INEv: In-Network Evaluation for Event Stream Processing

Anonymous Author(s)

ABSTRACT

Complex event processing (CEP) detects situations of interest by evaluating queries over event streams. Once CEP is used in networked applications, the distribution of query evaluation among the event sources enables performance optimization. Instead of collecting all events at one location for query evaluation, sub-queries can be placed at network nodes to reduce the data transmission overhead. Yet, existing techniques either place such sub-queries at exactly one node in the network, which neglects the benefits of truly distributed evaluation, or are agnostic to the network structure, which neglects transmission costs incurred by the absence of direct network links.

To overcome the above limitations, we propose INEV graphs for in-network evaluation of CEP queries with rich semantics, including Kleene closure and negation. Our idea is to introduce fine-granular routing of *partial* results of sub-queries as an additional degree of freedom in query evaluation: We exploit events already disseminated in the network as part of one sub-query, when evaluating another one. We show how to instantiate INEv graphs by splitting a query workload into sub-queries, placing them at network nodes, and forwarding of their results to other nodes. Also, we characterize INEv graphs that guarantee correct and complete query evaluation, and discuss their construction based on a cost model that unifies transmission and processing latency. Our experimental results indicate that INEv graphs can reduce transmission costs for distributed CEP by up to eight orders of magnitude compared to baseline strategies.

CCS CONCEPTS

• **Information systems → Data streams**.

KEYWORDS

event stream processing, operator placement, in-network evaluation

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1 INTRODUCTION

Complex event processing (CEP) comprises models and methods to evaluate queries over streams of event data [24]. It enables the detection of *situations of interest* in applications that span, for instance, electrical grids [21], finance [45], and urban transportation [9]. In essence, a CEP query matches a pattern of events, characterized in terms of the types of events, their ordering, and a time window.

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Adopting CEP in networked applications that integrate multiple event sources (e.g., smart meters or payment terminals) [43] induces a design space related to the location of query evaluation:

A *centralized* model gathers the events of all sources at a single network node to evaluate queries over a unified stream [24]. While such a model fosters traceability, it suffers from limited scalability: It requires sending *all* events over the network, although most of them are not required to construct the matches of a query.

A *distributed* model for CEP exploits event processing capabilities of network nodes [22]. Data transmission is reduced by assigning (partial) queries to network nodes, so that query evaluation is no longer realized at a single location. The construction of a plan for distributed query evaluation is challenging, though, due to the large search space induced by the following design choices:

D1 How to *split* a query workload for distribution: One may consider queries in isolation [44], take into account sharing opportunities between queries [36], split each query according to its operator hierarchy [22], or consider query rewritings [4, 41].

D2 How to *place* (sub-)queries in the network: For a query, one may consider single-node [20, 34] or multi-node placements [4, 5].

D3 How to *forward* query matches between network nodes to assemble the matches: Here, one may assume direct links between all nodes [5] or consider the network topology [22, 34].

The design choices shall be taken such that query evaluation is correct and complete, stays within a certain latency bound, and minimizes the data transmission between nodes. Yet, even the partial task of single-node placements with minimal transmission costs, known as operator placement, is an NP-hard problem [11].

There is a notable research gap, since, so far, exploration of the above design space is limited. Existing work considers only simple splits of a query and single-node placements, while incorporating the network topology [22]; or relies on rich query rewritings and multi-node placements, but neglects the network structure [4].

In this paper, we address this gap with a novel model for in-network evaluation of CEP workloads. It is based on the following insight: To exploit the optimization potential of query rewritings and multi-node placements under arbitrary network topologies, fine-granular forwarding of *partial* matches of sub-queries is required. Compared to existing work on distributed CEP, we hence add an additional degree of freedom in query evaluation to leverage the dissemination structure of events in the network:

- We propose INEv graphs as a model for in-network evaluation of a CEP workload, grounded in a rich semantics that supports Kleene closure and negation. INEv graphs include an explicit selection of partial matches for forwarding between nodes.
- We formally show correctness and completeness of the model, and provide a cost model to reason on its efficiency.
- We present an algorithm to construct an efficient INEv graph, which approximates an intractable optimal solution. Our algorithm incorporates sharing opportunities between multiple queries of a workload. Moreover, we present strategies for adapting INEv graphs to react to network changes.

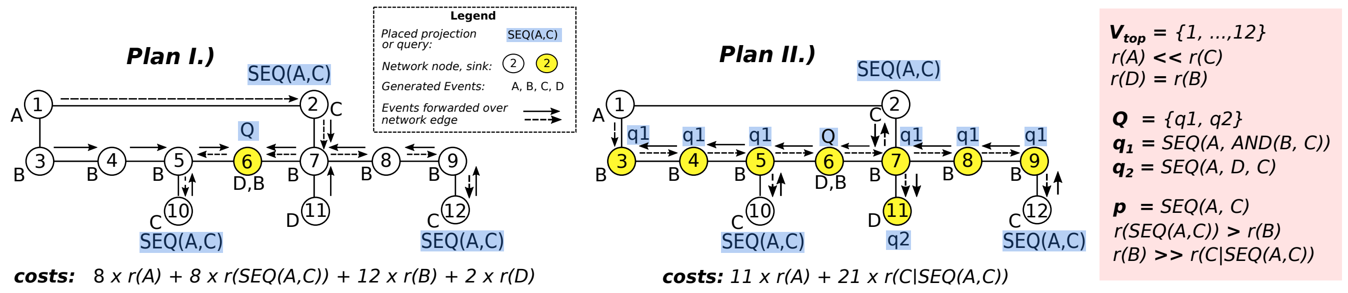

Legend
Placed projection or query: SEQ(A,C)
Network node, sink:
Generated Events: A, B, C, D
Events forwarded over network edge
Plan I.)
Plan II.)
costs: 8 x r(A) + 8 x r(SEQ(A,C)) + 12 x r(B) + 2 x r(D)
costs: 11 x r(A) + 21 x r(C|SEQ(A,C))
V_top = {1, ...,12}
r(A) << r(C)
r(D) = r(B)
Q = {q1, q2}
q1 = SEQ(A, AND(B, C))
q2 = SEQ(A, D, C)
p = SEQ(A, C)
r(SEQ(A,C)) > r(B)
r(B) >> r(C|SEQ(A,C))

Figure 1: Motivating example for in-network evaluation of CEP queries.

We evaluate INEv graphs in simulation experiments and with an implementation that is based on a framework for distributed computing. Our results indicate that INEv graphs reduce transmission costs by up to eight orders of magnitude compared to baseline strategies.

In the remainder, we first provide a motivating example (§2), give preliminaries of distributed CEP (§3), and formalize the addressed problem (§4). We then introduce INEv graphs for in-network evaluation of CEP queries and study their properties (§5), before turning to their construction (§6). Finally, we discuss experimental results (§7), review related work (§8), and conclude the paper (§9).

2 MOTIVATING EXAMPLE

Consider a networked application in the context of smart grids, i.e., demand response (DR) management [26]. Here, consumers shall react to requests by a utility to reduce their energy consumption for a certain time period to avoid costly handling of peak demands. CEP may help to monitor these responses and enables immediate reaction in case of non-conforming behaviour [37].

Figure 1 illustrates a network of event sources, where a controller (node 1) generates events about DR requests (events of type A). The other nodes denote consumers, classified as households (nodes 3-9) that report their base consumption (B). Some households are linked to further devices (nodes 2, 10-12), such as charging points for vehicles, that schedule energy consumption for short (C) and long (D) durations. The rates of event generation differ. DR requests (A) occurr with a much lower rate than consumption events (B-D).

For monitoring responses to DR requests, a workload Q of CEP queries, such as q_1 and q_2 in Figure 1, is evaluated. The queries detect patterns of events representing requests (A) and subsequent events about current (B) and scheduled (C, D) consumption.

Centralized model. For centralized evaluation, all relevant events are gathered at one node. Aiming at minimal transmission costs, the node that generates the largest portion of the relevant events and has the shortest distance to other nodes qualifies for query evaluation. In our example, node 6 is suitable, as it generates events of two types (B, D) and is the most central node in the network. The transmission cost of centralized query evaluation at node 6 is given by the rates of the event types and the number of hops that the respective events need to be sent over the network, i.e., $3 \cdot r(A) + 12 \cdot r(B) + 8 \cdot r(C) + 2 \cdot r(D)$.

Distributed models. Query evaluation as sketched in plans I and II realizes distributed CEP. The plans incorporate query rewriting when *splitting* the queries for distribution, i.e., queries q_1 and q_2 are evaluated based on the sub-query $SEQ(A, C)$. Using $SEQ(A, C)$, which is not part of the operator hierarchy of q_1, for the evaluation of both queries also leverages sharing opportunities for q_1 and q_2. The plans adopt a multi-node *placement*, i.e., $SEQ(A, C)$ is placed at all source nodes of C events (2, 10, 12). As these events occur with a high rate, sending the rare A events to sources of C reduces transmission costs compared to a single-node placement of $SEQ(A, C)$.

However, a simple mechanisms to *forward* query results yields superfluous data transmission. Consider plan I, in which A events are forwarded to each node evaluating sub-query $SEQ(A, C)$ via the shortest path (the routing tree of A events is illustrated with dashed arrows). Then, the results of sub-query $SEQ(A, C)$ and all B and D events are forwarded to node 6, which evaluates the queries q_1 and q_2. This plan has a transmission cost of $8 \cdot r(A) + 8 \cdot r(SEQ(A, C)) + 12 \cdot r(B) + 2 \cdot r(D)$, thereby improving over the centralized evaluation plan (no transmission of high-rate C events). However, the plan ignores the potential for optimization that is induced by the A events already disseminated in the network.

In plan II, events of type A, needed at nodes 2, 10, and 12 to evaluate $SEQ(A, C)$, are sent along a routing tree that contains all nodes generating B and D events (again, illustrated with dashed arrows). As such, each of these nodes receives all A events. Therefore, instead of forwarding the matches of $SEQ(A, C)$, it suffices to forward *partial* results, i.e., all C events that are part of the matches. The rate of these C events is smaller than the rate with which matches of $SEQ(A, C)$ materialize, since a single event may, in general, be part of a large number of matches. With the rate of the respective C events being smaller than those of B and D events, multi-node placements of queries q_1 and q_2 at nodes generating either B or D events become viable. With these multi-node placements, the transmission cost of plan II is $11 \cdot r(A) + 21 \cdot r(C|SEQ(A, C))$, which, compared to plan I, saves the rates of sending B and D events.

3 PRELIMINARIES

3.1 System Model

An *event* is an occurrence of a phenomena, for which the semantics is given by an *event type* [7, 24]. The latter defines a schema, a set of attributes. We write $\mathcal{E} = \{\epsilon_1, \ldots, \epsilon_n\}$ for the set of event types.

Event network. An *event network* $\Gamma = (G_{top}, f, r)$ is defined by a topology graph $G_{top} = (V_{top}, E_{top})$, a function $f : \mathcal{E} \rightarrow 2^{V_{top}}$ that assigns event types to (source) nodes, and a function $r : \mathcal{E} \rightarrow \mathbb{R}$ that assigns an average occurrence rate to an event type. We consider event networks, in which event sources also have computational capabilities and assume homogeneity in their ability to take part in the query evaluation.

The topology graph G_{top} is a connected, undirected graph. Any exchange of events between two nodes $n, m \in V_{top}$ has to happen along a path in E_{top}. With $r(\epsilon)$ as the *local rate* for an event type $\epsilon \in \mathcal{E}$, we refer to $R(\epsilon) = |f(\epsilon)| \cdot r(\epsilon)$ as the *global rate* for the network-wide occurrences of an event type. Thus, we assume that the number of occurrences per time unit is roughly the same for events of the same type and independent of their source node.

EXAMPLE 1. *Figure 1 illustrates an event network with event types $\mathcal{E} = \{A, B, C, D\}$ and nodes $\{1, \ldots, 12\}$, where, for instance, $f(D) = \{6, 11\}$. Also, we already discussed that $r(C) \gg r(A)$. For node 12 to send events to node 7, the events need to be forwarded along the path $\langle(12, 9), (9, 8), (8, 7)\rangle$.*

Global trace. Interleaving the occurrences of events at all nodes by their timestamp yields a *global trace* of the network, which is assumed to be totally ordered. The global trace is never materialised, but required as a conceptual notion to define an unambiguous semantics of queries over events generated in a network. It is the equivalent to collecting and ordering all events at a single node.

3.2 Query Language

We adopt a common query model for CEP [8, 24], defined as follows.

Syntax. A query $q = (O, \beta)$ is an ordered tree of operators, annotated with predicates and a time window. The operators O are the vertices of the query tree. We distinguish composite operators O_c that encode some ordering for child operators, and primitive operators O_p that refer to an event type. The function $\beta : O_c \nrightarrow O^k$ with $k \in \mathbb{N}$ assigns a sequence of child operators to a composite operator. A composite operator $o \in O_c$ has a semantic type, denoted by $o.sem \in \{AND, SEQ, OR, NSEQ, KL\}$.

We write $\mathcal{E}(q)$ for the set of event types referenced by primitive operators of query q. To simplify the notation, we assume that each event type is referenced by at most one primitive operator of a query.

Semantics. The semantics of a query are defined over the global trace of an event network. Evaluating a query yields a set of *matches*, each being a sequence of events of the global trace. In addition to sequencing, conjunction, and disjunction, we incorporate a Kleene closure *KL* with one primitive operator as a child, and *NSEQ* that negates an operator between two other operators, see [31]. The set of matches for a query is defined inductively over the operator tree:

- A primitive operator creates a match for each event of the event type referenced by the operator.
- An *AND* operator constructs a match for the interleaving of matches of all its child operators.
- A *SEQ* operator constructs a match for the concatenation of matches of its child operators in the specified order.
- An *OR* operator constructs a match for each match of one of its child operators.
- A *KL* operator constructs a match for each (arbitrary long) sequence of matches of its child operator.
- A *NSEQ* constructs a match for a sequence of matches of its first and last child operator, if no match of the middle child occurs in between.

The above construction is applied only for events that satisfy the predicates and the time window defined by the query. Our semantics corresponds to a *greedy* event selection strategy, also known as *unconstrained* [13] or *skip-till-any-match* [1]. It does not impose any restriction on the number of times an event can participate in matches. Hence, the number of matches may grow exponentially in the number of processed events [47], which constitutes a particularly challenging evaluation scenario.

Table 1: Overview of notations for networks and queries.

Notation	Explanation
$\mathcal{E} = \{\epsilon_1, \ldots, \epsilon_n\}$	Universe of event types
$\Gamma = (G_{top}, f, r)$	Event network: topology graph $G_{top} = (V_{top}, E_{top})$, sources of event types $f : \mathcal{E} \to 2^{V_{top}}$, rates $r : \mathcal{E} \to \mathbb{R}$
$r(\epsilon)$, $R(\epsilon)$	Local and global rate of an event type ϵ
$q = p = (O, \beta)$	Query q (or projection p) with composite and primitive operators $O = O_c \cup O_p$ and their tree structure $\lambda : O_c \nrightarrow O^k$
$\mathcal{E}(q)$, $\mathcal{E}(p)$	Event types of a query q and a projection p
Q	Query workload: a set of queries
$c = (\mathfrak{P}, \lambda)$	Combination with projections $\mathfrak{P}$ and λ defining the inputs of a projection
Π_q, C_q, Π_Q, C_Q	All possible projections and combinations of query q and query workload Q
$\sigma(o)$, $\sigma(q)$, $\sigma(p)$	Selectivity of an operator, a query, or a projection

Given an event network $\Gamma = (G_{top}, f, r)$, the evaluation of a query $q = (O, \beta)$ can be captured in terms of the *rate*, with which matches are generated. For a primitive operator $o \in O_p$ that only references an event type $\epsilon \in \mathcal{E}$, the rate corresponds to the local rate of the event type in the network and the operator selectivity $\sigma(o)$, which is induced by the predicates defined the query over the attributes of the event type, i.e., $r(o) = \sigma(o) \cdot r(\epsilon)$. For a composite operator $o \in O_c$ with $\lambda(o) = \langle o_1, \ldots, l_k\rangle$ and selectivity $\sigma(o)$, the rate is defined inductively:

$$r(o) = \begin{cases} \sigma(o) \cdot k \cdot \prod_{1 \leq i \leq k} r(o_i) & \text{if } o.sem = AND, \\ \sigma(o) \cdot \prod_{1 \leq i \leq k} r(o_i) & \text{if } o.sem = SEQ, \\ \sigma(o) \cdot \sum_{1 \leq i \leq k} r(o_i) & \text{if } o.sem = OR, \\ \sigma(o) \cdot r(o_1) \cdot r(o_3)) & \text{if } o.sem = NSEQ, \\ \sigma(o) \cdot 2^{r(o_1)} & \text{if } o.sem = KL. \end{cases}$$

Based thereon, the rate $r(q)$ and the selectivity $\sigma(q)$ of a query q are defined as the rate and selectivity of its root operator, respectively.

Query workload. In the remainder, we consider a query workload Q, which is a set of queries that do not contain any *OR* operator. Since any query containing an *OR* operator can be split into multiple queries, this does not constrain the expressiveness of our model. Also, without loss of generality, we assume that all queries of a workload are defined over the same time window.

3.3 Query Splitting and Placement

To enable distributed CEP, a query is split into sub-queries, which are then placed at network nodes for evaluation. Below, we summarize essential notions for these steps based on [4].

Query projections and combinations. We consider a splitting mechanism that decomposes a query q into *projections*, where a projection $p = (O, \beta)$ is a query itself that is restricted to a subset of the event types referenced in q, i.e., $\mathcal{E}(p) \subset \mathcal{E}(q)$. A projection also inherits the predicates of q defined over $\mathcal{E}(p)$, as well as the time window of q. In contrast to hierarchical notions of sub-patterns [38], matches of a projection are not necessarily contiguous sub-sequences of query matches. We denote the set of all possible projections for a given query q by Π_q.

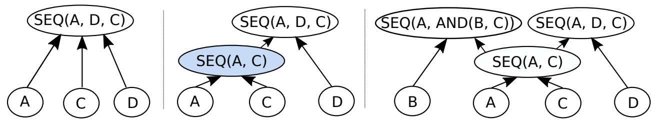


Figure 2: Query tree of the query q_2 of Figure 1 (left); a combination for q_2 (middle) and for the query workload Q (right).

Projections that jointly realize correct and complete evaluation of a query are captured by the notion of a *combination* [4]. We formalize a combination $c = (\mathfrak{P}, \lambda)$ of a query q as a directed acyclic graph (DAG) having a set of projections $\mathfrak{P} \in \Pi_q$ as its vertices. The function $\lambda : \Pi_q \longrightarrow \Pi_q^k$ with $k \in \mathbb{N}, k > 1$, assigns to a projection p its predecessors in c, which we refer to as *inputs* of p, as matches of these predecessors are used to construct the matches of p. In contrast to the operator tree of a query, a combination is formalized as a DAG as matches of one projection can be input to the generation of matches of multiple other projections. We denote the set of all combinations of a query q as C_q. For a query workload Q, the set of all combinations for its queries is denoted by C_Q. Here, sharing opportunities are exploited by representing a projection only once in the combination of the workload, even if it would be part of the combinations of multiple queries.

Example 2. *Figure 2 shows a combination for distributed evaluation of q_2 of our example; and a combination for the workload Q. The projection $SEQ(A, C)$ is used to evaluate both queries in Q.*

Below, we consider a function *split* : $Q \longrightarrow C$ for the decomposition of a workload query into a combination for distribution.

Placements. To evaluate a query in a network $\Gamma = (G_{top}, f, r)$ with $G_{top} = (V_{top}, E_{top})$, based on a combination $c = (\mathfrak{P}, \lambda)$, a *placement* assigns the respective projections to network nodes. That is, a function *place* : $\Pi_q \longrightarrow 2^{V_{top}}$ defines for each projection $p \in \mathfrak{P}$ a set of network nodes to evaluate p.

We distinguish between single-node and multi-node placements for a projection p. In a single-node placement, exactly one node n evaluates p. Then, *all* events of the inputs of p are gathered at node n. In a multi-node placement, a set of nodes collectively evaluates p, so that the generated matches of p are partitioned between the nodes of the placement. Specifically, this partitioning is induced by one of the inputs $i \in \lambda(p)$ of p, referred to as the *partitioning input*, and the placement is given by the respective sources of i. As such, a multi-node placement avoids that events of the partitioning input are sent over the network. However, to ensure that all matches of p are generated, events of all other, non-partitioning inputs of p need to be forwarded to the sources of the partitioning input. From that it follows that multi-node placements are beneficial, when the rates of some event types (to be used as partitioning inputs) are significantly higher than those of others, as high-rate event types are not longer sent over the network.

Example 3. *In Figure 1, the rate of C events is high. Hence, in plan I, there is a multi-node placement for $SEQ(A, C)$ at source nodes of C, so that a sub-query matching only C events is the partitioning input. For q_1 and q_2, a single-node placement at node 6 is used, which requires sending all matches of $SEQ(A, C)$ as well as all B and D events to node 6.*

Table 2: Notations for in-network query evaluation.

Notation	Explanation
ψ	Transmission cost of workload Q in event network Γ
ℓ	Latency of workload Q in event network Γ
$os(p)$	Output selector: Maps a set of event types or $\equiv$ to a projection p
$I = (V, E)$	INEv graph with vertices V and edges E; a vertex $v = (v_{proj}, v_{node}, v_{graph}, v_{os}) \in V$ represents a projection, network node, a forwarding graph and an output selector

4 PROBLEM STATEMENT

We formalize the in-network evaluation problem for CEP queries as follows. Given an event network $\Gamma = (G_{top}, f, r)$ and query workload Q, this problem is grounded in three functions:

- A function *split*, see §3.3, to compute a combination for Q.
- A function *place*, see §3.3, to compute a placement for the projections of a given combination at the nodes of Γ.
- A function *forward* to compute a sub-graph of the topology graph G_{top} for a given placement *place*(p) of a projection p, which determines how to send matches of the inputs $\lambda(p)$ of p to the nodes that evaluate p, given by *place*(p).

In-network evaluation aims to reduce the rate with which events are sent over the network. Given an instantiation of the three functions *split*, *place* and *forward*, distributed evaluation of workload Q in the network Γ has a *transmission cost*, denoted by $\psi \in \mathbb{R}$, that captures the total rate with which nodes send events over the network.

Example 4. *For plan I in our example, the split function returns the combination c illustrated in Figure 2 for query workload Q. The placement function is defined as $place(SEQ(A, C)) = \{2, 10, 12\}$, $place(q_1) = \{6\}$, and $place(q_2) = \{6\}$. For each resulting placement, the forwarding function denotes a sub-graph, i.e., for the placement of $SEQ(A, C)$ at node 2, it returns the graph $G_{sub} = (V, E)$, with $V = \{1, 2\}$, $E = \{(1, 2)\}$, to send A events to node 2.*

Moreover, query evaluation induces a latency with which matches of queries are generated [48]. For distributed CEP, the latency induced by centralized evaluation of a query workload denotes a meaningful bound to consider. For an instantiation of the functions *split*, *place* and *forward*, the *latency* of the obtained plan to evaluate query workload Q in the network Γ is captured as $\ell \in \mathbb{R}$. Let $\tau \in \mathbb{R}$ be the latency of the centralized evaluation of Q in Γ, i.e., no splitting of queries, all queries are placed at a single node, and all events generated in the network are sent to this node. Based thereon, we formulate the problem of in-network evaluation of CEP queries:

Problem 1. *Let Γ be an event network and Q be a query workload. The problem of in-network evaluation of Q in Γ is to instantiate functions split, place, and forward, s.t. ψ is minimal and $\ell \leq \tau$.*

5 IN-NETWORK EVALUATION GRAPHS

To address the above problem, we propose the model of an *in-network evaluation (INEv) graph*. Given a query workload and an event network, such a graph formalizes a combination of the workload, a placement of the respective projections, and the sub-graphs used to forward the inputs of each projection. Below, we first introduce output selectors used to guide the forwarding of events (§5.1). Then, we define INEv graphs and show their correctness and completeness (§5.2). Based on models for the transmission cost (§5.3) and latency (§5.4), we elaborate on optimal INEv graphs (§5.5).

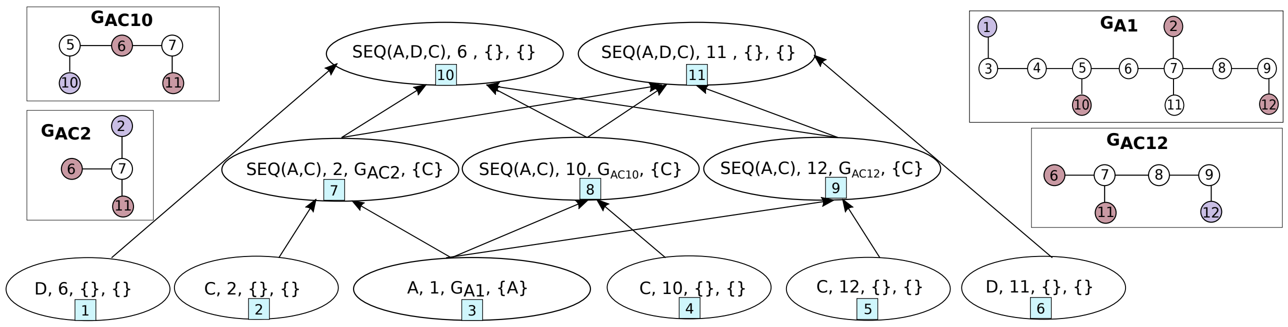


Figure 3: INEv graph for a query workload $Q = \{q_2\}$ and the event network of Figure 1.

5.1 Output Selectors

When forwarding events during in-network evaluation of a query, we aim at exploiting the resulting dissemination for query evaluation. That is, events that are forwarded in the network can also be processed by the nodes on the path used for forwarding. As a consequence, a node on such a path no longer needs to receive the events of all types of all inputs of the projections placed at it.

To realize this idea, we introduce the notion of an *output selector*. For two projections $p, p' \in \Pi_q$ of a query q, one being an input of the other one, $p \in \lambda(p')$, it limits the types of events that are sent from nodes hosting the projection p to nodes hosting the projection p' that is evaluated based on p. Formally, an output selector is a function $os : \Pi_q \rightarrow 2^{\mathcal{E}(q)} \cup \{\equiv\}$. It assigns to a projection $p \in \Pi_q$ a subset of event types to forward or the symbol $\equiv$, which indicates that no output selection is applied. As such, a node hosting the projection p either forwards the individual events of the types mentioned in the output selector, or the matches of the projection.

Example 5. *In plan II of Figure 1, A events are forwarded along all nodes generating B and D events. For example, node 6 receives all A events and, thus, needs only the C events contained in matches of SEQ(A,C) to locally generate the matches of SEQ(A,C). Hence, we have os(SEQ(A,C)) = $\{C\}$.*

5.2 INEv Graphs

Definition. An in-network query evaluation (INEv) graph captures, for a given event network Γ and query workload Q, an instantiation of the three functions *split*, *place* and *forward*, see §4. As such, it defines (i) the combination used to decompose the workload Q; (ii) the placement for each projection of the combination; and (iii) the paths used to forward events in the network to evaluate the projections along with an output selector per projection.

Definition 1 (INEv Graph). *Let $\Gamma = (G_{top}, f, r)$ an event network with the topology graph $G_{top} = (V_{top}E_{top})$. Moreover, let G^{sub}_{top} be the set of all sub-graphs of G_{top}. Given a query workload Q, an INEv graph is a directed, acyclic graph $I = (V, E)$ with vertices $V \subseteq \Pi_Q \times V_{top} \times G^{sub}_{top} \times (2^{\mathcal{E}} \cup \{\equiv\})$, and edges $E \subseteq V \times V$.*

Given an INEv graph $I = (V, E)$, we use the following notation for a vertex $v = (v_{proj}, v_{node}, v_{graph}, v_{os}) \in V$: v_{proj} is the projection; v_{node} is the network node; v_{graph} is the sub-graph of the topology graph; and v_{os} the output selector of the projection.

Exploiting existing results for query splitting and placement for distributed CEP, see §3.3, parts of the structure of an INEv graph are derived directly from the definition of a query workload and an event network. That is, an INEv graph contains a vertex for each pair of an event type referenced in a query and any node in the network that is a source of this type. Moreover, there is a vertex for each projection of the combination and the nodes of the placement of the projection. Edges in an INEv graph capture dependencies between projections. That is, for two vertices $v, v' \in V$, a directed edge $(v, v') \in E$ denotes that matches of v_{proj} are used to generate matches of v'_{proj}.

However, INEv graphs go beyond existing models by incorporating mechanisms to guide the forwarding of events in the network. This is realized by specifying the sub-graph v_{graph} and the output selector v_{os} for each vertex v in the INEv graph. We illustrate the intuition behind them with an example.

Example 6. *Figure 3 shows an INEv graph for the query workload $Q = \{q_2\}$ with q_2 = SEQ(A, C, D) according to plan II of Figure 1. It contains a vertex for each pair of the event types A, C and D, and their sources in the graph G_{top} (vertices 1-6). Moreover, it contains vertices 7-9 for the placement of projection p_1 = SEQ(A, C) at nodes 2, 10, and 12; vertices 10 and 11 to place q_2 at nodes 6 and 11. Since matches of q_2 are generated using matches of p_1, there is an edge between the respective vertices. A vertex of a projection that is sent over the network contains a sub-graph of G_{top} that shows over which edges the projection is forwarded, e.g., G_{AC2} for vertex 7 defines that matches of SEQ(A,C) generated at node 2 are sent to the nodes 6, 7, and 11.*

The last entry of each vertex defines the selected output. For projection p_1, only the C events in matches of p_1 are forwarded, as indicated by the output selectors of vertices 7-9. Also, if outputs are not sent due to them being a partitioning input of a projection, the output selector is the empty set, e.g., in vertices 2, 4, and 5, as the sub-query matching only C events is a partitioning input for p_1.

Correctness and completeness. We now turn to the characterization of correctness and completeness of query workload evaluation with INEv graphs, i.e., we aim to ensure that all matches, and only those, are generated at nodes hosting the queries of the workload. To this end, we rely on existing results for the characterization of well-formed combinations [4]. Intuitively, using a well-formed combination to determine and place the projections to use for query evaluation ensures that (i) events of all types referenced in the queries and from all nodes in the network are incorporated; and (ii) that matches generated by any projection and the queries of the workload at a specific node can actually be generated based on the events sent to the node. Furthermore, for well-formed combinations of workloads containing the NSEQ operator, only negation-closed projections are considered. As such, for a query q of a workload Q that contains an $NSEQ$ operator with child operators $\langle o_1, o_2, o_3\rangle$, all projection in Π_q that may be used for the construction of the combination C_Q that contain o_2 also contain o_1 and o_3.

For the correct evaluation of workloads containing Kleene closure, a well-formed combination guarantees that for each Kleene closure operator based on the (primitive) child operator o_i all matches of o_i are taken into account. To this end, the following holds for an INEv graph $I = (V, E)$: Let $V_{kleene} \subseteq V$ be a set of vertices in I denoting projections having the child operator o_i of a Kleene closure operator as partitioning input of a multi-node placement. Then, it must hold that vertices V_{kleene} have the same set of successor vertices in I. This way it is ensured that *all* matches of o_i are available for the evaluation at at least one node in the event network.

The characterization of correct and complete query evaluation based on a well-formed combination, however, was obtained for event networks that are cliques, i.e., under the assumption that each node can directly send events to any other node and that all events of matches are forwarded. We therefore need to show under which circumstances, explicit forwarding as realized in INEv graphs does not compromise correctness and completeness. Intuitively, this means that (i) if a node n' evaluates a projection p' for which a projection p hosted at node n is an input, $p \in \lambda(p')$, the node n must be contained in the graph used to forward results of p' in the network; and (ii) whenever an output selector is used for the projection p', all events of the event types that are not selected are forwarded to node n hosting the projection p.

Definition 2 (Well-Formed Forwarding). *Let $I = (V, E)$ be an INEv graph and let $pre : V \longrightarrow 2^V$ assign to a vertex its predecessor vertices in I. The INEv graph defines* well-formed forwarding, *if for each vertex $v \in V$ with predecessors, i.e., $pre(v) \neq \emptyset$, it holds that for all predecessors $u \in pre(v)$:*

(i) v_{node} is contained in the set of nodes of u_{graph}.
(ii) if $u_{os} \subset \mathcal{E}(v_{proj})$, then for all vertices $w \in V$ for which there exists an event type $\epsilon \in \mathcal{E}(w_{proj}) \cap \mathcal{E}(v_{proj}) \setminus u_{os}$, the node v_{node} is contained in the set of nodes of w_{graph}.

Combining the notions of a well-formed combination and well-formed forwarding, the correctness and completeness of query evaluation with INEv graphs follows directly.

Property 1. *Each match generated for a query $q \in Q$ at a network node with an INEv graph based on a well-formed combination and using well-formed forwarding, is indeed a match of q; and all matches of q are generated at one of the network nodes.*

Example 7. *In Figure 3, vertex 7, which describes the placement of $p = SEQ(A, C)$ at node 2, evaluates p based on its locally generated events of type C and the A events generated at node 1. As such, node 2 must be in the forwarding graph G_{A1} of vertex 3.*

5.3 Transmission Cost Model

Turning to the efficiency of query evaluation with INEv graphs, we now consider the induced transmission costs. While the latter is given as the sum of the rates with which events are sent over the network per time unit, our cost model derives this total rate from the transmission costs per node in the event network. This cost depends on whether projections hosted by a node are subject to a single-node placement or a multi-node placement, to which nodes events are sent during query evaluation, and which output selectors are employed.

To compute the transmission cost for a vertex in an INEv graph, we incorporate an assumption on multi-node placements, as follows. Consider an INEv graph $I = (V, E)$ and a projection p that is placed on multiple nodes, which is represented by the vertices $V_p \subseteq V$, such that for all $v \in V_p$ it holds that $v_{proj} = p$. Then, the partitioning input of the projection needs to be a projection that references a single event type, which must also be generated by the nodes of the respective vertices in V_p. Put differently, the INEv graph must contain vertices that place the partitioning input, a projection over a single event type, at the same nodes as the vertices in V_p. This assumption is motived by the general idea behind multi-node placements: Sending the partitioning input over the network may thwart the cost reduction aimed at with multi-node placements. In addition, considering more complex projections over those referencing a single event type will not lead to improvements, since any multiple-node placement of them could be exploited transitively.

Example 8. *In Figure 3, there is a multi-node placement for projection $p = SEQ(A, C)$ with vertices 7-9, i.e., $V_p = \{7, 8, 9\}$. For p, a partitioning input referencing event type C is used. Hence, there is a second set of vertices $\{2, 4, 5\}$ for this input, such that the nodes of these vertices correspond to the nodes of the vertices in V_p.*

For an INEv graph $I = (V, E)$, we define a function $tc : V \longrightarrow \mathbb{R}$ that assigns transmission costs to the vertices. It is based on the *total rate* $R(p)$ of a projection p, i.e., the rate with which matches of p are generated. If a vertex $v \in V$ does not contain any output selection ($v_{os} = \equiv$), matches of its projection v_{proj} are sent over the forwarding graph v_{graph} with v's portion of the total rate $R(v_{proj})$.

Once output selection is adopted, however, we need to consider the selectivity of the projection per event type. We capture this aspect with the notion of a *single selectivity* $\sigma(\epsilon, p)$, which defines for an event type $\epsilon \in \mathcal{E}(p)$, the probability that an ϵ event is contained in a match of p. As such, the rate of distinctive ϵ events in matches of p is given by $\sigma(\epsilon, p) \cdot R(\epsilon)$, which is always less than the rate $r(p)$ of the projection. However, in case of the partitioning input being part of the selected output, the rate with which events are sent depends on the local rate of the referenced event type, instead of the total rate, times the single selectivity. The intuition here is that nodes hosting a projection in a multi-node placement access only their locally generated events.

Integrating both cases, we arrive at the following definition of the cost function. As above, let $V_p \subseteq V$ denote the set of vertices of an INEv graph $I = (V, E)$ with their projection being p and let $part(p)$ denote the (single) event type of the partitioning input of the projection. Then, for a vertex $v \in V$ with $v_{graph} = (V_v, E_v)$ as its forwarding graph, the transmission cost is defined as:

$$tc(v) = \begin{cases} |E_v| \cdot R(v_{proj}) \; / \; |V_p| & \text{If } v_{os} = \equiv. \\ |E_v| \cdot \displaystyle\sum_{\epsilon \in v_{os} \setminus part(v_{proj})} \big(\sigma(\epsilon,\, v_{proj}) \cdot R(\epsilon)\big) + & Otherwise. \\ r(part(v_{proj})) \cdot \sigma(part(v_{proj}),\, v_{proj}) & \end{cases}$$

Based on the transmission costs per vertex, we derive the total transmission costs, incorporated in Problem 1. For an INEv graph $I = (V, E)$ this cost is given as

$$\psi(I) = \sum_{v \in V} tc(v).$$

Example 9. *In Figure 3, the cost of vertex 4 is 0. Since C is the partitioning input of the multi-node placement of p, its rate does not add to the transmission costs. The cost of vertex 3 is given by the total rate of A (i.e., the local rate, as there is only one source of A events) multiplied by the number of edges of G_{A1}. Hence, the cost is $11 \cdot r(A)$. For projection SEQ(A, C) with selected output C, vertices 7-9 have an output rate of $r(C) \cdot \sigma(C, p)$. As C is a partitioning input of SEQ(A, C), the local rate is used.*

5.4 Latency Model

Having discussed a model for the transmission cost, we now reflect on the latency of query evaluation, as it provides a constraining factor in-network evaluation, see Problem 1. As usual, the latency of a match of a query is the time between its occurrence and the occurrence of the latest event that led to the match's creation. It includes a processing latency inherent to query evaluation and a transmission latency observed between network nodes.

Processing latency. We model the latency induced by query evaluation at a particular node by the number of partial matches created and maintained. The reason being that for many query evaluation algorithms, whether they are based on automata [1] or operator trees [31], the time complexity depends on the number of maintained partial matches, which, in turn, depends on the query selectivity and rates of its inputs.

Let $I = (V, E)$ be an INEv graph and let $pm(p)$ be the rate with which partial matches are generated during the evaluation of a projection p. Note that if p is evaluated with a multi-node placement, the rate $pm(p)$ is partitioned among the nodes of the placement. Hence, the processing latency induced by a vertex $v \in V$ is:

$$\ell_p(v) = \frac{pm(v_{proj})}{|\{u \mid u \in V \land u_{proj} = v_{proj}\}|}.$$

Transmission latency. The transmission latency of a match is given as the number of hops that need to be traversed in order to provide for the inputs necessary to generate the respective match.

Let $w, v \in V$ and let w be a predecessor of v in the INEv graph $I = (V, E)$. If $w_{node} \neq v_{node}$, i.e., the vertices describe placement at different network nodes, matches of w_{proj} need to be forwarded to evaluate v_{proj}. The number of hops that need to be traversed is given by the length of the shortest path between the nodes w_{node} and v_{node} in the forwarding graph w_{graph} of w.

Example 10. *In Figure 3, matches of q_2 are generated at node 6 (vertex 10) based on matches of SEQ(A, C) generated at node 10 (vertex 8). Here, the transmission latency, i.e., the length of the shortest path between nodes 6 and 10 in the forwarding graph G_{A10}, is 2.*

Let $pre(v)$ denote the set of predecessors of v and let $d(G, m, n)$ denote the length of the shortest path between the nodes m and n within the graph G. Based thereon, the transmission latency induced by a vertex $v \in V$ in an INEv graph $I = (V, E)$ is:

$$\ell_t(v) = \begin{cases} 0 & \text{If } pre(v) = \emptyset, \\ \max\{d(w_{graph}, v_{node}, w_{node}) \mid w \in pre(v)\} & \text{Otherwise.} \end{cases}$$

Overall latency. To model the overall latency, we combine the processing latency and the transmission latency in a weighted manner. While the former is influenced by the processing capacity of network nodes, the latter depends on properties of the underlying networking infrastructure. We therefore employ a factor $\xi \in \mathbb{R}$ to denote the ratio between the two sources of latency. Again, let $pre(v)$ denote the predecessors of a vertex $v \in V$ in an INEv graph $I = (V, E)$. Then, the latency for vertex v is the processing latency, scaled by ξ, the maximal transmission latency from a predecessor, and the maximal overall latencies of the backwards closure of required inputs. Formally, the overall latency is defined inductively:

$$\ell_v(v) \begin{cases} 0 & \text{If } pre(v) = \emptyset, \\ \ell_p(v) \cdot \xi + \ell_t(v) + \max\{\ell_v(w) \mid w \in pre(v)\} & \text{Otherwise.} \end{cases}$$

Let $V_Q \subseteq V$ be the set of vertices of $I = (V, E)$ such that for each $v \in V_Q$, $v_{proj} \in Q$, i.e., the vertices in V_Q denote the evaluation of the queries in Q. Then, the latency induced by I is:

$$\ell(I) = \max\{\ell_v(v) \mid v \in V_Q\}.$$

5.5 Optimal INEv Graphs

Consider an event network Γ, a query workload Q, and a latency bound τ, as defined in Problem 1 for in-network evaluation of CEP queries. Then, an INEv graph $I = (V, E)$ with $\ell(I) \leq \tau$ is optimal, if there exits no other INEv graph $I' = (V', E')$ with $\ell(I') \leq \tau$, such that $\psi(I') < \psi(I)$.

However, we note that computation of optimal INEv graphs is computationally hard. INEv graphs require the placement of the projections of a combination, which is given as a DAG. In [11], it was shown that operator placement for query graphs given as DAGs is NP-hard. Moreover, as INEv graphs support multi-node placements, the problem of connecting a set of nodes of a graph with a minimal sub-graph needs to be solved. This problem is known as the Steiner tree problem, a classical NP-hard problem [23].

6 CONSTRUCTION

Constructing optimal INEv graphs is generally intractable, so that we propose an approach that first constructs a combination for a query workload before determining the placement, output selectors, and forwarding subgraphs for each projection of the combination. Following preliminary considerations (§6.1), we introduce our algorithm to derive a combination for a single query (§6.2), explain how sharing opportunities between multiple queries are leveraged (§6.3), and present a placement and forwarding mechanism (§6.4). We also state the complexity of our algorithms (§6.5) and propose adaptation strategies to handle changes in the event network (§6.6).

6.1 Preliminary Considerations

Suitable projections. Before generating a combination for a query q, we determine all possible projections Π_q. For each projection $p \in \Pi_q$, we assess if p can be used to reduce the transmission costs. This is the case when p's global rate is smaller than the sum of the rates of p's inputs. Over transitivity, this entails that p is beneficial, if

$R(p) > \sum_{\epsilon \in \mathcal{E}(p)} R(\epsilon)$. Intuitively, if the sum of the rates of p's inputs are lower than the rate of p itself, sending matches of p results in higher transmission costs than sending matches of p's inputs. Below, we write Π_{eval} for the set of projections that are suitable according to this condition.

Steiner tree-based forwarding. Due to multi-node placements and output selectors, INEv graphs contain vertices v for which the selected output v_{os} has to be forwarded to multiple nodes. To efficiently forward matches of v_{os}, a sub-graph of the topology graph that minimizes the number of edges shall be constructed. As mentioned, this requires to solve the Steiner tree problem and, thus, is intractable. We therefore employ a heuristic to construct Steiner trees based on Minimal Spanning Trees [28].

Multi-node placements. Let $c = (\mathfrak{P}, \lambda)$ be a combination. A multi-node placement shall be applied for projection p of that combination, if there exists a partitioning input $i \in \lambda(p)$ with a much higher rate than all other inputs of p. Let $ST(N', G_{top})$ be a Steiner tree in our topology graph G_{top} of a network $\Gamma = (G_{top}, f, r)$, which spans nodes N'. With $|ST(N', G_{top})|$ as the number of tree edges, we formulate a condition for the rate of the partitioning input i:

$$R(i) \cdot \delta > |ST(f(i), G_{top})| \cdot \sum_{p' \in \lambda(p) \setminus \{i\}} R(p') + R(p) \cdot \delta \qquad (1)$$

If $p \in Q$, matches of p do not have to be sent over the network and the last summand can be omitted. The right part of Eq. 1 approximates the network costs caused by a multi-node placement at i, given that the inputs $\lambda(p)$ are forwarded using a Steiner tree. If forwarding all inputs of p to the sources of i results in less transmission cost than gathering events of type i at some node (with cost $R(i) \cdot \delta$), a multi-node placement shall be used for p.

Kleene closure evaluation. To avoid superfluous data transmission, INEv graphs for workloads with Kleene closure materialize matches of these operators only at the query sink(s). Technically, for a query $q_{KL} \in Q$ with Kleene closure operators, a query q_{nKL} without these operators is considered. The query q_{KL} is transformed to q_{nKL} by removing each Kleene operator o_{KL} in q_{KL} and adding the child operator $\lambda(o_{KL})$ to the child operators of o_{KL}'s parent operator in the query tree of q_{KL} . The matches of q_{KL} are then generated based on the matches of q_{nKL} at the sinks.

6.2 Combination Generation

Our approach to generate a combination is motivated as follows. Consider a combination c of a query q that contains only one projection p, such that neither p nor q yield a multi-node placement, i.e., none of the inputs $\lambda(p)$ and $\lambda(q)$ fulfil Eq. 1. Then, matches of all inputs of p need to be sent to the node where p is placed. Subsequently, matches of p and the residual event types $\mathcal{E}(q) \setminus \mathcal{E}(p)$ are forwarded to the node where q is placed. Such a combination with single-node placements yields little potential for saving transmission costs over a centralized model, as we later confirm empirically. Hence, we aim to maximize the cost savings induced by multi-node placements.

To this end, we use dynamic programming to enumerate combinations for each suitable projection and recursively construct a combination for the query. As shown in Alg. 1, we first initialize a combination c with all projections in Π_{eval} (line 1). Then, we iterate over the projections based on a topological order, which ensures that all of projections p's potential inputs have been handled before

Algorithm 1: Generation of a combination.

```
input  : Event network $\Gamma$; query $q$; suitable projections $\Pi_{eval}$
output : Comb. $C_q = (\mathfrak{P}, \lambda)$; projections $MN \subset \mathfrak{P}$ for multi-node placement
1  $c = (\Pi_{eval}, \emptyset)$;                          // Initialize combination
2  for $p \in$ topoSort($\Pi_{eval}$) do                   // For each projection
3      $Pre \leftarrow (\Pi_{eval} \cap \Pi_p) \cup \mathcal{E}(p)$ ;     // Possible inputs of p
4      getInputs($p$, $Pre$, $\emptyset$);
5  if $\exists\ i \in \lambda(p)$ for which Eq. 1 holds then
6      $MN \leftarrow MN \cup \{p\}$
7  $c = (\{q\} \cup \lambda(q)^+, \lambda)$;
8  return $c$, $MN$;
   // Enumerate all possible sets of inputs for projection p
9  function getInputs($p$, $Pre$, $Inputs$)
       // Consider only set of inputs with all event types of p
10     if $Pre = \emptyset \wedge \cup_{i \in Inputs} \mathcal{E}(i) = \mathcal{E}(p)$ then
11         if getSavings($p$, $Inputs$) < getSavings($p$, $\lambda(p)$) then
12             $\lambda(p) \leftarrow Inputs$;
13     else
14         for $o \in Pre$ do                              // For each predecessor
15             $Pre' \leftarrow$ prune($Pre \setminus \{o\}$, $Inputs \cup \{o\}$);
16             getInputs($p$, $Pre'$, $Inputs \cup \{o\}$);
```

proceeding with p (line 2). For each projection p, the set of possible inputs (line 3) is used to enumerate all possible combinations (line 4), thereby recursively determining the inputs that maximize the savings. Once the set of inputs maximizing the savings has been computed for each projection, multi-node placements are considered if possible (line 6) and the final combination is derived (line 7).

Enumeration (getInputs). The enumeration of all possible sets of inputs for projection p proceeds recursively (line 9). The selection of input sets is guided by their estimated savings (line 11-line 12). Moreover, pruning strategies may exclude projections (line 15).

Savings estimation (getSavings). The savings of a projection and a set of inputs I are estimated inductively. We add up the savings of all inputs, which, in turn, are derived from their inputs. If an input yields a multi-node placement, using Eq. 1, we add the savings induced by the multi-node placement. Otherwise, we reduce the savings by the costs of sending events of all inputs over δ hops, where δ is the average shortest path distance in the network.

We further incorporate two heuristics to avoid a certain bias in the estimation. First, we ensure that savings induced by a *single* partitioning input to *many* multi-node placements are added only once to the savings of a combination. Second, we add savings that originate from projections, for which, due to being input to multiple other projections with multi-node placements, the induced transmission costs can be shared among the target projections.

Latency-based pruning (prune). For each considered combination, we estimated the induced latency based on the processing latency and the transmission latency (estimated based on the combination depth). Then, we prune for each projection all combinations that violate the latency bound τ (see Problem 1).

6.3 Multi-Query Sharing

We apply Alg. 1 to the queries of a workload Q to incrementally construct the combination C_Q. In this process, sharing opportunities between multiple queries are exploited, as follows.

Shared construction. Once the combinations derived for multiple queries share a projection, the results can be reused. Hence, the combination C_q derived for a query q by Alg. 1 is merged with the combinations for each previously processed query by unifying the respective sets of vertices and edges.

Sharing-based scoring. When constructing the combination for a workload iteratively, our two heuristics *sharedInputs* and *sharedMN-Savings* always rely on the (partial) combination for the subset of queries $Q' \subseteq Q$ considered so far. As such, when considering the next query q, the inputs and multi-node placements of queries in Q' are incorporated in the calculation of the savings of a combination for q, which fosters the reuse of projections between queries.

Resolving conflicting multi-node placements. Multi-node placements obtained for different queries may have the issue that the partitioning input of a placement for a first query, may not be a partitioning input of a placement for a second query. This is problematic, since all outputs of the partitioning input of the first query may need to be sent over the network to realize the multi-node placement for the second query. We avoid such *conflicting multi-node placements*, as follows. Once a query q has been processed by Alg. 1, all non-partitioning inputs of the obtained combination are added to a set $\Theta \subset \mathcal{E}(q)$. When applying Alg. 1 to the next query, multi-node placements with partitioning inputs in Θ are excluded. By maintaining the set Θ for all queries, we avoid conflicting multi-node placements in the generated combination of the query workload.

6.4 Forwarding Graph and Placement

After a combination for the query workload has been generated, Alg. 2 constructs the forwarding graph and places the projections.

Output selection. First, the output selectors for each projection of the combination are determined. For each projection p having a multi-node placement, all non-partitioning inputs of p in $\mathcal{E}(p)$ are added to the set of disseminated events *DissEv* (line 2). As the inputs of multi-node placements have to be forwarded along at least as many hops as there are nodes of the multi-node placement, their dissemination in the network can be exploited for output selectors. For each projection p, we check if event types in $\mathcal{E}(p)$ are contained in the set of disseminated events *DissEv* (line 5). If so, for p, it suffices to select types not in *DissEv* as output. Yet, this is only beneficial if the rate of the potential selected output is less than the rate of the projection itself (line 29). Accordingly, the output selector $os(p)$ is determined and the rate of p used for calculating the network transmission costs are updated.

Next, the set of inputs for each projection is extended regarding the output selectors (line 7). For each projection p having an input $o \in \lambda(p)$ with $os(o) \subset \mathcal{E}(o)$, the input of p is extended by $\mathcal{E}(o) \setminus os(o)$, i.e., the event types not contained in the selected output of p are added to the inputs of p. This ensures that the forwarding graphs calculated in the next step are well-formed (see §5.2).

Shared placement. If a projection i is input to multiple other projections, the forwarding graph for i is generated such that all of these projections are jointly considered. To this end, for each projection i, the set *Successors* is generated, which comprises the sources of event types that are partitioning input to a multi-node placement of a projection p having i as input (line 9).

Then, iterating over all projections, the vertices of an INEv graph are generated. If a projection p has a multi-node placement, for each input $i \in \lambda(p)$ and each source $n \in f(i)$, a Steiner tree is constructed that spans n and all nodes in *Successors* (line 14). The tree yields the forwarding graph v_{graph} of the vertex v having i as v_{proj} and n as v_{node}. The vertex v is added to the set V (line 15).

If a projection p has a single-node placement, we consider all nodes for p's placement (line 17). We choose the one that minimizes the transmission costs using the shortest path length to calculate the costs of the placement (line 20). Let m be the node chosen for a single-node placement of p (line 21). For each input in $i \in \lambda(p)$ and each source $n \in f(i)$, it is checked if a vertex v in V exists having v_{proj} and v_{node} given by i and n, respectively. If so, v_{graph} is extended by the nodes and edges of the shortest path from m to n (line 25). Otherwise, a new vertex is added to V (line 26).

Final INEv graph construction. Alg. 2 yields the vertices V of the INEv graph $I = (V, E)$ for the combination constructed for a query workload. The set of edges E contains all pairs of vertices $(v, w) \in V \times V$, for which $w_{proj} \in \lambda(v_{proj})$.

Algorithm 2: Forwarding graph construction & placement.

```
    input  : Event network $\Gamma = (G_{top}, f, r)$, combination $C_Q = (\mathfrak{P}, \lambda)$;
             projections $MN \subset \mathfrak{P}$ for multi-node placement
    output : Vertices $V$ of INEv graph $I = (V, E)$
 1  $costs, Successors \leftarrow \emptyset$ ;
 2  for $p \in MN$ do  // For each project. with multi-node placement
 3      $DissEv \leftarrow DissEv \bigcup (\lambda(p) \cap \mathcal{E}(p)) \setminus part(p)$
 4  for $p \in \mathfrak{P}$ do            // For each projection in the combination
 5      $os(p) \leftarrow$ getOS$(p, DissEv)$ ;               // Get output selector
 6  for $p \in \mathfrak{P}$ do            // For each projection in the combination
 7      $\lambda(p) \leftarrow \lambda(p) \bigcup \cup_{i \in \lambda(p)} \mathcal{E}(i) \setminus os(i)$   // Extend set of inputs ;
    // For all inputs of projections with multi-node placements
 8  for $i \in \bigcup_{p \in MN} \lambda(p) \setminus part(p)$ do
 9      $Successors[i] \leftarrow \{x \mid x \in f(part(p)) \wedge i \in \lambda(p)\})$ ;
10  for $p \in \mathfrak{P}$ do                               // For each projection $p$
11      if $p \in MN$ then              // If $p$ has a multi-node placement
12          for $i \in \lambda(p)$ do                        // For each input of $p$
13              for $n \in f(i)$ do                     // For each source of $i$
14                  $v_{graph} \leftarrow ST(Successors[i] \cup n, G_{top})$ ;
15                  $V \leftarrow V \cup (i, n, v_{graph}, os(i))$ ;
16      else                // Only single-node placement exists for $p$
17          for $m \in V_{top}$ do  // Consider each node for $p'$s placment
18              for $i \in \lambda(p)$ do                    // For each input of $p$
19                  for $n \in f(i)$ do                 // For each source of $i$
                        // Add costs for sending $i$ from $n$ to $m$
20                      $costs[m] \leftarrow costs + SP(m, n) \cdot r(i)$ ;
21          $m \leftarrow \text{argmin}\, costs[m]$ // Choose $m$ for placement of $p$;
22          for $i \in \lambda(p)$ do
23              for $n \in f(i)$ do
24                  if $v = (i, n, v_{graph}, os(i)) \in V$ then
25                      $v_{graph} \leftarrow v_{graph} \cup SP(m, n)$;
26                  else $V \leftarrow V \cup (i, n, SP(m, n), os(i))$;
27  return $V$
28  function getOS $(p, DissEv)$
29      if $\sum_{i \in \mathcal{E}(p) \setminus DissEv} R(i) \cdot \sigma_{(i,p)} < R(p)$ then return $\mathcal{E}(p) \setminus DissEv$;
30      else return $\equiv$;
```

6.5 Complexity of Construction

Identifying suitable projections requires to enumerate the set of projections, which has a cardinality of $|2^{\mathcal{E}(q)}|$. During the combination generation, for each suitable projection, all combinations are enumerated, which yields a time complexity of $O(|2^{\mathcal{E}(q)}| \cdot 2^{|2^{\mathcal{E}(q)}|})$.

Given a combination, to derive the forwarding graph and placement, we iterate over all projections and all inputs of a projection, which, again, can be at most $|2^{\mathcal{E}(q)}|$ per projection. For each source $f(i)$ of an input i, at most the number of network nodes $|V|$, a Steiner tree is constructed with a heuristic that runs in $O(|E| \cdot \log |V|)$ time. As such, the second step of our construction has a total time complexity of $O(|2^{\mathcal{E}(q)}| \cdot |2^{\mathcal{E}(q)}| \cdot |V| \cdot |E| \cdot \log |V|)$.

6.6 Adaptive Repair

Once event rates and data distributions in an event network change over time, the quality of an INEv graph may degrade as the construction of the combination, multi-node placements, output selectors, and forwarding graphs relies on network and query statistics. We therefore propose two strategies to adapt INEv graphs:

Repairing invalid projections. A projection becomes harmful, if its output rate becomes higher than the sum of its input rates. This situation can be locally detected by the network node hosting the respective projection. In this case, the node will forward the inputs of the projection directly instead of its matches.

Repairing invalid multi-node placements. For a projection to be beneficial for a multi-node placement, Eq. 1 has to hold. This is no longer the case, if the rate of the partitioning input decreases or the rates of the non-partitioning inputs of the placement increase. While the former does not add to the resulting network costs of the graph, the latter may incur significant overhead, as high-rate events have to be forwarded in the network excessively to all nodes of a multi-node placement. To mitigate this situation, for each multi-node placement, a (fall-back) single-node placement is computed during the INEv graph construction. Once a node locally detects the described situation, evaluation switches to the predefined single-node placement. All input sources and nodes of the, now invalid, multi-node placement are notified about the new single-node placement to forward their inputs respectively and evaluate the projection.

7 EXPERIMENTAL EVALUATION

We evaluated INEv graphs with the setup explained in §7.1. In §7.2, we present the results of simulation experiments, before §7.3 turns to a case study with real-world datasets.

7.1 Experimental Setup

Our implementation and experimental setup is publicly available.[1]

Dataset and queries. For simulation experiments, we used synthetic data to achieve a controlled setup. We generated event networks varying in their number of nodes, event types, distribution of event rates (*event skew*), the portion of event types generated per node (*event node ratio*), and the out-degree per node. For the event skew, we draw rates from a Zipfian distribution. If not stated otherwise, we used an event skew of 1.3, a network of 20 nodes, an event node ratio of 0.5, and an average out-degree of 3.

[1] https://anonymous.4open.science/r/INEv-7F88/README.md

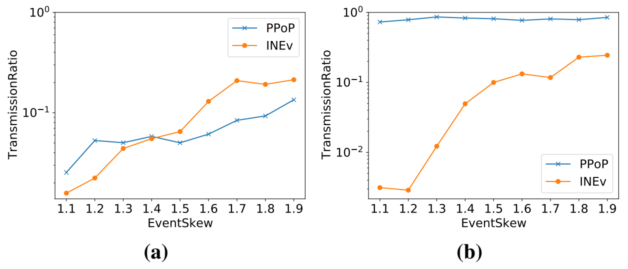


Figure 4: Comparison against the state of the art.

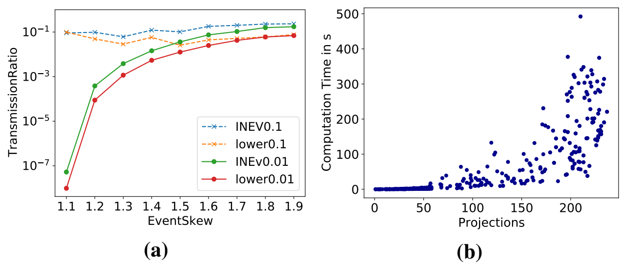


Figure 5: Computation time and closeness to lower bound.

We used a query generator to construct query workloads varying in their number of queries, query length, number of *KL* and *NSEQ* operators, event types, and selectivity scale, i.e., the range from which the selectivities are drawn uniformly. For example, a selectivity value of 0.1 denotes that the pairwise selectivities are between $1 - 10\%$. Based on the pairwise selectivities, we uniformly draw single selectivities to construct output selectors.

Baselines. We evaluated INEv graphs against a centralized baseline that does not employ query splitting and gathers all events required for the evaluation a query workload at one node. Here, we choose the node minimizing transmission costs.

We also considered a state-of-the-art approach for distributed CEP [22], which combines single-node operator placement and push-pull communication. The idea of push-pull-based CEP is to send (push) only events of types with low rates. These events may then trigger a request to pull events of high-rate types from their sources. Thus, push-pull communication, similar to a multi-node placement, benefits from skewed event rates. For the comparison, we used an exhaustive search algorithm presented in [22] that computes optimal push-pull operator placements.

Metrics. We compare the network transmission costs of in-network evaluation with INEv graphs against the costs of centralized evaluation: The *transmission ratio* is the cost induced by an INEv graph relative to the cost of the centralized evaluation. Moreover, we report on the computation time for the combination construction and the latencies and throughput induced by in-network evaluation.

Implementation. Simulation results are averaged over 50 runs per experiment, using a Python implementation of our algorithms.

Our latency and throughput experiments, as well as our case study, exploit an automata-based CEP engine, written in C#, which supports the generation of partial outputs as defined by output selectors and handles the out-of-order arrival of events caused by the distributed evaluation. Each node runs an instance of our CEP engine, and communication between the nodes is realized with Ambrosia [25], a framework for distributed computing.

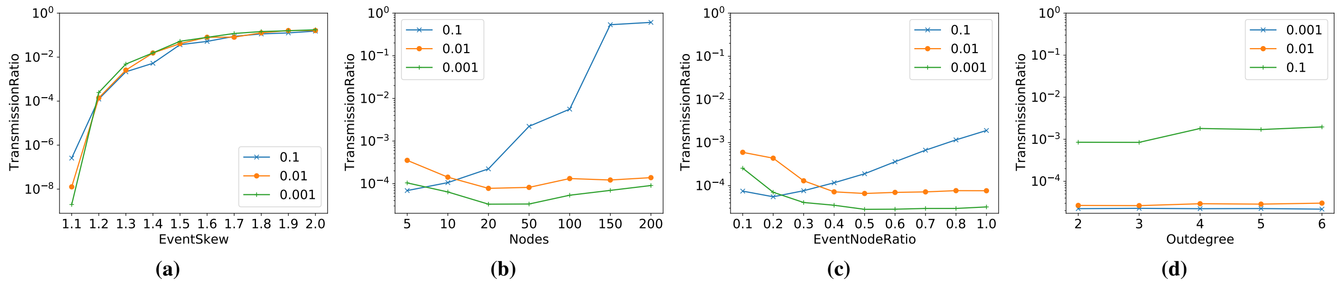


Figure 6: Transmission ratio of INEv graphs (lower is better) under varying network parameters and selectivity ranges.

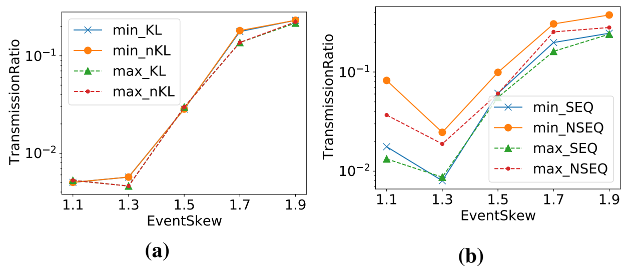


Figure 7: Influence of Kleene closure and negation.

7.2 Simulation Experiments

State-of-the-art comparison. Figure 4 compares query evaluation with INEv graphs against operator placement with a push-pull mechanism [22], denoted as *PPoP*. For a query defined over 6 event types and a network of 20 nodes, push-pull operator placement and INEv graphs show similar performance, see Figure 4a, if the number of events within a time window for each event type is ≤ 1. Yet, if events of a certain type occur more than once within the time window of the query, *PPoP* degrades to an optimal single-node placement, which shows a negligible reduction in transmission costs compared to centralized evaluation, see Figure 4b. In contrast, INEv graphs achieve a significant reduction in transmission costs.

Effectiveness. As computing optimal INEv graphs quickly becomes intractable, we approximated a lower bound for the transmission costs caused by an optimal INEv graph as follows: For each event type ϵ referenced in a query q, we check if there exists a projection $p \in \Pi_q$ for which either $R(p) < r(\epsilon)$ or $\sum_{\epsilon' \in \mathcal{E}(p)} R(\epsilon') < r(\epsilon)$. If so, we assume that an optimal solution comprises a combination in which ϵ is a partitioning input of a multi-node placement and, thus, events of this type are not sent over the network. Let $cand(q)$ denote the set of event types, for which the above holds true. Then, $\sum_{\epsilon \in \mathcal{E}(q) \setminus cand(q)} (R(\epsilon) - r(\epsilon)) \cdot \delta$ serves as a lower bound of transmission costs, assuming that all event types that are not partitioning inputs have to be forwarded over at least δ hops.

Figure 5a shows the closeness to the lower bound for a query containing 6 event types, when varying the event skew and the selectivity range (0.1 or 0.01). Our algorithms approximate the lower bound well and yield close-to-optimal INEv graphs for skewed event rates.

Efficiency. Next, we turn to the time needed for the combination generation. The runtime (in seconds) in Figure 5b for three random queries indicates that the number of possible projections to use in a combination is a critical parameter, as it increases the search space exponentially. However, due to our pruning strategies, we can handle queries based on up to 230 projections within an acceptable time.

Sensitivity. Next, we turn to the influence of various network and query parameters on our results. Figure 6 shows the transmission ratios for a single random query that references 7 event types, where line types represent different scales for the pairwise selectivities of the query. The event skew impacts the quality of INEv graphs the most (Figure 6a), leading to a reduction in transmission costs of up to eight orders of magnitude compared to a centralized evaluation. For larger network sizes and event node ratios (Figure 6b and Figure 6c), the number of sources per event type increases, leading to a reduced optimization potential for lower selectivities. As the global rates of the event types rise, less suitable projections for the evaluation can be found, and thus, fewer multi-node placements become possible.

The out-degree of nodes has little impact on the quality of INEv graphs (Figure 6d). For the selectivity range $1-10\%$, INEv graphs benefit from a small out-degree, since longer network paths lead to higher event dissemination that can be leveraged by output selectors.

Impact Kleene closure and negation. To study the impact of Kleene closure and negation, we generated two queries with the respective operator and derived counterparts without the operators, as follows. For Kleene closure, we transformed the respective query as described in §6.1. For the negation, we replaced the *NSEQ* operator with a *SEQ* operator. For each set of queries, we assigned the child of the Kleene closure operator, or the negated operator of the *NSEQ* operator, respectively, the event type having the highest ($max\_KL/NSEQ$) or lowest ($min\_KL/NSEQ$) rate.

Figure 7a shows that the Kleene closure operator has no impact on the transmission costs. Figure 7b indicates that the *NSEQ* operator restricts the number of projections considered for combination generation (as any projection needs to include all children of the operator), leading to potentially higher transmission costs, especially when the negated event has a low rate.

Multi-query setting. Figure 8 shows the quality of INEv graphs for workloads comprising 5, 10, and 20 queries over 6 event types, with a third of the workload queries comprising Kleene closure and *NSEQ* operators. We used selectivities between $0.1-1\%$ for this experiment. As discussed in §6.3, increasing the overlap in event types between the queries increases the number of conflicting multi-node placements. Figure 8a illustrates this effect. For 20 queries over 6 event types, due to conflicting multi-node placements, the INEv graphs degrade to a centralized model. Yet, workloads of sizes 5 and 10 still show improvements in the transmission ratio. Increasing the number of event types, the transmission ratios improve significantly.

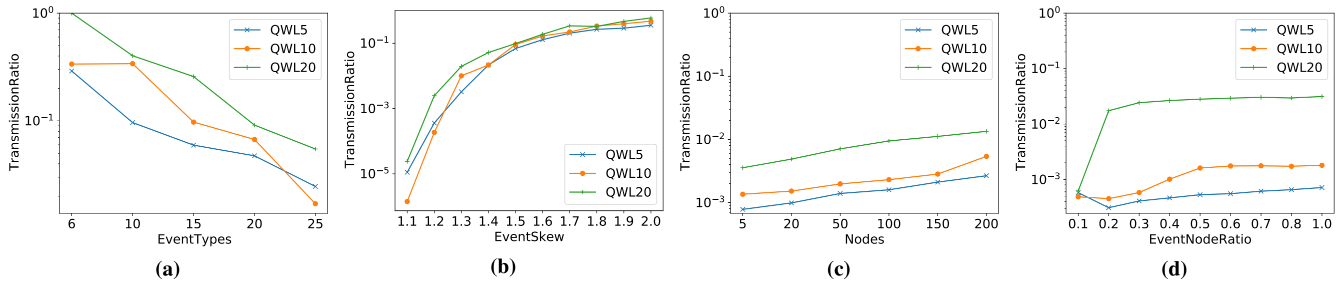


Figure 8: Transmission ratio for multi-query scenario for different workload sizes.

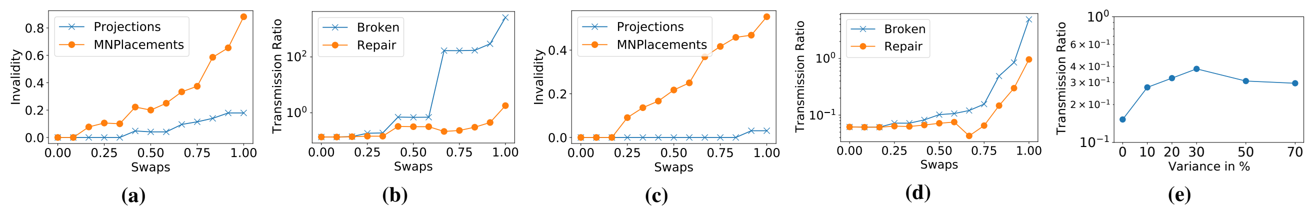


Figure 9: Experiments on the adaptivity of INEv graphs to changes in the event network.

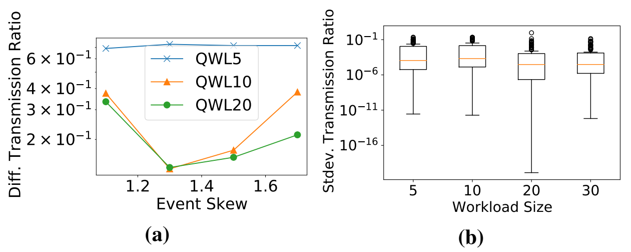


Figure 10: Incremental combination generation.

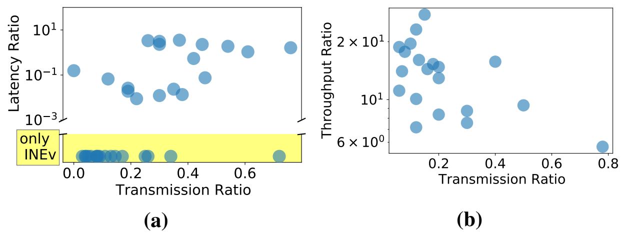


Figure 11: Detection Latency and Throughput.

Figure 8b, Figure 8c, and Figure 8d illustrate the sensitivity of the multi-query setup when considering 25 event types. The results confirm the trends obtained for the single-query scenario.

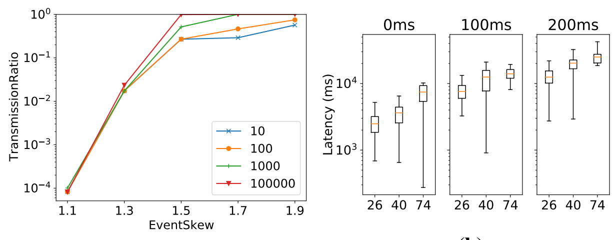
Benefit of sharing. To study how our combination generation and placement strategies leverage sharing opportunities, we generated workloads of sizes 5, 10, and 20 based on 10 event types. Figure 10a shows the ratio of transmission costs of our approach compared to a sharing-agnostic solution that treats each query in isolation (lower is better). Our approach reduces the transmission ratio, on average, by 30% and 80% for workloads of size 5 and 20, respectively.

Next, we assess the impact of the order in which the queries are processed during the incremental combination generation. For each workload size (between 5 and 30), we considered 50 workloads and for each workload, 50 different orderings of queries. Figure 10b reports the standard deviation of transmission ratios of INEv graphs based on combinations generated with different orderings. The standard deviation turns out to be small, i.e., < 0.001, suggesting that the order in which queries are processed has a negligible impact on the quality of the resulting combination. This result indicates a certain robustness when new queries are incorporated over time, as a complete re-computation of the combination may not be required.

Dynamicity. In Figure 9, we report on the effect of network changes on the quality of INEv graphs. For Figure 9a – Figure 9d, we considered a query workload of 15 queries, over 20 event types, and successively swapped their rates. We ordered the event types by their rates and stepwise increased the number of them having their rates swapped starting in the middle: For 0.1 *swaps*, the rates of the types having the $10th$ and $11th$ highest rates are swapped; and for 1.0 *swaps* the rates of all event types are swapped. We considered a selectivity range of 0.1 (Figure 9a, Figure 9b) and 0.001 (Figure 9c, Figure 9d). Figure 9a and Figure 9c report on the portion of projections and multi-node placements of the initial INEv graph (0 *swaps*) becoming invalid (see §6.1). The associated transmission ratios (*Broken*), and those resulting from the adaptation strategies proposed in §6.6 (*Repair*), are shown in Figure 9b and Figure 9d. Here, the transmission costs deteriorate with increasingly severe changes in the network. However, our adaptation strategy largely mitigates this effect.

In Figure 9e, we investigated the impact of variance in the event generation, with $x\%$ denoting that a variance of $x\%$ of the original rate can be observed over the duration of the experiment. The transmission ratios generally increase when the actual rates deviate from the estimates used for the respective INEv graph construction. However, for all considered variances, the resulting transmission ratios stay within a tight interval and only increase by at most 2.5×.

Application performance. Figure 11 summarizes the impact of INEv-based query evaluation on the overall latency and throughput relative to centralized evaluation. We evaluated 20 INEv graphs for different workloads and event rate distributions using our distributed CEP engine. Figure 11a shows the ratio of the latency (lower better) of INEv graphs inducing varying transmission ratios. For transmission ratios $< 20\%$, centralized evaluation could not keep up with INEv-based evaluation. The reason is that with low transmission costs, the number of events that need to be processed per node also



(a) (b)

Figure 12: Transmission latency experiments.

decreases, leading to fewer partial matches maintained per node. Moreover, for around a third of the evaluated workloads, no centralized evaluation was possible due to overload at the central node. Similar results were observed in our throughput experiment (Figure 11b).

Influence of transmission latency. Next, we explored the impact of the transmission latency and varied the latency ratio ξ (see §5.4), which scales the processing latency relative to the transmission latency. Using a workload of 5 queries over 7 event types, we varied the event skew. Figure 12a illustrates the trade-off between processing and transmission latency: With an event skew of 1.1, the number of multi-node placements in our plans is maximal, which minimizes processing latency. Decreasing the event skew, the number of high-rate event types, and thus, the savings in processing latency compared to a centralized model drops.

Furthermore, Figure 12b presents latency measurements of three INEv graphs (same query), involving 26, 40, and 74 hops, under different network delays. We configured the nodes to delay an event for 100*ms* (middle) and 200*ms* (right) before sending it over the network. While the INEv graph with 74 hops reduces network transmission costs the most, the increased transmission latency induced by the number of hops translates directly to the end-to-end latency.

7.3 Case Study

Citi Bike. We used one month of the Citi Bike dataset [19] containing a trace of 1 million events. Each event comprises a set of attributes, e.g., the duration, start and end station of a trip, a respective bike ID, and information about the driver. Based thereon, we derived 9 event types characterizing bike trips of varying duration. We used the end station ID to partition the data and thereby obtained local traces for 20 nodes. We created a random network topology, where nodes had an average out-degree of 3. Then, we defined 4 queries (also available in the aforementioned public repository) and generated INEv graphs which we evaluated using our distributed CEP engine. The resulting transmission ratios can be found in Table 3. Due to the high selectivities of the predicates that require events of a match to have the same bike ID, our generated INEv graphs resulted in a transmission ratio $\leq 0.05\%$ for all queries.

Cluster Monitoring. This study relied on the Google Cluster traces [46] comprising around 4.5 million events. The dataset includes 9 different event types related to task life-cycles. Each event in the data set contains attributes, such as the task priority within a job, a user ID, or machine ID. We partitioned the data based on the machine ID to obtain 20 local traces. Again, we used a random random network topology (avg. out-degree of 3). We used 4 queries

Table 3: Transmission ratios for case study.

	Q1	Q2	Q3	Q4	
Citi Bike	0.007%	0.05%	0.001%	0.008%	Transm. Ratio
Cluster Monitoring	0.006%	0.008%	0.2%	0.009%	

describing common monitoring scenarios. Based thereon, we derived the selectivities for a time window of 30 minutes which reflects the life-time of the majority of jobs. Again, the resulting selectivities were surprisingly high, which resulted in INEv graphs having a transmission ratio $\leq 0.2\%$ for all queries (see Table 3).

8 RELATED WORK

CEP optimization. Various angles have been followed to optimize the evaluation of CEP queries, including load shedding [14, 48], prefetching [49], sub-pattern sharing [12, 36], or parallelization [10]. In particular, approaches for query rewriting are related to our work. To maximize result sharing, query rewriting based on arbitrary projections was proposed in [27], but only for a centralized setting where data transmission costs do not occur. Query rewriting to reduce intermediate results in distributed CEP was considered in [41]. Unlike our INEv graph model, however, this work neglects the optimization potential induced by multi-node placements and the network's topology. Push-pull communication in distributed CEP [3] aims at reducing transmission costs by leveraging skewed event rates, as also done in INEv graphs. However, the model of [3] does not consider in-network processing, rendering it topology-agnostic.

In-network processing. In-network processing was investigated for relational stream processing [2, 15, 32, 34, 42] and for CEP [16, 20, 30]. While these approaches exploit the network topology for placement decisions, no rewriting or splitting of queries based on the given topology or distribution of event sources is considered. In [22], operator placement was extended with the aforementioned push-pull paradigm [3]. While the proposed placement strategy incorporates operator reuse among queries, no prior rewriting is applied to enhance sharing opportunities. Distributed CEP with multi-node placements was addressed in [4, 5] for clique event networks. INEv graphs, in turn, can handle any network topology.

Distributed stream joins. The reduction of network transmission has also been explored for distributed evaluation of continuous relational queries [29, 35, 39, 40, 50]. For instance, selective broadcasting may reduce data transmission in distributed stream join processing [35, 39], which, similarly to multi-node placements, exploits skewed data distributions. Yet, query rewritings to foster selective broadcasts are not considered. All of the above approaches target a single query and assume a clique network or completely ignore the topology.

Distributed databases. Our setting resembles horizontally fragmented relations in distributed databases [33], but without fragmentation rules that could be exploited for query optimizations. Semi-join reducers [6, 17, 18] are similar to our output selectors, which also restrict the results to be sent over the network. However, in INEv graphs, the data disseminated already in the network is incorporated.

9 CONCLUSIONS

We proposed INEv graphs as a model for in-network evaluation of CEP queries. INEv graphs define how to split queries, place them at network nodes, and forward partial results, thereby fostering use of disseminated events in the network to reduce transmission costs. We introduced algorithms for the construction of INEv graphs that exploit sharing opportunities in multi-query settings. Our evaluation shows that our algorithms yield close-to-optimal results and reduce transmission costs by up to eight orders of magnitude.

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