On-Demand Re-Optimization of Integration Flows

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Abstract

Integration flows are used to propagate data between heterogeneous operational systems or to consolidate data into data warehouse infrastructures. In order to meet the increasing need of up-to-date information, many messages are exchanged over time. The efficiency of those integration flows is therefore crucial to handle the high load of messages and to reduce message latency. State-of-the-art strategies to address this performance bottleneck are based on incremental statistic maintenance and periodic cost-based re-optimization. This also achieves adaptation to unknown statistics and changing workload characteristics, which is important since integration flows are deployed for long time horizons. However, the major drawbacks of periodic re-optimization are many unnecessary re-optimization steps and missed optimization opportunities due to adaptation delays. In this paper, we therefore propose the novel concept of on-demand re-optimization. We exploit optimality conditions from the optimizer in order to (1) monitor optimality of the current plan, and (2) to trigger directed re-optimization only if necessary. Furthermore, we introduce the PlanOptimalityTree as a compact representation of optimality conditions that enables efficient monitoring and exploitation of these conditions. As a result and in contrast to existing work, re-optimization is immediately triggered but only if a new plan is certain to be found. Our experiments show that we achieve near-optimal re-optimization overhead and fast workload adaptation.

Keywords: Integration Flows, Optimization, Workload Adaptation

1. Introduction

Increasing amounts of data as well as technical and organizational issues, like new technologies and pragmatic behavior, fundamentally changed the scope of data management towards distributed data management across numerous heterogeneous systems, applications, and small devices [1]. For this reason, the seamless and efficient integration of these systems becomes more and more

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crucial for an IT infrastructure and it is seen as one of the most expensive challenges information technology faces today [2].

In order to cope with the high degree of system heterogeneity and complex procedural integration tasks, imperative integration flows are modeled and executed to exchange data between these systems [3]. There are many important application domains such as enterprise information systems, financial messaging, energy data management, telecommunications, or health care management [4]. Integration flows are deployed once and then repeatedly executed by an integration platform, often over months and years. Examples of such platforms are ETL tools (Extraction Transformation Loading), EAI servers (Enterprise Application Integration) or MOM systems (Message-Oriented Middleware), which have converged more and more in the past [3, 5].

In general, there are two major types of use cases for integration flows. First, *horizontal integration* refers to data synchronization between operational systems by EAI or MOM tools. Data exchange is triggered on updates and hence realized by propagating many small messages [6]. Second, *vertical integration* refers to consolidating data of operational systems into data warehouse infrastructures by ETL tools. There is an increasing demand of operational business intelligence that also requires immediate data synchronization in order to achieve up-to-date operational reports [7, 8, 9]. This immediate synchronization is realized with techniques like increased delta load frequencies or even update-driven data propagation (trickle feeds) [7, 10].

Both types of use cases lead to the execution of many independent plan instances of integration flows over time. Additionally, often low message latency is required due to the need for up-to-date information and potentially blocking source systems. The high load combined with low latency requirements inherently leads to a need for optimization to overcome the performance bottleneck. Existing work on optimizing integration flows can be classified as follows into *rule-based*, *cost-based*, and *adaptive cost-based* approaches:

Rule-Based Optimization applies static rewrite rules (e.g., algebraic simplifications) during initial deployment of an integration flow (optimize-once) [11, 12, 13, 14]. While this approach imposes low optimization overhead, many optimization opportunities cannot be exploited because rewriting often requires dynamic cost-based decisions.

Cost-Based Optimization exploits the full optimization potential by applying dynamic rewritings based on estimated costs [10, 13, 15, 16]. Existing approaches are still only executed once during initial plan deployment (optimize-once). These works are important steps towards adaptive behavior but they cannot adapt the deployed integration flows to changing workload characteristics [17, 18, 19] such as varying cardinalities, selectivities, or execution times.

Reasons for workload changes are manifold such as varying usage schemes of external systems [20] or varying network properties [18]. For example, consider a web shop, where new orders are immediately propagated to a central system. Time-varying numbers of orders cause changing input cardinalities (load shifts). Fluctuating order frequencies per product category reason changing selectivities (data shifts). Varying utilization of external systems or network

speeds—especially, in wide-area networks—influence execution times. Workload characteristics in real productive systems change significantly over time as shown by surveys on eLearning query workloads [21], Website requests [20], and storage workload traces [22]. Missing adaptation to such workload changes is a serious problem because integration flows are deployed for long time horizons. Clearly, existing approaches could easily be extended to an adaptive optimize-always model by triggering optimization for each new plan instance or even permanently. However, due to many short-running plan instances, this is inefficient and thus reasons the need for dedicated re-optimization models.

Adaptive Cost-Based Optimization tries to repeatedly improve the current plan according to the changing workload characteristics. In contrast to traditional adaptive query processing [17], many consecutive instances of deployed integration flows are executed over time. This allows for efficient, asynchronous, inter-instance plan re-optimization. Here, the state-of-the-art is *periodic re-optimization*, where optimization is triggered with fixed optimization interval [4, 23]. On the positive side, this simple model ensures full optimization potential and robust workload adaptation with moderate optimization overhead. On the negative side, it has the drawbacks of (1) many unnecessary re-optimization steps, (2) adaptation delays, where we miss optimization opportunities, (3) maintenance of statistics that might not be used by the optimizer, and (4) the optimization interval as a high-influence parameter.

Contributions

The main contribution of this paper is the novel concept of *on-demand re-optimization* for integration flows. This overcomes drawbacks of existing techniques and ensures near-optimal adaptive re-optimization. The core idea is to exploit optimality conditions from the optimizer for *monitoring optimality* of the current plan and triggering *directed re-optimization* only if necessary. Furthermore, we make the following detailed contributions that also reflect the structure of this paper (an extended and revised version of [4], Chapter 6):

- First of all, we give a concise background description of integration flows and their optimization in Section 2. Additionally, we present the vision and solution overview of on-demand re-optimization in Section 3.
- Second, we introduce the monitoring of optimality in Section 4. We define the `PlanOptTree` as a compact representation of optimality conditions as well as we describe algorithms for creating `PlanOptTrees` and for monitoring optimality during statistic maintenance.
- Third, we introduce the directed re-optimization in Section 5. This includes algorithms for determining the re-optimization search space, directed re-optimization for example optimization techniques and updating `PlanOptTrees` after re-optimization.
- Fourth, we describe detailed results of our experiments in Section 6, where we achieve near-optimal optimization overhead and workload adaptation.

- Finally, we extensively survey related work in Section 7 and conclude the paper in Section 8.

2. Background and Preliminaries

As a foundation, we first briefly describe the background of integration flows and their optimization. Subsequently, we systematically analyze drawbacks of existing techniques for adaptive cost-based optimization.

2.1. Integration Flows

An integration flow is an imperative workflow description consisting of control-flow-, data-flow-, and interaction-oriented operators that receive, extract, transform, and propagate data in the form of messages. Often control-flow-oriented languages such as BPEL (Business Process Execution Language), extended by relational operators, are used to specify these integration flows [4, 7, 14]. Compared to pure data flows, these imperative control flows additionally express temporal dependencies between operators, e.g., execute operator o_1 *before* o_2. Intermediate results of integration flows are represented as messages, where each message is modeled as $msg_i = (t_i, d_i)$ with $t_i \in \mathbb{Z}^+$ being the message creation timestamp and d_i being a tree of name-value data elements. Formally, an integration flow is defined as follows:

Definition 1 (Integration Flow). *A plan P of an integration flow is a sequence of* atomic *or* complex *operators $o = \{o_1, o_2, \ldots\}$, where complex operators recursively contain operator sequences. We denote the total number of operators as $m = |o|$. Each operator o_i may have an arbitrary number of input variables $\{ds_{in_1}(o_i), \ldots, ds_{in_{k1}}(o_i)\}$ and output variables $\{ds_{out_1}(o_i), \ldots, ds_{out_{k2}}(o_i)\}$ spanning a directed graph of (temporal and data) dependencies δ. An instance p_i of a plan P is instantiated in a time-based manner or for each received message, and it executes o once. Due to complex operators such as iterations and alternatives some operators may be executed multiple times or not at all.*

The following example shows such an integration flow. We use this as running example throughout the whole paper.

Example 1 (Integration Flow). *New product orders are propagated from a specific ERP system s_1 to a DWH s_2 using plan P as shown in Figure 1. An ERP adapter instance receives the incoming messages and transforms them into an internal XML representation. Plan instances are initiated and executed for each received message in arrival order (`Receive` operator). We then execute three different `Selection` operators in order to filter special-purpose orders, where in this case each `Selection` applies an expensive probe filter. Such a filter probes all returned elements of a given XPath expression against a hashset of disjunctive predicates and discards elements where this probe is unsuccessful. Subsequently, a `Switch` operator redirects the control flow using content-based*

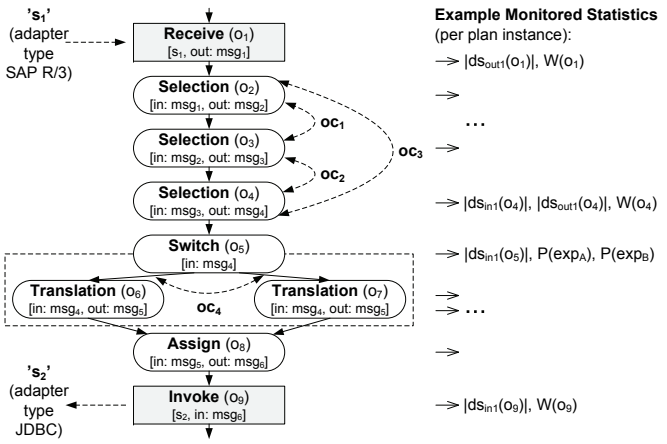


Figure 1: Running Example Integration Flow.

predicates to specific `Translation` *operators that apply XML message transformations. Finally, the result is loaded into the DWH using* `Assign` *and* `Invoke` *operators as well as a DB adapter instance.*

Integration flows such as our example are deployed once into an integration platform and then repeatedly executed.

System Architecture: The major commercial integration platforms such as SAP Process Integration, IBM Message Broker, or MS Biztalk Server all exhibit a common system architecture. Inbound adapter instances (e.g., s_1 in Example 1) receive messages from external systems, transform them into an internal presentation (e.g., XML), and append them to persistent inbound message queues. For each received message a plan instance is executed, in serial order of message arrival. Those plans interact (read/write) with external systems via outbound adapter instances (e.g., s_2), which are—similar to inbound adapters—an abstraction of different types and instances of external systems.

2.2. Optimization of Integration Flows

Regarding the existing high performance demands on integration platforms, we now give an overview of adaptive cost-based re-optimization of integration flows [4, 23].

Cost Model: As a foundation for cost-based optimization and due to the specific characteristics of (1) missing statistics (external and unknown data), (2) arbitrary interactions with external systems (black-box), and (3) control-flow-oriented operators, we employ a *double-metric cost model*. Essentially, we monitor and incrementally maintain runtime statistics such as execution times $W(o_i)$ and input/output cardinalities $|ds|$ at operator level. These statistics are fed into operator-type-specific cost formulas of cardinality-dependent costs $C(o_i)$ (tailor-made for known operators, linear for black-box interactions) and execution times $W(o_i)$. The execution time of a rewritten subplan P' can then

be estimated by an aggregate (e.g., sum for operator sequences) over adjusted operator costs with

$$\hat{W}(o_i') = \hat{C}(o_i')/C(o_i) \cdot W(o_i). \quad (1)$$

This time-based cost model enables the comparison of all different types of operators, allows to take parallelization into account, and it is self-adjusting to changing workload characteristics.

Optimization Algorithm: Our optimization algorithm then uses this cost model as a basis for cost-based optimization techniques. We use a transformation-based approach in order to preserve semantic correctness of the initially specified, imperative plan. In order to ensure low latency, our basic optimization objective is to minimize the *average* plan execution time with

$$\phi : \min \hat{W}(P) \quad (2)$$

but it can be combined with techniques for throughput optimization by taking message waiting times into account. The algorithm essentially iterates over the hierarchy of operator sequences and applies optimization techniques. Finally, it recompiles and exchanges plans. Each optimization technique relies on specific optimality conditions for certain rewriting pattern. We employ techniques from traditional data management, techniques from programming language compilers, and new tailor-made techniques for integration flows.

Adaptive Re-Optimization: Furthermore, we use *periodic re-optimization* for adaptation to changing workloads [23]. The simple yet effective basic idea is to periodically trigger re-optimization with an optimization interval Δt to adapt the deployed plan to the current runtime statistics. We use an example to illustrate this re-optimization model.

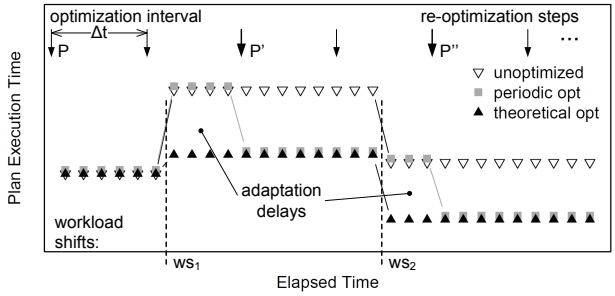
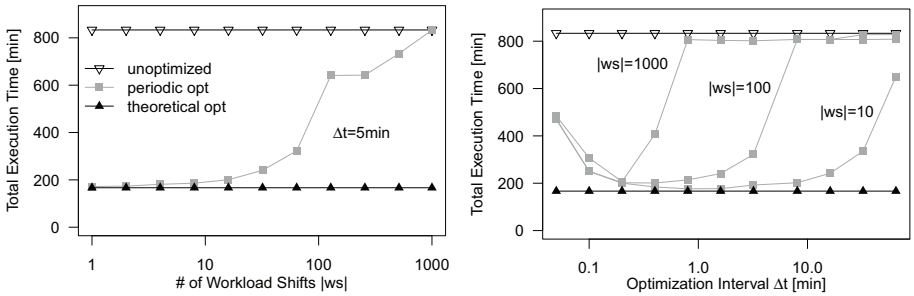


Figure 2: Example Periodic Re-Optimization.

Example 2 (Periodic Re-Optimization). *Figure 2 shows the plan execution times in a scenario with two workload shifts. Periodic re-optimization triggers re-optimization with an optimization interval Δt. After a workload shift occurred (e.g., ws_1), the next re-optimization will find the new optimal plan (e.g., P') but there is an adaptation delay until plan rewriting takes place. If no workload shift has occurred during Δt, we do not find a new plan and thus execute unnecessary re-optimization steps.*



(a) Workload Shifts (b) Optimization Interval

Figure 3: Sensitivity of Periodic Re-Optimization.

To summarize, periodic re-optimization exhibits several drawbacks. First, there are adaptation delays, where we miss optimization opportunities. Second, we might execute many unnecessary full re-optimization steps. Third, we might gather statistics that are not used by the optimizer. Fourth, the optimization interval is a parameter that requires tuning. Since the severity of these drawbacks depends on the workload, we systematically quantify the problems (1), (2), and (4) by the following sensitivity analysis.

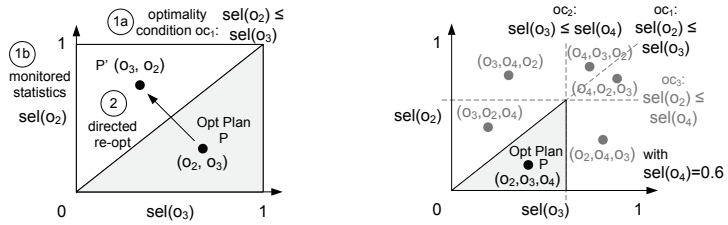
Example 3 (Sensitivity Analysis). *Assume a scenario, where we serially execute* $n = 100{,}000$ *instances of plan* P*. Let* $|ws|$ *denote the number of workload shifts that occur uniformly distributed every* $n/|ws|$ *plan instances. Furthermore, let* $W(P) = 0.5\,\text{s}$ *be the unoptimized plan execution time, let* $W(P') = 0.1\,\text{s}$ *be the optimized plan execution time, and let* $W(opt) = 2\,\text{s}$ *be the optimization time. Figure 3 then shows the total runtime when using periodic re-optimization with optimization interval* Δt*. Figure 3(a) shows the influence of* $|ws|$ *with fixed* $\Delta t = 5\,\text{min}$*. For increasing workload dynamics, periodic re-optimization degenerates from near-optimal performance to the unoptimized case. Figure 3(b) illustrates the impact of* Δt*. For small* Δt *there is high re-optimization overhead and for large* Δt *there are high adaptation delays. In case of almost static workloads (*$|ws| = 10$*), the overall performance is indeed fairly in-sensitive to* Δt*. However, as workload dynamics increase (*$|ws| = 100$ *and* $|ws| = 1{,}000$*) the sensitivity increases and thus it becomes difficult to find a good* Δt*. Finally, it is noteworthy that the alternative approach of triggering re-optimization if statistics have changed significantly has the same conceptual problem. Due statistic fluctuations, a sensitivity parameter is required for deciding on change significance. If it is chosen too high, there are high adaptation delays; if chosen too low, there are many unnecessary re-optimization steps.*

We conclude that periodic re-optimization is a simple indeed effective technique if workload changes are rare events or if the workload is exactly known. On the downside, the overall performance can degenerate to the performance of the unoptimized case.

3. Solution Overview

In this paper, we present the novel *on-demand re-optimization* model that achieves both, robust and near-optimal adaptive re-optimization. Our core idea is (1) to monitor optimality of the current plan via optimality conditions and (2) to apply directed re-optimization if conditions are violated. The following example illustrates these two basic concepts.

Example 4 (On-Demand Re-Optimization). *Consider the subplan* $P = (o_2, o_3)$ *consisting of two* `Selection` *operators (see Figure 1). The search space for this subplan is illustrated as a plan diagram*[2] *in Figure 4(a). The plan* (o_2, o_3) *is optimal as long as* $oc_1 : sel(o_2) \leq sel(o_3)$ *(with* $sel(o_i) = |ds_{out}(o_i)|/|ds_{in}(o_i)|$*), i.e., the selectivity of* o_2 *is lower or equal to the selectivity of* o_3*. Thus, the optimality condition* oc_1 *models optimality of the current plan (1a). Then, we maintain only necessary statistics that are involved in this optimality condition, i.e.,* $sel(o_2)$ *and* $sel(o_3)$*, and use them for continuously monitoring of optimality (1b). If* oc_1 *is violated, we use this condition for directed re-optimization in order to determine* $P' = (o_3, o_2)$ *as the new optimal plan (2). As shown for a larger subplan* $P = (o_2, o_3, o_4)$ *in Figure 4(b), we maintain only optimality conditions of the current (optimal) plan, i.e.,* oc_1 *and* oc_2 *instead of all possible plans. For the sake of a clear presentation, we use this simple example throughout the whole paper but—as we will exemplify in Subsection 5.2—the basic concepts apply to arbitrary operators and optimization techniques.*



(a) Plan Diagram $P(o_2, o_3)$ (b) Plan Diagram $P(o_2, o_3, o_4)$

Figure 4: Plan Search Space Partitioning.

For enabling on-demand re-optimization, we introduce the `PlanOptTree` data structure as a compact representation for arbitrary optimality conditions. The `PlanOptTree` of a current plan indexes monitored and derived statistics as well as current optimality conditions. We then use it for incremental online statistics maintenance and checking of optimality conditions. This continuous

[2]Traditional two-dimensional plan diagrams [24] rely on a complete what-if search space analysis, while we model break-even points of plans via multi-dimensional optimality conditions.

monitoring of optimality allows us to immediately trigger re-optimization if necessary, i.e., if violated conditions guarantee that we will find a plan with lower costs. In addition, the violated conditions can also be exploited for directed re-optimization.

Example 5 (`PlanOptTree`). *The `PlanOptTree` of our running example (Figure 1) is shown in Figure 5. It includes two optimality conditions (oc_1, oc_2) for expressing the ordering of the `Selection` operators o_2, o_3 and o_4 according to their selectivities (oc_3 is omitted due to transitivity) and the condition oc_4 expressing branch prediction of the `Switch` operator o_5 regarding its cost-weighted path frequencies.*

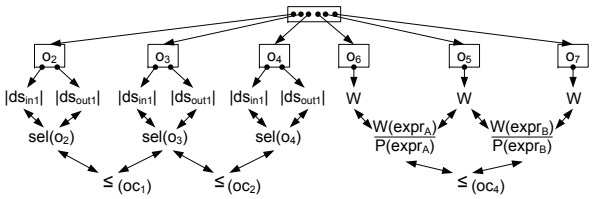


Figure 5: `PlanOptTree` of the Running Example.

In the following, we explain the monitoring of optimality and directed re-optimization using `PlanOptTrees` in detail.

4. Monitoring Optimality

In this section, we formally define the `PlanOptTree` and show how to create a `PlanOptTree` during initial plan optimization. Furthermore, we explain how to use it for statistic maintenance and discuss when to trigger re-optimization.

4.1. Plan Optimality Trees

A `PlanOptTree`, which general structure is shown in Figure 6, models plan optimality and it is defined as follows:

Definition 2 (`PlanOptTree`). *Let P denote the* optimal *plan with regard to the current statistics, let m be the number of operators, and let s be the number of statistics per operator. Then, the `PlanOptTree` is defined as a graph of five strata representing all optimality conditions of P:*

- RNode (stratum 1): *A single Root Node refers to m' ($1 \leq m' \leq m$) operator nodes (ONode).*
- ONode (stratum 2): *An Operator Node specifies a unique plan operator via a node identifier nid and it refers to s' ($1 \leq s' \leq s$) statistic nodes (SNode).*

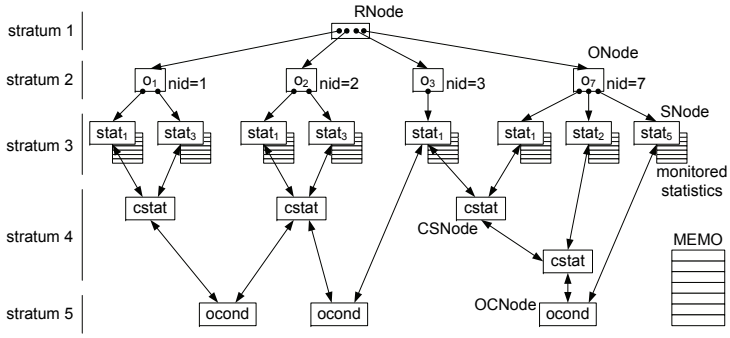


Figure 6: General `PlanOptTree` Structure.

- SNode (stratum 3): *A Statistic Node exhibits one of the s atomic statistic types s_j (e.g., input cardinality), where this type must be unique for the parent operator o_i. Each SNode maintains a sliding window of statistic tuples monitored for (o_i, s_j), a single aggregate, as well as references to child sets of complex statistic nodes (CSNode) and optimality condition nodes (OCNode).*

- CSNode (stratum 4): *A Complex Statistic Node is a mathematical expression using all referenced parent SNodes or CSNodes as operands, where a CSNode can refer to SNodes of different operators. Further, a CSNode refers to child sets of CSNodes and OCNodes. Hence, arbitrary hierarchies of CSNodes are possible. CSNodes can also be constants or external values.*

- OCNode (stratum 5): *An Optimality Condition Node is defined as a boolean expression $op_1\ \theta\ op_2$, where θ denotes an arbitrary binary comparison operator and the operands op_1 and op_2 refer to any CSNode or SNode, respectively. The optimality condition is defined as violated if the expression evaluates to false. In addition, each OCNode refers to its source of creation in terms of the originating optimization technique.*

References to nodes of strata 1 and 2 are unidirectional, while nodes of strata 3-5 are bidirectional. Furthermore, a `PlanOptTree` includes a `MEMO` structure[3] *in order to optionally mark subgraphs that have already been evaluated because nodes might be reachable over multiple paths.*

The defined general `PlanOptTree` structure exhibits the following four fundamental properties:

[3]For clarity of presentation, we omit the usage and maintenance of this `MEMO` structure in our algorithms. From a high-level perspective, it can be understood as a lookup table for memoization in order to reuse results of subgraphs and to prevent redundant computations.

- *Optimality:* Since a `PlanOptTree` models plan optimality, we will only find a plan with lower cost if at least one optimality condition is violated. Thus, there is no need for re-optimization until we detect a violation.
- *Transitivity:* If statistics are included in multiple optimality conditions, we can leverage transitively given optimality conditions. For this reason, potentially only a subset of all relevant optimality conditions are required to monitor the optimal plan.
- *Minimality:* A `PlanOptTree` includes only operators and statistics that are included in optimality conditions. Thus, we achieve minimal statistics monitoring and minimal condition evaluation (see transitivity) under the requirement of still ensuring optimality.
- *Directed Re-Optimization:* In case of violated optimality conditions, the knowledge of still valid conditions can be exploited for reducing the re-optimization search space to a subset of the original search space.

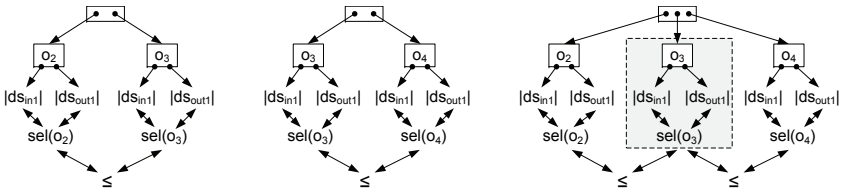
These properties hold for a *complete* `PlanOptTree` that is defined to cover all relevant optimality conditions of a plan. Otherwise, we would have redundancy or missing conditions.

4.2. Creating PlanOptTrees

During initial deployment of a plan, the full cost-based optimization is executed once and an initial `PlanOptTree` is created. Subsequently, we solely rely on incremental and directed re-optimization by leveraging this `PlanOptTree`. We now explain how to create the initial `PlanOptTree`.

Our transformation-based optimization algorithm (described in Subsection 2.2) recursively iterates over the hierarchy of operator sequences and changes the current plan by applying optimization techniques. For on-demand re-optimization, we extended the optimizer in a way that it does not only change the current plan but additionally, each applied optimization technique also returns a *partial* `PlanOptTree` representing optimality conditions for the considered subplan. The use of partial `PlanOptTrees` at the optimizer interface is reasonable because directed re-optimization potentially considers only subplans and thus can only return partial `PlanOptTrees`. Creating the initial `PlanOptTree` then reduces to merging all partial `PlanOptTrees` to a minimal representation. In the following, we describe an example and the general-case algorithm.

Example 6 (Merging Partial `PlanOptTrees`). *Recall the running example plan P and assume the two partial `PlanOptTrees` shown in Figures 7(a) and 7(b). These `PlanOptTrees` have been created by applying selection reordering on operators (o_2, o_3, o_4). In detail, they consist of ONodes, SNodes, a CSNode `Selectivity`, and an OCNode. Both partial `PlanOptTrees` include operator o_3 and its selectivity CSNode. Therefore, we add only o_4 and its child nodes from pot_2 to pot_1. When doing so, the dangling reference from the new optimality condition to $sel(o_3)$ of pot_2 is modified to refer to the existing $sel(o_3)$ of pot_1. The final merged `PlanOptTree` pot is shown in Figure 7(c).*



(a) Partial pot_1 (b) Partial pot_2 (c) Merged pot

Figure 7: Merging Partial `PlanOptTrees`.

Algorithm A-PC (`PlanOptTree` Creation): The A-PC (see Algorithm 1) creates the initial `PlanOptTree` by recursively iterating over all operators and merging respective partial `PlanOptTrees`. In case of complex operators, we recursively invoke the A-PC, where all subcalls have access to the *root* `PlanOptTree`. At each operator (atomic or complex), we apply all operator-type-related optimization techniques, where each technique returns resulting partial `PlanOptTrees`. Some optimization techniques directly optimize whole sequences of operators during the first invocation on an operator of this sequence, where invocations for other operators of this sequences are then ignored.

Algorithm 1 `PlanOptTree` Creation (A-PC)

```
Require: operator op, global PlanOptTree root (initially NULL)
 1: o ← op.getSequenceOfOperators()
 2: for i ← 1 to |o| do                                   // for each operator o_i
 3:   if type(o_i) ∈ (Plan, Switch, Fork, Iteration) then          // complex
 4:     A-PC(o_i)                  // recursive invocation for complex operators
 5:   else                                                      // atomic operators
 6:     ppot ← getPartialOptTree(o_i)
 7:     if root = NULL then
 8:       root ← ppot
 9:     else                                        // merge partial PlanOptTrees
10:       for all on ∈ ppot.onodes do                        // for each ONode on
11:         if root.containsONode(on.nid) then
12:           eon ← root.getOperator(on.nid)
13:           for all sn ∈ on.snodes do                    // for each SNode sn
14:             if eon.containsSNode(sn.type) then
15:               eson ← eon.getSNode(sn.type)
16:               modifyDanglingRefs(eon, eson, on, sn)
17:             else
18:               eon.snodes.add(sn)
19:         else
20:           root.onodes.add(on)                          // add operator subtree
21: return root
```

For example, the first invocation of selection reordering on operator o_2 will reorder the sequence (o_2, o_3, o_4) and returns pot_1 and pot_2. If no `PlanOptTree` exists so far, the first partial `PlanOptTree` is used as *root*; otherwise, we merge the partial `PlanOptTree` with the existing *root*. When merging, we check the existence of operators as well as statistic nodes, and we add new nodes if required. For complex statistic nodes, we modify dangling references in order to recursively change the references of complex statistics and optimality conditions to the existing `PlanOptTree`. Identical CSNodes are determined by ID or equivalence of input nodes and CSNode class.

Optimizations: Context knowledge of operators can be exploited for optimization. For example, we reuse the output cardinality SNode of operator o_i as input cardinality SNode for operators with data dependencies to o_i (partially applied in our examples) because these statistics are per se equivalent. In general, reusing statistics is beneficial for expensive statistic maintenance approaches.

Complexity Analysis: Clearly, the space complexity of a `PlanOptTree` and the time complexities of `PlanOptTree` algorithms depend on the complexity of applied optimization techniques and their optimality conditions. Regarding monitoring optimality, the `PlanOptTree` is indeed optimal due to its properties of transitivity and minimality. However, for certain plan structures and problems, efficient bounds can be established. For example, Appendix A shows a worst-case complexity of $\mathcal{O}(m^2)$ for *local* reordering sequences of operators.

The `PlanOptTree` represents plan optimality via optimality conditions based on current statistics. Hence, only the update of statistics can cause the need for re-optimization.

4.3. Updating and Evaluating Statistics

In order to enable immediate re-optimization in case of violated optimality conditions, we use the `PlanOptTree` also for incremental online statistic maintenance and continuous monitoring of plan optimality via optimality conditions.

A `PlanOptTree` maintains statistics that are required for monitoring optimality conditions. Atomic statistics are as usual gathered at operator-level during plan execution and immediately inserted into the `PlanOptTree`, where unnecessary statistics are declined. Every SNode exhibits a state in terms of *aggregated* atomic statistics (e.g., average input cardinality) because we optimize the *average* case. Different aggregation methods or even time series models can be used. By default, we employ the *simple exponential smoothing*:

$$\mathrm{EMA}_t = \mathrm{EMA}_{t-1} + \alpha\left(s_t\left(o_i\right) - \mathrm{EMA}_{t-1}\right) \quad \text{with} \quad \alpha \in [0,1]. \tag{3}$$

Included statistics $s_t(o_i)$ exhibit exponentially decaying weights due to the recursive computation, where α is used to adjust the smoothing sensitivity. Here, general-purpose optimization algorithms such as L-BFGS-B [25] can be used for parameter estimation. This EMA is suitable for incremental statistics maintenance with sliding window semantics because (1) it relies on positive incremental maintenance for new values anyway, (2) it can adapt fast to workload changes,

and (3) it does not require negative maintenance for expired values due to decaying weights. After incremental statistics maintenance, we also update the hierarchy of relevant complex statistic measures (CSNodes), and finally we evaluate relevant optimality conditions (OCNodes) as well as trigger re-optimization on-demand, i.e., only if required because a plan with lower costs exists.

Robustness Strategies: Triggering re-optimization naïvely for any violated optimality condition ensures immediate adaptation but might cause the problem of *frequently changing plans* (instability). There are two potential reasons. First, by assuming independence of monitored conditional selectivities, data correlation can lead to cyclic re-optimizations. Second, if statistics are close to a break-even point and fluctuate to some extend for different reasons, we might also have frequent plan changes. We explicitly address these issues of instability with the following strategies:

- *Correlation Tables:* Data correlations are addressed by computing conditional selectivities via so-called correlation tables. The idea is to maintain selectivities over multiple versions of a plan, where we store and maintain a row of unconditional and conditional selectivities for each pair of operators with data dependencies in the current plan. Until we are able to monitor and use the unconditional selectivity, we assume statistical independence only. However, using statistics from multiple plan versions prevents us from making wrong decisions multiple times. Starvation due to outdated statistics is avoided by a time-based decay. The integration into the `PlanOptTree` is done via a CSNode `ConditionalSelectivity` that maintains and reads the correlation table. This lightweight approach is effective for groups of few correlated attributes.

- *Lazy Condition Violation:* In order to overcome the problem of statistic fluctuations and serialized statistic updates, we trigger re-optimization lazily, i.e., only if the condition is violated τ_1 times (lazy count). As a heuristic, we set this count to the number of SNodes of the `PlanOptTree` because often already small lazy counts are sufficient. Furthermore, the condition must be violated at least by a relative cost threshold τ_2 and a true condition evaluation resets the lazy count.

- *Minimal Existence Time:* As a fall-back mechanism for all problems of instability, we introduce Δt as minimal existence time of a plan. We collect statistics but do not evaluate optimality during Δt after the last re-optimization. However, Δt is only the minimal interval between re-optimizations; afterwards, we continuously monitor optimality and adapt the plan if necessary in order to prevent adaptation delays.

Putting it altogether, we now describe the overall statistic maintenance algorithm and analyze existing parameters.

Algorithm A-IS (Insert Statistics): The A-IS (see Algorithm 2) is invoked as we measure statistics. It then realizes incremental online statistics maintenance for each operator statistic and triggers re-optimization if required.

Algorithm 2 Insert Statistics (A-IS)

Require: operator id *nid*, statistic *type*, statistic *value*, *lastopt*

```
1: if (on ← root.getOperator(nid)) = NULL or
      (sn ← on.getSNode(type)) = NULL then
2:   return                                          // statistic not required
3: sn.maintainAggregate(value)
4: ret ← true
5: if (time − Δt) > lastopt then                     // min existence time
6:   for all cn ∈ sn.csnodes do                      // for each CSNode cn
7:     ret ← ret and cs.computeStats()
8:   for all oc ∈ sn.ocnodes do                      // for each OCNode oc
9:     ret ← ret and oc.isOptimal()
10: if ¬ret then
11:   A-PTR()                        // actively triggering re-opt (start thread)
```

Starting from the root, we search the operator node by *nid*, then search the statistic node of this operator by *type* and finally, if the node exists, maintain the aggregate. Furthermore, if the minimum existence time is exceeded, we check optimality conditions. For this purpose, we recursively compute and check relevant complex statistic measures and optimality conditions that are reachable over child references. During checking optimality, we also update the specific lazy counters. If there is at least one violated optimality condition that reached the lazy count, we trigger re-optimization by starting an *asynchronous* re-optimization thread.

Asynchronous Re-Optimization: In contrast to synchronous mid-query optimization—where the remaining plan depends on the optimizer output—we do not block plan execution and statistic maintenance. Furthermore, all additional triggers for re-optimization are simply rejected as long as the optimizer thread is running. Finally, after successful optimization, we switch plans on the next possible point—i.e. just before starting the next plan instance—and enable re-optimization again.

Parameter Analysis: The parameters of on-demand re-optimization have fairly static influence and thus do not require much tuning. First, if the minimal existence time Δt is smaller than the interval between workload shifts, there are no changes. Otherwise, adaptation delays linearly increase. Second, adaptation delays also linearly increase with increasing lazy count τ_1. However, Δt and τ_1 can be kept low by default as we will show in our evaluation. All other parameters are the same for both on-demand and periodic re-optimization.

To summarize, the monitoring of plan optimality and re-optimization on-demand minimizes adaptation delays and at the same time prevents unnecessary re-optimization steps.

5. Directed Re-Optimization

Once re-optimization has been triggered by violated optimality conditions during statistic maintenance, we exploit these conditions for directed re-optimization of the current plan. We first determine the reduced re-optimization search space. Then, we apply directed re-optimization instead of full re-optimization. Finally, we incrementally update the existing `PlanOptTree` according to the new conditions.

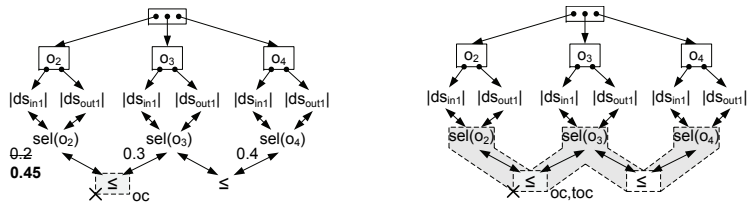
5.1. Re-Optimization Search Space

Since directed plan re-optimization aims at considering only a subset of the complete search space as already shown in Figure 4, we first need to determine this reduced re-optimization search space. We exploit violated optimality conditions for determining (1) the optimization techniques that produced these conditions and (2) the minimal set of operators that need to be reconsidered by those techniques. Generally speaking, the re-optimization search space consists of the set of operators, affected by violated optimality conditions. In case of multiple violated conditions, this is the union of affected operators. In order to guarantee optimality, we also need to take the *transitivity* property of the `PlanOptTree` into account.

In general, we follow a bottom-up approach to determine this re-optimization search space. We start at each violated optimality condition and traverse all optimality conditions that are reachable over *transitivity connections*. Such a transitivity connection is defined as an atomic or complex statistic node connected with two or more optimality conditions. Transitivity chains of arbitrary length are possible, where the end is given by the lack of transitive connections or by the first condition that is still optimal. Finally, termination is guaranteed because the `MEMO` structure prevents cycles.

Example 7 (Re-Optimization Search Space). *Assume the `PlanOptTree` of Example 6. During initial optimization, selectivities of* $sel(o_2) = 0.2$, $sel(o_3) = 0.3$ *and* $sel(o_4) = 0.4$ *resulted in the optimality conditions shown in Figure 8(a). Re-optimization was triggered because the selectivity of operator* o_2 *changed to* $sel(o_2) = 0.45$ *and thus violates* $sel(o_2) \leq sel(o_3)$. *Hence, we would directly reorder operators* o_2 *and* o_3 *during re-optimization. Due to the transitivity of optimality conditions, we need to check the selectivity of operator* o_4 *as well, because we do not know if the implicit optimality condition of* $sel(o_2) \leq sel(o_4)$ *(given by* $sel(o_2) \leq sel(o_3)$ *and* $sel(o_3) \leq sel(o_4)$*) still holds. We traverse the `PlanOptTree` as shown in Figure 8(b) and see that this transitive condition is violated as well, while the second optimality condition* $sel(o_3) \leq sel(o_4)$ *is still valid.*

Algorithm A-TR (Trigger Re-Optimization): The A-TR (see Algorithm 3) adds all violated optimality conditions to the set $\mathcal{C}$ and then it recursively traverses transitivity chains for each condition in $\mathcal{C}$ in order to collect transitively violated conditions. There, we check transitivity filters (direction of operands



(a) Violated OCNode (b) Transitive OCNode

Figure 8: Re-Optimization Search Space.

Algorithm 3 Trigger Re-Optimization (A-TR)

Require: plan P, invalid optimality conditions $\mathcal{C}$

1: $\mathcal{C}' \leftarrow \mathcal{C}$
2: **for all** $oc \in \mathcal{C}$ **do** *// for each OCNode*
3: **for all** $oc1 \in oc.op1.ocnodes$ **do** *// for each OCNode of op1*
4: **if** $oc1.\theta = oc.\theta$ **and** $oc1.op2 = oc.op1$ **then**
5: **if** $\neg oc1.\texttt{isOptimal}(oc1.op1.agg, oc.op2.agg)$ **then**
6: $\mathcal{C}' \leftarrow \mathcal{C}' \cup oc1$
7: $\texttt{rCheckTransitivity}(oc, oc1.op1, left)$
8: **for all** $oc2 \in oc.op2.ocnodes$ **do** *// for each OCNode of op2*
9: **if** $oc2.\theta = oc.\theta$ **and** $oc2.op1 = oc.op2$ **then**
10: **if** $\neg oc2.\texttt{isOptimal}(oc2.op2.agg, oc.op1.agg)$ **then**
11: $\mathcal{C}' \leftarrow \mathcal{C}' \cup oc2$
12: $\texttt{rCheckTransitivity}(oc, oc2.op2, right)$
13: PPOT $\leftarrow \texttt{optimizePlan}(P, \mathcal{C}')$ *// apply directed re-opt*
14: $\texttt{A-UP}(\text{PPOT}, \mathcal{C}')$ *// update PlanOptTree*

and comparison operator) and transitive optimality filters. Finally, we invoke the optimizer with all violated conditions $\mathcal{C}'$ as re-optimization search space. After successful re-optimization, we update the `PlanOptTree` (A-PPR).

Optimality Analysis: Directed re-optimization with the reduced search space and full re-optimization create equivalent plans. The intuition is as follows. Any rewriting possibility between operators is represented by an explicit or a transitive optimality condition. Arbitrary complex optimality conditions can be used to prevent the starvation in local minima. All operators included in violated explicit or transitive conditions are used by directed re-optimization. Hence, directed re-optimization guarantees optimality. For a detailed analysis, we refer to Appendix B.

5.2. Example Optimization Techniques

Based on the determined re-optimization search space, we apply directed re-optimization. As this depends on the concrete optimization techniques, we exemplify the monitoring of optimality and directed re-optimization for local

selection reordering, heuristic join reordering, and heuristic vectorization. On-demand re-optimization is applicable for arbitrary operators and optimization techniques because a `PlanOptTree` can represent arbitrary optimality conditions. However, since the `PlanOptTree` complexity depends on the used optimization techniques, it is especially practical for local and heuristic rewrites.

5.2.1. Selection Reordering

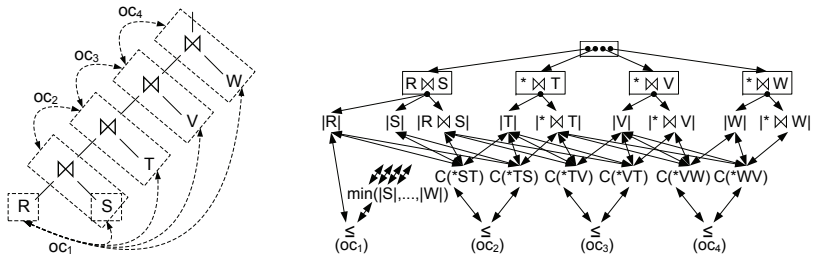
Our running example optimization technique selection reordering applies local rewriting decisions via a variant of bubble sort with an average time complexity of $\mathcal{O}(m^2)$. This exchange-based sort algorithm is well-suited for rewriting imperative plans because it allows for on-the-fly correctness checks. The optimality condition is $sel(o_i) \leq sel(o_j)$, where operator o_i is a data-flow predecessor of operator o_j. As shown throughout the paper, on-demand re-optimization then requires $m-1$ optimality conditions for monitoring optimality of m `Selection` (or selective) operators. In the best-case, the re-optimization search space comprises a single violated condition, where we directly reorder the two involved operators with $\mathcal{O}(1)$. In the worst case, all optimality conditions are violated such that we need to sort all m operators with $\mathcal{O}(m^2)$.

5.2.2. Heuristic Join Reordering

Join ordering heuristics are typically used if the number of joins exceed certain limits or if we assume independence of selectivities [26, 27]. In the following, we first describe our used heuristic join reordering algorithm and subsequently discuss our extensions for on-demand re-optimization.

Preliminaries: We consider (1) only left-deep join trees (no zig-zag trees, no bushy trees), (2) without cross-products, and (3) only one join implementation, but we decide on join implementations afterwards. Using these assumptions and our asymmetric cost functions, there exist at most—i.e., for clique queries—$n!$ alternative plans for joining n datasets [27]. Using our cost model, the costs of, for example, a nested loop join are computed by $C(R \bowtie S) = |R| + |R||S|$ and the join output cardinality can be derived by $|R \bowtie S| = f_{R,S} \cdot |R||S|$ with a join filter selectivity of $f_{R,S} = |R \bowtie S|/(|R||S|)$. Thus, the costs of a left-deep join tree $(R \bowtie S) \bowtie T$ are $C((R \bowtie S) \bowtie T) = |R| + |R||S| + f_{R,S} \cdot |R||S| + f_{R,S} \cdot |R||S||T|$.

Algorithm: Our basic algorithm is again an exchange-based join reordering heuristic and it relies on binary reordering decisions between subsequent join operators (e.g., $((* \bowtie R) \bowtie S) \bowtie *$ vs. $((* \bowtie S) \bowtie R) \bowtie *$). The underlying observation is—similar to Bellman's Principle of Optimality used for dynamic programming—that the costs of subplans before and after such a local reordering are independent of that order. Hence, we just compare $C((* \bowtie R) \bowtie S) \leq C((* \bowtie S) \bowtie R)$. The algorithm works as follows: first, we select the input dataset with the smallest cardinality and reorder it with the existing first join operand if possible. Second, we iterate over all joins and reorder adjacent join pairs if possible and if beneficial. This algorithm basically applies to clique and star queries only, while for arbitrary query types, groups



(a) Opt. Conditions (b) Example `PlanOptTree`

Figure 9: Example Join Reordering.

of operators are reordered similar to the IKKBZ algorithm [27]. In general, this heuristic algorithm exhibits an average time complexity of $\mathcal{O}(m^2)$.

On-Demand Re-Optimization: For monitoring plan optimality of arbitrary left-deep join trees, we require m optimality conditions. Figure 9(a) shows an example join reordering of $R \bowtie S \bowtie T \bowtie V \bowtie W$ ($m = 4$ operators, clique query) and its optimality conditions. First, one condition monitors the minimal cardinality of the first dataset with $oc_1 : \ |R| \leq \min(|S|, |T|, |V|, |W|)$. Second, there are $m - 1$ conditions monitoring the ordering of join operators. For example, the optimality of executing $* \bowtie S$ before its successor $* \bowtie T$ is given if the following condition holds:

$$\begin{aligned} oc_2 :& |R| + |R||S| + f_{R,S} \cdot |R||S| + f_{R,S} \cdot |R||S||T| \\ & \leq |R| + |R||T| + f_{R,T} \cdot |R||T| + f_{R,T} \cdot |R||T||S|, \end{aligned} \tag{4}$$

where oc_2 can be algebraically simplified. It is possible to monitor all cardinalities $|R|, \ldots, |W|$ but only the conditional selectivities $f_{R,S}, \ldots, f_{*,W}$. Hence, we either assume statistical independence of selectivities with $f_{R,T} = f_{(R \bowtie S),T}$ or we use our correlation table as described in Subsection 4.3. The `PlanOptTree` of this example is shown in Figure 9(b). Finally, directed re-optimization sorts only operators in violated conditions such that we have a re-optimization time complexity of $\mathcal{O}(m^2)$ for the worst case but $\mathcal{O}(1)$ for the best case.

5.2.3. Heuristic Vectorization

Plan vectorization is an integration-flow-specific optimization technique [28]. The core idea is to rewrite instance-based plans (operator-at-a-time) into vectorized plans with pipelined message execution (one thread per operator) in order to exploit pipeline parallelism over multiple plan instances. This increases message throughput and still ensures semantic correctness for control flows. We introduced the cost-based vectorization that computes the optimal grouping of operators to a minimal number of k execution buckets (threads). This ensures the optimal degree of pipeline parallelism but achieves less message latency and less resource contention (threads, cache). Cost-based vectorization is a generalization of execution strategies because instance-based plans ($k = 1$) and fully vectorized plans ($k = m$) are specific cases.

Algorithm: The objective is to minimize k under the constraint that bucket execution times do not exceed the execution time of the most expensive operator because it limits the pipeline throughput anyway (convoy effect [29]):

$$\phi : \min_{1 \leq k \leq m} \quad | \quad \forall i \in [1,k] : \sum_{o_j \in b_i} W(o_j) \leq W(o_{max}). \tag{5}$$

This problem exhibits an exponential complexity of $\mathcal{O}(2^m)$. Hence, we apply the following heuristic algorithm: First, we determine the maximum operator execution time. Second, depending on the plan structure (*flow*/*sequence*), we group operators, similar to bin packing heuristics, in a first-fit/next-fit manner with a time complexity of $\mathcal{O}(m^2)/\mathcal{O}(m)$. In any case, the total algorithm complexity is dominated by dependency graph creation with $\mathcal{O}(m^3)$.

On-Demand Re-Optimization: Plan optimality for a *sequence* of operators is then monitored via k ($1 \leq k \leq m$) optimality conditions. First, one condition ensures that each bucket b_i fulfills the constraint that its total execution time does not exceed the execution time of the most time-consuming operator with $oc_1 : \max(W(b_i), \ldots, W(b_k)) \leq W(o_{max})$. Second, regarding the next-fit approach of our heuristic algorithm, for each bucket except the first one $(k-1)$, one condition monitors if the first operator o_j of this bucket b_i still cannot be assigned to the previous bucket b_{i-1} with $oc_i : W(b_{i-1}) + W(o_i) \geq W(o_{max})$. Directed re-optimization starts at the bucket determined by oc_i. Hence, we have a re-optimization time complexity of $\mathcal{O}(1)$ for the best case and $\mathcal{O}(m)$ for the worst-case, but dependency graph creation is not required.

Table 1: Analysis of Example Optimization Techniques.

Optimization Technique	Traditional Algorithm	$\|oc\|$	Directed Reopt	
			Best	Worst
Selection Reordering (5.2.1)	$\mathcal{O}(m^2)$	$\mathcal{O}(m)$	$\mathcal{O}(1)$	$\mathcal{O}(m^2)$
Join Reordering (5.2.2)	$\mathcal{O}(m^2)$	$\mathcal{O}(m)$	$\mathcal{O}(1)$	$\mathcal{O}(m^2)$
Vectorization (5.2.3)	$\mathcal{O}(m^3)$	$\mathcal{O}(m)$	$\mathcal{O}(1)$	$\mathcal{O}(m)$

5.2.4. Discussion of Complexity Analysis

Table 1 summarizes the complexity analysis of the presented example techniques. We compare the time complexity of the full algorithms, monitoring optimality ($|oc|$) and directed re-optimization. Based on these observation we can draw two important conclusions.

First, monitoring optimality is commonly more efficient than full re-optimization. Keeping all possible plans is prohibitive as this would result in many cases in factorial time and space complexity for creating all plans. In contrast, our idea relies on monitoring optimality of the current (optimal) plan only. Generally speaking, we benefit from monitoring optimality whenever the complexity of deciding if a solution is optimal is lower than the complexity of finding the optimal solution. This holds for many optimization problems.

Second, there are many cases, where we can benefit from directed re-optimization. Commonly, the best-case re-optimization is constant because a single violated condition can enable to directly infer the new optimal plan, while the worst-case (e.g., all conditions violated) is equal to the traditional algorithm. The benefit of directed re-optimization is due to (1) a reduced search space per technique, and (2) potentially reconsidering only a subset of techniques. The latter is especially important in scenarios, where we have a mixture of static optimization decisions and high dynamics for other decisions. Furthermore, directed re-optimization allows for step-wise re-optimization, which is beneficial for incrementally learning conditional statistics and sometimes in highly dynamic scenarios, where we have many re-optimizations. We refer to Appendix B for an analysis of convergence properties of step-wise re-optimization.

Finally, there is a trade-off between monitoring and re-optimization efficiency. So far we realized on-demand re-optimization for example techniques, including the here presented ones. The specific `PlanOptTree` design, especially for complex optimization techniques, constitutes interesting future work.

5.3. Updating PlanOptTrees

Directed re-optimization considers only a subset of operators and thus, can only return partial `PlanOptTrees` of rewritten subplans. We therefore incrementally update the existing `PlanOptTree` with new partial `PlanOptTrees` after successful re-optimization. The result is equivalent to creating the `PlanOptTree` from scratch (A-PC).

Algorithm A-UP (Update `PlanOptTree`): The A-UP starts bottom-up from all violated optimality conditions and removes those OCNodes except for transitively violated conditions because the new partial `PlanOptTree` is aware of them. Then, it recursively removes statistic nodes that do not refer to any child nodes and were affected by re-optimization. This removes only nodes included in violated optimality conditions. Finally, we apply the merge of A-PC (Subsection 4.2) for new partial `PlanOptTrees`, copy statistics if necessary, and switch plans as described in Subsection 4.3.

To summarize, directed re-optimization reduces the overhead per re-optimization step, especially for techniques with large search space. Future work might consider reusing plans and `PlanOptTrees`. Finally, we start over with monitoring optimality during statistic maintenance (Subsection 4.3).

6. Experimental Evaluation

Our experiments study the behavior of on-demand re-optimization regarding total execution times, optimization times, and workload adaptation properties. We compare it with periodic re-optimization and unoptimized execution (i.e., the initial optimal plan). To summarize, the major results are:

- Execution time improvements increase with increasing workload dynamics due to immediate adaptation.

- We gain optimization time improvements for static workloads due to no unnecessary re-optimizations.
- Overheads for statistic maintenance, monitoring optimality, and `PlanOptTree` algorithms are negligible.
- Directed re-optimization benefits increase with the plan size and the complexity of optimization.

6.1. Experimental Setting

We ran our experiments on an IBM blade LS20 with two AMD Opteron 270 processors, each a 2 GHz Dual Core, and 9 GB RAM, where we used Linux openSUSE 9.1 (32 bit) as the operating system. Our WFPE (workflow process engine) is a prototype integration platform including our cost-based optimizer. The WFPE is implemented using Java 1.6 as the programming language and consists of approximately 37,000 lines of code. It includes several inbound and outbound adapters for the interaction with external systems, where we currently support files, databases, and Web services.

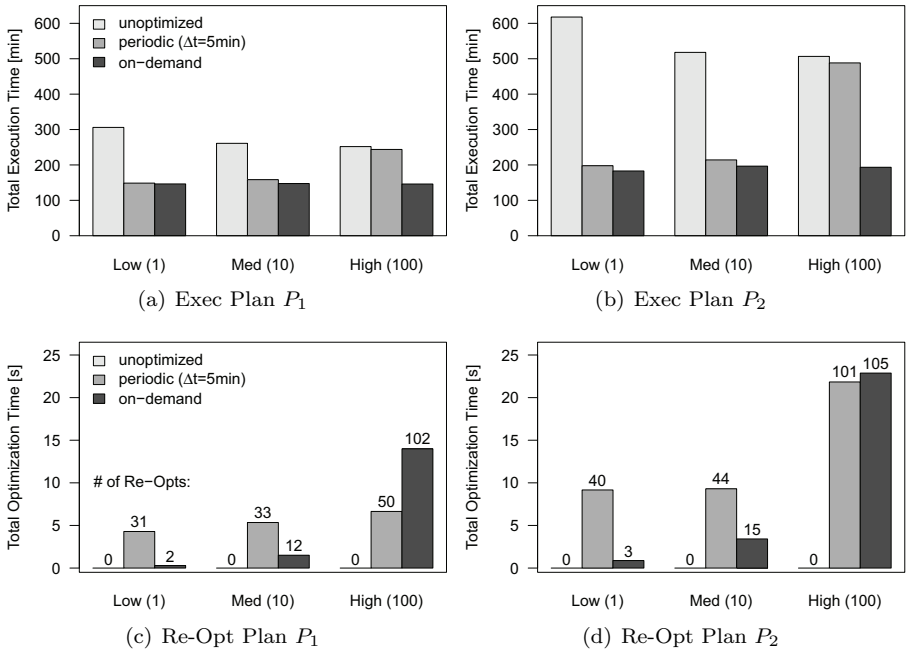
The test integration flows are four plans with different characteristics: Plan P_1 with $m = 9$ is our simple running example shown in Figure 1. Plan P_2 with $m = 19$ is more complex, where we receive messages, load data from four systems, apply schema transformations, join all datasets (clique query type) and finally send the results to another system. The related optimality conditions are shown in Figure 9. For both plans, the benchmark drivers invoke synchronous inbound adapters and we use file outbound adapters as external systems in order to reduce external influences. Furthermore, we use two additional plans P_3 and P_4 (described in detail later on), where we vary the number of operators up to 100 in order to investigate the influence of plan sizes. All experiments use synthetic data because we want to generate workloads with different selectivities and cardinalities. Any relative time improvements are specified as $(1 - t_2/t_1)$, where t_1 represent the baseline, and thus are upper-bounded by 100%.

Our default parameters are as follows. Both optimization models use `EMA` ($\alpha = 0.5$) for statistics aggregation and a relative cost threshold of $\tau_2 = 0.0$. For clarity of presentation, we disabled all optimization techniques except selection and join reordering. The periodic re-optimization interval is $\Delta t = 5\,\text{min}$. On-demand uses a minimal existence time of $\Delta t = 1\,\text{s}$, a lazy condition count of $\tau_1 = 10$, and our `MEMO` structure.

6.2. End-to-End Overall Comparison

In a first series of experiments, we investigate the major characteristics of on-demand and periodic re-optimization as well as unoptimized execution in terms of their total execution times and optimization times.

Scenario Setup: We use the described plans P_1 and P_2 and execute different workload scenarios, each with $n = 100{,}000$ plan instances but different dynamics in terms of the number of workload shifts $|ws|$): low ($|ws| = 1$), med ($|ws| = 10$), and high ($|ws| = 100$). We use uniform data distributions for all



(a) Exec Plan P_1 (b) Exec Plan P_2

(c) Re-Opt Plan P_1 (d) Re-Opt Plan P_2

Figure 10: Overall Comparison Results with Changing Workload Dynamics.

scenarios. For plan P_1, we use an input data size (per plan instance) of 400 KB and selectivities of $\{1.0, 0.8, 0.1\}$ for the three `Selection` operators. A single experiment thus executed P_1 on 38.1 GB of input data. For plan P_2, we use an input data size of 167 KB and cardinalities of $\{200\,\text{KB}, 67\,\text{KB}, 100\,\text{KB}, 33\,\text{KB}\}$ for the four loaded datasets in order to make plan execution times comparable to P_1. Workload shifts are realized by shifting the selectivities (P_1) or cardinalities (P_2) round robin to the front (e.g., $sel(o_1) = sel(o_2)$, etc), done every $n/|ws|$ plan instances. By shifting selectivities/cardinalities $|ws|$ times, the workload dynamics include both different impact and frequency of workload shifts. The results are shown in Figure 10.

Execution Time: Figures 10(a) and 10(b) present the most important results in the form of total execution times that already include all monitoring and optimization overheads. The runtime for unoptimized execution is not constant because the initially bad plan becomes optimal[4] from time to time. For static to medium dynamics, on-demand achieves only slight improvements because there are only few workload shifts and thus total adaptation delays are low. However, for dynamic workloads, periodic degenerates to unoptimized. In

[4]The runtime for unoptimized execution is decreasing with increasing workload dynamics because the initially very bad plan is used less often for dynamic workloads. For example, the initial plan of P_1 is used for 50% of plan instances on low, 36% on med, and 34% on high.

contrast, on-demand shows almost constant execution time. The slight increase for high dynamics is reasoned by the lazy count of $\tau_1 = 10$ per workload shift. The relative benefits depend on the optimization techniques and workload characteristics. For example, in our dynamic scenarios, we achieved improvements of 40.0% for plan P_1 and 60.4% for plan P_2.

Optimization Time: In addition, Figures 10(c) and 10(d) show the related total optimization times and number of re-optimization steps. Unoptimized does not exhibit these overheads. Although periodic optimization uses a fixed optimization interval Δt, we observe increasing optimization times with increasing workload dynamics because the resulting number of re-optimization steps directly depends on the total execution time. For on-demand, the number of re-optimizations is almost equal to the number of workload shifts. The additional steps are caused by initial optimization and smoothed statistics that led to multiple re-optimizations for some workload shifts. In these scenarios, we benefit only slightly from directed re-optimization due to a rather small search space. However, we reduced the total optimization time for static workloads by 93.1% for plan P_1 and by 90.4% for plan P_2.

6.3. Workload Adaptation in Depth

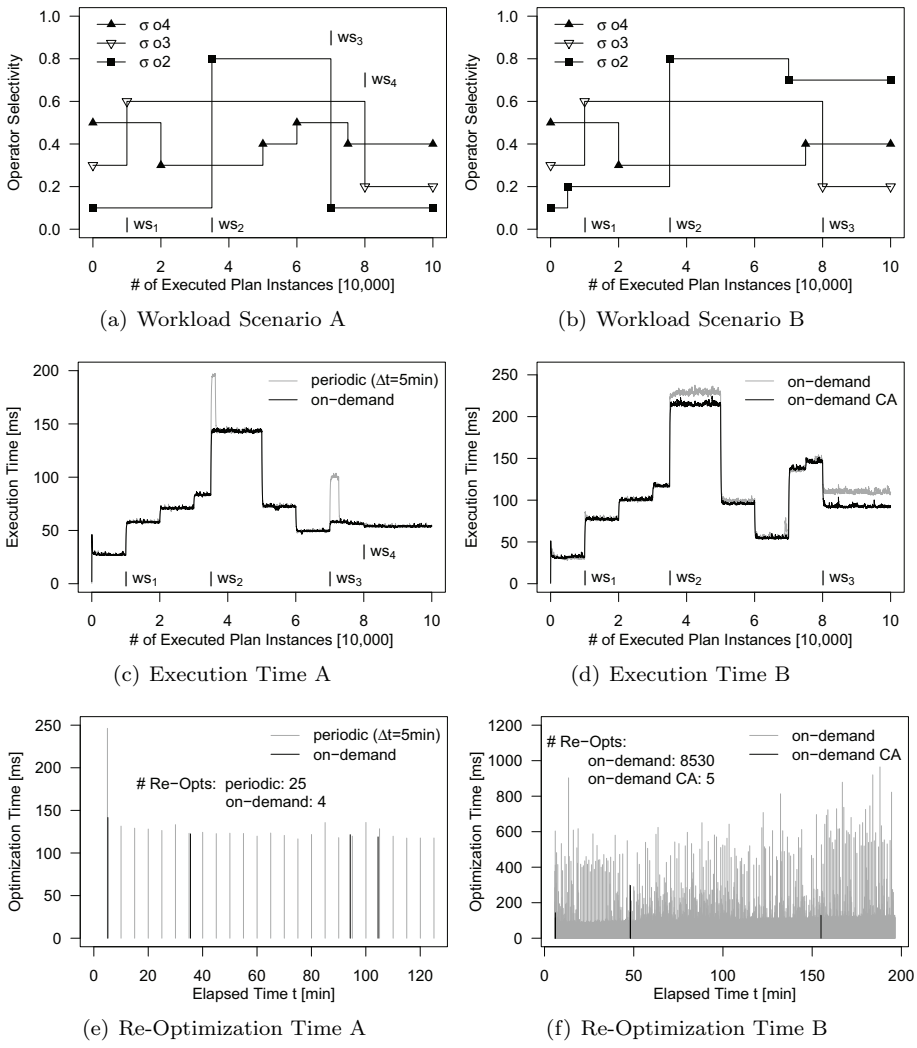
In a second series of experiments, we now have a more detailed look at workload adaptation in specific scenarios. The purpose is to quantify adaptation properties rather than an overall performance comparison as discussed before.

6.3.1. Simple-Plan Scenario

Scenario Setup: Scenario A consists of n = 100,000 plan instances of plan P_1 and compares periodic and on-demand re-optimization. We varied the selectivities of the three `Selection` operators as shown in Figure 11(a). The input data was generated without correlations and we varied its cardinality with $\{1, 3, 4, 5, 5, 2, 1, 3, 3, 3\}$ (in 100 KB). There are four workload shifts (ws_1, ws_2, ws_3, and ws_4), where crossing selectivities cause new optimal plans.

Runtime Results: Figure 11(c) shows the smoothened and sampled execution times of periodic and on-demand. Beside the cardinality-dependent execution times, we observe adaptation delays for periodic, where we miss optimization opportunities (ws_2 and ws_3). The workload shifts ws_1 and ws_4 have only minor influence due to unchanged minimum operator selectivity (o_2). In contrast, on-demand immediately adapts plans, which led to a cumulative execution time improvement of 2.5%. Figure 11(e) shows the optimization time (incl. recompilation, etc) per re-optimization step. We see that periodic triggers optimization with fixed interval. It took 25 steps in this scenario. In contrast, on-demand was only triggered if necessary (at workload shifts) such that we only required four steps and achieved a cumulative optimization time improvement of 84.3%. Single directed re-optimizations are not significantly faster than full re-optimizations due to the small search space. The high execution and optimization times at the beginning are caused by Java just-in-time compilation.

Statistic Maintenance Overhead: Table 2 shows the statistics maintenance and monitoring overhead of on-demand. For that we investigate the



(a) Workload Scenario A (b) Workload Scenario B

(c) Execution Time A (d) Execution Time B

(e) Re-Optimization Time A (f) Re-Optimization Time B

Figure 11: Simple-Plan Workload Adaptation Scenario (without/with correlation).

Table 2: Overhead Statistics/Condition Monitoring.

Traditional	Minimal	POT c_1	POT c_2	POT c_3
159 ms	73 ms	172 ms	314 ms	470 ms

algorithm A-IS in detail. We use the operator statistic trace from Scenario A that consists of 2,100,000 atomic statistics. Traditional is the baseline (as used for periodic re-optimization), where all statistics of all operators are maintained. Minimal refers to a hypothetical scenario, where we know the required

statistics and maintain only these. The relative difference between both is the benefit we gain by maintaining only relevant statistics. In contrast, POT monitoring includes the overhead of our `PlanOptTree`. Although the A-IS algorithm declines unnecessary statistics, it is slower than Traditional because for each statistic tuple, we compute the hierarchy of complex statistics and evaluate optimality conditions. We distinguish three configurations: c_1 refers to statistic maintenance without condition evaluation, while c_2 and c_3 (without/with the `MEMO` structure) show the small absolute overhead of continuously monitoring optimality. In this scenario, using the `MEMO` structure is slightly slower due to simple optimality conditions. To summarize, the overhead for statistic maintenance and monitoring at operator granularity is negligible compared to the overall execution time of Scenario A (see Figure 11(c)).

PlanOptTree Algorithm Overhead: We also investigated the other `PlanOptTree` algorithms for (1) `PlanOptTree` creation (A-PC), (2) triggering re-optimization (A-TR), and (3) `PlanOptTree` updating (A-UP). For this experiment, we varied the number of `Selection` operators of plan P_1 up to $m = 35$ operators, generated random statistics, and for A-TR/A-UP, we forced one violated condition. Even for $m = 35$, the mean execution time of 100 repetitions was 0.57 ms (A-PC), 0.02 ms (A-TR), and 0.21 ms (A-UP), respectively. Hence, these overheads are also negligible compared to the overall optimization time in Scenario A (see Figure 11(e)).

All Optimization Techniques: On-demand, with selection reordering enabled, reduced the total unoptimized execution time of Scenario A from 151.7 min to 123.9 min. With all of our cost-based optimization techniques enabled (e.g., batched execution, parallel flows, message pipelining), we reduced this total execution time even to 69.2 min. Accordingly, the relative improvements of on-demand to periodic re-optimization increased almost linearly.

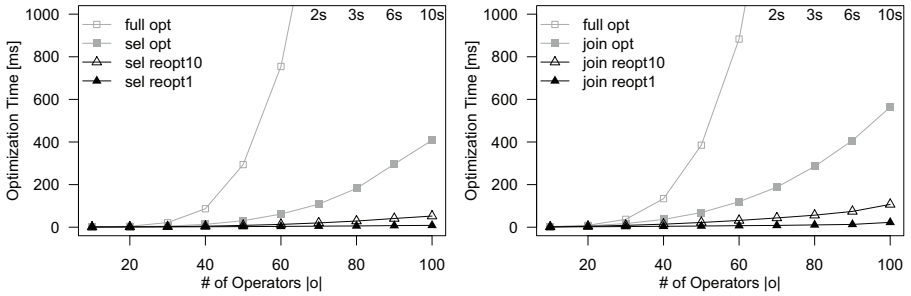
6.3.2. Simple-Plan Scenario with Correlation

In the interest of a fair evaluation, we now investigate a possible limitation of on-demand re-optimization: the problem of frequent plan changes caused by correlation.

Scenario Setup: Scenario B executes again $n = 100{,}000$ instances of plan P_1. We use the input cardinalities of Scenario A but generated correlated data. Figure 11(b) shows the conditional selectivities $sel(o_2)$, $sel(o_3|o_2)$, $sel(o_4|o_2 \wedge o_3)$, while we set $sel(o_3|\neg o_2) = 1.0$ and $P(o_4|\neg o_2 \vee \neg o_3) = 1.0$. Hence, there are strong correlations and the selectivities $sel(o_3)$ and $sel(o_4)$ depend on the operator ordering[5] (only ws_2 and ws_3 are real workload changes). We compare on-demand and on-demand CA (with correlation table, see Subsection 4.3).

Runtime Results: Figures 11(d) and 11(f) show again the execution and optimization times. Without the correlation table selection reordering changes

[5]For example, from ws_3 to the end, we have conditional selectivities of $sel(o_2) = 0.7$, $sel(o_3|o_2) = 0.2$, $sel(o_4|o_2 \wedge o_3) = 0.4$ but total selectivities of $sel(o_2) = 0.7$, $sel(o_3) = 0.44$, $sel(o_4) = 0.92$. This leads to different operator orderings.



(a) Selection Reordering P_3 (b) Join Reordering P_4

Figure 12: Directed Re-Optimization Results.

the plan back and forth (up from ws_1), even in case of a constant workload because it wrongly assumes statistical independence. Due to immediate re-optimization and the small minimal existence time of $\Delta t = 1\,\text{s}$, we executed 8,530 re-optimization steps. In addition, the permanent change between sub-optimal and optimal plans led to a degradation of the execution time because non-optimal plans were used (e.g., after ws_2 and ws_3). With the correlation table, the number of re-optimization steps was reduced to 5. There, all three workload shifts have been recognized, where both ws_1 and ws_2 required two re-optimizations each. For ws_1, this was due to reverting the wrong decision, while for ws_2, this was due to multiple crossing selectivities, which were learned incrementally via step-wise directed re-optimization. As a result of the reduced number of re-optimization steps and preventing suboptimal plans, we also achieved a 4.4% total execution time improvement.

6.4. Directed Re-Optimization in Depth

In our third series of experiments, we analyzed the benefit of directed re-optimization. We generated plans with varying numbers of `Selection` (P_3) and `Join` (P_4) operators $|o| \in [10, 100]$ and measured full and directed re-optimization time. In contrast to previous experiments, the optimizer was tested standalone (without dependency graph maintenance, plan compilation, etc). We fixed the input cardinalities and randomly generated operator selectivities. For directed re-optimization, we randomly picked $k_1 = 1$ and $k_2 = 10$ operators and generated new statistics for them to violate optimality conditions. All measurements were repeated 100 times.

Figure 12 shows the results for the optimization techniques selection reordering (Figure 12(a), Subsection 5.2.1, Plan P_3) and join reordering (Figure 12(b), Subsection 5.2.2, Plan P_4). With all optimization techniques enabled, we observe a full optimization time that empirically grows with $\mathcal{O}(n^5)$ (the not shown measurements are annotated at the top right). Here, the optimization time is mainly dominated by the technique of parallel flow rewriting. With all other optimization techniques disabled, the optimization time of both full selection reordering (*sel opt*) and full join reordering (*join opt*) increase still quadratically.

For full *re*-optimization, these techniques required similar optimization times due to dependency checking. In contrast, the directed re-optimization times for one (*reopt1*) and ten (*reopt10*) changed operator selectivities (which led to multiple violated optimality conditions) increase almost linearly with the number of plan operators and with the number of violated conditions. Thus, benefits of directed re-optimization increase with increasing number of operators and with increasing complexity of optimization techniques. Even for ten changed operators, we gain significant benefits. Comparing selection reordering and join reordering, the latter took understandably longer but both show the same typical behavior. To summarize, we benefit from the reduced re-optimization search space per technique and from reconsidering only a subset of techniques.

7. Related Work

On-demand re-optimization belongs to the research field of adaptive query processing (AQP) [17, 30] that addresses unknown/mis-predicted statistics or changing workloads. AQP also inspired our work but the different runtime model of integration flows requires a different optimization model. We aim at optimizing many consecutive plan instances of a deployed integration flow, which work on new input data. In the following, we show the relationship of on-demand re-optimization to important areas and techniques of AQP.

Plan-Based Adaptation in DBMS: Traditional *inter-query* optimization aims at optimizing individual query instances. Adaption in this context mainly reduces to the decision when and how to update statistic of the underlying database [17] but optimization happens on granularity of single or multiple concurrent (for sharing opportunities) queries. In contrast, existing work on AQP mainly use *inter-operator* or *intra-operator* re-optimization of single query instances in order to account for mis-predicted cardinalities of intermediates. Regarding inter-operator, we distinguish *reactive* and *proactive* approaches [31]. *Reactive*, *inter-operator* re-optimization uses the traditional optimizer to create a plan, intermediate results are materialized, and if estimation errors are detected, the remaining plan is reactively re-optimized. Examples are ReOpt [32] that invokes the optimizer if statistics differ significantly, and Progressive Optimization [33] that uses validity ranges of statistics. In contrast, *proactive*, *inter-operator* re-optimization proactively creates switchable plans before execution. Rio [31] computes bounding boxes (similar to validity ranges) around all used estimates and then creates robust or switchable plans. During runtime one of three paths can be chosen based on the real statistics (below, estimate, above). Another proactive technique is Parametric Query Optimization (PQO). Due to unknown query parameters during query compile time, PQO [34] and Progressive PQO (PPQO) [35] optimize a query into possible candidate plans and pick the most-suitable plan when parameters are bound. *Intra-operator* approaches triggered re-optimization even during operator runtime. For example, corrective query processing [18] creates new plans for unprocessed data only and the results are combined by stitch-up phases. On-demand differs in several ways. First, our re-optimization scope is not a single query but the average

case of short-running plan instances of a deployed plan. Hence, fine-grained adaptation (inter/intra-operator) based on intermediate results of a single plan instance is not applicable. Second, we use optimality conditions instead of validity ranges (or bounding boxes). Those validity ranges are defined as absolute cardinalities for subplans, which does not necessarily mean that the subplan is suboptimal. In contrast, we trigger re-optimization only if necessary, i.e., if a new plan is certain to be found and our approach allows for directed re-optimization. Furthermore, we do not enumerate alternative plans beforehand but monitor optimality of the current (optimal) plan only.

Adaptation of Continuous-Query (CQ) in DSMS: CQ-based adaptation differs in its re-optimization scope of a standing query. Existing work is classified as *routing-* or *rewriting-based* adaptation. *Routing-based* approaches do not rely on predefined plans but route tuples along different stateful operators. An example is Eddies [36, 37] with its eddy operator. Dynamic decisions on routing paths via routing policies enable fine-grained adaptation [36, 38, 39] but might incur significant overhead. This overhead can be reduced by routing groups of tuples as done by the self-tuning query mesh [19]. For *rewriting-based* adaptation, the optimizer requests relevant statistics and re-optimization is triggered periodically or on significant changes [30]. Rewriting CQs requires state migration (e.g., tuples in hash tables) [40] to prevent missing tuples, duplicates, or changed tuple orders. Hence, reordering relies on extensive statistic profiling. The Adaptive-Greedy algorithm [41] even uses a so-called matrix view for conditional selectivity profiling and directed re-optimization for the specific technique of reordering stream filters (selection reordering). On-demand differs again in several ways. First, the re-optimization scope of CQs and integration flows are similar but CQs are stateful that requires state migration on re-optimization. Second, in contrast to *passive* structures such as matrix views [41], on-demand enables monitoring optimality and directed re-optimization for *arbitrary* optimization techniques and actively triggers re-optimization that overcomes the need for determining *when* to re-optimize.

Adaptation of Integration Flows: Related work of optimizing integration flows use *rule-based* [11, 12, 13, 14], *cost-based* [10, 13, 15, 16], and *adaptive cost-based* [4, 13] approaches. Rule- and cost-based techniques (optimize-once) cannot adapt the plan to changing workloads. Adaptive cost-based approaches either use an optimize-always model that triggers optimization for each plan instance [13] or periodic re-optimization [4, 23] that triggers re-optimization with a fixed time interval. On-demand achieves near-optimal re-optimization behavior and thus overcomes the drawbacks of existing adaptive cost-based approaches.

8. Conclusions

To summarize, we introduced the concept of on-demand re-optimization that exploits optimality conditions for re-optimization of integration flows. The `PlanOptTree` —as a compact representation of optimality conditions—enables us to monitor plan optimality during online statistic maintenance and to immediately trigger directed re-optimization if the current plan is not optimal.

The experiments have shown that on-demand re-optimization achieves near-optimal re-optimization behavior in terms of monitoring and re-optimization overhead as well as adaptation delays. In conclusion, on-demand re-optimization perfectly adapts to the dynamics of the current workload, i.e., there are no re-optimizations for static but many immediate re-optimizations for dynamic workloads. Hence, we benefit from minimized adaptation delays and reduced re-optimization efforts. Finally, on-demand re-optimization is also applicable in other areas. For example, it can be extended for re-occurring queries, continuous queries or workflows of MapReduce jobs. In addition, future work might investigate on-demand re-optimization for specific optimization techniques.

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Appendix A. Analysis of `PlanOptTree` Complexity

For certain plan structures and problems, worst-case complexity bounds can be guaranteed. Here, we focus on local operator reordering for a sequence of operators. For m operators, there are $m!$ alternative plans.

Proposition 1 (Local Operator Reordering `PlanOptTree` Complexity). *Monitoring local optimality of a sequence of m operators has a worst-case `PlanOptTree` space complexity of $\mathcal{O}(m^2)$ nodes and accordingly, the algorithms A-IS, A-TR, and A-UP have a worst-case time complexity of $\mathcal{O}(m^2)$.*

Proof. Assume a plan P of a sequence of m operators o. A minimal `PlanOptTree` has at most m ONodes, $m \cdot s$ SNodes, $2 \cdot |oc|$ CSNodes (two complex statistics nodes for each binary optimality condition), and $|oc|$ OCNodes. Each operator can be included at most in one local optimality condition per dependency (in case of a data dependency this subsumes any temporal dependency). Then, an arbitrary operator o_i with $1 \leq i \leq m$ can—in the worst case—be the target of $i-1$ dependencies δ_i^-, and it can be the source of $m-i$ dependencies δ_i^+. Based on the equivalence of $\delta^- = \delta^+$ and thus, $|\delta^-| = |\delta^+|$, the maximum number of optimality conditions is inherently given by

$$|oc| = \sum_{i=1}^{m} (i-1) = \frac{m(m-1)}{2}. \tag{A.1}$$

The total number of nodes is therefore $m + s \cdot m + 3 \cdot m(m-1)/2$. Since s is a constant, we have $\mathcal{O}(m^2)$ nodes in the worst case. Processed nodes are memoized such that the algorithms A-IS, A-TR, and A-UP access at most $\mathcal{O}(m^2)$ nodes per invocation. Hence, Proposition 1 holds. □

Appendix B. Analysis of Directed Re-Optimization

In the general case, but depending on the `PlanOptTree` design per optimization technique, we can give correctness guarantees for directed re-optimization. Here, we focus on (1) equivalence to full re-optimization and (2) convergence of step-wise re-optimization, for reordering sequences of operators.

Appendix B.1. Directed Re-Optimization

Proposition 2 (Directed Operator Reordering Equivalence). *Directed re-optimization (re-ordering) of all operators $o' \in P$ included in violated optimality conditions $\mathcal{C}'$ of a `PlanOptTree` (for a sequence of m operators o), is equivalent to the full re-optimization of all operators $o \in P$.*

Proof. Assume all dependencies between operators o of plan P to be a directed graph $G = (V, E)$ of vertexes (operators) and edges (dependencies). Then, the re-optimization of P is a graph homomorphism $f : G \to H$. In order to prove Proposition 2, we show that

$$\forall o_i \notin o' : \quad \big(v_{pre(o_i)} \in G \equiv v_{pre(o_i)} \in H\big) \wedge \big(v_{suc(o_i)} \in G \equiv v_{suc(o_i)} \in H\big)\,, \tag{B.1}$$

where $v_{pre(o_i)}$ denotes the set of predecessors of operator o_i and $v_{suc(o_i)}$ denotes the set of successors of o_i. (1) If there exists a homomorphism $f : G \rightarrow H$ such that

$$v_j \prec o_i \in G \wedge o_i \prec v_j \in H, \tag{B.2}$$

then, the order $v_j \prec o_i$ is represented by an optimality condition oc with $o_i, v_j \in oc$ or by a transitive optimality condition toc with $o_i, v_j \in toc$. The same is true for successors of o_i. (2) The `PlanOptTree` allows for arbitrary optimality conditions between operators and input statistics. Hence, during re-optimization, $f : G \rightarrow H$, the globally optimal solution will be found. (3) Further, all operators o' included in violated optimality conditions $\forall o_i \in oc'$ with $oc' \in \mathcal{C}'$ or transitive optimality conditions $\forall o_i \in toc'$ with $toc' \in \mathcal{C}'$ are used by $f : G \rightarrow H$. As a result,

$$\nexists \left(o_i \notin o' \wedge \left(\left(v_{pre(o_i)} \in G \neq v_{pre(o_i)} \in H\right) \vee \left(v_{suc(o_i)} \in G \neq v_{suc(o_i)} \in H\right)\right)\right), \tag{B.3}$$

such that both directed re-optimization and full re-optimization results in the same plan. Hence, Proposition 2 holds. □

Appendix B.2. Step-Wise Directed Re-Optimization

Proposition 3 (Step-Wise Directed Re-Optimization Convergence). *For optimization problems* $\min \hat{W}(P)$ *with a single minimum, step-wise directed re-optimization converges to the same plan* P' *as directed re-optimization if the workload* ω *is* static *in the time interval* $[T_1, T_2]$ *with* $\nexists ws_i \in [T_1, T_2]$.

Proof. Assume a finite plan search space $\mathcal{S}$ and exact runtime statistics. (1) For an optimization problem with a single minimum, we have

$$P' = \arg\min_{\forall P \in \mathcal{S}} \hat{W}(P) = \operatorname*{opt}_{\forall P \in \mathcal{S}}(P), \tag{B.4}$$

independent of the optimization start point plan P because for problems with a single minimum, there is by definition only one local optimum and hence it is also the global optimum. (2) Given a static workload ω in the time interval $[T_1, T_2]$ with $\nexists ws_i \in [T_1, T_2]$ directly implies that the optimal plan $P' = \arg\min_{\forall P \in \mathcal{S}} \hat{W}(P)$ is constant in $[T_1, T_2]$. (3) By definition of the `PlanOptTree`, any partial re-optimization step addresses at least one optimality condition oc_i and all of its transitive optimality conditions $toc(oc_i)$. Each partial re-optimization $P'_{oc_i} = \text{opt}_{oc_i}(P)$ reduces the plan costs with $\hat{W}(P'_{oc_i}) < \hat{W}(P)$. Thus, no cycles are possible. Re-optimization steps are triggered as long as at least one optimality condition oc_i is violated. Without loss of generality, assume $T_1 = 0$ and $T_1 = \infty$. Then, we can conclude that step-wise directed re-optimization in the finite search space $\mathcal{S}$ converges to $P' = \arg\min_{\forall P \in \mathcal{S}} \hat{W}(P)$. Hence, Proposition 3 holds. □

Given our monotonic operator cost function (see Subsection 2.2), any plan optimization problem $\min \hat{W}(P)$ can be transformed into an optimization problem with a single minimum by adding new optimality conditions, i.e., by conceptually transforming it into a higher-dimensional space. However, this property clearly depends on the specific `PlanOptTree` design.