

DecoPa: Query Decomposition for Parallel Complex Event Processing

Anonymous Author(s)

ABSTRACT

Systems for Complex Event Processing (CEP) enable the detection of predefined patterns in event streams. While the evaluation of CEP queries is computationally hard, scalability may be achieved by parallelization. Yet, existing approaches for parallel CEP are driven by static query properties, such as partitioning keys and states of the evaluation model. They largely neglect the rates with which processing units may ingest and compare events for query evaluation.

In this paper, we present an approach for parallel CEP that is based on a flexible decomposition of CEP queries. Our idea is to guide the decomposition by the sustainable throughput of each processing unit, in order to maximize the overall performance. To this end, we introduce DeCoPa plans for parallel CEP, provide a cost model for them, elaborate on their correctness and optimality, and present an algorithm for their construction. Experiments using a DeCoPa implementation in Flink illustrate throughput gains of up to 12 orders of magnitude compared to state-of-the-art approaches.

KEYWORDS

Complex Event Processing, Parallel Processing, Stream Processing

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1 INTRODUCTION

Complex Event Processing (CEP) is a computational paradigm that enables real-time pattern detection over streams of events [16], finding use in domains like finance [27], healthcare [28], and transportation [6]. It enables the detection of *situations of interest* by matching CEP queries, which are characterized in terms of their event types, the ordering thereof, a set of predicates, and a time window [16].

Having low-latency processing of high-frequency event streams as its primary objective, a plethora of methods have been introduced to enhance the efficiency of CEP, including parallelization schemes [7, 32], state sharing mechanisms [19, 23], and query rewriting [13, 29]. However, the evaluation of CEP queries is inherently difficult. When

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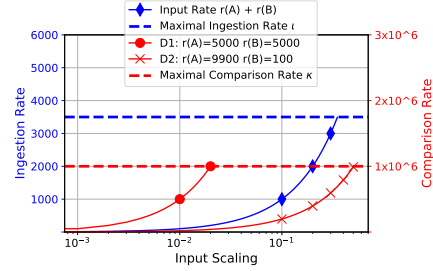


Figure 1: Illustration of sustainable throughput.

adopting a permissive query semantics, known as *unconstraint* [10] or *skip-till-any-match* [33], it may be necessary to compare all events of the types referenced in a CEP query that occur within the same time window in a stream against each other, in order to evaluate the query predicates. As such, common evaluation algorithms show an exponential worst-case time complexity, while the issue is even exacerbated once CEP queries contain Kleene closure operators [33].

The efficiency of a CEP system is assessed in terms of its *sustainable throughput*, i.e., the maximal number of events that can be processed per time unit without generating back-pressure in terms of an increasing queueing of events [18]. For a CEP system, the sustainable throughput is dominated by two factors: the maximal number of events that can be ingested per time unit (ingestion rate ι) and the maximal number of comparisons between events, i.e., predicate evaluations, that can be made per time unit (comparison rate κ). Either rate is influenced by the semantics of CEP queries as well as the adopted CEP system, in terms of its implementation and the adopted hardware. However, once measurements of both rates for a query q evaluated by a system s are available, they can be combined with information on the distribution of event rates and predicate selectivities to determine the sustainable throughput of s for q . In particular, if sustainable throughput cannot be reached at all, the rate with which events are fetched from event sources needs to be adjusted in order to prevent an overload situation.

EXAMPLE 1. For illustration purposes, consider a system with a max ingestion rate $\iota = 4000\text{e}/\text{min}$ and a max comparison rate $\kappa = 100000/\text{min}$ for a CEP query $q = \text{AND}(A, B)$ that matches joint occurrences of events of types A and B that satisfy a set of predicates q_π and occur within a time window $q_t = 1\text{min}$. Let $r(A), r(B)$ denote the number of occurrences of A and B events per minute and $c \in (0, 1]$ be a scaling factor for these rates. Then, sustainable throughput requires that $\iota > c \cdot (r(A) + r(B))$. To evaluate the predicates q_π , each incoming A event is compared against B events within the time window, which results in $c \cdot r(A) \cdot r(B)$ comparisons. Considering also the comparisons for incoming B events, sustainable throughput requires that $\kappa > 2 \cdot r(A) \cdot r(B) \cdot c$.

For the above setting, *Fig. 1* shows the sustainable throughput for two event rate distributions $D1, D2$, for an increasing scaling factor. Here, the left and right y-axes describe the resulting ingestion rate and comparison rate, respectively, to achieve sustainable throughput, while the max ingestion and comparison rates ι and κ of the system are marked with dashed lines. The example illustrates that the required ingestion rate is independent of the event rate distribution, unlike the comparison rate. Hence, depending on the event rate distribution, the sustainable throughput may be limited either by the max comparison rate, as for $D1$, or by the ingestion rate, as for $D2$.

In this paper, we argue that the interplay between ingestion rates and comparison rates shall guide the parallelization of CEP queries. Once a CEP system comprises multiple processing units, each of these units must achieve sustainable throughput. Yet, existing approaches for parallel CEP, whether they are data-parallel [17, 22], state-parallel [8], or follow a hybrid model [31, 32], organize the distribution of the load based on static query properties, such as partitioning keys or the number of states of the evaluation model. As such, they neglect the ingestion rates and comparison rates of processing units and, therefore, cannot maximize the overall throughput.

Against this background, we present DeComposition-based Parallelization (DeCoPa) of CEP queries as an approach for throughput maximizing parallel evaluation of CEP workloads. It is based on the following contributions:

- We introduce DeCoPa plans as a model that encodes the decomposition of a CEP query and a partitioning of the event stream in order to facilitate parallel query evaluation.
- We provide a flexible cost model to reason about the (maximal) throughput that can be achieved for the evaluation of DeCoPa plans in different processing contexts.
- We show the correctness of DeCoPa plans and characterize their optimality in terms of throughput maximization.
- We present an algorithm for the construction of DeCoPa plans, also lifting them to a multi-query setting.

We evaluate the parallel evaluation of CEP workloads based on DeCoPa plans with an implementation based on the CEP library of Flink [9], using real-world and synthetic datasets. Our results show that DeCoPa plans yield up to 12 orders of magnitude higher throughput compared to state-of-the-art approaches for parallel CEP.

In the remainder, we first review related work and provide a motivating example (§2), before giving preliminaries (§3) and formalizing the problem setting (§4). Next, we introduce DeCoPa plans, including a cost model, and elaborate on their properties (§5). Subsequently, we present an algorithm to construct DeCoPa plans (§6). Finally, we present evaluation results (§7) and conclude (§8).

2 BACKGROUND

2.1 Related Work

Due to the exponential complexity of CEP query evaluation [33], various optimization strategies have been proposed, including parallelization and query decomposition. While we build upon ideas for decomposition in CEP [13, 20, 29], distributed CEP for operator placement [2, 3, 26], and multi-query optimization [19, 23, 24], our approach introduces a novel perspective. We focus on optimizing sustainable throughput in a parallel processing context, by guiding the decomposition by the processing capacity.

The three primary paradigms for parallel CEP are data-parallel, state-parallel, and hybrid parallel approaches [16, 25]. In [17] data-parallel CEP based on partitioning keys is proposed and cannot be applied when those are not given. Window based approaches [21, 22], assign processing units event stream partitions corresponding to different windows characterized e.g., by the query's time window or predicates. When using sliding time windows with significant overlap under a permissive selection policy, windows-based parallelization can lead to substantial data replication. Run-intra-based parallelism (RIP) [7] is a form of data-parallelism where runs of an evaluation automaton are parallelized by sending overlapping batches of events to processing units. RIP was designed for contiguous event selection with a maximum match length and its adaption to selection strategies with unbounded match lengths requires batch sizes, which strain the processing unit's maximal ingestion rates.

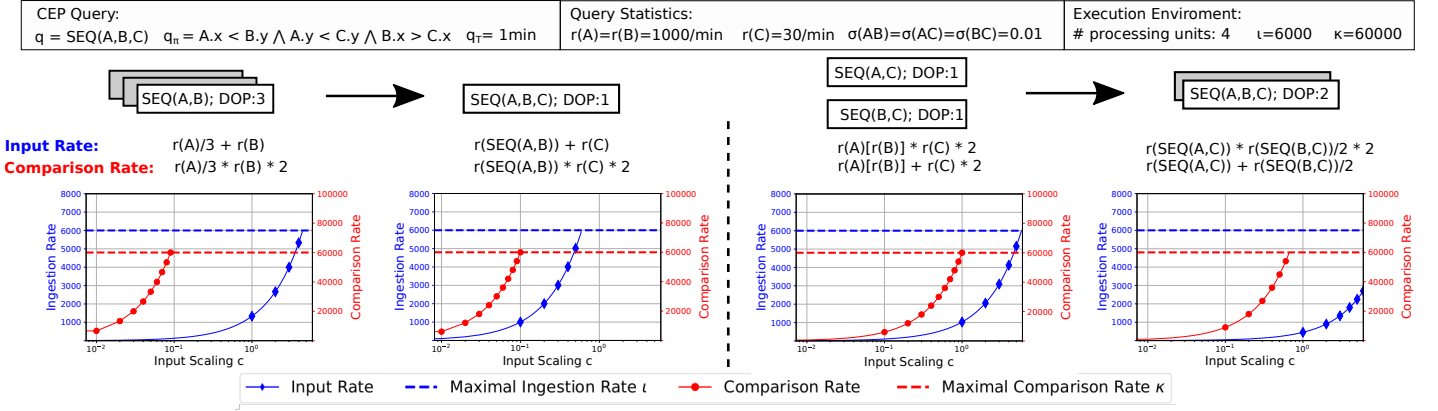
State-based approaches split the CEP query's evaluation automaton into states and assign each state a single processing unit [8], which limits the degree of parallelism by the number of states.

Hybrid parallelism combines state-parallelism with data-parallelism, further parallelizing the evaluation of each state by assigning its evaluation to a set of processing unit, proportional to the states' expected load. Variations of hybrid models consider shared-nothing or shared-memory settings [31, 32]. For the shared-nothing context, see [31], the input stream of each state, comprising primitive events from the global input stream and matches produced by previous states, is partitioned based on its expected input event. Hyper-sonic [32] adopts a similar approach in a shared-memory context. Processing units are divided into two groups: match-workers and event-workers. Each group processes either incoming matches from previous states or events from the primitive event stream, which reduces the required comparison costs. However, the approach is feasible only without extensive data replication, since all processing units can access all input events belonging to their state. We consider the more general, shared-nothing context. While we also employ the parallelization of states, i.e., sub-queries, we propose to decompose queries to meet processing constraints before assigning resources.

2.2 Motivating Example

Fig. 2 illustrates two parallelization schemes for the evaluation of the CEP query $q = SEQ(A, B, C)$ defined over event types A, B, C . For a triple of events (A_i, B_j, C_k) to represent a match of q , they must fall into the time window $q_T = 1min$ and satisfy the predicates q_π , e.g., for the attributes of A_i, B_j it must hold $A_i.x < B_j.y$. The occurrences of the event types are given by $r(A) = r(B) = 1000$ and $r(C) = 30$ per minute, and the selectivities of each pairwise predicate in q_π is given by $\sigma(X) = 0.01$ with $X \in \{AB, AC, BC\}$. The query q is evaluated in parallel on a set of 4 processing units each having a max ingestion rate $\iota = 6000e/min$ and max comparison rate $\kappa = 60000e/min$.

Hybrid Parallel Inspired. Plan I shows a naive decomposition of the query derived from the states of an evaluation automaton for q . As such, the sub-query of the plan, $SEQ(A, B)$, is induced by the partial matches per state. As the sub-query is evaluated in parallel, the plan illustrates the main characteristics of the aforementioned hybrid approaches. The first step takes as input A and B events, to generate matches of the sub-query $SEQ(A, B)$ which are then forwarded to construct matches of $SEQ(A, B, C)$ by incorporating C events from

Figure 2: Two plans for the parallel evaluation of the query q on 4 processing units.

the input stream. $\text{SEQ}(A, B)$ is evaluated in parallel by 3 processing units, each receiving a third of the rate of the A 's and all B 's. With $r(A) = r(B) = 1000e/\text{min}$, for a scaling factor $c \in (0, 1]$, the number of events to ingest is given by $c \cdot (r(A)/3 + r(B))$ and the comparisons to be made are $c \cdot r(A)/3 \cdot r(B) \cdot 2$. The query q is evaluated based on $\text{SEQ}(A, B)$ matches and C events by a single processing unit ingesting $c \cdot (r(\text{SEQ}(A, B)) + r(C))$ events and subsequently carrying out $c \cdot r(\text{SEQ}(A, B)) \cdot r(C) \cdot 2$ comparisons. The plots show, how the comparison rate and ingestion rate grow with c . As all processing units must achieve sustainable throughput, the first crossing of either ι or κ marks the maximal throughput that can be achieved, which happens for plan I at $x = 0.09$ where κ is exceeded for $\text{SEQ}(A, B)$.

Decomposition-based Parallel. Plan II leverages query composition by deriving the matches of q based on the two sub-queries $\text{SEQ}(A, C)$ and $\text{SEQ}(B, C)$, with processing units of both sub-queries receiving the same C events to guarantee complete query evaluation. Given the event occurrences and scaling factor, the number of events to ingest is given by $c \cdot (r(A)[r(B)] + r(C))$ and comparisons by $c \cdot r(A)[r(B)] \cdot r(C) \cdot 2$ for the processing unit matching $\text{SEQ}(A, C)$ and $\text{SEQ}(A, B)$, respectively. Two processing units are allocated to the matching of query q , yielding for each processing unit $c \cdot (r(\text{SEQ}(A, B))/2 + r(\text{SEQ}(A, C)))$ events to ingest and, analogously, to carry out $c \cdot r(\text{SEQ}(A, B))/2 \cdot r(\text{SEQ}(A, C)) \cdot 2$ comparisons. Sustainable throughput can be reached up to a scaling factor of around $c = 0.65$ with the comparison rate for matching q being the limiting factor. Consequently, with the decomposition-based parallelization scheme, 7× higher throughput can be achieved, while leveraging the same number of processing units.

3 PRELIMINARIES

3.1 Query Language

Let $\mathcal{E} = \{\epsilon_1, \dots, \epsilon_n\}$ be a set of event types defining a schema as a set of attributes [16]. An *event* is an instantiation of an event type, which denotes a state change in some system, and is assigned a unique identifier $e.id$, an occurrence timestamp $e.t$, and its type $e.type \in \mathcal{E}$.

Syntax. A query $q = (G_q, q_\pi, q_t)$ comprises a pattern tree G_q , describing the event pattern required by the query, a set of predicates q_π and time window q_t . We restrict our model to predicates that are

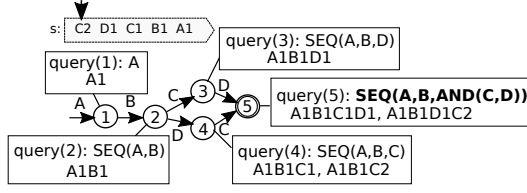
Table 1: Overview of notations for queries and splits.

Notation	Explanation
$e.id, e.t, e.type$	Unique identifier, timestamp and type of event
$\mathcal{E} = \{\epsilon_1, \dots, \epsilon_n\}$	Universe of event types
$q = (G_q, q_\pi, q_t)$	CEP query with pattern tree G_q , predicates q_π and time window q_t .
$G_q = (F, \varphi)$	Pattern tree with pattern functions F , complex pattern functions F_c and primitive pattern functions F_p
$f.sem$	Semantic type of pattern function f of a pattern tree
$types(q)$	Event types referenced in query q
Q	Query workload
$Kleenetype_q, \Omega_q$	Child of KL pattern function, order constraints of query q
$s(q) = (S_q, E_q)$	Split of query q into DAG of sub-queries S_q

defined over at most two event types referenced in the query. The pattern tree $G_q = (F, \varphi)$ is an ordered tree, having patterns functions F as its vertices, which either refer to a single event type or encode some pattern for its child operators in the tree. We denote the former as primitive pattern functions F_p and the latter as complex pattern functions F_c . The function $\varphi : F \rightarrow F^k$ with $k \in \mathbb{N}$ assigns to a pattern function a sequence of children. A pattern function has a semantic type, denoted as $f.sem$, which is for a complex pattern function one of $\{AND, SEQ, OR, KL\}$ and for a primitive pattern function given as event type in \mathcal{E} . For a query with the primitive pattern functions F_p its pattern tree, we use $types(q) = \bigcup_{f \in F_p} f.sem$ to denote the event types referenced in the query q .

We restrict our query model to queries for which the pattern tree comprises at most one pattern function f with $f.sem = KL$, which has exactly one child given as primitive pattern function. A query workload Q , is a set of queries. We split any query containing an OR pattern function into query workload, so that this does not constrain our model's expressiveness.

Semantics. To define the semantics of a query $q = (G_q, q_\pi, q_t)$ we introduce the a set of *order constraints* Ω_q and the *Kleenetype_q*, which can both be derived from the query tree $G_q = (F, \varphi)$. The *Kleenetype_q* comprises the semantic type of the primitive pattern function that is child of a pattern function of type KL , i.e., is given by $\{f_i.sem \mid f_i \in \varphi(f) \wedge f \in F \wedge f.sem = KL\}$. For the definition of the order constraints, let $\phi(f)$ denote the leaf nodes in a pattern tree that are reachable from the pattern function f , and $root(q)$ denote the root pattern function of G_q . The set of order constraints for a pattern function f is inductively defined as:

Figure 3: Partial-match based query evaluation of q .

$$\Omega(f) = \begin{cases} \bigcup_{i \in \varphi(i)} \Omega(i) & \text{if } f.sem \in \{KL, AND\} \\ \bigcup_{i \in \varphi(i)} \Omega(i) \cup \bigcup_{\substack{(k_i, k_j) \in \\ \{(x_i, y_j) | x_i, y_j \in \varphi(f) \\ \wedge i < j\}}} \phi(k_i) \times \phi(k_j) & \text{if } f.sem = SEQ. \end{cases}$$

The order constraints Ω_q of a query q are given by $\Omega(\text{root}(q))$.

The semantic of a query is defined over a stream of events $s = \langle e_1, \dots, e_n \rangle$ ordered by their occurrence timestamp. Let $m \subseteq s$ be a subset of the events in s and $q = ((PF, \varphi), q_\pi, q_t)$ be a query with $Kleenetype_q$ and order constraints Ω_q . Then, m is a match of q if:

- (i.) all events in m occur within the time window q_t and fulfill the pairwise predicates q_π ,
- (ii.) $\cup_{e \in m} e.type = types(q)$,
- (iii.) m fulfills Ω_q , i.e. $\forall (\epsilon_i, \epsilon_j) \in \Omega_q, (e_i, e_j) \in 2^m, e_i.type = \epsilon_i \wedge e_j.type = \epsilon_j \rightarrow e_i.t < e_j.t$,
- (iv.) $|\{e \mid e \in m \wedge e.type \in Kleenetype_q\}| \geq 1 \wedge \forall \epsilon \in types(q) \setminus Kleenetype_q, |\{e \mid e \in m \wedge e.type = \epsilon\}| = 1$.

We consider the least restrictive matching semantics known as *unconstrained* [10] or *skip-till-any-match* [1] which does not constrain the number of times an event can be used for query matching.

3.2 Partial Match based Query Evaluation

We assume a partial match based query evaluation mechanism as it is realized by NFA based CEP evaluation and implemented in common stream processing engines [9, 14]. That is, matches of a query q are constructed incrementally by extending *partial matches* denoting matches of sub-queries of q , with the sub-queries referring to the states of an evaluation automaton. In Fig. 3 an evaluation automaton for the query $q = SEQ(A, B, AND(C, D))$ is illustrated¹. Each state refers to a sub-query for which matches are generated, e.g., partial matches of state 3 refer to matches of the sub-query $SEQ(A, B, D)$. In the example, the partial matches for each state (matches for each sub-query) are shown after evaluating q on the stream s up to the event $C2$. Let $query(k)$ denote the sub-query of q evaluated at state k . An arriving event e_i causes the extension of a partial match $pm = \{e_{j1}, \dots, e_{jn}\}$ of state k to a partial match of state $k + 1$ if $e_i \cup pm$ yields a match of the query $query(k + 1)$.

3.3 System Model

For the parallel evaluation, a CEP query workload is processed in a shared nothing cluster comprising the processing units P , i.e., compute nodes or physical cores which can each process a CEP (sub)-query. The processing units employ a partial match based CEP query evaluation mechanism and are homogeneous in terms of their processing capabilities, i.e., they have an equivalent maximal

¹For illustration purposes, q is only defined in terms of its pattern.

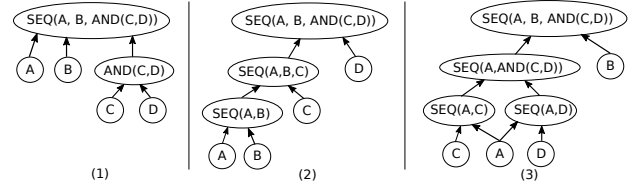


Figure 4: Different Query Splits

ingestion rate ι , and maximal comparison rate κ for a given set of query predicates. The processing units can directly exchange events, i.e., the underlying system topology yields a complete graph.

The event stream upon which the query workload is evaluated arrives at a shuffling process which distributes each event in the stream to a set of processing units based on a parallelization plan.

4 PROBLEM SETTING

4.1 Query Splits

A query split function, denoted as $s : q \rightarrow (S_q, E_q)$, decomposes a CEP query q into a DAG having sub-queries S_q of q as vertices. Fig. 4 illustrates three different query splits for $SEQ(A, B, AND(C, D))$ as they have been proposed for distributed and parallel CEP query evaluation. (1) shows a syntactic query split, as proposed for operator placement in [15]. That is, sub-queries are derived from the complex pattern functions of the pattern tree of a query. (2) shows a split as it is used for state-based (and hybrid) parallelization approaches [31, 32]. The split is derived from the order of states of an evaluation automaton processing the query in the order of the leaf nodes of its pattern tree. As such, the sub-queries of the split are defined by queries for which (partial) matches are constructed in each state of a respective automaton. We denote such a split as left-deep (*ld*) split of a query. (3) shows a split that decomposes the query into sub-queries over arbitrary subsets of the event types in $types(q)$ proposed for in-network evaluation in [2, 3].

We consider sub-queries defined over arbitrary event types of a query for the instantiation of the query split function. Though, to use the matches of a sub-query for generating matches of a query, we consider *valid sub-queries*.

DEFINITION 1 (VALID SUB-QUERY). Let $q = (G_q, q_\pi, q_t)$ be a query having $Kleenetype_q$ and order constraints Ω_q and $o = (G_o, o_\pi, o_t)$ be a query with $Kleenetype_o$ and Ω_o . The query o is a valid sub-query of q if the following holds:

- i. $o_t = q_t$
- ii. $types(o) \subseteq types(q)$
- iii. $o_\pi \subseteq q_\pi$
- iv. $Kleenetype_o \subseteq Kleenetype_q$
- v. $\Omega_o \subseteq \Omega_q$

A correct query split enables correct and complete query evaluation based on the matches of the sub-queries in the split. Let s denote a sequence of events and let $m(q, s)$ be the set of all matches of a query q that can be found in s . Moreover, let $pred(q_s)$ be the set of predecessor sub-queries of q_s in a split DAG. Then, for the split $s(q) = (S_q, E_q)$ of the query q to enable correct and complete query matching, for each sub-query $o \in S_q$ it must hold that $m(o, s) \in \times_{i \in pred(o)} m(i, s)$. To this end, we consider *valid splits*.



Figure 5: Binary (left) and unary (right) Kleene split for q_{kleene} .

DEFINITION 2 (VALID SPLITS). Let $s(q) = (S_q, E_q)$ be a split of the query q . The split $s(q)$ is valid if the following holds for each sub-query $o \in S_q \cup \{q\}$:

- i. $pred(o)$ are valid sub-queries of o
- ii. $\cup_{i \in pred(o)} types(i) = types(o)$

PROPERTY 1. Valid splits enable correct and complete query matching.

In the remainder, we consider only *binary splits* in which each sub-query has at most two predecessors in the split DAG.

Kleene Splits. For the decomposition of queries comprising Kleene closure, we consider two types of splits. Given the split $s(q) = (S_q, E_q)$ for the query q and let $q_{kleene} \in S_q$ denote a sub-query which comprises a pattern function f in its pattern tree, such that $f.sem = KL$ and let none of q_{kleene} 's predecessors in the split $s(q)$ comprise Kleene closure in its pattern tree. Moreover, let $\epsilon_{kleene} \in Kleenetype_q$.

- o In a binary split, q_{kleene} has two preceding sub-queries o_i, o_j whereas o_i is given as the (primitive query) having only one pattern function f_i in its query tree with $f_i.sem = \epsilon_{kleene}$ and o_j as a query that can be obtained from q_{kleene} by removing the pattern functions f_{j1}, f_{j2} with $f_{j1}.sem = \epsilon_{kleene}$ and $f_{j2}.sem = KL$ from q_{kleene} 's pattern tree.
- o In a unary split, q_{kleene} has only one preceding sub-query, $strip(q_{kleene})$, which can be obtained from q_{kleene} by removing the pattern function f with $f.sem = KL$ from the pattern tree of q_{kleene} .

Fig. 5 shows a binary and unary split for the query $SEQ(KL(A), B, C)$.

The matching complexity of the evaluation of queries with Kleene closure based on binary and unary splits differs and is critical for the design of parallelization plans, which we will discuss later.

4.2 Problem Formulation

Given a query q defined over the event types $\mathcal{E}(q)$ and let $D : \mathcal{E}(q) \rightarrow \mathbb{R}$ assign to each event type its occurrences per time window q_t of the query. The query q shall be evaluated by a set of P of homogeneous processing units for which ι denotes the maximal number of events that can be ingested per time window q_t . For the evaluation of the predicates q_π , let κ be the maximal number of comparisons that a processing unit can realize per time window. Decomposition-based parallel query evaluation leverages query splits to decompose q into a set of sub-queries S_q which are then processed by the processing units. A parallelization plan \mathcal{P} describes the split and resource assignment. Evaluating a parallelization plan \mathcal{P} , such that κ and ι are respected, is only possible up to a certain value of the parameter c which denotes the fraction of the occurrences D of the event types to be processed per time window by a processing unit.

EXAMPLE 2. In Fig. 2, two parallelization plans for evaluating the query q on 4 processing units are shown. The split and resource assignment of plan 1 enable sustainable throughput for a maximal scaling value of $c = 0.09$, and for plan 2 of $c = 0.65$.

Table 2: Notations for DecoPa plans.

Notation	Explanation
ι, κ	maximal ingestion and comparison rate for a query and processing unit
$o = (o_q, o_{pe}, o_{part})$	operator o with respective query, processing units and partitioning type
$PG = (O, E)$	parallelization graph with operators O and edges E
$pre(o), suc(o)$	Preceding and succeeding operators of o with respect to parallelization graph
$leaves(PG), root(PG)$	Leaf operators and root operator of PG
$r(q)$	occurrence rate of a query q
$\sigma(q)$	selectivity induced by the predicates q_π of query q
ι_o, κ_o	ingestion and comparison costs of an operator o

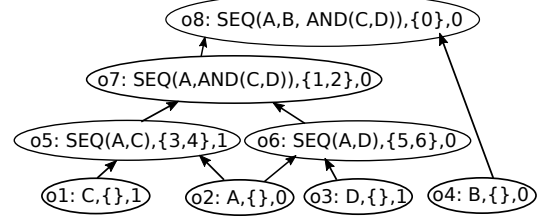


Figure 6: Parallelization Plan for the evaluation of the query $SEQ(A, B, AND(C, D))$ on 7 processing units.

PROBLEM 1 (EFFICIENT PARALLEL CEP EVALUATION). For a query and set of processing units with κ, ι , the problem of efficient parallel CEP evaluation is to construct a parallelization plan \mathcal{P} that respects κ and ι , such that c is maximal.

5 DECOMPOSITION-BASED PARALLELIZATION

We propose Decomposition-based Parallel (DecoPa) plans to address the problem of efficient, parallel CEP. We formally define DecoPa plans (§5.1) before turning to their execution (§5.2). Then, we define a flexible cost model that can be used to compare DecoPa plans in terms of their throughput gain (§5.3), and investigate formal properties as well as the computational complexity of constructing optimal DecoPa plans (§5.4). Finally, we lift DecoPa plans to query workloads and elaborate on adaptivity (§5.5).

5.1 DecoPa Model

A decomposition-based parallel (DecoPa) plan comprises the information necessary to enable parallel evaluation of a given CEP query on a set of processing units. Moreover, it encodes the partitioning scheme of the input event stream which is to be instantiated by a shuffling process to distribute incoming events to processing units.

We leverage binary query splits to achieve throughput optimizing DecoPa plans. That is, a query is decomposed into a graph having sub-queries as vertices and each sub-query having at most two predecessors. To evaluate the query, the sub-queries are evaluated in parallel by processing units.

The basic building block of a DecoPa plan is an *operator* which specifies a sub-query, a set of processing units to evaluate the sub-query on and a flag denoting if matches of the sub-query shall be broadcasted or partitioned among the processing units.

DEFINITION 3 (OPERATOR). Let Q be a set of queries and P a set of processing units. An operator is a triple $(Q, 2^P, \{0, 1\})$.

For an operator $o = (o_q, o_{pu}, o_{part})$, o_q denotes the sub-query of the operator, o_{pu} are the processing units and o_{part} is the partitioning type, i.e., if o_{part} is set to 0, matches of o_q are broadcasted, otherwise they are partitioned.

DEFINITION 4 (DECOPA PLAN). Given a set of operators V_O . A DecoPa plan is a directed acyclic graph $PG = (V_O, E_O)$ having V_O as vertices and E_O as edges.

Given a DecoPa plan $PG = (V_O, E_O)$ and operator $o \in V_O$, we denote $pre(o) = \{o_1 \mid (o_1, o_2) \in E_O\}$ as the preceding and $suc(o) = \{o_2 \mid (o_1, o_2) \in E_O\}$ and succeeding operators of o in PG . Moreover, let $leafs(PG) = \{o_i \mid o_i \in V_O \wedge pre(o_i) = \emptyset\}$ denote the leaf operators and $root(PG) = \{o_i \mid o_i \in V_O \wedge suc(o_i) = \emptyset\}$ the root operators of a parallelization plan.

EXAMPLE 3. Fig. 6 illustrates a parallelization plan for the query $q = SEQ(A, B, AND(C, D))$ evaluated on the processing units $\{0, \dots, 6\}$, having the operators $\{o_1, \dots, o_8\}$ as vertices. The operator o_5 evaluates the query $o_q = SEQ(A, C)$ is evaluated by the processing units $o_{pu} = \{3, 4\}$ and as $o_{part} = 1$ its matches are partitioned. For o_7 , $pre(o_7) = \{o_5, o_6\}$ and $suc(o_7) = \{o_8\}$. Moreover, $root(PG) = \{o_8\}$ and $leafs(PG) = \{o_1, \dots, o_4\}$.

5.2 Execution of DecoPa Plans

To execute a DecoPa plan $PG = (V_O, E_O)$ each operator $o \in V_O$ is instantiated by the set of processing units o_{pu} . The leaf operators $leaf(PG)$ of a parallelization plan stand for the primitive event types in the input stream and describe if instances thereof are partitioned among or broadcasted to their succeeding operators in PG . Based on the leaf operators a shuffling process is instantiated. Let e be an instance of event type ϵ and o^{leaf} an operator in PG for which $o_q^{leaf} = \epsilon$. If $o_{part}^{leaf} = 0$, e is forwarded to all processing units of the succeeding operators $suc(o^{leaf})$. Otherwise, i.e., $o_{part}^{leaf} = 1$, for each operator $o^{suc} \in suc(o^{leaf})$ instances of ϵ are sent in a round-robin manner to the processing units in o_{pu}^{suc} .

A processing unit $u \in o_{pu}$ of the operator $o \in V_O$ matches the sub-query o_q based on matches of the sub-queries $\{o_q^p \mid o^p \in pre(o)\}$. To this end, u realizes partial match based query evaluation and compares each incoming match to its locally maintained partial matches, to form new matches of o_q . As for the leaf operators, if $o_{part} = 0$, each match of the sub-query o_q generated by the instance u is broadcasted to the processing units of the successors of o . If $o_{part} = 1$, for each operator $o^s \in suc(o)$ partitions of the matches of sub-query o_q^s are distributed among its processing units o_{pu}^s . The partitioning scheme employed for distributing the matches of o_q depends on the matching semantic of each succeeding operator of o :

1. *(binary-split)* For a succeeding operator o^s matching the query o_q^s with a binary split, matches of o_q can be distributed in a round-robin manner among the processing units o_{pu}^s .
2. *(unary-split)* If o is the (only) preceding operator of an operator o^{KL} which generates matches of Kleene Closure based on a unary split, then $o_q = strip(o^{KL})$ (§4.1). Let ϵ be the event type of $Kleenetype_{q_{KL}}$. To generate all matches of o_q^{KL} , each match of o_q that is identical in its events of the types in $types(q) \setminus \epsilon$ needs to be processed by the same processing unit of o^{KL} . To this end, a hash-based partitioning on the IDs

of the events of type $types(q) \setminus \epsilon$ is applied at the processing units of o_q .

EXAMPLE 4. For the evaluation of Fig. 6, a shuffler distributes events of type C among the processing units of operator o_5 , i.e., events of type C are forwarded alternately to the processing units $\{3, 4\}$. Analogously, D events are distributed among the processing units of o_6 . All A events are forwarded to all processing units of the operators o_5, o_6 and all B events to the processing unit of o_8 . Based on its respective share of C events and A events, each processing unit of o_5 generates matches of the query $SEQ(A, C)$ and, forwards the matches alternately to the processing units of o_7 . Each processing unit of o_6 forwards all matches to the processing units of o_7 . The processing units of o_7 generate matches of $SEQ(A, AND(C, D))$ based on matches of $SEQ(A, C)$ and $SEQ(A, D)$ and forward all respective matches to the processing unit 0 of o_8 which generates matches of the query q .

5.3 Cost Model

5.3.1 Output rates of Queries. To reason about the ingestion and comparisons to be made by a processing instance of an operator, we capture the rates with which matches of (sub)-queries are generated based on known distributions of event type occurrences and predicate selectivities. To this end, we assume that the predicates are independent. Given an event type universe \mathcal{E} , let $d : \mathcal{E} \rightarrow \mathbb{R}$ assign to the event types in \mathcal{E} their number of occurrences per time unit u . Given the query $q = (G_q, q_\pi, q_t)$, we assume for simplification, that the occurrences d of event types in $types(q)$ are given with respect to the time window q_t , i.e., $u = q_t$. Moreover, let $\sigma(q)$ define the selectivity of the predicates q_π . The rate of a query is inductively defined along the pattern functions of the queries pattern tree $G_q = (F, \varphi)$. The rate of a primitive pattern function $f_p.sem \in F$ with semantic type $f_p = \epsilon$, is given by $d(\epsilon)$. For a complex pattern function $f_c \in F$, with $\varphi(f) = \langle f_1, \dots, f_k \rangle$ the rate is defined inductively:

$$r(f) = \begin{cases} k \cdot \prod_{1 \leq i \leq k} r(f_i) & \text{if } f.sem = AND, \\ \prod_{1 \leq i \leq k} r(f_i) & \text{if } f.sem = SEQ, \end{cases}$$

Let $root(G_q)$ be the root pattern function of the pattern tree of the query q , then the rate of q is defined as $r(q) = \sigma(q) \cdot r(root(G_q))$.

Kleene Closure. As discussed in §3.1, we restrict our language model to queries comprising at most one occurrence of Kleene Closure and in which Kleene Closure can be applied to a single primitive event type only. To define the output rate of a query containing Kleene Closure q_{KL} , we first define the query q_{KL}^- that is obtained by removing the pattern function corresponding to $\epsilon_{KL} \in Kleenetype_{q_{KL}}$ and its parent node from the pattern tree of q_{KL} . Let for the predicates of q_{KL} , π_{KL} denote the predicates that need to hold for each pair of ϵ_{KL} events that can be part of a valid q_{KL} match and π_{rest} denote predicates that are defined over tuples of event types in $types(q_{KL}^-)$ and ϵ_{KL} with σ_{KL} and σ_{rest} being the selectivities of the former and latter. Now, we can define the rate of the query q_{KL} as follows:

$$r(q_{KL}) = r(q_{KL}^-) \cdot \sum_{i=0}^{r(\epsilon_{KL})} \binom{r(\epsilon_{KL})}{i} \cdot \sigma_{KL}^{i-1} \cdot \sigma_{rest}^i.$$

The first factor in the equation indicates the rate of the sub-matches that can be part of a match of q_{KL} and do not contain ϵ_{KL} and therefore is given by $r(q_{KL}^-)$. Each such sub-match of q_{KL}^- can be

combined with the different matches of a sub-query $KL(\epsilon_{KL})$ which comprises sequences of events of type ϵ_{kleene} for which the predicates $\pi_{rest} \cup \pi_{KL}$ hold.

5.3.2 Costs of Operators. For a given DecoPa plan $PG = (V_O, E_O)$, each processing unit of an operator $o \in V_O$, generates matches of the query o_q based on the matches generated by its preceding operators $pre(o)$. Let c denote the fraction of event type rates evaluated.

Input costs. The input costs $\hat{\iota}_o$ of an operator are defined as follows:

$$\hat{\iota}_o = \sum_{o^{pre} \in pre(o)} c \cdot r(o_q^{pre}) * \frac{1}{(|o_{pu}| - 1) \cdot o_{part}^{pre} + 1}$$

. That is, for each predecessor operator o^{pre} for which matches are partitioned, i.e., $o_{part}^{pre} = 1$, each processing unit o_{pu} receives an equivalent share² of the matches of o_q^{pre} . Otherwise, each processing unit o_{pu} receives all matches of o_q^{pre} .

Comparison Costs. The comparison costs $\hat{\kappa}_o$ of an operator o capture the number of comparisons between the events received from preceding operators and the partial matches maintained carried out by a processing unit of o per time unit. It depends on the number of matches generated per preceding operator, the different classes of partial matches maintained by the processing unit and the number of partial matches per class. The classes of partial matches in turn, depend on the semantics of the query o_q of the operator o .

SEQ,AND. Let o_q be a query comprising only *SEQ* and *AND* pattern functions in its pattern tree and let $o1, o2 \in pre(o)$ denote the preceding operators of o . Each processing unit evaluating o_q maintains two classes of partial matches, each comprising its received partitions of all matches of $o1_q, o2_q$ respectively that can be found per time window of q . The concrete number of instances in each class of partial matches equals the share of matches each processing unit receives from its predecessors, i.e., $r(o1_q)/|o_{pu}|$ if $o1_{part} = 1$, $r(o1_q)$ otherwise; analogously for $o2$.

To match o_q , each incoming match of $o1_q$ has to be compared again all partial matches of type $o2_q$ and vice versa, resulting in comparison costs of

$$\hat{\kappa}_o = c \cdot 2 \cdot \frac{r(o1_q)}{(|o_{pu}| - 1) \cdot o1_{part} + 1} \cdot \frac{r(o2_q)}{(|o_{pu}| - 1) \cdot o2_{part} + 1}.$$

Kleene Comparisons. An operator o^{KL} matching Kleene Closure is an operator for which the respective query o_q^{KL} comprises Kleene Closure and none of the queries of the predecessors of o^{KL} comprise Kleene Closure. We distinguish between a unary and a binary split for decomposing the evaluation of Kleene Closure which yield differing comparison costs respectively.

For a unary split, matches of o_q^{KL} are generated based on matches of $strip(o_q^{KL})$ (see §4). A processing unit generating o_q^{KL} matches from $strip(o_q^{KL})$ has to maintain only one class of partial matches which comprises valid matches of o_q^{KL} : An incoming match of

$strip(o_q^{KL})$ already represents a match of o_q^{KL} and as such instantiates a partial match of the class. Moreover, partial matches of type o_q^{KL} can be extended to further matches of o_q^{KL} after processing incoming matches of $strip(o_q^{KL})$. Hence, the number of partial matches of type o_q^{KL} is given by $r(o_q^{KL})$. Let o^{strip} be the preceding operator of o^{KL} matching $strip(o_q^{KL})$. Then, the comparison rate of o^{KL} matched with a unary split is

$$\hat{\kappa}_{o^{KL}} = c \cdot \frac{1}{(|o_{pu}^{KL}| - 1) \cdot o_{part}^{strip} + 1} \cdot r(strip(o_q^{KL})) \cdot r(o_q^{KL}).$$

Let $\epsilon_{KL} \in Kleenetype_{KL,q}$ and o^{pre-KL} denote the preceding operator comprising ϵ_{KL} and $o^{pre-noKL}$ the second preceding operator. Moreover, let q_{KL} denote a query that is obtained by inserting the Kleene Closure pattern function into the pattern tree of o_q^{pre-KL} as parent node of the respective pattern function of ϵ_{KL} . To evaluate o_q^{KL} based on o_q^{pre-KL} and $o_q^{pre-noKL}$, three classes of partial matches need to be maintained per processing unit of o^{KL} . One class comprises matches of type $o_q^{pre-noKL}$ which are instantiated whenever a match of $o_q^{pre-noKL}$ is received. The second class comprises matches of q_{KL} , which are derived from received matches of o_{pre-KL} . The third class contains matches of the operators query o_q^{KL} which need to be maintained as they can be extended to further matches of o_q^{KL} based on received o_{pre-KL} matches. The number of instances in each partial match class per time unit, equals the rates of the respective queries for which matches are maintained in the class. Thus, the resulting comparison costs of binary Kleene Closure evaluation are given by:

$$\hat{\kappa}_{o^{KL}} = c \cdot \left(\frac{r(o_q^{pre-noKL})}{(|o_{pu}^{KL}| - 1) \cdot o_{part}^{pre-noKL} + 1} \cdot r(q_{KL}) + c \cdot r(o_q^{pre-KL}) \cdot \left(\frac{r(o_q^{pre-noKL})}{(|o_{pu}^{KL}| - 1) \cdot o_{part}^{pre-noKL} + 1} + r(q_{KL}) + r(o_q^{KL}) \right) \right)$$

EXAMPLE 5. Fig. 7 shows both cases of the binary matching procedure for which matches of q are generated based on A and B events. To this end, besides the partial match class containing matches of q , which again can be extended to further matches of q , a second partial match class contains the received instances of A events and a third class contains matches of the query $KL(B)$. If an A event is received, it is compared against all partial matches of type $KL(B)$ to form new matches of q which are sent to a potential next operator and kept in state for further matching. If a B event is received, it is compared against matches in all classes, to create new matches of $KL(B)$ or extend matches from class A or q to further matches of q .

5.4 Correctness and Optimality

For this section, let $PG = (V_O, E_O)$ be a DecoPa plan for the evaluation of the query q on the processing units P . The maximal ingestion rate of each processing unit in P is given by ι and the maximal comparison rate that can be achieved for the evaluation of the predicates q_π of the query is given by κ . Moreover, let D be the distribution of occurrences of the event types referenced in q .

²While this assumption holds for non-kleene matching, for unary Kleene splits, due to the hash-based partitioning scheme, processing units can receive varying shares of matches. Those may differ in their size due to skewed attribute values. However, this is not considered in our cost model.

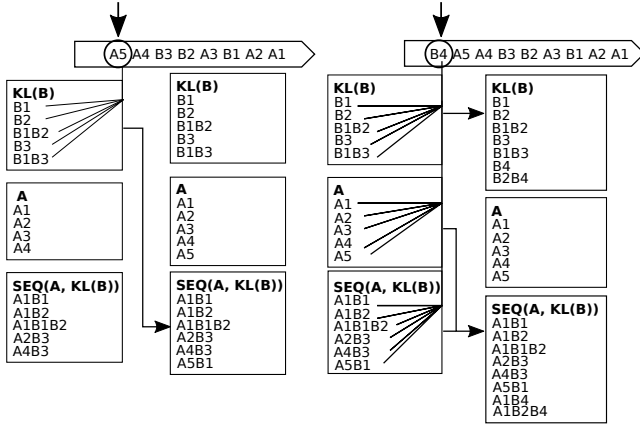


Figure 7: Comparisons for binary Kleene Closure matching.

Correctness. To enable correct parallel query evaluation, our objective is to ensure, that the execution of the DecoPa plan PG on the processing units P yields all matches of q at the processing units of the operator $root(PG)$. To this end, the processing units of each operator $o \in V_O$ must jointly generate all matches of o_q .

DEFINITION 5 (STRUCTURAL VALIDITY). *The DecoPa plan PG is structural valid, if the following properties are satisfied:*

- 1 *There exists a correct split $s(q) = (S_q, E_q)$ of the query q such that $i : V_O \rightarrow S_q$ with $\forall o \in V_O, i(o) = o_q$ yields an isomorphism between the vertex sets V_O and S_q .*
- 2 *For all operators $o \in V_O$, there exists at most one predecessor in $o^{pre} \in pred(o)$ for which $o_{part}^{pred} = 1$.*
- 3 *Let o^{KL} denote an operator which matches Kleene closure with a binary split and $o^{kleeneType} \in pre(o^{KL})$ denote o^{KL} 's predecessor for which the respective query comprises the Kleene type, then $o_{part}^{kleeneType} = 0$ must hold.*

The definition of a structural valid DecoPa plan implies correctness:

THEOREM 1. *Evaluating a structural valid DecoPa plan for a query q and the processing units P , all matches of q are generated at a subset of P .*

PROOF. (sketch.) Because of (1.), for each operator o , based on the matches of preceding operators, correct matches of o_q can be generated. Hence, $root(PG)$ generates correct matches of q . To enable complete evaluation for an operator o having two preceding operators o^i, o^j , each match of o_q^j must be combined with each match of o_q^i by at least one processing unit of o . This may not be the case, if a processing unit receives only partitions of the matches of both o_q^i and o_q^j . Though, this case is excluded by (2.). For correct Kleene matching all events of the Kleene type must be processed by the same processing unit, which follows from (3.). \square

Throughput Validity. Given a scaling factor c which scales the occurrences D of the event types in q . The parallelization plan PG is throughput valid for the scaling factor, when all processing units involved in the execution of PG yield sustainable throughput.

DEFINITION 6 (THROUGHPUT VALIDITY). *PG is throughput valid for a $c \in \mathcal{R}$, if $\kappa \leq \max \{\hat{\kappa}_o \mid o \in V_O\} \wedge \iota \leq \max \{\hat{\iota}_o \mid o \in V_O\}$.*

Optimality. A parallelization plan PG is optimal, if it maximizes (sustainable) throughput for q .

DEFINITION 7 (OPTIMALITY). *Let the evaluation plan PG for the evaluation of q on P processing instances be structural valid and throughput valid for c . PG is optimal, if there exists no other structural valid parallelization plan PG' for q, P such that PG' is throughput valid for a scaling factor c' and $c' > c$.*

To construct an optimal DecoPa plan, a split and respective resources assignment must be determined, such that the maximal comparison and input costs of the resulting operators are minimized (Def. 7). Even for a restricted version, which considers only ld splits for the plan construction, the problem of constructing optimal DecoPa plans is NP-hard, which can be shown by a reduction from optimal join-ordering for left-deep trees which is known to be NP-hard [12].

THEOREM 2. *Optimal DecoPa plan construction is NP-hard.*

PROOF. (sketch.) For a join-ordering instance comprising the relations R_1, \dots, R_n and the pairwise selectivities Σ of the join predicates, we can construct a ld -DecoPa plan using $|R_1|, \dots, |R_n|$ as event rates together with Σ to instantiate the cost functions. We choose $\iota = 0$ and assume enough resources to balance out the comparisons of the operators, such that the comparison costs of all operators are equivalent with the consequence, that to maximize c , the sum of comparison costs of its operators needs to be minimized. The underlying split of the optimal DecoPa plan optimizes the join-ordering for the given problem instance. \square

5.5 Generalization of DecoPa Plans

Multi-Query Setting. The definition of DecoPa plans extends naturally to workloads consisting of multiple queries. Let PG_1, \dots, PG_n be DecoPa plans for the queries of the workload $Q = q_1, \dots, q_n$. Unifying the sets of operators and edges of the DecoPa plan, we obtain a DecoPa plan PG_Q for the workload having a set of root operators for the queries in Q . If a multi-query DecoPa plan PG_Q has multiple operators referencing the same sub-query s_q , processing units can be shared by keeping only one operator for s_q . In the next section, we discuss strategies for promoting the sharing of sub-queries and processing units during the construction of multi-query DecoPa plans.

Adaptivity. The effectiveness of a given DecoPa plan for a query relies on the rates of the event types of the query and the predicate selectivities. A change thereof over time, can be identified by each processing unit if the number of matches of the query evaluated deviates from the predicted rates and prompt the construction and deployment of a new DecoPa plan. Revising only some operators of a DecoPa plan instead of a complete new construction, by either employing load balancing strategies or substituting certain sub-queries will be targeted in future work.

6 CONSTRUCTION

As the optimal DeCoPa construction is intractable, this section is devoted to the efficient construction thereof. We discuss preliminary considerations on the partitioning, resource assignment and sub-query selection (§6.1) before turning to the decomposition of a

query into a split graph and the subsequent DecoPa plan instantiation (§6.2). Then, we elucidate the extension to a multi-query scenario (§6.3) and state the complexity of our construction algorithm (§6.4).

6.1 Preliminary Considerations.

Resource assignment. The number of available processing units influences the choice of splits that can be used for the construction of a DecoPa Plan, as shown in Fig. 2: If only 2 processing units were available instead of 4, the right plan could not be used for the evaluation of q . Let $s(q) = (S_q, E_q)$ be a split for the query q , P a set of processing with ι and κ , and c a scaling factor. Moreover, let $S_{q_c} \subset S_q$ denote the sub-queries defined over more than one primitive event type. Given that $|P| > |S_{q_c}|$, we assign the resources to each sub-query respecting ι and κ : Let $s_q \in S_{q_c}$ be a (non-Kleene) sub-query with a binary split having pre_1, pre_2 as preceding sub-queries in $s(q)$ and let $r(pre_1) \geq r(pre_2)$. The resources allocated to s_q are given by: $pu(s_q) = \max\{\frac{pre_1 \cdot pre_2 \cdot 2}{\kappa}, \frac{1}{(\iota - pre_2)} \cdot pre_1\}$. For Kleene matching, the numerator of the left part reflects the respective comparison costs as discussed in §5.3. If there are not enough processing units, i.e., $|P| < \sum_{s_q \in S_{q_c}} pu(s_q)$, no throughput valid plan can be constructed for c based on the given split. Remaining resources $|P| - \sum_{s_q \in S_{q_c}} pu(s_q)$ are distributed among the sub-queries proportionally, to approximate equivalent comparison costs for each operator.

Partitioning Scheme. If an operator o has more than one processing unit assigned, the evaluation of o_q is jointly done by the processing units o_{pu} . As we only consider the construction of structural valid DecoPa plans, at most one of the preceding operators $pre_1, pre_2 \in pred(o)$ can have $pre_{i_{part}} = 1$ (see Def. 5). To minimize the input costs $\hat{\iota}_o$ of each operator, we construct DecoPa plans, such that the operator pre_1 , for which $r(pre_{1_q}) > r(pre_{2_q})$, partitions its matches. The comparison costs $\hat{\kappa}_o$ are unaffected by this choice.

Rate-Reducing Subqueries. As the comparison and input costs of operators in a DecoPa plan are defined based on the match rates of the sub-queries in the underlying query split, we consider only *rate-reducing* sub-queries for the construction of query splits: That is, we restrict the search space by considering only sub-queries s_q , which have an output rate lower than the maximal rate of the comprised primitive event types, i.e., $r(s_q) < \max_{\epsilon \in types(q)} d(\epsilon)$. This way, the negative impact of high rate event types on the comparison and input costs of a DecoPa plan is contained.

6.2 DecoPa Plan Instantiation

As shown in Alg. 1, we employ dynamic programming to construct DecoPa plans. The function $Plan(s, PU)$ instantiates a DecoPa Plan for a given split s and processing units PU , assigning the processing units and partitioning as explained in the previous section. To compare plans, we use the cost function $costs(P)$, to assign to a plan P its sum of comparison. In a first step all rate-reducing subqueries SQ are enumerated for q (line 1). As the rate-reducing sub-queries may not suffice to construct a complete binary split for the query, a set of ld splits is sampled for q and each sub-query in SQ (line 3). For each sub-query, we determine the ld split inducing the least costs when instantiated in a (ld -)DecoPa plan, assigning one processing unit to each sub-query (line 2). Based on the best ld split and the respective costs, two maps, one for keeping the current best split ($Splits$), one for keeping the minimal costs ($PCosts$), are

Algorithm 1: DecoPa Construction.

```

input : query  $q$ ; processing units  $totalPU$ 
output : DecoPa plan

/* Generate set of rate reducing subqueries. */
1  $SQ \leftarrow getRateReducingSQs(q)$ 
2 for  $sq \in SQ \cup q$  do // For each subquery and  $q$ 
3    $ldSplits \leftarrow sampleLdSplits(sq)$ ; // Sample  $ld$  splits of  $sq$ 
4   for  $ld \in ldSplits$  do // For each  $ld$  split
5     if  $costs(Plan(ld, |types(sq) - 1|)) < PCosts[sq]$  then
6        $PCosts[sq] \leftarrow costs(Plan(ld, |types(sq) - 1|))$ 
7        $Splits[sq] \leftarrow ld$ 

7 for  $sq \in topoSort(SQ \cup q)$  do // Iterate over sorted  $SQ$ 
/* Assign processing units proportionally to  $sq$  */
8  $PU[sq] \leftarrow (PCosts[sq] / \sum_{i \in SQ} PCosts[i]) * |totalPU|$ 
/* Adjust plan costs with processing units */
9  $PU[sq] \leftarrow costs(Plan(ld, PU[sq]))$ 
/* Determine predecessor candidates */
10  $PredC \leftarrow \{x | x \in SQ \wedge types(x) \subset types(sq) \wedge PCosts[x] < PCosts[sq]\}$ 
/* Loop over candidate predecessors */
11 for  $(s1, s2) \in \{(s1, s2) | s1, s2 \in PredC \wedge s1 \neq s2 \wedge types(s1) \cup types(s2) = types(sq)\}$  do
/* Split graphs of  $s1, s2$  */
12  $G_{s1} = (V_1, E_1), G_{s2} = (V_2, E_2) \leftarrow Splits[s1], Splits[s2]$ 
/* Construct candidate split of  $G_{s1}, G_{s2}$  */
13  $SplitC = ((V_1 \cup V_2 \cup \{sq\}), (E_1 \cup E_2 \cup \{(sq, s1), (sq, s2)\}))$ 
/* Update, if  $SplitC$  improves costs */
14 if  $costs(Plan(SplitC, PU[sq])) < PlanCosts[sq]$  then
15    $PCosts[sq] \leftarrow costs(Plan(SplitC, PU[sq]))$ 
16    $Splits[sq] \leftarrow SplitC$ 
17 return  $Plan(Splits[q], totalPU)$ 
```

initialized for each sub-query and q (line 5-line 6). In the main loop, we iterate over each subquery $sq \in SQ$ sorted in a topological order (line 7): First, we compute for sq a number of processing units, which we use to instantiate candidate DecoPa plans (line 8). That is, we assign to sq processing units proportional to the costs of the best (ld -)DecoPa plan with respect to the costs of the (ld -)DecoPa of all other sub-queries. Then, $PCosts$ of sq are updated with the costs of the best ld -DecoPa plan instantiated with this number of processing units (line 9). The respective number of processing units does not necessarily equal the final number of processing units assigned to sq when used in a Plan and only serves as heuristic for the cost function during the split enumeration. Next, the set of predecessor candidates $PredC$ given by the rate reducing sub-queries of sq and for which the determined costs are less than the currently estimated costs of sq (line 10) is computed. Due to the ordered processing, final splits and respective costs for each potential predecessor were already constructed in an earlier iteration. Then, for each tuple in $PredC$ which yields a potential set of predecessors of sq in a structural valid split, i.e., covers the event types of sq , a split is constructed by combining the splits of the predecessors in a split graph having sq as root (line 12- line 13). The costs of a plan instantiating this potential split $SplitC$ with the predetermined processing units are computed and the split for the plan introducing minimal costs is kept (line 15 - line 16). In the last iteration the query q is processed and a respective split is constructed. The total number of processing units are assigned to the sub-queries in the split to finalize the DecoPa plan for the query (line 17).

6.3 Multi-query Construction

To efficiently parallelize the evaluation of multi-query workloads, we enhanced our construction to foster sharing of operators between queries and assign processing units proportionally with respect to all queries in Q . If the queries differ in their time windows and predicates, the query workload can be ‘normalized’ by choosing the maximal time window for the evaluation and for each tuple of event types the conjunction of predicates thereof within all query predicates of the workloads queries. Before processing the queries in Q , each query q , is transformed to a query q' for which the pattern trees’ structure comprises a root pattern function f with $f.sem = AND$ with the children $\phi(f)$ being primitive pattern functions defined over $types(q)$. The resulting queries have no order constraints, which allows to share each sub-query defined over a subset of event types referenced in multiple queries. We process the queries sorted based on their sum of comparisons for a DecoPa plan having an ld split, determined in a pre-processing step. Starting with the query having maximal costs, Alg. 1 is run twice for each query. In the first round, the considered sub-queries are restricted to those already used in a split of a query processed in an earlier iteration. For the second round, all sub-queries are considered. The resulting split inducing lower costs is chosen for each query. The final assignment of processing units for the DecoPa plan of the workload, is done after all query splits have been constructed, such that processing units are shared for sub-query evaluation.

6.4 Complexity of Construction

To enumerate the set of rate-reducing sub-queries of a query q , each subset of $types(q)$ needs to be considered which yields a time complexity of $O(2^{|types(q)|})$. For the construction of the DecoPa plan, k ld splits are sampled for each rate reducing sub-query, introducing additional time complexity of $O(k \cdot 2^{|types(q)|})$. In the main loop, to construct the split, for each sub-query sq tuples of sub-queries of s are enumerated, yielding time complexity $O(2^{|types(q)|} \cdot (2^{|types(q)|})^2)$.

7 EVALUATION

We evaluated DecoPa plans for parallel CEP query evaluation in several experimental setups. Below, we first review our evaluation setup (§7.1), before turning to a state-of-the-art comparison (§7.2). Then, we present our results for real-world data experiments (§7.3) and a sensitivity analysis based on synthetic data (§7.4).

7.1 Evaluation Setup

Data Sets and Queries. We evaluated DecoPa plan based query evaluation on two real-world data sets: the Google Cluster traces [11], and the Citi Bike data set [30]. Moreover, we used synthetic data in a sensitivity analysis to achieve a controlled setup for investigating the influence of different workload characteristics.

The Google Cluster data set has 9 event types, corresponding to state transitions in the task life-cycle of jobs. The Citi Bike data set contains events denoting bike rentals from which we derived 9 event types based on the age, customer type, and rental length. For each data set, we evaluated three queries of which two comprise different nestings of the *AND* and *SEQ* pattern function, and one comprises Kleene closure. For the Google Cluster trace, we used a sub-trace of the events generated in 48 hours comprising 7 million events,

for Citi Bike the queries were evaluated on a trace covering bike rentals within a month, comprising 1 million events. The predicate used in the Google Cluster queries, requires decreasing values for the requested CPU- and memory capacity as well as decreasing priority for consecutive events in a match. For the the Citi Bike queries, the predicate is satisfied if the distance between the start locations of each tuple of rides is greater than 6 kilometers. That is, to be considered as a match of a query, a set of rides needs be geographically dispersed. The Google Cluster queries are evaluated over a time window of 10, for Citi Bike, we used a time window of 24 hours. The predicates yielded a selectivity of 0.07% (Google Cluster) and 0.05% (Citi Bike). Both data sets showed skewed event rate distribution with differences in the event rates of up to 5 orders of magnitude.

For the synthetic data, we generated different event rate distributions which were drawn from a Zipfian process with a skew parameter set to 1.2 resulting in fairly skewed event rates. Based on the event rates, we instantiated a Poisson process to generate event traces. We constructed queries with varying lengths and semantics as well as query workloads of different size. To simulate query predicates, we drew uniformly selectivities from the range 1 – 10%. If not stated otherwise, the time window used was 1 minute.

Baselines. As discussed, none of existing approaches for parallel CEP considers decomposition. Thus, we used for all investigated baseline strategies an ld split with the ordering directly derived from the respective query. For a centralized baseline, all sub-queries of the respective split are processed by a single processing units, for the state-based baseline, each sub-query is evaluated by a single processing unit. As baseline representing hybrid-parallel approaches [31, 32], we assigned to each sub-query processing units relative to the expected load in terms of comparison costs and chose to partition the maximal input of each operator among its processing units. As discussed, RIP [7] was proposed for query evaluation with a contiguous event selection strategy and a given maximal match-length. To adapt RIP to our setting, we assigned batches of 2 time windows to the processing units in a round-robin manner with two consecutive batches overlapping in one time window. In the remainder we use *Hybrid* to refer to the hybrid-parallel baseline and *Stateparallel* and *RIP*-inspired for the other baselines accordingly.

Metrics. If not stated otherwise, we compared the DecoPa based query evaluation against the baseline approaches in terms of the resulting throughput gain over a centralized query evaluation. To this end, we determined the maximal scaling factor $c_{centralized}$ for a given problem instance that could be achieved for centralized evaluation and the scaling factor c_{other} for a respective other approach and report on the ratio $c_{other}/c_{centralized}$. Moreover, we measured the detection latency resulting from the parallel evaluation.

Implementation. We implemented our construction algorithm and cost models in Python and deployed the resulting DecoPa plans on processing units running FlinkCEP [9]. The shuffling process that can be instantiated based on a DecoPa plan was not part of the experimental setup but realized by a pre-processing step in which event traces for each processing unit were generated given a DecoPa plan. To enhance flexibility, event sources were decoupled from the FlinkCEP instances, and events were exchanged between sources and processing units, and among processing units, using TCP sockets. We investigated the DecoPa based query evaluation in a single-node

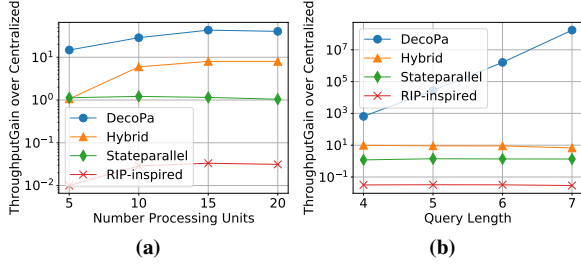


Figure 8: Comparison against State-of-the-art approaches.

Table 3: Throughput gain for real-world data sets.

		Citi Bike			Google Cluster		
		Q1	Q2	Q3	Q1	Q2	Q3
5	DecoPa	52.4×	212.8×	758.5×	578.0×	13.1×	3.1×
	Hybrid	1.0×	2.9×	155.2×	2.1×	1.2×	3.1×
10	DecoPa	204.9×	436.3×	3714.8×	1989×	20.1×	8.2×
	Hybrid	3.1×	3.7×	155.2×	2.2×	1.2×	5.1×
15	DecoPa	370.3×	899.5×	6508.7×	3411×	33.0×	13.3×
	Hybrid	5.3×	6.4×	311.5×	2.2×	1.2×	8.0×
20	DecoPa	428.1×	1442.2×	8585.7×	4209×	53.4×	18.8×
	Hybrid	5.3	10.7×	311.5×	2.2×	1.2×	10.2×

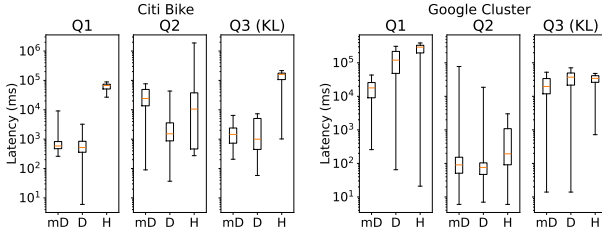


Figure 9: Latency comparison for real-world data sets.

server-based setup on a NUMA node with 4 Intel Xeon E7-4880 (60 cores, 1TB RAM) and in a cluster-based setup comprising 20 Raspberry Pi 4B nodes.

7.2 State-of-the-Art Comparison

Fig. 8 shows the throughput gain over centralized for DecoPa and all other baseline strategies. In Fig. 8a a query of length 4 is evaluated with a varying number of processing units available. DecoPa achieves the highest throughput gain, followed by Hybrid with both approaches scaling in the number of processing units. This can be also observed for our RIP inspired baseline, although the throughput achieved by the approach is less than what can be achieved by the centralized baseline as more events need to be processed by a processing unit due to the batch based parallelism, such that the ingestion rate ι is strained. As expected, the throughput-gain of state-based parallelism is independent of the number of processing units. Fig. 8b illustrates the throughput gain for queries of varying length with the number of processing units set to 15. DecoPa achieves a significant throughput gain of more than 7 orders for queries of length of 7, which is due to longer queries providing more possibilities for decomposition. The other approaches are almost unaffected by a varying query length with a slight down trend visible for Hybrid. In the remainder, we compare DecoPa only against Hybrid as the latter achieved the best results compared to the other baseline approaches.

7.3 Experiments with Real-World Data Sets

The experiments were conducted in the Raspberry Pi cluster by deploying one processing unit per Raspberry Pi. The maximal ingestion rate ι determined for the Raspberry Pis was given by 2500 events per minute. We measured the maximal comparison rate κ for each data set based on the respective predicates. With the predicate for Citi bike involving more complex computations, we used $\kappa = 80000$ for the Citi Bike queries and $\kappa = 500000$ for the Google Cluster queries. Table 3 shows the throughput gain for DecoPa and Hybrid over centralized for the three queries of each data set with varying numbers of processing units. For both data sets, DecoPa based evaluation achieves a throughput gain of up to 3 orders of magnitude compared to both centralized and Hybrid. In general, it can be observed that DecoPa scales well with the number of processing units for all evaluated queries, with Q1 of the Citi Bike data set even quadrupling its throughput gain, when processing units are doubled. The highest increase in throughput gain is for most queries achieved, when the number of processing units is raised from 5 – 10, as with 10 processing units, more intricate splits can be considered for the construction. Hybrid did not scale for the queries Q1 and Q2 of the Google Cluster data when adding resources, which is due to the very high-rate event types in the Google Cluster data. Combining two of the latter results in high comparison costs which can not be reduced by assigning only 5 – 10 more resources. Query 3 of both data sets contains the Kleene operator. While the sensitivity analysis shows that due to using unary splits, DecoPa plans can significantly optimize throughput for queries with Kleene, this result is not as pronounced for the real-world data sets as we could define Kleene closure only on medium- or low-rate event types as otherwise, no practically usable scaling factor could be achieved for the evaluation.

We compared DecoPa and Hybrid in terms of latency (Fig. 9), by evaluating (1) the throughput-maximizing DecoPa plan on the event rates scaled with the respective scaling factor (mD), (2) a DecoPa plan on the event rates scaled with the maximal scaling factor obtained from Hybrid (D), and (3) the Hybrid plan for the rates scaled with its respective maximal scaling factor (H). For all queries, except Q2 of the Citi Bike, D and mD yield lower latencies than H , which is a remarkable result as, e.g., for Q1 of Citi bike, almost 100× more throughput is achieved while minimizing latency by 2 orders of magnitude. As Kleene is defined over fairly low rates, even in the DecoPa plans binary splits were used, resulting in equivalent latencies for Q3 of Google cluster for all three experiments. The Kleene query Q3 of Citi Bike, minimized latency by 2 orders of magnitude.

7.4 Sensitivity Analysis

Our sensitivity analysis focuses on the influence of different query characteristics and processing contexts on the resulting throughput gain and latency of DecoPa. The experiments were conducted in the server-based setup, where processing units were instantiated by the server cores, which yielded a maximal ingestion rate of $\iota = 6500$. We simulated predicate evaluation with a resulting $\kappa = 60000$, if not stated otherwise. The results represent the median values obtained from a set of 50 experiments with the boxes in Fig. 10 depicting the 25th and 75th percentiles. To compare DecoPa and Hybrid in terms of induced latency, we again constructed DecoPa plans for the

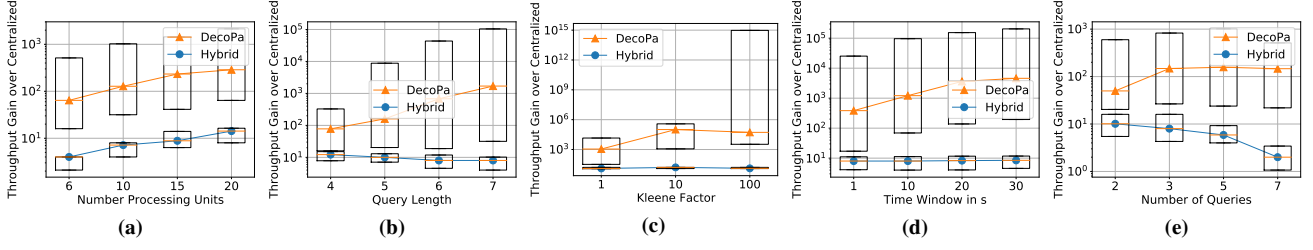


Figure 10: Throughput gain compared to centralized for varying queries, processing contexts and event rate characteristics.

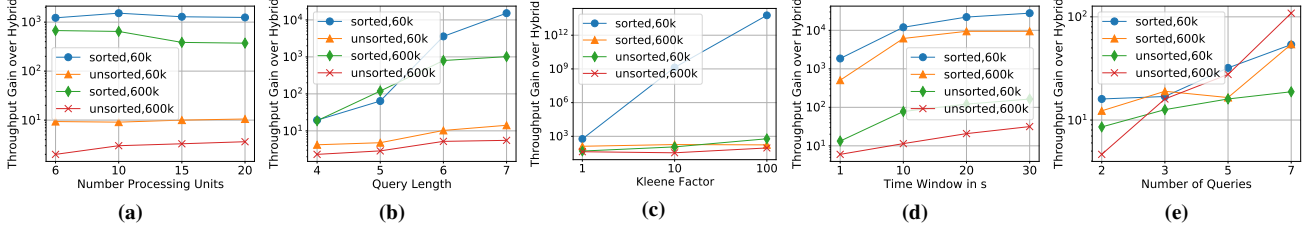


Figure 11: Throughput gain over hybrid for varying queries, processing contexts and event rate characteristics.

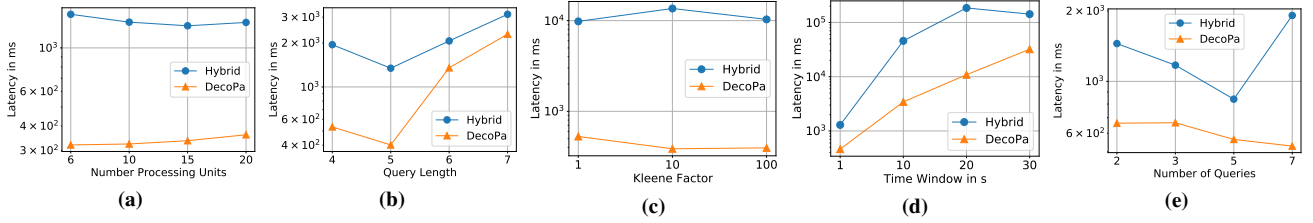


Figure 12: Comparison of detection latency of DecoPa and Hybrid for maximal scaling factor of Hybrid approach.

maximal scaling factor that could be determined for Hybrid. Fig. 11 provides an overview of the throughput gain in comparison to Hybrid across different $\kappa = 60k$ and $\kappa = 600k$. A lower κ , which reflects a more complex predicate evaluation, yields more optimization potential. For each κ , plans were constructed for queries in which the event types referenced in the query were ordered increasingly based on their rates, which denotes the worst case for Hybrid. The combination of lower κ values and ordered events produced the most substantial throughput optimization. As discussed in the previous sections, DecoPa scales well with increasing resources with the most optimization potential when raising the number of processing units from 5 – 15.

Time Window. We varied the time windows for the query evaluation from 1 – 30 minutes. Longer time windows increase the number of partial matches and thus, influence the resulting comparison costs of each operator. As rate reducing sub-queries constrain the number of partial matches maintained per operator, in this experiment a throughput gain of up to 5 orders of magnitude was achieved. For this parameter, naturally, the highest latencies can be observed.

Query Length. Increasing query lengths yield the highest optimization potential for decomposition, with the number of possible sub-queries available growing exponentially in the query length. As such, a throughput gain of 5 and 4 orders of magnitude could be achieved against centralized and Hybrid respectively.

Kleene Closure. To investigate the impact of Kleene closure, we varied the rate of the event type upon which Kleene closure is defined by setting it to 1 \times , 10 \times , and 100 \times the average rate of the remaining types of the query. While DecoPa plans mostly employed

unary splits, the Hybrid approach, underlying an *ld* split, naturally employs binary Kleene splits. The latter entail more comparisons due to the three classes of partial matches to maintain, which was confirmed in our experiments reaching up to 12 orders of magnitude throughput gain and 1 order of magnitude lower latencies compared to Hybrid.

Multiquery. We examined the effect of our strategies for multi-query scenarios by constructing DecoPa plans for workloads of up to 7 queries. Sharing operators between queries, allows to make more use of the available processing units which is reflected in the results for throughput gain which scales proportionally compared to Hybrid, where the possible degree of parallelization per sub-query decreases with a growing number of queries with no sharing is exploited.

8 CONCLUSIONS

In this paper, we proposed DecoPa plans for the parallel evaluation of CEP workloads. Compared to existing approaches, DecoPa plans consider event rates and the processing context to construct throughput-maximizing query splits, tailored for parallel evaluation. We formalized DecoPa plans and discussed properties thereof. With optimal DecoPa plan construction being NP-hard, we propose a dynamic programming based construction as well as strategies to cater for multi-query scenarios. Our experimental evaluation showed the benefits of DecoPa plans compared to state-of-the-art approaches. Especially for computationally demanding query characteristics, such as long time windows and Kleene closure, we achieved a throughput gain by up to multiple orders of magnitude over baseline strategies.

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