percentage next to the execution node represents the ratio of the time spent by the physical operator to the total execution time of query split. The colored line represents the boundary of subqueries. The number above the relational algebra represents the estimated and actual size of intermediate results. As the estimation results at the subquery boundaries are precise, we just show the actual value.

7.1 The First Case

As shown in Figure 13, there is a big gap between the cardinality estimation errors in PostgreSQL and query split. We use q-error [26], the factor by which the estimation differs from the true cardinality, to measure the quality of cardinality estimation. The average q-error in PostgreSQL is 246, while in query split it is only 5.

Another major difference in the execution plan between PostgreSQL and query split is about how to deal with the join with table \( ci \). In PostgreSQL, the execution plan directly join \( ci \) with the current intermediate result by nest loop. However, it’s unwise because both left and right subtree are huge. As shown in Figure 13(a), this nest loop costs too much time. In contrast, the decision of query split is much better. As shown in Figure 13(b), execution plan in query split first decreases the size of table \( ci \) by joining with entity relations \( chn \) and \( rt \). Note that although \( chn \) is huge as well, merge join can be applied without sorting and use much less time. Then, after the size of \( ci \) is reduced, it is joined with \( S_2 \). This
decision effectively improves a time-consuming join in PostgreSQL and speeds up the query execution (from 128s to 48s).

7.2 The Second Case

![Join Graph](image1)

![Execution Plan](image2)

Figure 14: The detail of query execution for example 2

As shown in Figure 14, there is also a big gap between the cardinality estimation errors in PostgreSQL and query split. The average q-error in PostgreSQL is 11310, while in query split it is 37.

Figure 14(a) illustrates that the poor performance of PostgreSQL is due to using too much time to join table mi, where two huge inputs are involved. As shown in Figure 14(b), in query split, the optimizer postpones the join with mi, and instead decreases the size of inputs first. So when the join with mi happens in query split, the size of another input is relatively small, which makes the execution faster.

7.3 Our Findings

Now we can generalize two findings from case studies. First, the plan produced by query split is close to optimal plan. This is due to two reasons:

- The execution plan in each subquery is near-optimal. By gathering runtime statistics after the execution of each subquery, optimizer can get precise statistics of base relations in subqueries. Meanwhile, the size of each subquery is small. Under such conditions, cardinality estimation of the database optimizer is relatively accurate.

- By considering both result size and execution time, we can make a decent decision on subquery execution order. We postpone the execution of long-time join and decrease its size by replacing original inputs with other subqueries’ results.

Second, we find that both queries are dominated by a very slow physical operator that consumes a massive piece of time (i.e. merge join and nest loop join), which takes more than half of the total execution time. We study this topic further in Section 7.4 to reveal remaining bottlenecks of query execution when the join order is good enough, and thus can help us further improve the query execution performance.

7.4 A Further Study on Physical Operator

The phenomenon that the execution time is dominated by a single physical operator is in fact quite common in JOB. To study this topic further, we classify queries in JOB according to the operator that takes the longest time during execution, as shown in Table 5.

Table 5: The physical operators that dominate JOB queries

| physical operator | query lds |
|-------------------|-----------|
| hash join         | 23, 24    |
| merge join        | 28, 30, 61|
| index scan        | 1, 2, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 15, 16, 17, 19, 20, 21, 22, 29, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 42, 45, 46, 47, 48, 49, 53, 54, 55, 56, 57, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91 |
| sequential scan   | 14, 18, 25, 26, 27, 41, 43, 44, 45, 50, 51, 52, 58, 59, 60 |

We find that most queries are dominated by an index scan and other queries are dominated by hash join, merge join, or sequential scan. In the following part, we will discuss each of these operators.

7.4.1 Hash Join and Merge Join. It is possible further improve hash join and merge join by using a new and faster physical operator, directmap join. In hash join, to fetch an inner tuple, we need two random memory accesses: one for probing the hash table, another for accessing the inner tuple. If we reduce the number of memory accesses to once, we can achieve a faster execution speed.

By combining probing and accessing data together, directmap join can fetch a matching inner tuple through one memory access. Like hash join, directmap join consists of two phases: build phase and probing phase. In build phase, we copy the data of inner relation into a two-dimension array called map, which can be treated as a combination of hash table and relation data. Due to the join attribute values in JOB being non-negative integer and having limited range, we simply use the original value as hash value (hash(x) = x), and each row of map is used to store an inner tuple.

In probe phase, for each tuple from outer relation with join attribute value x, we fetch the corresponding row map[x] and return the inner tuple if it is not empty. In this way, when probing and accessing an inner tuple, we only use one random memory access. We will explain the detailed implementation of directmap join in Appendix F.

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4Note that our conclusion is derived from JOB, in which the number of queries is limited, and queries are human-write. The above reasons may cause our conclusion to be particular for JOB but not general for other benchmarks.
We use directmap join in those join operator constraint queries (query 23, 24, 28, 30, 61), and compare their execution time with previous results. The end-to-end latencies are shown in Figure 15. Query 28, 30, 61 have more than 50% improvement in end-to-end latency, and query 23, 24 have nearly 25% improvement. The result proves that directmap join can greatly improve the total execution time for queries with join operator as bottleneck.

![Figure 15: The effect of directmap on queries with join operator bottleneck](image)

7.4.2 Index Scan and Sequential Scan. Unlike hash join and merge join, the queries dominated by index scan and sequential scan are hard to improve due to three reasons:

1. The use of scan operators is inevitable.
2. As far as we know, apart from index scan and sequential scan, there are no other comparable scan operators. In other words, if the optimizer has chosen the better scan operator between index scan and sequential scan, then there is little room for further improvement.
3. According to the cost model in PostgreSQL [7], we substitute the true cardinality into the cost model and find the scan operator decision made by the optimizer is indeed correct in query split.

From above three points, we conclude that there is no room to further improve index scan and sequential scan in query split. Hence, under the dynamic query optimization framework, for most queries dominated by a scan operator, query split is already a nearly optimal solution. Although there might exist some other strategies to further improve scan operators, such strategy are beyond the scope of our paper.

8 RELATED WORK

Our work is relevant to three research directions: (a) the literatures that studies the intrinsic difficulty of accurate cardinality estimation; (b) adaptive query processing; (c) researches that aim to improve accuracy of cardinality estimation. We state existing works in these directions respectively in Section 8.1, 8.2, and 8.3.

8.1 Difficulty of Cardinality Estimation

In theory, Ioannidis and Christodoulakis [15] conclude that estimation errors grow exponentially with join size. They study the natural join and assume there is an error on the estimated distribution of join attributes in each relation.

Leis et al. [23] pay attention to practice and use experiments to show that even commercial cardinality estimators produce large errors in real workload. They introduce a new benchmark called “join order benchmark”, which is a simple but challenging benchmark for nowadays database systems. Their experiments suggest that although cardinality estimator can deal with cardinality estimation for the query with only one relation, there are still no techniques that can accurately estimate cardinality with high correlated join predicates.

Their research shows the requirement for new query optimization frameworks and the intrinsic difficulty of accurate cardinality estimation, which inspires our research on dynamic query optimization.

8.2 Adaptive Query Processing

According to reference [2], there are three families in adaptive query processing: plan-based system (reoptimization), routing-based system and continuous-query-based system.

8.2.1 Reoptimization. The most relevant work in the literature is reoptimization. The reoptimization remains the architecture of the traditional database: optimizer and executor. Reoptimization monitors the execution of the current plan and re-optimizes whenever the actual condition differs significantly from the estimations made by the optimizer.

Reopt [18] and Pop [25] are the two most representative studies of the reoptimization. Reopt adds statistic collection operators to the query execution plan and collects statistics after a segment has been executed. When finding that the collected statistic deviates too much from estimation, the database triggers reoptimization and optimizes the unexecuted part by the collected statistic.

The idea of Pop is the same as Reopt, but makes improvements in several aspects. First, Pop can trigger reoptimization in more join nodes, compared to Reopt can only trigger reoptimization at the node where query results are not pipelined. Second, Pop use more complex analysis to decide whether to re-optimize.

And Conquest [28] extends the reoptimization to a parallel execution environment. To decrease the time of collecting the intermediate statistics, sampling reoptimization [37] throws the plan to sampling-based estimator. In recent work, Cuttlefish [19] uses reinforcement learning techniques to explore possible physical operators of an execution plan during query execution and exploits the fastest ones. However, Cuttlefish can only modify the physical operator, but fails to change the join order.

The recent research [31] simulates reoptimization in PostgreSQL. They first observe the error by the “explain” command and materialize the intermediate result that deviates too much from estimation as a temporary table. Then they rewrite the query by replacing the materialized part with the temporary table, and finally they call the optimizer again. Their result shows that reoptimization in PostgreSQL can sharply improve the execution time.

Compared to the reactive interleaving strategy in reoptimization, the high-level concept called “dynamic query optimization” has diverse interleaving pattern. The new dynamic query optimization query split we propose in the paper has two differences with reoptimization. First, query split re-optimize unexecuted subqueries after executing a subquery, which is proactive interleaving, while reoptimization re-optimize the unexecuted part of query in a reactive way. Second, because whether to do reoptimization depends on the execution result, how many times for stopping pipeline and
collecting runtime statistics in reoptimization is unknown. In the worst case, reoptimization can happen after each join, which causes great overhead. On the contrary, query split is robust for the times of plan modification, because we decide when to call optimizer again in advance.

8.2.2 Routing-based system. Routing-based systems eliminate the traditional optimizer and query plans. They process queries by routing tuples through a pool of operators. The idea of the routing-based system can be traced back to INGRES [36], which is the earliest database system. In INGRES, each tuple could be executed in a different order. The routing-based system eliminates the concept of execution plan by routing tuples one by one. Eddies [1] adds a new operator called ripple join, and Eddies can change the join order in ripple join.

Both dynamic query optimization and routing-based system break the unidirectional pipeline between optimizer and executor. However, compared to dynamic query optimization, routing-based systems totally abandon optimizer and executor, which may cause great effort on implementation in current RDBMS.

8.2.3 Continuous-query-based System. Continuous-Query-based, or CQ-based, systems are used for queries that will run many times or a very long time, which is prevalent in the data stream systems. Although CQ-based systems also support variable execution plan during execution, however, there is a huge gap between CQ-base systems and our work. CQ-base systems pay attention to the runtime change of stream characteristics and system conditions, rather than cardinality estimation error for a given query.

8.2.4 Others. Dynamic query plan [3, 6, 10] and parametric query optimization [16] are proposed to change the query plan without calling the optimizer again. They give a set of possible optimal plans to the executor instead of giving one single optimal plan and during execution, the plans can switch to each other. However, it’s hard to control the number of possible optimal plans, and it is expensive to identify those possible optimal plans in optimizer. More severely, the real optimal plan even never falls into the possible optimal plans.

Similar to other adaptive query processing techniques, these works also pay attention to a flexible execution plan. But compared to our work, the use of optimizer and executor in dynamic query plan and parametric query optimization is not interleaved, which leads to a great overhead to maintain multiple execution plans.

8.3 Cardinality Estimation
Cardinality estimation techniques [12] are also relevant. The researches in cardinality estimation techniques aim to improve cardinality estimation. There are two main research areas: data-driven cardinality estimator [5, 9, 11, 14, 21, 22, 35, 38–40], query-driven cardinality estimator [8, 13, 20, 24, 30, 34]. The data-driven cardinality estimator approximates the data distribution of a table by mapping each tuple to its probability of occurrence in the table. The query-driven cardinality estimator uses some models to learn the mapping between queries and cardinalities.

We need to emphasize that there is no conflict between dynamic query optimization and cardinality estimation. On the contrary, query split benefits from the improvement of cardinality estimation on small join. Making an optimal plan in each subquery can significantly enhance total performance.

9 CONCLUSION
The intrinsic difficulties of cardinality estimation makes it a hard-solved problem, however, dynamic query optimization can help the database optimizer avoid these difficulties. In this paper, we propose query split, a proactive strategy of dynamic query optimization. Using run-time statistics and proactively interleaving the optimizer and executor, query split reaches near-optimal latency in Join Order Benchmark. Our results suggest that dynamic query optimization can effectively improve the speed of query execution. Furthermore, the case study shows that under the dynamic query optimization framework, most queries are dominated by a physical operator. The result implies that the execution time on the query can be hugely improved by improving the operator and there is no room for further improving under the dynamic query optimization framework.

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A EQUVALECE RULE
This appendix shows the concrete formulas that can be used to obtain the normal form of SPJ query. Because all selection-projection-join queries are relational algebra expressions that consist of only selection, projection and join, we can transform them to a normal form by equivalence rule:

- For each join expression, we can rewrite it as selection after Cartesian product:
  \[ r_1 \bowtie r_2 = \sigma_{Q}(r_1 \times r_2) \]
- We can change the order between projection and Cartesian product:
  \[ \Pi_A(r_1) \times \Pi_B(r_2) = \Pi_A(\Pi_B(r_1 \times r_2)) \]
- When selection is executed after projection, we can change their orders:
  \[ \sigma_A(r_1) \times \sigma_B(r_2) = \sigma_A(\sigma_B(r_1 \times r_2)) \]
- When selection is executed after projection, we can change their orders:
  \[ \sigma_A(\Pi_B(r_1)) = \Pi_A(\sigma_B(r_1)) \]

B PROOF OF THEOREM 1
This appendix shows the proof of Theorem 1.

Proof. Recall that \( q(R, S, P) \) is an SPJ query, \( Q \) is the set of sub-queries. And \( Q \rightarrow_q q \). The proof is by induction on the \(|Q|\).

First, we prove the statement holds when \(|Q| = 1\), in which \( Q = \{q_1(R_1, S_1)\} \). Apparently the only way that \( Q \rightarrow_q q \) is \( q = q_1 \). So the statement clearly holds for \(|Q| = 1\).

Now, assume that the statement holds when \(|Q| = n - 1\). Now when \(|Q| = n\), \( Q = \{q_1(R_1, S_1), \ldots, q_n(R_n, S_n)\} \).

Without loss of generality, we denote the first executed subquery as \( q_1(R_1, S_1) \) and discuss two case: the first one is

\[ \forall q_i(R_i, S_i) \in Q, i > 1, s.t. R_i \cap R_1 = \emptyset \]

and another one is

\[ \exists q_i(R_i, S_i), \in Q, i > 1, s.t. R_i \cap R_1 \neq \emptyset \]

Case 1: We denote \( Q' = \{q_2(R_2, S_2), \ldots, q_n(R_n, S_n)\} \) and its reconstruction result without projection is \( Q'_{rec} \).

Because

\[ \forall q_i(R_i, S_i) \in Q, i > 1, s.t. R_i \cap R_1 = \emptyset \]
According to Merge phase, the reconstruction result of $Q$ is

$$\text{Recon} = \Pi p(\sigma_{S_i}(r_{M_i} \times ... \times r_{M_k}) \times \text{Recon'})$$

where $r_{M_i} \in R_i$.

On the other hand, the execution result of $q(R, S, P)$ is

$$\text{Exec} = \Pi p(\sigma_{S_i}(r_1 \times ... \times r_N))$$

where $r_1 \in R$

As we know,

$$\forall_{q_i(R_i, S_i)} \in Q, i > 1, s.t. R_1 \cap R_i = \emptyset$$

Hence,

$$\text{Exec} = \Pi p(\sigma_{S_i}(r_{M_i} \times ... \times r_{M_k}) \times \sigma_{S_j}(r_{N_i} \times ... \times r_{N_k}))$$

where $r_{M_i} \in R_i$ and $r_{N_i} \in R - R_i$

Note that $|Q'| = n - 1$ and $\sigma_{S_i \cup ... \cup S_j}(r_{N_i} \times ... \times r_{N_k})$ is the execution result of $Q'$ without projection, using the induction hypothesis,

$$\text{Recon'} = \sigma_{S_i} \sigma_{S_j}(r_{N_i} \times ... \times r_{N_k})$$

where $r_{N_i} \in R - R_i$

Clearly $\text{Exec} = \text{Recon}$.

Case 2: There exists at least a pair of $\{q_i(R_i, S_i), q_j(R_j, S_j)\}$ such that $R_i \cap R_j \neq \emptyset$.

We also denote a set $W$ which $W = \{q_k(R_k, S_k) \in Q; k > 1, R_k \cap R_i \neq \emptyset\}$.

When we execute $q_i$, and then according to replacement reconstruction algorithm, for every $q_j \in W, R_1$ is added to $R_i$. We denote these new-formed $q_j$ as $q'_j$ and $R'_i = R_i \cup R_1$. These new-formed subqueries $q'_j$ consist a new set $W'$.

According to Loop(modify), after we execute $q_i$, $q_i$ is removed from $Q$. The new-formed set of subqueries is denoted by $Q'$. Then, we prove $Q' \rightarrow_c q$.

$$Q' = W' \cup (Q \setminus W \setminus \{q_1\})$$

And thus,

$$R(Q') = R(W') \cup (Q \setminus W \setminus \{q_1\}))$$

$$= R(W') \cup R(Q \setminus W \setminus \{q_1\})$$

$$= R(W') \cup R(Q) \setminus R(W) \setminus R(q_1)$$

Because $R'_i = R_i \cup R_1$, so $R(W') = R(W) \cup R_1$.

$$R(Q') = R(Q)$$

Similarly,

$$S(Q') = S(Q)$$

Hence, $Q' \rightarrow_c q$.

Because $|Q'| = n - 1$, using the induction hypothesis, statement holds for $Q'$, as well as for $Q$.

Thus, statement holds for $|Q| = n$.

## C POSTGRESQL CONFIGURATION

This appendix shows the configuration parameters we use in PostgreSQL. We set the memory limit per operator work_mem to 2 GB, the shared memory buffer shared_buffers to 512 MB and the size of the operating system’s buffer cache used by PostgreSQL effective_cache_size to 96 GB.

We modified the parameters of the cost model in order to fit our experimental settings. There are five configuration parameters for cost model, and we determine their value by ordinary least squares. We first execute SELECT queries, for example, “select * from A;” and “select * from A where A.id < 1000;”. Then we obtain their latency and the true cardinality. Next, as we know the true cardinality, the cost model of scan operator becomes the linear combination of cost model parameters. We let the estimated cost of the plan equal to the latency, and use ordinary least squares method to calculate the approximation value of five parameters. By this way, we set seq_page_cost to 3, set random_page_cost to 3, set cpu_tuple_cost to 0.07, set cpu_index_cost to 0.07, set cpu_operator_cost to 0.02 on our computer.

## D THE DETAIL OF OPTIMAL PLAN

This appendix describes the details of optimal plan. In order to know the least execution time that PostgreSQL can achieve, we design an optimizer that can make optimal plans. We achieve this by building a simple history-recording optimizer and use the same query as input repeatedly. During whole iteration, we record the true cardinality of executed intermediate relations, and when we meet the intermediate relation that appeared before, we replace the cardinality estimation with its true cardinality. So, as more and more true cardinalities have been known, the plan made by the optimizer is closer to the optimal plan.

The implementation of history-recording optimizer is based on a history list. Each member in the history list contains a bitmap as the token of intermediate relation and its true cardinality. The length of bitmap represents how many base relations in the query, each bit represents a base relation, and we set the bit as 1 if the corresponding base relation is involved in the intermediate relation. For example, given a query $q = r_1 \bowtie r_2 \bowtie r_3 \bowtie r_4$, the bitmap of intermediate relation $r_1 \bowtie r_2 \bowtie r_3$ as 1100, $r_2 \bowtie r_3 \bowtie r_4$ as 0110 and $r_3 \bowtie r_4$ as 1110.

However, as some intermediate results may not appear in the execution plan during whole iterations, we have to encourage the optimizer to try the join orders that it haven’t explored. This is achieved by artificially decreasing the cost of new join orders. More specifically, as the cost is relevant to the relation size, we decrease the estimation size of new intermediate relation by multiplying a factor (we use 0.1 for most queries, 0.5 for some huge queries).

Due to history-recording and encouragement for new join orders, the plan changes during the iteration, and when the plan stops changing, this plan is the optimal plan.

## E RE-POSTGRESQL

This appendix describes the implementation of Re-PostgreSQL. Re-optimization consists of three key points: when to collect statistics, what kinds of statistics to be collected, and how to modify the execution plan.
We choose to do the collection at each physical operator. For what we call the optimizer again to make a new execution plan for the whole query is executed. This appendix describes the implementation of directmap join.

The kinds of statistics to be collected and the overhead of reoptimization is a trade-off. The more kinds of statistic collected, the better execution plan will be made. However, the time used to collect statistics increase as well, which increase the total execution time.

When deviation appears, reoptimization need to consider how to modify the execution plan with new statistics. Discarding the whole execution and generating a new execution plan could be simple, but need significant overhead. Another more feasible way is to suspend the process of tuples, reserve the executed part and modify the part of the original query that has not started executing yet.

Now, we describe our implementation of reoptimization in PostgreSQL from these three parts. For the timing to collect statistics, We choose to do the collection at each physical operator. For what kinds of statistics to be collected, we just collect the rows, number of distinct values, and most common value and its frequency if most common value exists, because they are basic statistics in PostgreSQL, and is enough to generate a better execution plan. At last, as soon as we collect the statistics from a materialized result, we call the optimizer again to make a new execution plan for the remainder of the original query, and we output the final result when the whole query is executed.

### F DETAIL OF DIRECTMAP JOIN

This appendix describes the implementation of directmap join.

In the build phase, we copy inner relation into a two-dimensional array called map, which can be treated as a special hash table with the data of inner relation. The hash function of map is $\text{hash}(x) = x$. Note that this simple hash function only works when the join attribute value is a non-negative integer, which is satisfied in JOB but not in all benchmarks. And each row of map is used to store a data tuple, and by given hash function, the data tuple is stored at the row whose row number equals the value of the data tuple’s join attribute.

Except for data slot, each row of the map also contains a header. Header consists of three components: valid, previous, and next. valid represents if the data slot has been occupied by an inner tuple. However, it is common that several tuples have the same value on the join attribute, which causes a conflict. previous and next are used to solve this conflict. They respectively store the row number of previous or next tuple that has the same join attribute value. Hence, they maintain a list of the tuples that have the same value on the join attribute.

We fetch inner tuple from scan operator one by one to create map. There would be three conditions when we receive an inner tuple.

**Condition 1**: if an inner table tuple $t_1$ comes, we first calculate the row number of the row that it will store in according to its value of the join attribute. Then we check valid to ensure the target row is empty. If valid is 0, we store $t_1$ in the target row and set previous and next to N/A.

**Condition 2**: if previous equals to $N/A$, we call $t_2$ as host tuple, which means the join attribute value of $t_2$ equals to the row number. Then we place the new-come inner tuple $t_1$ to an empty row. And we need to find the lastest-stored tuple $t_3$ that has the same join attribute value and its corresponding row number. This can be achieved by using next to access the next tuple and its row, and repeating until next equals to $N/A$. Next, we set previous of $t_1$ as the row number of $t_3$, next of $t_1$ as $N/A$, and next of $t_3$ as row number of $t_1$. We call the new-come tuple $t_1$ as “guest tuple”, which means the join attribute value of the tuple is not equal to the row number of the row where it stores.

**Condition 3**: if we find the row is occupied by a "guest tuple" $t_2$, we first move $t_2$ to a new empty row, then fit $t_1$ in this row as "host tuple" and set the previous and next to $N/A$. As $t_2$ is in a list where all members have the same join attribute value, we have to modify previous of $t_2$’s next cell and next of $t_2$’s previous cell to fit the new row number of $t_2$.

If valid is 1, which indicates that the row has been occupied by another inner tuple $t_2$, we check previous of the row.

Figure 16: The illustration of condition 2

| map | valid | previous | next | data slot |
|-----|-------|----------|------|-----------|
| [0] | 1     | N/A      | N/A  | NULL      |
| [1] | 1     | N/A      | N/A  | Inner Tuple $t_1$ |
| [2] | 1     | N/A      | N/A  | Inner Tuple $t_2$ |
| [3] | 0     | N/A      | N/A  | NULL      |

Figure 17: The illustration of condition 3

After introducing how to build map, we describe how to return a join result in probe phase. As shown in Figure 18, we first fetch an outer tuple, and then we get the join attribute value of outer tuple as row number to fetch the corresponding row in map. After we fetch the corresponding row from map, we check its valid word. If empty, we fetch the next outer tuple and repeat above steps. Otherwise,
we check its next. If \( N/A \), which means there is only one tuple has given join attribute value, we return the join result and fetch next outer tuple. If not \( N/A \), we not only return the join result, but also need to fetch the successors that have the same join attribute value by setting the row number as the value of next.

Figure 18: How directmap join works

There is another problem is how to combine directmap join with PostgreSQL optimizer. By our design, whether the optimizer chooses the directmap join operator depends on the a heuristic judgment and its cost model.

A heuristic judgment is used to control the memory usage, as the size of map is no less than the maximum of join attribute, which means directmap join sacrifices memory to earn speed. First, we ensure that the inner relation must be a base relation or a subquery result to avoid too much confliction. Then, we check the ratio \( t = f_r/n_r \), where \( f_r \) is the estimated number of tuples after applying the predicate on inner relation, and \( n_r \) is the size of inner relation. As map size is no less than the maximum of appeared join attribute values, we use \( n_r \) to approximate the map size. And \( f_r \) equals the number of rows that we actually use in map. Hence, the ratio can roughly estimate the ratio of how much memory that we actually use for storage and allocate for directmap join, which reflects the memory utilization rate of directmap join. If the ratio is less than a threshold, we think it’s memory-wasteful to create a map, so we abandon the consideration of using directmap join.

Second, we set the cost model of directmap join by imitating the cost model of hash join. As directmap join reduced twice memory access to once, we half the fetch cost by CPU. To show our change in fetch cost, we divide the cost of hash join by two as the cost of directmap join.