DISCES: Systematic Discovery of Event Stream Queries

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Abstract

M1 R1O1 The continuous evaluation of queries over an event stream provides the foundation for reactive applications in various domains. Yet, knowledge of queries that detect distinguished event patterns that are potential causes of the situation of interest is often not directly available. However, given a database of finite, historic (sub-)streams that have been gathered whenever a situation of interest was observed, one may aim at automatic discovery of the respective queries. Existing algorithms for event query discovery incorporate ad-hoc design choices, though, and it is unclear how their suitability for a database shall be assessed.

In this paper, we address this gap with DISCES, an algorithmic framework for event query discovery. DISCES outlines a design space for discovery algorithms, thereby making the design choices explicit. We instantiate the framework to derive four specific algorithms, which all yield correct and complete results, but differ in their runtime sensitivity. We therefore also provide guidance on how to select one of the algorithms for a given database based on a few of its essential properties. Our experiments using simulated and real-world data illustrate that our algorithms are indeed tailored to databases showing certain properties and solve the query discovery problem several orders of magnitude faster than existing approaches.

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1 Introduction

Systems for complex event processing (CEP) continuously evaluate a set of queries over streams of event data [8, 15]. As such, they facilitate the analysis and anticipation of situations of interest based on event patterns, thereby enabling reactive and proactive applications in various domains, including, for instance, supply chain management [18], urban transportation [4], and computational finance [7].

CEP systems provide a rich model for the specification of event queries [3]. Queries typically define conditions over the attribute values of events to establish their relevance for a pattern and to correlate them; and they impose constraints on the ordering of events and their occurrence within a certain window over the stream.

M1 M2 M3 R1O1 Queries to detect the event patterns that are linked to a situation of interest enable predictive applications [10, 29]. That is, the occurrence of the situation may be anticipated in order to to prevent or mitigate it. However, while domain experts may have assumptions on the factors that contribute to a situation, the precise characterization of the respective event patterns is difficult.

M2 M4 R1O1 R2O1 For illustration purposes, consider a cluster monitoring scenario, in which events denote state transitions of jobs [27]. For instance, in Fig. 1, the event e_{11} would indicate that the job with ID 1 has been *scheduled* on the compute node producing the event stream S_1 with *low* priority. A situation of interest is the materialization of stragglers, i.e., nodes with comparatively large delays. While a domain expert may understand that stragglers are linked to the interference of jobs, the specific execution patterns causing them are not known.

M1 R1O1 R2O1 Similar use cases are observed in e.g., in urban transportation, where queries shall anticipate delays based on events that represent movements of vehicles [4]. As another example, in computational finance [7], queries over events that denote transactions and stock price changes help to predict fraudulent behaviour.

M1 M3 R1O1 R2O1 To support the specification of event queries, approaches for automated query discovery have been proposed [14, 24]. Given a database of finite, historic (sub-)streams, each including at least one materialization of the situation, they discover queries that match the streams, thereby generalizing the observations. Unlike machine learning approaches, the resulting queries provide a traceable and explainable characterization of the patterns that are correlated with the situation of interest. They can be reviewed and refined by domain experts, before they are used to anticipate (and potentially mitigate) the respective situation in the future, or to understand potential causes for the situation based on the commonalities of the streams (similar to discovering frequent item sets [21] or frequent sequences [22]).

M4 R1O1 R2O1 In our example in Fig. 1, for instance, streams of three nodes that became stragglers in the past are given. For this setting, queries that characterize common event patterns are discovered. The example shows a query in SASE notation [34], in which scheduling of a low-priority job is followed by an event of a high-priority job (on the same node), before another event occurs for the first job.

Solving the problem of event query discovery is computationally hard, though. The search space of candidate queries grows exponentially in the query length and the size of the domain of the payload data. Existing discovery approaches [14, 24] explore this space in *one* specific way, which may be suitable for one database, but leads to intractability for another one. Yet, the assumptions on the database that motivate the taken design choices are implicit, so that it is unclear for which database an algorithm can be expected to work.

In this paper, we take up the general idea of event query discovery, and aim at answering the following questions:

(i) *What are the design choices in query discovery?*
(ii) *How to choose a design for a given database?*
(iii) *How to provide feedback on the algorithmic performance?*

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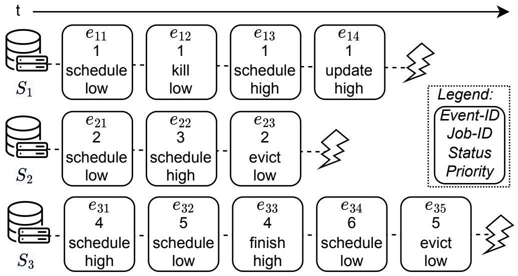

```
PATTERN SEQ (E e1, E e2, E e3)
WHERE e1.Job-ID = e3.Job-ID AND e1.Status = schedule
AND e1.Priority = low AND e2.Priority = high
```

M4 **Figure 1: Three streams emitted by nodes in a compute cluster.**
R1O1 **Each event carries an identifier (e.g., e_{11}), a job ID (e.g., 1), a**
R2O1 **state transition (e.g., *schedule*), and a priority (e.g., *low*). A query in SASE notation [34] defines a pattern over the streams.**

M5 By addressing these questions, we provide a conceptual foundation
R3O1 to study solutions to the problem of event query discovery. For the first time, this enables a systematic description and realization of the various algorithmic design choices, and outlines their implications in the practical use of discovery algorithms for a given stream database. Specifically, our contributions and the paper structure following a problem formalization (§2), are summarized as follows:

(1) We present DISCES (§3) as a framework for the design of algorithms for event query discovery. It captures a set of fundamental design choices to define discovery algorithms.
(2) We instantiate the framework to derive four discovery algorithms (§4). They all provide correct and complete results, yet they differ in their exploration of the space of candidate queries.
(3) We provide means to guide event query discovery (§5). First, we show how to choose among our algorithms based on a few essential properties of a given stream database. Second, we provide hints on how to resolve intractability or ineffectiveness of discovery based on abstractions of the events' payload data.

We evaluated the algorithms devised within the DISCES framework in experiments using simulated and real-world data (§6). Our results
M5 highlight that our algorithms are more effective and more efficient
R3O1 than the state of the art. We discover more expressive queries and solve the discovery problem several orders of magnitude faster than existing, complete approaches; with runtimes that are comparable to strategies that approximate the result. Moreover, we show that our algorithms are indeed tailored to databases that show certain properties, thereby providing insights into the practical applicability of our techniques. Finally, we review related work (§7) and conclude (§8).

2 Problem Setting

Below, we introduce a model for queries over event streams (§2.1), before turning to the problem of query discovery (§2.2).

2.1 Event Streams and Queries

Event streams. We adopt a model of multivariate event streams, similar to the one of relational data stream processing [2]. It is based
M8 on the notion of an **event schema**, which is a tuple of attributes
R2O2 $\mathcal{A} = (A_1, \ldots, A_n)$. Each attribute A_i, $1 \leq i \leq n$, is of a primitive data type, for which the finite domain is denoted by $\mathrm{dom}(A_i)$.

Without loss of generality, we assume that all events have a single schema and that all domains are distinct, i.e., $\cap_{i=1}^{n} \mathrm{dom}(A_i) = \emptyset$. If events actually have different attributes, they may be modelled with an event schema that is the union of all possible attributes, assigning a dedicated symbol that is ignored in the discovery process to attributes that are not set. The schema includes an alphabet $\Gamma =$ $\bigcup_{i=1}^{n} \mathrm{dom}(A_i)$, i.e., the set of all attribute values. An **event** $e =$ M8
$(a_1, \ldots, a_n)$ is a tuple of attribute values that instantiates the event R2O2
schema, i.e., $a_i \in \mathrm{dom}(A_i)$ for $1 \leq i \leq n$, and we write $e.A_i$ to refer to the value of attribute A_i of event e. The starting point for query discovery is an **event stream**, a finite sequence of events $S = \langle e_1, \ldots, e_l \rangle$ that are ordered by their occurrence time, with $|S|$ denoting its length. It represents a finite subsequence recorded of a potentially unbounded sequence of events. Here, we write $S[i]$ for the i-th event in the stream. A **stream database** is a set of streams $D = \{S_1, \ldots, S_d\}$, which may overlap in their contained events. A stream database D induces the supported stream alphabet $\Gamma_D \subseteq \Gamma$, containing all values that occur in every stream, i.e., $\Gamma_D = \{a \in \Gamma \mid \forall\, S \in D : \exists\, j \in \{1, \ldots, |S|\}, i \in \{1, \ldots, n\} : S[j].A_i = a\}$.

Event queries. Queries over event streams describe sequences of events that are correlated by predicates over their attribute values [15, 34]. While many models include a time window for event occurrences, in our setting, the temporal context is induced by the streams of a database. Hence, we do not model a time window explicitly, but note that it may be derived from the maximal time difference of events observed in one of the streams.

To capture event queries, we adopt a linearized representation, inspired by [17], that is well suited to describe discovery algorithms. Let $\mathcal{A} = (A_1, \ldots, A_n)$ be an event schema, $\mathcal{X}$ a finite set of variables with $\mathcal{X} \cap \Gamma = \emptyset$, and $\_ \notin \mathcal{X} \cup \Gamma$ a placeholder symbol. Then, a **query term** $t = (u_1, \ldots, u_n)$ is an n-tuple built of attribute values, M8
variables, and placeholders, i.e., $u_j \in \mathrm{dom}(A_j) \cup \mathcal{X} \cup \{\_\}$, $1 \leq j \leq n$, R2O2
such that not all its components are placeholders, i.e., it holds that $u_j \in \mathrm{dom}(A_j) \cup \mathcal{X}$ for at least one $1 \leq j \leq n$. The empty query term ε is the n-tuple comprising only placeholders, i.e., $\varepsilon = (\_, \ldots, \_)$. An event query is a finite sequence of query terms, $q = \langle t_1, \ldots, t_k \rangle$, with $q[i]$ denoting the i-th term. In a query, variables need to occur in at least two query terms for the same attribute, i.e., for any term $q[i] = (u_1, \ldots, u_n)$ with $u_j \in \mathcal{X}$, $1 \leq i \leq k$ and $1 \leq j \leq n$, there exists another query term $q[p] = (u'_1, \ldots, u'_n)$ with $u_j = u'_j$,
$1 \leq p \leq k$ and $p \neq i$. The **empty query** $\langle \varepsilon \rangle$ contains only the empty M8
query term. The universe of all possible queries is Q. R2O2

Intuitively, each query term characterizes an event that should be matched by the query. For each attribute, the term enforces a distinct value or permits any value of the respective domain. In the latter case, a placeholder models the absence of a constraint, whereas a variable that is used multiple times enforces equal attribute values. This way, equivalence predicates over attributes of events are modelled.

Queries built of terms that contain only attribute values (and placeholders) are called **type queries**; those built of terms of only M8
variables (and placeholders) are called **pattern queries**; while those R2O2
that combine attribute values and variables are called **mixed queries**.

To define the query semantics, let $q = \langle t_1, \ldots, t_k \rangle$ be an event query and let $S = \langle e_1, \ldots, e_l \rangle$ be an event stream. A **match** of q in S is an injective mapping $m : \{1, \ldots, k\} \rightarrow \{1, \ldots, l\}$, such that:

- for each query term $q[i] = (u_1, \ldots, u_n)$, $1 \leq i \leq k$, the mapped event $S[m(i)] = (a_1, \ldots, a_n)$ has the required attribute values, i.e., $u_j = a_j$ or $u_j \in \mathcal{X} \cup \{\_\}$ for $1 \leq j \leq n$;
- variables are bound to the same attribute values, i.e., for query terms $q[i] = (u_1, \ldots, u_n)$ and $q[p] = (u'_1, \ldots, u'_n)$, $1 \leq i, p \leq k$, it holds that $u_j \in \mathcal{X}$, $1 \leq j \leq n$, with $u_j = u'_j$ implies that $S[m(i)].A_j = S[m(p)].A_j$; and
- the order of the events in the stream is preserved, i.e., for $1 \leq i < p \leq k$, it holds $m(i) < m(p)$.

If there exists a match for query q in stream S, we say that S supports q (q matches S); and write $S \models q$. Table 1 lists our notations.

M4 Example 1. *Taking up the example from Fig. 1, the stream*
R1O1 *database is represented in our models as follows:*
R2O1

Stream	*Event*	*Job*	*Status*	*Prio*
S_1	e_{11}	*1*	*schedule*	*low*
	e_{12}	*1*	*kill*	*low*
	e_{13}	*1*	*schedule*	*high*
	e_{14}	*1*	*update*	*high*
S_2	e_{21}	*2*	*schedule*	*low*
	e_{22}	*3*	*schedule*	*high*
	e_{23}	*2*	*evict*	*low*

Stream	*Event*	*Job*	*Status*	*Prio*
S_3	e_{31}	*4*	*schedule*	*high*
	e_{32}	*5*	*schedule*	*low*
	e_{33}	*4*	*finish*	*high*
	e_{34}	*6*	*schedule*	*low*
	e_{35}	*5*	*evict*	*low*

The query $q = \langle (x_0, \_, \_), (\_, \_, high), (x_0, evict, \_) \rangle$ *describes three consecutive events (but not necessarily* immediately *consecutive) in which the first and the last event have the same job id, the priority of the second event is high and the status of the last event is evict. The query does not match* S_1*. It matches* S_2 *and* S_3*, with* e_{21}, e_{22}, e_{23} *and* e_{32}, e_{33}, e_{35}*, respectively.*

2.2 Query Discovery

Given a stream database, the problem of event query discovery relates to the identification of event queries that are supported by all streams, i.e., for which there exists at least a single match for each stream. However, there may exist queries that are supported by all streams, but which are comparable in the sense that one of them is stricter than another one. Formally, a query q is defined as stricter than a query q', denoted by $q \prec q'$, if (i) for any possible stream S (not necessarily contained in a given stream database), $S \models q$ implies $S \models q'$, and (ii) there exists a stream S, such that $S \models q'$, but $S \not\models q$.

In event query discovery, we are only interested in the strictest queries that are supported by all streams. The reason being that these queries denote the most concise characterization of the patterns linked to a situation of interest. For a stream database D, we therefore consider a notion of descriptiveness [16]: A query q is **descriptive**
M8 for D, if it is supported by D and there does not exist a query q' that
R2O2 is stricter, $q' \prec q$, and that is also supported by the stream database D.
Based thereon, we formulate the problem of event query discovery:

Problem 1 (Event Query Discovery). *Given a stream database* $D = \{S_1, \ldots, S_d\}$*, the problem of event query discovery is to construct the set of queries* Q*, such that:*

- *Q is correct: each $q \in Q$ creates at least a single match for all streams, i.e., for all $q \in Q$ and $S \in D$ it holds that $S \models q$;*
- *Q is descriptive: only the strictest queries are considered, i.e., for all $q, q' \in Q$ it holds that neither $q \prec q'$ nor $q' \prec q$;*
- *Q is complete: if a query q is both correct and descriptive, then it holds that $q \in Q$, i.e., Q contains all queries that are both correct and descriptive.*

Table 1: Overview of notations.

Notation	Explanation
$\mathcal{A} = (A_1, \ldots, A_n)$	An event schema, a tuple of attributes
$\Gamma = \bigcup_{i=1}^{n} \mathrm{dom}(A_i)$	The stream alphabet
$e = (a_1, \ldots, a_n)$	An event, a tuple of attribute values
$e.A_i$	The value a_i of attribute A_i of event e
$S = \langle e_1, \ldots, e_l \rangle$	An event stream, a finite sequence of events
$S[i]$	The i-th event of the event stream S
$D = \{S_1, \ldots, S_d\}$	A stream database, a set of event streams
Γ_D	The supported stream alphabet of stream database D
$\mathcal{X}$	A finite set of query variables, $\mathcal{X} \cap \Gamma = \emptyset$
$\_$	A placeholder symbol, $\_ \notin \mathcal{X} \cup \Gamma$
$t = (u_1, \ldots, u_n)$	A query term, an n-tuple of attribute values, variables, and placeholders with $u_j \in \mathrm{dom}(A_j) \cup \mathcal{X} \cup \{\_\}$, $1 \leq j \leq n$, such that not all its components are placeholders
$\varepsilon = (\_, \ldots, \_)$	The empty query term, an n-tuple of placeholders
$q = \langle t_1, \ldots, t_k \rangle$	An event query, a finite sequence of query terms
$q[i]$	The i-th term of the query q
$\langle \varepsilon \rangle$	The empty query containing only the empty query term
$S \models q$	The stream S supports the query q, i.e., there exists a match

Example 2. *Consider the following two queries:*

$$q_1 = \langle (x_0, schedule, low), (\_, \_, high), (x_0, \_, \_) \rangle$$
$$q_2 = \langle (x_0, schedule, low), (x_0, \_, \_) \rangle.$$

Query q_1 is the representation of the query from Fig. 1 in our model. M4
Both queries match the stream database of Example 1. Also, q_1 is R1O1
stricter than q_2: Any stream that matches q_1 will also match q_2, but R2O1
not vice versa. Query q_1 is even descriptive for the given database.

3 The DISCES Framework

This section introduces DISCES as a framework for the systematic design of algorithms to address the problem of event query discovery. We first discuss dimensions along which design choices are captured (§3.1), before turning to their combination (§3.2).

3.1 Dimensions of Design Choices

The DISCES framework includes four dimensions for design choices that guide how the space of candidate queries is explored. These dimensions, illustrated in Table 2, refer to the following properties of the search through that space, which are detailed in the remainder:

Direction: The search proceeds bottom-up or top-down.

Strategy: The approach is depth-first or breadth-first.

Construction: Type and pattern queries are initially constructed separately, or mixed queries are immediately considered.

Attributes: Attributes are initially considered separately, or immediately incorporated comprehensively.

Direction. When traversing the space of candidate queries, two directions may be considered: Bottom-up approaches start with the most generic query possible and, by adding attribute values or variables, generate stricter queries. The traversal stops, once the streams in the database no longer support the explored queries. Top-down approaches start with a most specific query, i.e., a shortest stream of the given database. Then, they explore the search space by deleting attribute values or exchanging them with variables; stopping whenever queries that are supported by all streams of the database have been found. Considering the example in Table 2, a bottom-up approach evaluates the query $\langle (a, \_, \_) \rangle$ before the more specific query $\langle (a, 5, 11) \rangle$, and vice versa for a top-down approach.

Table 2: Illustration of the dimensions that are incorporated in the design of discovery algorithms as part of the DISCES framework.

Direction			Strategy	Construction: Separated | Unified			Attributes: Separated | Comprehensive		
	$\langle(a,5,11)\rangle$		$\boxed{\underline{\langle(a,5)\rangle}}$	$\langle(x,y),(x,y)\rangle$	$\langle(a,5)\rangle$	$\langle(x,5),(x,\_)\rangle$	$\langle(x),(a),(x)\rangle$	$\langle(5),(7)\rangle$	$\langle(x,5),(x,7)\rangle$
bottom up	$\uparrow \ \vdots \ \downarrow$	top down	$\uparrow$	$\uparrow$	$\uparrow$	$\uparrow$	$\uparrow$	$\uparrow$	$\uparrow$
			$\boxed{\underline{\langle(a,\_)\rangle}; \langle(\_,5)\rangle}$	$\langle(x,\_),(x,\_)\rangle$	$\langle(a,\_)\rangle$	$\langle(x,\_),(x,\_)\rangle$	$\langle(x),(x)\rangle$	$\langle(5)\rangle$	$\langle(x,5),(x,\_)\rangle$
	$\langle(a,\_,\_)\rangle$		$\underline{\text{DFS}}$ | $\boxed{\text{BFS}}$	pattern queries	type queries	mixed queries	attribute 1	attribute 2	all attributes

Strategy. To explore candidate queries, one may adopt a depth-first search (DFS) strategy. Then, the space is traversed by generalizing or specializing the queries until a query with a different support behavior is reached, i.e., a non-supported query is generalized until it is supported (top-down direction) or a supported query is specialized until it is no longer supported (bottom-up direction). A different strategy is to adopt breadth-first search (BFS), i.e., to first explore all queries containing an equal number of non-placeholders, before continuing with those with less (top-down direction) or more (bottom-up direction) non-placeholders. In Table 2, assuming a bottom-up search direction, from query $\langle(a,\_)\rangle$, DFS would continue with the stricter query $\langle(a,5)\rangle$, whereas BFS would first consider queries with the same number of non-placeholders, such as $\langle(\_,5)\rangle$.

Construction. Another algorithmic choice is whether to construct type queries and pattern queries separately or with a unified approach. The former means that the space of candidate type queries and the space of candidate pattern queries are explored independently, before merging the results to also obtain the descriptive mixed queries. Note that the isolated discovery of type queries corresponds to the common problem of maximal frequent sequence mining [6, 12, 13]. In a unified approach, in turn, all query structures are explored as part of a single search space. In Table 2, a separated approach would explore pattern queries, e.g., $\langle(x,\_),(x,\_)\rangle$ and subsequently $\langle(x,y),(x,y)\rangle$, and type queries, e.g., $\langle(a,\_)\rangle$ and then $\langle(a,5)\rangle$ before merging them. A unified approach would directly construct mixed queries and explore, for instance, $\langle(x,5),(x,\_)\rangle$ after $\langle(x,\_),(x,\_)\rangle$.

Attributes. Similarly, the attributes of an event schema induce a design choice for the exploration of the space of candidate queries. We may first explore each attribute separately, before merging the results to obtain the final set of descriptive queries; or rely on a comprehensive approach that explores all attributes simultaneously. Again, Table 2 illustrates this design choice: We may consider the first attribute, exploring $\langle(x),(x)\rangle$ followed by $\langle(x),(a),(x)\rangle$, and the second attribute, exploring $\langle(5)\rangle$ followed by $\langle(5),(7)\rangle$ and merging them afterward; or immediately consider both attributes, by exploring $\langle(x,5),(x,\_)\rangle$ and then $\langle(x,5),(x,7)\rangle$.

3.2 Combination of Design Choices

Having described fundamental choices in the design of discovery algorithms, we review their interplay and underlying assumptions.

First, the choice regarding the search direction, top-down vs. bottom-up, relates to an important assumption on the application scenario. A top-down search strategy will commence with a shortest stream of the database as a query, and step-wise generalize it until queries supported by the whole database are found. Hence, such an approach can be expected to work efficiently, if descriptive queries are only slightly shorter than the shortest stream in the database. In application scenarios such as cluster monitoring, see Fig. 1, delay M1
monitoring in urban transportation, or fraud handling in compu- R1O1
tational finance, however, queries commonly contain solely a few R2O1
terms and are generally much shorter than the available streams. Hence, a top-down exploration of candidate queries will quickly become intractable, due to the sheer size of the respective search space. In the remainder, we therefore focus on the instantiation of algorithms that adopt a bottom-up direction for the search.

Second, we focus on the combination of search strategies (DFS vs. BFS) and the construction approach (type/pattern-separated vs. unified). As mentioned above, the separate construction of type queries and pattern queries enables us to incorporate existing results: The discovery of type queries in isolation corresponds to the maximal frequent sequence mining (MFSM) problem [1]. Since state-of-the-art algorithms for the MFSM problem rely on BFS, we adopt it as the search strategy in any approach that is based on the separate construction of type queries and pattern queries.

In contrast, for the unified construction of queries, a BFS search strategy is harmful. A bottom-up, unified construction of queries following BFS will explore mixed queries, for which it is known that they cannot be descriptive. For instance, the mixed queries $\langle(a),(a),(x_0),(x_0)\rangle$ and $\langle(x_0),(x_0),(b),(b)\rangle$ will be considered as candidates if the queries $\langle(a),(a),(b),(b)\rangle$ and $\langle(x_0),(x_0),(x_1),(x_1)\rangle$ are supported by the stream database, even though the mixed queries cannot be descriptive. A separated construction of queries avoids the issue, as does the combination of a unified construction with DFS.

Third, the question whether to consider the attributes separately or comprehensively is largely orthogonal to the above design choices. Hence, the separate or comprehensive treatment of attributes may be combined with either of the above design choices.

Based thereon, we derive the four combinations of design choices listed in Table 3, which can be deemed suitable to design efficient algorithms for the problem of event query discovery.

Table 3: Combination of design choices for discovery algorithms.

	Direction	Strategy	Construction	Attributes
B-S-S	bottom-up	$\underline{\text{B}}$FS	$\underline{\text{S}}$eparated	$\underline{\text{S}}$eparated
B-S-C	bottom-up	$\underline{\text{B}}$FS	$\underline{\text{S}}$eparated	$\underline{\text{C}}$omprehensive
D-U-S	bottom-up	$\underline{\text{D}}$FS	$\underline{\text{U}}$nified	$\underline{\text{S}}$eparated
D-U-C	bottom-up	$\underline{\text{D}}$FS	$\underline{\text{U}}$nified	$\underline{\text{C}}$omprehensive

4 DISCES Algorithms

Having introduced the DISCES framework to capture important choices in the design of discovery algorithms, we now turn to its instantiation. We first introduce algorithms to generate query candidates (§4.1), to match query against a stream database (§4.2), and to merge queries (§4.3). Based thereon, we propose four specific discovery algorithms (§4.4) that realize the above design choices.

4.1 Query Candidate Generation

Our discovery algorithms rely on an iterative generation of query candidates, which are then matched against a stream database. As detailed in §3, we follow a bottom-up direction in the exploration of candidate queries and step-wise generate stricter queries for a given query q. Initially, this query q is the empty query, which will be elaborated further later. The child queries of q are those obtained by inserting a new variable, by inserting a variable that has been present already, or by inserting an attribute value; either way, considering an existing query term or a newly added query term.

Variables are inserted in a certain order, which is reflected in a total order $<$ over a set of variables $\mathcal{X}$. To simplify the notation, we write $\mathcal{X}^<$ for the sequence of variables induced by $<$ over $\mathcal{X}$. Also, our construction employs at most $s/2$ variables with $s = \min_{S \in D} |S|$ being the minimal stream length in the stream database. Hence, the size of $\mathcal{X}$ and the length of $\mathcal{X}^<$ are bounded.

Query candidate generation, formalized in Alg. 1, takes as input a query q; an event schema $\mathcal{A}$; a supported alphabet Γ_D; a parent dictionary P that is modelled as a function $P : Q \rightarrow Q$, mapping child queries to their parent; a sequence of variables $\mathcal{X}^<$; and a Boolean flag b to control whether variables shall be inserted. The algorithm returns the set of child queries for q.

Alg. 1 is divided into three parts, following an initialization (line 1 - 4), each capturing one type of insertion. It is designed such that **all** child queries are obtained by insertion of a single symbol (attribute value or variable) are constructed **exactly once**. The generation relies on the auxiliary function NEXT (line 20 - 31). Given a query, it generates query candidates by inserting a given symbol (variable or attribute value) in any query term following a given position in the query, if the query contains a placeholder for that attribute. In addition, it generates candidates by appending a new query term to the query that is empty except for the given symbol for the given attribute. Based thereon, the three parts of the main algorithm include:

Insertion of a new variable (line 7 - 10). For each attribute, we consider all query terms after the last occurrence of any attribute value (g) and after the first occurrence of the last inserted variable (f). Using function NEXT, a single new variable $\mathcal{X}^<[v+1]$ is introduced by replacing a placeholder or adding a new query term.

EXAMPLE 3. *Consider the stream database from Example 1 and query* $q = \langle (x_0, \_, \_), (\_, \_, high), (x_0, evict, \_)\rangle$. *To generate new query candidates, we first add a new variable:*

$$q_1 = \langle (x_0, \_, \_), (\_, \_, high), (x_0, evict, x_1), (\_, \_, x_1)\rangle$$
$$q_2 = \langle (x_0, \_, \_), (\_, \_, high), (x_0, evict, \_), (x_1, \_, \_), (x_1, \_, \_)\rangle$$
$$q_3 = \langle (x_0, \_, \_), (\_, \_, high), (x_0, evict, \_), (\_, x_1, \_), (\_, x_1, \_)\rangle$$
$$q_4 = \langle (x_0, \_, \_), (\_, \_, high), (x_0, evict, \_), (\_, \_, x_1), (\_, \_, x_1)\rangle$$

Assuming that 'evict' was the symbol lastly added to q, we do not insert existing variables. However, we add supported attribute values ('schedule', and 'high' and 'low', respectively), after the last occurrence of an attribute value:

$$q_5 = \langle (x_0, \_, \_), (\_, \_, high), (x_0, evict, high)\rangle$$
$$q_6 = \langle (x_0, \_, \_), (\_, \_, high), (x_0, evict, low)\rangle$$
$$q_7 = \langle (x_0, \_, \_), (\_, \_, high), (x_0, evict, \_), (\_, schedule, \_)\rangle$$
$$q_8 = \langle (x_0, \_, \_), (\_, \_, high), (x_0, evict, \_), (\_, \_, high)\rangle$$
$$q_9 = \langle (x_0, \_, \_), (\_, \_, high), (x_0, evict, \_), (\_, \_, low)\rangle$$

Algorithm 1: CHILDQUERIES: Query Cand. Generation

```
Input:  Query $q$, event schema $\mathcal{A}$, supported alphabet $\Gamma_D$,
        parent dictionary $P$, sequence of query variables $\mathcal{X}^<$,
        Boolean flag $b \in \{True, False\}$ whether to insert variables.
Output: Updated parent dictionary $P$.
1  $g \leftarrow$ position of last inserted attribute value in $q$;
2  $f \leftarrow$ first position of last inserted variable in $q$;
3  $z \leftarrow \max(g, f)$;
4  $n \leftarrow |\mathcal{A}|$;
5  if $b = True$ then                          /* Shall variables be inserted? */
6      $v \leftarrow$ number of distinct query variables in $q$;
       /* Insert a new variable $\mathcal{X}^<[v+1]$ */
7      foreach $A \in \mathcal{A}$ do
8          foreach $q' \in$ NEXT$(q, z, A, \mathcal{X}^<[v+1], n)$ do
9              foreach $q'' \in$ NEXT$(q', z + |q'| - |q|, A, \mathcal{X}^<[v+1], n)$ do
10                 $P(q'') \leftarrow q$;
       /* Insert last inserted variable $\mathcal{X}^<[v]$ */
11     $l \leftarrow$ last position of last inserted variable in $q$;
12     $s \leftarrow$ last inserted symbol in $q$;
13     if $s = \mathcal{X}^<[v]$ then
14         $A \leftarrow$ attribute $A \in \mathcal{A}$ with $s \in \mathrm{dom}(A)$;
15         foreach $q' \in$ NEXT$(q, l, A, \mathcal{X}^<[v], n)$ do $P(q') \leftarrow q$ ;
   /* Insert new supported attribute value */
16 foreach $A \in \mathcal{A}$ do
17     foreach $a \in (\Gamma_D \cap \mathrm{dom}(A))$ do
18         foreach $q' \in$ NEXT$(q, z, A, a, n)$ do $P(q') \leftarrow q$ ;
19 return $P$
   /* Function to generate the next candidate queries */
20 NEXT (query $q$, start pos. $s$, attribute $A$, symbol $y$, number of attributes $n$)
21 $Q' \leftarrow \emptyset$;
22 foreach $i \in \{s, \ldots, |q|\}$ do
       /* Generate candidate by replacing placeholder with
          given variable/attribute value $y$ */
23     if $q[i].A = \_$ then
24         $q' \leftarrow q$;
25         $q'[i].A \leftarrow y$;
26         $Q' \leftarrow Q' \cup \{q'\}$;
       /* Generate candidate by including new query term that
          only contains given variable/attribute value $y$ */
27     $e' \leftarrow \varepsilon$;
28     $e'.A \leftarrow y$;
29     $q' \leftarrow \langle q[1], \ldots, q[i], e', q[i+1], \ldots, q[|q|]\rangle$;
30     $Q' \leftarrow Q' \cup \{q'\}$;
31 return $Q'$
```

Insertion of existing variable (line 13 - 15). To avoid redundant generation of child queries, this step is realized solely if the last insertion into the query had been the last inserted variable, i.e., $s = \mathcal{X}^<[v]$. Again, insertion of the variable is realized using NEXT.

Insertion of attribute value (line 16 - 18). For each query term after the last occurrence of any attribute value (g) and after the first occurrence of the last inserted variable (f), we insert a supported attribute value of the respective attribute. Again, this is realized by replacing a placeholder or by appending a query term.

4.2 Query Matching

As our algorithms explore the space of candidate queries incrementally, the evaluation of a query may benefit from the match results obtained for less strict queries at an earlier stage. Therefore, for each stream and query, we track the last position of the first match. For a stricter query, we then rely on this information and consider only the additional parts of a query and the remaining parts of the stream in the search for a match, thereby avoiding redundant computation.

Algorithm 2: MATCH: Matching a Query

```
Input:  Query $q$, event schema $\mathcal{A}$, stream database $D$, parent query $q_p$,
        stream matches dictionary $T$.
Output: Match result $M \in \{True, False\}$, updated stream matches dict. $T$.
1  $U \leftarrow \emptyset$;
2  foreach $S \in D$ do $U(S) \leftarrow \emptyset$;
3  foreach $S \in D$ do
4      $N \leftarrow \emptyset$;          /* Set of matching positions of query $q$ */
       /* Consider each assignment of attribute values to
          variables as obtained for the parent query $q_p$ */
5      foreach $\langle a_1, \ldots, a_k \rangle \in \mathrm{dom}(T(q_p)(S))$ do
           /* Replace variables in $q$ with attribute values */
6          $q_{rep} \leftarrow \mathrm{REPLACE}(q, \langle a_1, \ldots, a_k \rangle)$;
           /* If replacement yielded type query, match it */
7          if $q_{rep}$ is a type query then
8              $T \leftarrow \mathrm{MATCHSTREAM}\ (q_{rep}, S, \mathcal{A}, T)$;
9              if $T(q_{rep})(S)(\langle\rangle) \neq \circ$ then
10                 $N \leftarrow N \cup \{T(q_{rep})(S)(\langle\rangle)\}$;
11                 $U(S)(\langle a_1, \ldots, a_k \rangle) \leftarrow T(q_{rep})(S)(\langle\rangle)$;
12         else
               /* Consider all bindings for the one variable
                  that is still contained in $q_{rep}$ */
13             $A \leftarrow$ attribute $A \in \mathcal{A}$ of the variable in $q_{rep}$;
14             foreach $a \in \mathrm{dom}(A)$ do
15                 $q_{rep} \leftarrow \mathrm{REPLACE}(q_{rep}, \langle a \rangle)$;
16                 $T \leftarrow \mathrm{MATCHSTREAM}\ (q_{rep}, S, \mathcal{A}, T)$;
17                 if $T(q_{rep})(S)(\langle\rangle) \neq \circ$ then
18                     $N \leftarrow N \cup \{T(q_{rep})(S)(\langle\rangle)\}$;
19                     $U(S)(\langle a_1, \ldots, a_k, a \rangle) \leftarrow T(q_{rep})(S)(\langle\rangle)$;
20     if $N = \emptyset$ then return False, $T$ ;
21 $T(q) \leftarrow \{U(S) \mid S \in D\}$;
22 return True, $T$;
   /* Function to match a type query against a single stream */
23 MATCHSTREAM (query $q$, stream $S$, event schema $\mathcal{A}$, stream match. dict. $T$)
   /* Construct a parent query, dropping the last query term */
24 if $|q| = 1$ then $p \leftarrow \langle \varepsilon \rangle$;
25 else $p \leftarrow \langle q[1], \ldots, q[|q| - 1] \rangle$;
26 $s \leftarrow \langle q[|q|] \rangle$;
27 if $S \notin \mathrm{dom}(T(p))$ then $T \leftarrow \mathrm{MATCHSTREAM}(p, S, \mathcal{A}, T)$;
   /* Get last matching position of parent query $p$ in $S$ */
28 $m_p \leftarrow T(p)(S)(\langle\rangle)$;
   /* Try to extend the match of the parent; capture the
      obtained match position $m$ or $\circ$ for no match */
29 if $\exists\, i \in \{m_p + 1, \ldots, |S|\} : s \models S[i]$ then
30     $T(q)(S)(\langle\rangle) \leftarrow m_p + \mathrm{argmin}_{i \in \{m_p+1,\ldots,|S|\}}\ s \models S[i]$;
31 else $T(q)(S)(\langle\rangle) \leftarrow \circ$;
32 return $T$
```

To realize the above idea, our matching algorithm maintains a stream matches dictionary. M6 R3O2 Intuitively, the dictionary stores where in each stream, the first match for a certain variable binding was found. This information is valuable, since our exploration proceeds by constructing child queries by appending query terms, and by replacing placeholders only after the last inserted symbols. As such, the position of the first match of a query in a stream denotes the starting point for the search for matches of all of its child queries.

More precisely, the dictionary is a multi-nested map of signature $T : Q \rightarrow \{D \rightarrow \{\Gamma^* \rightarrow \mathbb{N}\}\}$. The outer level is a function that maps a query q to a set of functions, which, at the second level, map a stream S to another set of functions that capture the information about matches. The latter set of functions maps a sequence of attribute values $\langle a_1, \ldots a_k \rangle \in \Gamma^*$ to a position $m \in \mathbb{N}$, where k corresponds to the number of distinct variables in query q. When accessing the multi-nested map with $T(q)(S)(\langle a_1, \ldots a_k \rangle)$, we obtain the last position of the first match of query q with query variables $\langle x_1, \ldots, x_k \rangle$ in stream S, when each variable x_i is assigned the value a_i, $1 \leq i \leq k$. If q does not contain any variables, the sequence of bound attribute values is empty, i.e., $T(q)(S)(\langle\rangle)$ points to the last position of the first match of q in S.

EXAMPLE 4. *Consider $q = \langle (x_0, \_, \_), (\_, \_, high), (x_0, evict, \_) \rangle$ and stream S_3 from Example 1:*

Stream	*Event*	*Job Id*	*Status*	*Priority*
S_3	e_{31}	*4*	*schedule*	*high*
	e_{32}	*5*	*schedule*	*low*
	e_{33}	*4*	*finish*	*high*
	e_{34}	*6*	*schedule*	*low*
	e_{35}	*5*	*evict*	*low*

The parent query is $p = \langle (x_0, \_, \_), (\_, \_, high), (x_0, \_, \_) \rangle$ and its entry in the stream matches dictionary is $T(p) = \{S_3 \mapsto \{\langle 5 \rangle \mapsto 5\}\}$. To match q, we replace the variables with the according value: M6 R3O2

$$q_{rep} = \langle (5, \_, \_), (\_, \_, high), (5, evict, \_) \rangle.$$

For the parent query $p_{rep} = \langle (5, \_, \_), (\_, \_, high), (5, \_, \_) \rangle$, we get the match information as $T(p_{rep}) = \{S_3 \mapsto \{\langle\rangle \mapsto 5\}\}$, i.e., there is a match of p_{rep} in S_3 at position 5. When searching for a match for q_{rep}, we only need to consider the stream positions starting at 5, where, in this instance, a match for q_{rep} is indeed found.

We formalize our approach to query matching in Alg. 2. The algorithm iterates over each stream S in the database D (line 3). For each stream, the variables within query q are replaced by suitable attribute values using the information about matches of the parent query q_p (line 5), as kept in the stream matches dictionary T. If the replacement yields a type query (line 7), then it can be evaluated directly. Otherwise (line 13), all possible bindings for the remaining variable (there can only be one, as q is a child of q_p) are considered.

The evaluation of a type query for a specific stream is then formalized in function MATCHSTREAM (line 23-32). It constructs the parent type query by dropping the last query term, and checks for the last matching position in stream S as a starting point for matching (line 27, obtaining it recursively, if it is not available). That is, for query q, we check the remaining part of the stream for matches of the added part, i.e., the last query term of q (line 29).

4.3 Query Merging

In the DISCES framework, some algorithms separate the discovery of (i) type queries and pattern queries, and (ii) queries per attribute. In either case, queries need to be merged at a later stage. Here, we focus on the merging of type queries and pattern queries, while the algorithm to merge queries obtained for individual attributes can be found in the appendix of the accompanying technical report [5].

Alg. 3 defines our approach to merge a set of type queries Q_t and a set of pattern queries Q_p. Our idea is to exploit the hierarchy among the type/pattern queries, and step-wise create mixed queries that become slightly more specific by incorporating exactly one additional attribute value or variable, respectively, in each step.

The algorithm maintains a queue O of merge options. Each element in O comprises a type query q_t, a pattern query q_p, a mixed query q_m constructed from q_t and q_p, and an evolved query q_e that

Algorithm 3: MERGEMIXEDQUERYSET: Query Merging

```
Input:  Stream database $D$, event schema $\mathcal{A}$, type query set $Q_t$,
        pattern query set $Q_p$, parent dictionary $P$, stream matches dict. $T$.
Output: Set of merged queries $Q$.
1  $Q \leftarrow \emptyset$; $O \leftarrow$ empty queue;
   /* Initialize the queue of merge options, incorporating the
      roots of the hierarchies of type/pattern queries */
2  foreach $q_t \in (Q_t \setminus \mathrm{dom}(P))$, $q_p \in (Q_p \setminus \mathrm{dom}(P))$ do
3      foreach $q \in \{q' \in \mathrm{dom}(P) \mid P(q') \in \{q_t, q_p\}\}$ do
4          $O$.ENQUEUE$(q_t, q_p, \langle\varepsilon\rangle, q)$;
5  while $O$ not empty do
6      $(q_t, q_p, q_m, q_e) \leftarrow O$.DEQUEUE$()$;
       /* Construct queries by merging $q_e$ into $q_m$ */
7      $C, P \leftarrow$ MERGEMIXEDQUERIES$(q_t, q_p, q_m, q_e, P)$;
8      for $q_n \in C$ do
9          $M, T \leftarrow$ MATCH$(q_n, \mathcal{A}, D, P(q_n), T)$;
           /* For matching queries, derive new merge options */
10         if $M = True$ then
11             $Q \leftarrow \{q_n\} \cup Q \backslash \{q_m, q_e\}$;
12             if $q_e$ is a type query then
13                 foreach $q \in \{q' \in P \mid P(q') = q_n\}$ do
14                     $O$.ENQUEUE$(q_e, q_p, q_n, q)$;
15                 foreach $q \in \{q' \in P \mid P(q') = q_p\}$ do
16                     $O$.ENQUEUE$(q_e, q_p, q_n, q)$;
17             else
18                 foreach $q \in \{q' \in P \mid P(q') = q_n\}$ do
19                     $O$.ENQUEUE$(q_t, q_e, q_n, q)$;
20                 foreach $q \in \{q' \in P \mid P(q') = q_t\}$ do
21                     $O$.ENQUEUE$(q_t, q_e, q_n, q)$;
22 return $Q$;
```

is derived from q_t or q_p by adding one attribute value or variable, respectively. The queue is initialized with the root queries of the hierarchies (line 2-4), i.e., the type and pattern queries without a parent, while the evolved query corresponds to one of their children.

While the queue O is not empty, each tuple (q_t, q_p, q_m, q_e) is used to create more specific queries by merging q_e into q_m through function MERGEMIXEDQUERIES (line 7), described below. Then, each of the resulting queries $q_n \in C$ is matched against the stream database (line 9). If all streams support the query (line 10), the set of merged queries is adjusted (line 11) and further merge options are inserted into the queue (line 12-21), which realizes a traversal of the hierarchy of type queries and pattern queries.

The merging of the evolved query p_e into the mixed query p_m is formalized in Alg. 4, which also takes the associated type query q_t and pattern query q_p, and the parent dictionary P as input. It first determines an index i_m (line 4-8). It indicates until which query term the query q_m cannot change anymore without creating a conflict with queries q_t and q_p that form the basis for its construction. Here, the function MERGETERMS merges query terms (line 27-32), per attribute, returning the empty term (line 30), in case of a conflict.

Based on index i_m, mixed queries are constructed by incorporating an additional attribute value (line 9-17), either in one of the existing query terms or as a new query term, for all possible positions. Subsequently, if the evolved query is not a type query, further mixed queries are constructed (line 18-25), by replacing the query terms after i_m of the original query with those of the evolved query, potentially merging the last term of the original query and the first of the evolved query. All these mixed queries are collected in the result set Q, while maintaining the parent dictionary P for the queries.

Algorithm 4: MERGEMIXEDQUERIES: Merging of Queries

```
Input:  Type query $q_t$, pattern query $q_p$, mixed query $q_m$, evolved query $q_e$,
        parent dictionary $P$.
Output: Set of merged queries $Q$, updated parent dictionary $P$.
1  $i_t, i_p, i_m \leftarrow 0, 0, 0$;
2  $Q \leftarrow \emptyset$;
3  $j \leftarrow$ position of last inserted symbol in query $q_m$;
   /* Determine the index after which $q_m$ may still change */
4  while $i_m < j$ do
5      if MERGETERMS $(q_t[i_t], q_m[i_m]) \neq \varepsilon$ then $i_t \leftarrow i_t + 1$;
6      if MERGETERMS $(q_p[i_p], q_m[i_m]) \neq \varepsilon$ then $i_p \leftarrow i_p + 1$;
7      $i_m \leftarrow i_m + 1$;
8      if MERGETERMS $(q_t[i_t], q_m[i_m]) = \varepsilon \wedge$
         MERGETERMS $(q_p[i_p], q_m[i_m]) = \varepsilon$ then break ;
9  if $q_e$ is a type query then
       /* Merge by incorporating an add. attribute value */
10     for $k \in \{i_m, \ldots, |q_m|\}$ do
11         $q' \leftarrow \langle q_m[1], ..., q_m[k-1], q_t[|q_t|], q_m[k], ..., q_m[|q_m|]\rangle$;
12         $Q \leftarrow Q \cup \{q'\}$; $P(q') \leftarrow q_m$;
13     for $k \in \{i_m, \ldots, |q_m|\}$ do
14         $t \leftarrow$ MERGETERMS $(q_t[|q_t|], q_m[k])$;
15         if $t \neq \varepsilon$ then
16             $q' \leftarrow \langle q_m[1], ..., q_m[k-1], t, q_m[k+1], ..., q_m[|q_m|]\rangle$;
17             $Q \leftarrow Q \cup \{q'\}$; $P(q') \leftarrow q_m$;
18 else
       /* Merge by incorporating query terms of $q_e$ */
19     if $i_p = |q_p| \vee i_t = |q_t|$ then
20         $q' \leftarrow \langle q_m[1], ..., q_m[i_m], q_e[i_p], ..., q_e[|q_e|]\rangle$;
21         $Q \leftarrow Q \cup \{q'\}$; $P(q') \leftarrow q_m$;
22     $t \leftarrow$ MERGETERMS $(q_m[i_m], q_e[i_p])$;
23     if $t \neq \varepsilon$ then
24         $q' \leftarrow \langle q_m[1], ..., q_m[i_m - 1], t, q_e[i_p + 1], ..., q_e[|q_e|]\rangle$;
25         $Q \leftarrow Q \cup \{q'\}$; $P(q') \leftarrow q_m$;
26 return $Q, P$
   /* Function to merge two query terms */
27 MERGETERMS (query term $t_1$, query term $t_2$, event schema $\mathcal{A}$)
28 $t_m \leftarrow t_1$;
29 foreach $A \in \mathcal{A}$ do
30     if $t_1.A \neq t_2.A \wedge t_1.A \neq \_ \wedge t_2.A \neq \_$ then return $\varepsilon$;
31     if $t_1.A \neq t_2.A$ then $t_m.A = t_2.A$;
32 return $t_m$
```

4.4 Realizations of Query Discovery

Using the above auxiliary algorithms, we can now instantiate four discovery algorithms, as outlined already in Table 3. Below, we provide formalizations for two of the algorithms, D-U-C and B-S-C, and summarize the other two algorithms (for which a formalization can be found in [5]). We close with a discussion of their properties.

D-U-C: DFS, pattern-type unified, attribute comprehensive. The algorithm, given in Alg. 5, employs a DFS strategy, constructs mixed queries directly, and incorporates all attributes right away.

For a stream database D, an event schema $\mathcal{A}$, and a sequence of query variables $\mathcal{X}^{<}$ (see §4.1), it returns a set of descriptive queries. It starts with the empty query $\langle\varepsilon\rangle$, which is pushed to a stack of queries to explore. While this stack is not empty, candidate queries are assessed and generated (line 6-15). That is, a query is popped from the stack and matched. Following a successful match, child queries are generated using function CHILDQUERIES and extracted from the parent dictionary P into a set C. If child queries exist, they are added to the stack; otherwise, the current query is added to the preliminary result set.

Algorithm 5: D-U-C

```
Input:  Stream database $D$, event schema $\mathcal{A}$, sequence of query var. $\mathcal{X}^<$,
        Boolean flag $b \in \{True, False\}$ whether to output only desc. queries.
Output: Set of descriptive queries $Q$, updated parent dictionary $P$.
$Q \leftarrow \emptyset$;
$\Gamma_D \leftarrow \{a \in \Gamma \mid \forall\, S \in D : \exists\, j \in \{1, ..., |S|\}, i \in \{1, ..., n\} : S[j].A_i = a\}$;
$q \leftarrow \langle \varepsilon \rangle$; $P(q) \leftarrow \langle \varepsilon \rangle$;
foreach $S \in D$ do $T(q)(S)(\langle\rangle) \leftarrow 0$ ;
/* Explore queries that are pushed to the stack */
$O \leftarrow$ empty stack; $O$.PUSH$(q)$;
while $O$ not empty do
    $q \leftarrow O$.POP$()$;
    $M, T \leftarrow$ MATCH$(q, \mathcal{A}, D, P(q), T)$ ;
    if $M = True$ then
        /* For queries supported by the stream database,
           explore their children */
        $P \leftarrow$ CHILDQUERIES$(q, \mathcal{A}, \Gamma_D, P, \mathcal{X}^<, True)$;
        $C \leftarrow \{q' \in \text{dom}(P) \mid P(q') = q\}$;
        if $C \neq \emptyset \wedge b = True$ then
            foreach $q' \in C$ do $O$.PUSH$(q')$;
        else $Q \leftarrow Q \cup \{q\}$;
    else if $b = False$ then $Q \leftarrow Q \cup \{P(q)\}$;
if $b = True$ then $Q \leftarrow$ DESCRIPTIVEQUERIES$(Q, \Gamma_D, \mathcal{A}, \mathcal{X}^<)$ ;
return $Q, P$
```

Finally, a function DESCRIPTIVEQUERIES (see our technical report [5]) selects the descriptive queries from all those supported by the database, by a syntactic comparison of query terms.

B-S-C: BFS, pattern-type separated, attribute comprehensive. In Alg. 6, we show how discovery is realized with BFS, considering type queries and pattern queries separately, while incorporating all attributes at once. In general, the algorithm follows a similar structure compared to the previous one. However, the exploration is based on candidate queries that are maintained in queues to realize a BFS strategy. Also, the assessment of queries and generation of child queries is conducted separately for type queries (line 6-14) and pattern queries (line 16-24). Once this exploration ended, mixed queries are considered using function MERGEMIXEDQUERYSET.

D-U-S: DFS, pattern-type unified, attribute separated. This algorithm is a variant of D-U-C. It first discovers queries separately per attribute, before merging them. That is, the algorithm runs the D-U-C algorithm (Alg. 5) per attribute, i.e., on a projection of the streams and of the event schema on one attribute. With flag b being *False*, all queries supported by the database are collected, not only descriptive ones. Finally, queries discovered per attribute are merged.

B-S-S: BFS, pattern-type separated, attribute separated. This is a variant of B-S-C, adopting BFS and the separated discovery of type queries and pattern queries. Yet, it first considers queries per attribute, before merging them. As such, it adopts the strategy explained above for D-U-S, just with B-S-C as the base algorithm.

Correctness, descriptiveness, completeness. The four presented algorithms solve the problem of event query discovery (Problem 1). Given a stream database, all four algorithms, construct a set of queries Q that is correct, descriptive, and complete:

Algorithm 6: B-S-C

```
Input:  Stream database $D$, event schema $\mathcal{A}$, sequence of query var. $\mathcal{X}^<$,
        Boolean flag $b \in \{True, False\}$ whether to output only desc. queries.
Output: Set of descriptive queries $Q$, updated parent dictionary $P$.
1  $Q \leftarrow \emptyset$;
2  $\Gamma_D \leftarrow \{a \in \Gamma \mid \forall\, S \in D : \exists\, j \in \{1, ..., |S|\}, i \in \{1, ..., n\} : S[j].A_i = a\}$;
3  $q \leftarrow \langle \varepsilon \rangle$; $P(q) \leftarrow \langle \varepsilon \rangle$;
4  foreach $S \in D$ do $T(q)(S)(\langle\rangle) \leftarrow 0$ ;
   /* Explore type queries based on a queue */
5  $O_{type} \leftarrow$ empty queue; $O_{type}$.ENQUEUE$(q)$;
6  while $O_{type}$ not empty do
7      $q \leftarrow O_{type}$.DEQUEUE$()$;
8      $M, T \leftarrow$ MATCH$(q, \mathcal{A}, D, P(q), T)$;
9      if $M = True$ then
10         $Q_{type} \leftarrow Q_{type} \cup \{q\}$;
11         $P \leftarrow$ CHILDQUERIES$(q, \mathcal{A}, \Gamma_D, P, \mathcal{X}^<, False)$;
12         $C \leftarrow \{q' \in \text{dom}(P) \mid P(q') = q\}$;
13         if $C \neq \emptyset$ then
14             foreach $q' \in C$ do $O_{type}$.ENQUEUE$(q')$;
   /* Explore pattern queries based on a queue */
15 $O_{pattern} \leftarrow$ empty queue; $O_{pattern}$.ENQUEUE$(q)$;
16 while $O_{pattern}$ not empty do
17     $q \leftarrow O_{pattern}$.DEQUEUE$()$;
18     $M, T \leftarrow$ MATCH$(q, \mathcal{A}, D, P(q), T)$;
19     if $M = True$ then
20         $Q_{pattern} \leftarrow Q_{pattern} \cup \{q\}$;
21         $P \leftarrow$ CHILDQUERIES$(q, \mathcal{A}, \emptyset, P, \mathcal{X}^<, True)$;
22         $C \leftarrow \{q' \in \text{dom}(P) \mid P(q') = q\}$;
23         if $C \neq \emptyset$ then
24             foreach $q' \in C$ do $O_{pattern}$.ENQUEUE$(q')$;
   /* Merge the found type queries and pattern queries */
25 $Q, P \leftarrow$ MERGEMIXEDQUERYSET$(D, \mathcal{A}, Q_{type}, Q_{pattern}, P, T)$;
26 if $b = True$ then $Q \leftarrow$ DESCRIPTIVEQUERIES$(Q, \Gamma_D, \mathcal{A}, \mathcal{X}^<)$;
27 return $Q, P$
```

Correctness: Algorithm MATCH returns the match result *True*, only if for each stream, at least one match is found for some binding of attribute values to the variables. Here, MATCHSTREAM exploits that the index of a match of a type query in a stream can only be larger or equal to the minimal index of the matches of a query obtained by removing the last query term. Now, consider the individual discovery algorithms: D-U-C (with flag $b = True$) collects in Q only matching queries. Similarly, B-S-C enqueues in Q_{type} and $Q_{pattern}$ only matching queries, while the queries obtained by merging these sets in MERGEMIXEDQUERYSET are checked by MATCH to be part of the result set. For D-U-S and B-S-S, correctness follows from D-U-C and B-S-C returning only matching queries, and MERGEATTRIBUTEQUERIES only adding matching merged queries to Q_m.

Descriptiveness: The result set Q contains only descriptive queries, as all four algorithms filter non-descriptive queries in a post-processing step (function DESCRIPTIVEQUERIES in Alg. 5 and Alg. 6).

Completeness: While we provide a comprehensive discussion of completeness properties in our technical report, we summarize the main arguments as follows: First, we note that CHILDQUERIES may inductively generate any query according to our model starting with the empty query for a given schema and sequence of query variables. Any placeholder of an existing query term may be replaced by any attribute value of the respective domain or a variable, and a new query term may also be inserted for any of these values or variables. For D-U-C, completeness then follows as any possible child of a matching query, derived by inserting one additional attribute value or variable, is explored. For B-S-C, in addition to the generation of all child queries of matching queries, MERGEMIXEDQUERYSET and MERGEMIXEDQUERIES generate any possible interleaving of query terms, as well as elements of query terms from these queries. For D-U-S and B-S-S, our argument rests further on the completeness of the merging of queries per attribute, which unfolds all combinations.

M7
R3O4

Runtime complexity. We list the worst-case time complexity of our individual algorithms in Table 4 (with MergeMixedQuerySet being dominated by Match). Based thereon, we conclude that the presented algorithms do not differ in their overall runtime complexity. In addition to the large search space, the source of computational complexity is the exponential running time of our algorithm for solving the matching problem. This, however, cannot be avoided, since the matching problem is NP-hard in general [16]. For a more efficient implementation of the matching problem, it would be desirable to avoid the term $|\Gamma|^{|\mathcal{X}|}$, e.g., by obtaining a running time of $O(\text{poly}(|D|, |\Gamma|) \cdot 2^{|\mathcal{X}|})$ (note that for constant queries, this would be a polynomial running time). Unfortunately, due to the $W[1]$-hardness of the matching problem parameterized by $|\mathcal{X}|$ [16], such running times are excluded as well (under common complexity theoretical assumptions). These complexity bounds justify our approach where, instead of trying to optimize an algorithm for the matching problem, we exploit the fact that the matching problem is solved repeatedly, for instances that are structurally similar (see §4.2).

5 Guidance on Query Discovery

To guide the use of our algorithms in application scenarios, we now discuss how to choose among the algorithms for a given stream database (§5.1), before outlining how to give feedback if their application turns out to be intractable or ineffective (§5.2).

5.1 Algorithm Selection

Our idea is to guide the selection of a discovery algorithm based on characteristic properties of a stream database. The properties may hint at which of the algorithms can be expected to be particularly efficient, as it caters for the structure of the database. To realize this idea, we may leverage database properties that (i) can be computed efficiently (i.e., in linear time in the size of the streams), and (ii) enable us to separate the performance characteristics of the algorithms.

One may assume that the size of the stream database D, e.g., the number of streams $|D|$ and the minimum stream length $\min_{S \in D} |S|$, are important properties for event query discovery. Yet, based on our complexity analysis, we observe that these properties have a minor impact on the runtime of discovery algorithms. The reason being that the size of a database does not characterize the size of the space of candidate queries that needs to be explored by the discovery algorithms. We therefore consider the following four properties:

Number of attributes $|\mathcal{A}|$. The property captures the number of attributes in the event schema. It can be expected to indicate whether the separate or unified handling of type queries and pattern queries is more beneficial. The overhead induced by the merging of separately discovered queries can be expected to increase significantly with the number of attributes. Hence, a higher value of $|\mathcal{A}|$ shall render D-U-S and D-U-C more efficient compared to B-S-S and B-S-C.

Number of supported attribute values $|\Gamma_D|$. We consider the size of the supported alphabet, i.e, the number of supported attribute values that appear in the database. With a large alphabet, the separated discovery of type queries and pattern queries can be expected to be beneficial, i.e., B-S-S and B-S-C shall be most efficient. The reason being that we expect many pattern queries to be present, which, under a unified construction, would always be extended with a large number of attribute values during the exploration.

Table 4: Worst-case complexity of algorithms.

Function	Complexity
ChildQueries	$O\left(\lvert q\rvert^2 \cdot n^2 + \lvert q\rvert \cdot \lvert\Gamma_D\rvert \cdot n\right)$
Match	$O\left(\lvert D\rvert \cdot \lvert\Gamma\rvert^{\lvert\mathcal{X}\rvert}\right)$
MergeMixedQueries	$O\left(\lvert q_t\rvert \cdot \lvert q_p\rvert \cdot n\right)$
MergeAttributeQueries (see [5])	$O\left(\max_{i \in \{1,\ldots,n\}}(\lvert q_i\rvert)^n\right)$
DescriptiveQueries (see [5])	$O\left(\lvert q\rvert \cdot n\right)$ per $q \in Q$

By $|q|$, we denote the length of the query q, i.e., the number of query terms. By n, we denote the number of attributes in the event schema $\mathcal{A}$.

Max of sum of supported attribute values ρ_S. The property is the maximum number over all streams and all attributes, of the summed up occurrences of all supported attribute values:

$$\rho_S = \max_{\langle e_1,\ldots,e_l\rangle \in D} \left(\sum_{i=1}^{l} \sum_{A \in \mathcal{A}} \mathbb{1}(e_i, A) \right) \text{ with } \mathbb{1}(e_i, A) = \begin{cases} 1, \text{if } e_i.A \in \Gamma_D \\ 0, \text{otherwise} \end{cases} .$$

If there is a large number of supported values for an attribute, approaches that handle attributes separately need to realize numerous merge operations for single-attribute queries. This overhead is avoided in D-U-C and B-S-C, which can be expected to run more efficiently than D-U-S and B-S-S, for higher values of this measure.

Min of sum of repeated attribute values ρ_R. The property captures the minimum number over all streams of the summed up repetitions of all attribute values within a stream S:

$$\rho_R = \min_{\langle e_1,\ldots,e_l\rangle \in D} \left(\sum_{i=1}^{l} \sum_{A \in \mathcal{A}} \mathbb{1}(e_i, A) \right) \text{ with}$$

$$\mathbb{1}(e_i, A) = \begin{cases} 1, \text{if } \exists\ j \in \{1, \ldots, l\}, i \neq j : e_i.A = e_j.A \in \Gamma \\ 0, \text{otherwise} \end{cases} .$$

Intuitively, the repetition of attribute values in a stream increases the size of the search space for pattern queries. As the repetitions may generally be spread over several attributes, approaches that separate discovery per attribute, i.e., D-U-S and B-S-S, can be expected to be more efficient than those with comprehensive handling of attributes.

The above properties can be expected to be correlated with differences in the runtime of the discovery algorithms. We later explore this aspect empirically, using a controlled experimental setup.

5.2 Feedback based on Algorithmic Performance

In practice, a stream database is typically not fixed, but subject to transformations as part of the extraction and preparation of the data. Various abstractions, such as event selection, projection of attributes, or discretization of attribute values, are commonly employed. Therefore, once a discovery algorithm does not terminate within reasonable time or yields an empty result set, feedback may be derived on how these abstractions influence the algorithmic performance.

Abstractions to reduce runtime. If event query discovery turns out to be intractable, the space of candidate queries may be reduced. Specifically, an attribute may be removed entirely or highly frequent values of an attribute may be made unique. In either case, the respective information will be ignored in the discovery procedure, which, assuming it is justified in the considered application scenario, can be expected to reduce the overall runtime of the discovery algorithms. Practically, the attributes with the smallest domains are suitable candidates for removal and a specialization of their attribute values.

Abstractions to increase the result size. In case no or only a very few descriptive queries are discovered, the impact of abstractions

M9 R2O3 on the result set shall be considered. While our discovery results are always complete and contain only descriptive queries for the given database, abstractions may change the input data and, hence, the output of discovery. For instance, in our cluster monitoring example, jobs are assigned a priority of value range $[1, 10]$. Let $\langle(8), (3), (7)\rangle$ and $\langle(9), (5), (9)\rangle$ be two streams of three events over a schema comprising solely the priority attribute. Then, discovery would not find any query. This changes when abstracting the streams to $\langle(high), (medium), (high)\rangle$ and $\langle(high), (high), (medium)\rangle$, i.e., reducing the domain of the attribute to three values for reasonable ranges of numeric values. Now, queries two queries, $\langle(high), (high)\rangle$ and $\langle(high), (medium)\rangle$, are discovered. The example illustrates that the reduction of attribute domains, e.g., by filtering or generalizing values, renders it more likely that regularities in the streams can be identified through the discovery of queries. As such, the attributes with the largest domains are suitable candidates for the filtering and generalization of their values.

6 Experimental Evaluation

To evaluate the DISCES framework, we first introduce an experimental setup (§6.1). Then, we compare our algorithms against the state of the art for event query discovery (§6.2). Finally, we evaluate the sensitivity of our algorithms with respect to the characteristics of a stream database (§6.4), before studying the effectiveness of our strategies to guide the application of discovery algorithms (§6.5).

6.1 Experimental Setup

M2 R1O1 **Datasets.** We leverage both real-world and synthetic data to evaluate our algorithms. Specifically, we rely on NASDAQ stock trade events [11] and the Google cluster traces [28]. We adopt the methodology from [14] for obtaining stream databases: Situations of interest are emulated by predefined queries. Each query is used to construct a stream database, i.e., each match of the query over the dataset yields one stream, selecting all events in a fixed window before the match. As such, the queries are only used to generate realistic stream databases, whereas the descriptive queries for these databases are *not* known. For each dataset, we consider three queries, as follows.

The event schema for the finance data comprises three attributes: stock name, volume, and closing value. The queries to construct streams capture two events with stock name 'GOOG' (F1); three events with stock names appearing in the sequence 'AAPL', 'GOOG', and 'MSFT' (F2); and four events for which the volume remains constant (F3). Events in the Google cluster traces have four attributes: job ID, machine ID, status, and priority. One query defines three events running on the same machine with identical job IDs, with the first and last ones of status 'submit', while the second one has status 'kill' (G1); one query checks for four events for the same machine with status 'finish' (G2); and one query detects job eviction resulting from the scheduling of another job on the same machine (G3).

Using these queries, we generated the stream databases summarized in Table 5 by evaluating the queries over the datasets. For each match (of the first 1000 matches), we constructed a stream by including the a or $b = a + 1$ events preceding the match. The values of a and b, listed in Table 5, have been determined experimentally using the IL-Miner [14] (described below), i.e., the state of the art for event query discovery: For a database with streams of length a, the IL-Miner was still able to compute results, whereas for streams of length b, it failed to compute results within 12 hours. As such, the databases characterize the computational limit of the state of the art, thereby providing a suitable basis for the comparison.

Table 5: Real-world stream databases used in the experiments.

		stream length a | b	number of streams	maximum query length
	F1	50 | 51	79	4
Finance	F2	40 | 41	1000	4
	F3	25 | 26	250	5
Google	G1-G3	7 | 8	1000	4

Table 6: Properties of the synthetic stream databases. M10 R1O2 R3O3

	$\lvert D\rvert$	$\lvert S\rvert$	$\lvert\mathcal{A}\rvert$	$\lvert\Gamma_D\rvert$	ρ_S	ρ_R
Scaling	**2,..., 90,000**	**20,..., 9,000**	3	2	5	5
E_1	2	20	**1,6,...,101**	2	5	5
E_2	2	102	1	**1,11,...,91**	$\lvert\Gamma_D\rvert$	0
E_3	2	20	3	3	**9,24,...,294**	6
E_4	2	20	3	0	0	**2,3,...,13**

M10 R1O2 R3O3 Moreover, we employed synthetic data for controlled experiments. To conduct a scalability analysis, we generated databases with up to 90,000 streams or 9,000 events per stream, respectively. To assess the impact of specific properties of a stream database, we generated databases for four evaluation scenarios, as follows. We first created a database of two streams that do not support any query. Here, the number of events per stream and the number of attributes may vary for each scenario. Then, the database is adapted by adding or replacing attribute values, as listed in Table 6, such that one database property increases while the others remain constant (except that increasing $|\Gamma_D|$ will also increase ρ_S).

Baselines. We compare the algorithms of the DISCES framework against the IL-Miner [14], the only existing algorithm to discover event queries with repeated attribute values (see §7). Since the IL-Miner, by default, cannot discover queries that comprise query terms that contain only variables, we consider two variants: one extended version that can discover these queries, thereby covering the full query model of the DISCES framework, and one lossy version that neglects queries with terms containing no attribute values.

Measures. We primarily measure the efficiency of event query discovery in terms of the algorithms' runtime. We report averages over five experimental runs, including error bars (mostly negligible).

Environment. We adopted Python-based implementations of the DISCES framework and the IL-Miner. All experiments were conducted on a server with a Xeon 6354 CPU @3,6GHz and 1TB RAM.

6.2 State-of-the-Art Comparison

First, we compare the runtimes of our algorithms and the extended IL-Miner, which supports our full query model. The results in Fig. 2 show that our algorithms are faster than the IL-Miner in all cases. For the scenarios based on the finance dataset, our algorithms are about five orders of magnitude faster. As discussed, we determined the stream lengths for the a and b scenarios as the computational limit of the state of the art, i.e., in all b scenarios, the IL-Miner cannot produce results within 12 hours. The algorithms of the DISCES framework enable us to get past this limit in all cases, without a notable increase in the runtime.

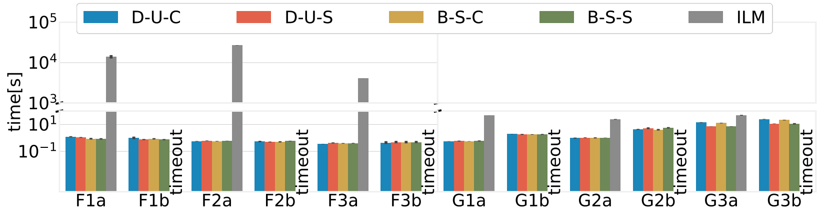

Figure 2: Runtime comparison with the state of the art.

Table 7: Comparison of our algorithms and the lossy IL-Miner.

Datasets	Avg $^{\text{Time Lossy ILM}}/_{\text{Time DISCES}}$	Desc(riptive)	Found	¬ Desc
F1b-F3b	0.42	8	0	4
G1b-G3b	2.9	19	1	2

A comparison with the lossy IL-Miner reveals that its improved runtime is traded for result correctness. The lossy IL-Miner yields similar runtimes compared to our algorithms, see Table 7, yet it discovers only a fraction of the queries. With the correct results containing 8 (finance) and 19 (Google) descriptive queries ('Desc'), the lossy IL-Miner discovers none or only one of them ('Found'), and additionally two and four queries that are not descriptive ('¬ Desc'). As such, it largely compromises the result quality not only in terms of descriptiveness, but also in terms of completeness.

6.3 Scalability Analysis

M10 R1O2 R3O3 We test the scalability of our algorithms, when increasing the number of streams and when increasing the minimal stream length in the database. Fig. 3 shows that adding streams yields higher runtimes mainly in beginning, from 2 to 10,000 streams. Afterwards, the trend is close to linear. Differences between the algorithms are small (D-U-C and D-U-S performing best). Similarly, increasing the minimal length of a stream does not reveal a particular trend or differences between the algorithms. These results are in line with our complexity analysis in §4.4, which points to both properties having a minor impact on the runtime performance. However, our results confirm the general feasibility of event query discovery with the DISCES framework also for larger problem instances.

6.4 Sensitivity Analysis

All of our algorithms show the same worst-case complexity, but incorporate different design choices. We explore the impact of these choices regarding properties of stream databases (as introduced in §5.1) in a sensitivity analysis. For the systematically generated stream databases from Table 6, the results are shown in Fig. 4.

For the properties introduced in §5.1, the results confirm our hypotheses. A higher number of attributes (E3) favours algorithms that avoid merging type and pattern queries: D-U-S and D-U-C outperform B-S-S and B-S-C, as merging queries becomes expensive with more attributes. Having more supported attribute values (E4) benefits algorithms that separate the discovery of type and pattern queries. B-S-S and B-S-C are more efficient under these conditions, due to the complexity of unified query handling with a large alphabet. As for the distribution of supported attribute values (E5), D-U-C and B-S-C perform better due to reduced merge operations. Conversely, repeated attribute values (E6) favour D-U-S and B-S-S, as these approaches minimize the search space for pattern queries.

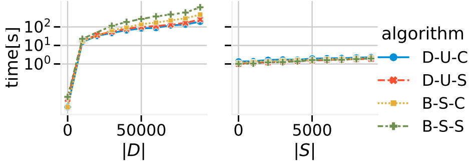

Figure 3: Scalability analysis.

M10 R1O2 R3O3

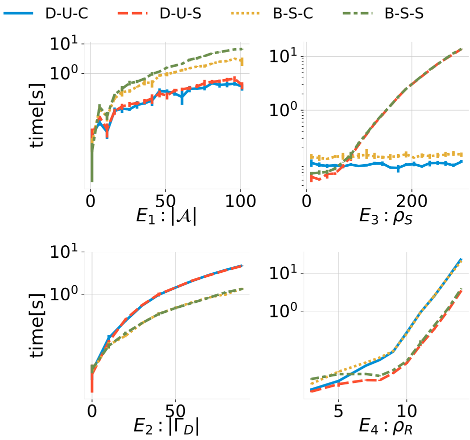

Figure 4: Sensitivity analysis using synthetic data.

In sum, our results confirm that the design choices captured in the DISCES framework influence the discovery efficiency as postulated. The properties of a stream database indeed play a crucial role in determining which algorithm performs best.

M11 R1O3 R3O5 To confirm our results obtained with synthetic data, we investigated the sensitivity of our algorithms using the Google dataset. To obtain the desired variations for each single database property, while largely keeping the underlying data distributions, we altered the existing stream databases $G1, G2, G3$, as follows. E_1: The alphabet $|A|$ was increased by taking one stream and copying an increasing subset of its events to the remaining streams. E_2: The number of attributes $|\Gamma_D|$ was altered by repeating the existing attribute values within an event. E_3: Property ρ_S was increased by copying a number of events within a stream for a subset of streams within the stream database. E_4: The variation in ρ_R is obtained selecting an event in each stream and adding it again to the stream.

Fig. 5 shows that the differences among the algorithms are less pronounced as for the synthetic data. Yet, there is clear evidence that the algorithms behave differently for the various properties. Also, the general trends observed for synthetic data are confirmed.

6.5 Guidance of Query Discovery

Algorithm selection. Next, we assess whether the above observations enable us to guide the selection of a discovery algorithm for the real-world data. From Table 8, we conclude that the differences in the number of attributes ($|\mathcal{A}|$) and supported attribute values ($|\Gamma_D|$) are too small to enable any differentiation, while the results for the repeated attribute values (ρ_R) relate to an inconclusive value range (see Fig. 4). Interestingly, the measure based on the supported attribute values (ρ_S) provides clues on the runtime performance. For

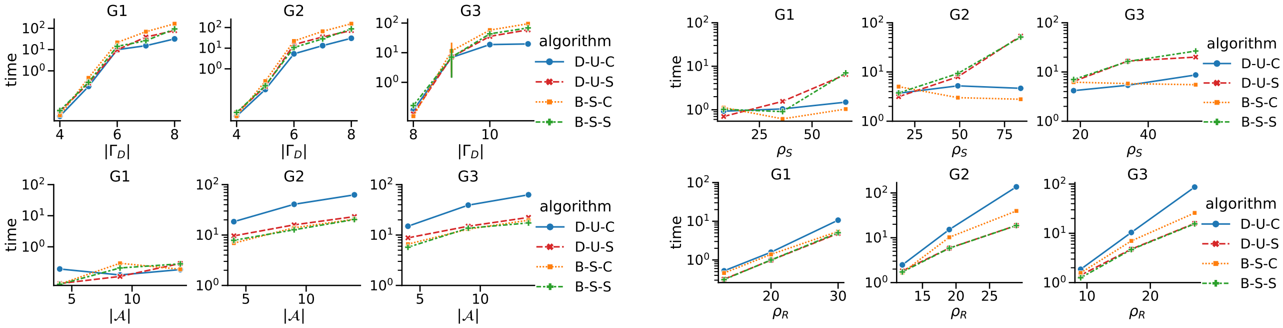

Figure 5: Sensitivity analysis using the Google cluster dataset. M11 R1O3 R3O5

Table 8: Correlation of runtime and database properties.

Algorithm Runtime				Database Properties			
D-U-C	D-U-S	B-S-C	B-S-S	ρ_R	ρ_S	$\lvert\mathcal{A}\rvert$	$\lvert\Gamma_D\rvert$
18.28	26.43	17.65	26.21	6	11	3	2
13.50	14.95	10.52	13.34	5	17	3	2
0.65	1.39	0.88	1.68	9	15	3	6
259.11	364.07	226.32	366.51	10	12	4	1
55.43	83.84	49.32	84.51	8	10	4	1
533.90	172.54	488.45	172.37	8	5	4	1

$\rho_S = 5$, the algorithms handling attributes separately (D-U-S and B-S-S) perform much better than those handling them comprehensively. For $\rho_S > 10$, the runtimes of our algorithms show the opposite trend. Hence, the considered database properties, assuming that their absolute values provide sufficiently strong indicators, indeed enable conclusions on the suitability of our algorithms.

Feedback mechanisms. Finally, we tested our mechanisms for feedback on the algorithmic performance. First, we assessed whether the exclusion of attribute values may reduce the discovery runtime. Fig. 6 shows the relative change in runtimes, when step-wise realizing such an exclusion. Here, E1 refers to the original database, while for E2-E4, we step-wise removed the most frequent values of the attribute of the smallest domain. As expected, the runtime decreases. Since the value distributions are skewed, excluding the most frequent value (E2) has the largest effect.

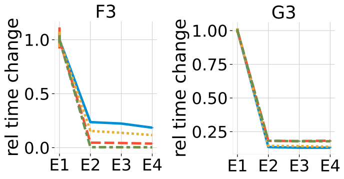

Figure 6: Exclusion.

Second, we study the abstraction of clustering of attribute values. C1 denotes the original dataset without clustering. Then, for the Google dataset, we clustered the 'priority' attribute, as adopted in [28] (C2) and [27] (C3). For the finance dataset, we clustered the 'close price' into 100 (C2) or 50 (C3) equally-sized clusters. Fig. 7 highlights that higher numbers of values within a cluster increase the runtimes. However, we motivated the abstraction with the desire to increase the result size. For the finance dataset, we obtain 18 (C1), 30 (C2), and 106 (C3) descriptive queries, while for the Google dataset, the result includes 202 (C1), 153 (C2), and 298 (C3) queries. We conclude that the expected trend materializes for our data, However, clustering may also lead to similar descriptive queries being merged into one, which may dominate the effect of having more descriptive queries due to smaller attribute domains.

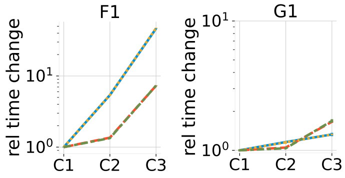

Figure 7: Clustering.

7 Related Work

Closest to our work are iCEP [24] and the IL-Miner [14], which both address the problem of event query discovery based on historic streams. Yet, both algorithms take ad-hoc design choices and adopt a restricted query model. iCEP cannot discover queries, in which attribute values occur multiple times. This limitation is addressed by the IL-Miner, which, however, cannot discover queries comprising only variables. We discuss these language limitations in more detail in our technical report [5]. However, we showed empirically that the lossy version of the IL-Miner suffers from incomplete results, while our algorithms outperform an extended version of it. M5 R3O1

Our query model and the notion of descriptiveness is inspired by [16, 17]. Yet, the discovery algorithms proposed in [16, 17] are limited to finding *some* descriptive queries, not all of them.

Machine learning approaches to anticipate situations of interest provide an alternative angle to stream-based monitoring [20, 25, 30]. The main drawback of these methods, however, is the lack of traceability of the derived predictions.

Event query discovery is linked to frequent sequence mining [1, 22, 32, 33], which considers solely the level of attribute values, though. Our query model embeds a finite sequence into another sequence that satisfies certain constraints. This problem setting is ubiquitous in foundational algorithmic research, e.g., in combinatorial string matching [9, 19]. Pattern discovery has also been investigated for time-series data [26, 31], which, again, works only on attribute values and ignores criteria to correlate events by means of variables.

8 Conclusions

In this paper, we systematically explored the design space for algorithms that discover event queries from a stream database. We captured the design choices in the DISCES framework and instantiated it to derive four discovery algorithms, which all provide correct and complete results. Our experiments highlight that our algorithms outperform the state of the art in event query discovery, significantly extending the size of the problem instances that are still tractable. Moreover, we studied the influence of database properties on the algorithms' efficiency and the discovery result, thereby providing an angle to improve their applicability.

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A Appendix

In this appendix, we provide additional details that, due to space restrictions, could not be included in the main part of the paper. In particular, this appendix covers the following aspects:

- A comparison of the query models adopted by different approaches for event query discovery (§A.1).
- Additional experimental results on a comparison of our algorithms with one that is based on representation learning (§A.2).
- A formalization of function MergeAttributeQueries to merge queries found per attribute (§A.3).
- A formalization of function DescriptiveQueries to select only the descriptive queries in a set of queries (§A.4).
- Formalizations of the D-U-S and B-S-S algorithms as instantiations of the DISCES framework (§A.5).
- A detailed discussion of completeness considerations for our algorithms (§A.6).

A.1 Query Model Comparison

We first consider the query model adopted in iCEP [24]. It is based on an notion of events that are typed and carry a set of attribute values. Queries are defined by operators that filter events, constrain their attribute values, or require their joint or ordered occurrence, within a certain time window.

Event query discovery with iCEP is organized in so-called learners, e.g., for learning the event types that are considered most relevant as they occur in all given streams. However, considering the sequence learner to discover an ordering of events, we note that it is applied solely on the level of characterizations of events that have been derived in earlier steps. Such characterizations correspond to query terms in our model. Hence, in comparison to the algorithms of the DISCES framework, iCEP is not capable to discover queries that include the same query term multiple times. For the database of our running example, see Example 1, for instance, the query $q_1 = \langle(\_, \text{schedule}, \_), (\_, \text{schedule}, \_)\rangle$ would not be discovered.

The IL-Miner [14], in turn, relies on an event and query model that is close to the one underlying the DISCES framework. That is, events have a relational schema and queries define sequences of event variables, which may be constrained by predicates. Such predicates may require an attribute value of an event to assume a certain value, or they impose correlation conditions by requiring the attribute values of two events to be the same.

The discovery procedure of the IL-Miner first determines so-called relevant event templates, i.e., sets of predicates that characterize relevant events. Then, frequent sequence mining is used to extract an order over these templates. While, this way, the above limitation discussed for iCEP is avoided, the approach is also more restricted than our algorithms of the DISCES framework. In particular, the IL-Miner can only discover queries for which the events are characterized by particular assignments of attribute values. Hence, queries that only require the equivalence of attribute values in events, but do not enforce any specific attribute values, cannot be discovered. Again, using our example scenario from Example 1, for instance, it would be impossible to discover the query $q_2 = \langle(\_, x_0, \_), (\_, x_0, \_)\rangle$.

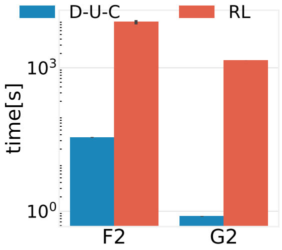

Figure 8: Runtime, RL approach.

Table 9: Comparison of our algorithms and the RL approach.

Dataset	Desc(riptive)	Found	¬ Desc	¬ Matching
F2b	1	0	1	4
G2b	1	0	1	3

A.2 Comparison against a Representation Learning Approach

To add another perspective, we report on experiments using a representation learning algorithm for event streams, as introduced in [20]. The approach learns a probabilistic automaton to capture events and dependencies that indicate a situation of interest. While the learned automaton is used for stream monitoring in [20], a query can be extracted from it by enumerating certain transition paths [23]. While this approach yields only type queries, no pattern queries or mixed queries, a comparison sheds light on the potential of learning-based techniques for event query discovery.

Since the algorithm can only discover type queries, we adapted one of our algorithms (D-U-C) to also return only these queries. This way, the outcome as well as the runtimes become comparable. For the datasets F2b and G2b, Fig. 8 shows the obtained runtime results, illustrating that our algorithm is at least two orders of magnitude faster than the baseline algorithm. The effectiveness of query discovery is summarized in Table 9. None of the descriptive queries is discovered by the baseline ('Found'), while only one matching, but not descriptive query is returned for either scenario ('¬ Desc'). Also, the construction based on representation learning yields several queries that are not supported by the stream database ('¬ Matching'). Hence, the learning-based approach compromises correctness, descriptiveness, and completeness and, due to high runtimes, is not suitable to address the problem of event query discovery.

A.3 Merge Attribute Queries

Our approach to merge queries found per attribute is defined as MergeAttributeQueries in Alg. 7. It takes as input a dictionary of matching queries for each attribute $Q_{\mathcal{A}} : \mathcal{A} \rightarrow 2^{Q}$, a parent dictionary P, an event schema $\mathcal{A}$, a stream database D, and a sequence of query variables $\mathcal{X}^{<}$; and returns a set of merged queries.

In essence, the algorithm is based on an exhaustive combination of all combinations of queries sourced from distinct attributes. Each resulting combination then is handled in several steps:

- Instance Generation: Initially, for every query found for an attribute, we systematically generate all feasible instances of the query within a single stream of the database.

Algorithm 7: MERGEATTRIBUTEQUERIES

```
Input:  Dictionary of matching queries for each attribute $\mathcal{Q}_{\mathcal{A}}$,
        parent dictionary $P$, event schema $\mathcal{A}$, stream database $D$,
        sequence of query variables $\mathcal{X}^{<}$.
Output: Set of descriptive queries $Q_d$.
$Q_m \leftarrow \emptyset$;
$\Gamma_D \leftarrow \{a \in \Gamma \mid \forall\, S \in D : \exists\, j \in \{1, ..., |S|\}, i \in \{1, ..., n\} : S[j].A_i = a\}$;
/* All combinations of queries from different attributes */
$L \leftarrow \bigtimes_{A \in \mathcal{A}} \mathcal{Q}_{\mathcal{A}}(A)$;
/* Stream matches dictionary */
$T \leftarrow \emptyset$;
foreach $(q_1, \dots, q_n) \in L$ do
    $I \leftarrow \emptyset$;
    foreach $q \in \{q_1, \dots, q_n\}$ do $I(q) \leftarrow \emptyset$;
    foreach $q \in (q_1, \dots, q_n)$ do
        /* Instance positions of query $q$ in $D$ */
        $I(q) \leftarrow$ GETINSTANCES$(q, D)$;
        if $\forall q' \in \mathrm{dom}(P) : P(q') \neq q$ then
            $P \leftarrow$ CHILDQUERIES$(q, \mathcal{A}, \Gamma_D, P, \mathcal{X}^{<}, True)$;
    /* All combinations of instance positions of queries
       from different attributes */
    $B \leftarrow \bigtimes_{q_A \in \{q_1, ..., q_n\}} I(q_A)$;
    foreach $(q'_1, \dots, q'_n) \in B$ do
        /* Translate instance tuple to query */
        $q_m \leftarrow$ INSTANCE2QUERY$((q'_1, \dots, q'_n), (q_1, \dots, q_n))$;
        $P \leftarrow$ CHILDQUERIES$(q_m, \mathcal{A}, \Gamma_D, P, \mathcal{X}^{<}, True)$;
        $q_p \leftarrow P(q_m)$;
        $M, T \leftarrow$ MATCH$(q_m, \mathcal{A}, D, q_p, T)$;
        /* Add merged query to result set */
        if $M = True$ then $Q_m \leftarrow Q_m \cup \{q_m\}$;
return $Q_m$;
```

Algorithm 8: DESCRIPTIVEQUERIES

```
Input:  Set of queries $Q$, supported alphabet $\Gamma_D$, event schema $\mathcal{A}$,
        sequence of query variables $\mathcal{X}^{<}$ over the set of query variables $\mathcal{X}$.
Output: Set of descriptive queries $Q_d$.
1  $Q_n \leftarrow \emptyset$;
   /* For each query $q$ in the query set $Q$, create queries
      which are less strict and therefore not descriptive */
2  foreach $q \in Q$ do
3      $R \leftarrow \emptyset$;
4      foreach $s \in \Gamma_D \cup \mathcal{X}$ do $R(s) \leftarrow \emptyset$;
5      foreach $i \in \{1, \dots, |q|\}$ do
6          foreach $A \in \mathcal{A}$ do
7              if $q[i].A \in \Gamma_D \cup \mathcal{X}$ then
8                  $q_n \leftarrow q$;
9                  $q_n[i].A \leftarrow \_$;
10                 $Q_n \leftarrow Q_n \cup$ NORMALFORM$(q_n)$;
11                 $R(q[i].A) \leftarrow R(q[i].A) \cup \{i\}$;
12     foreach $s \in \mathrm{dom}(R)$ do
13         if $s \in \mathcal{X} \wedge |R(s)| \geq 4$ then
               /* Find all combinations of partial replacements
                  of variable $s$ in query $q$ */
14             $G \leftarrow$ GENERATEREPLACEMENTS$(q, s)$;
15             $Q_n \leftarrow Q_n \cup G$;
16         if $s \in \Gamma_D \wedge |R(s)| \geq 2$ then
               /* Find all combinations of partial and complete
                  replacement of attribute type $s$ in query $q$ */
17             $G \leftarrow$ GENERATEREPLACEMENTS$(q, s)$;
18             $Q_n \leftarrow Q_n \cup G$;
19 $Q_d \leftarrow Q \backslash Q_n$;
20 return $Q_d$;
```

- Merge and Translation: Subsequently, we consolidate the instances of the queries per attribute, and translate them into a unified query.
- Query Matching: Following the merge, the obtained query is matched against the stream database. If a match is identified, the merged query is integrated into the result set.

A.4 Descriptive Queries

Our approach to select only the descriptive queries in a set of queries is given as DESCRIPTIVEQUERIES in Alg. 8. Given a set of queries Q, a supported alphabet Γ_D, an event schema $\mathcal{A}$, and a sequence of query variables $\mathcal{X}^{<}$ with $\mathcal{X}$ as the underlying set of query variables, it proceeds as follows. We iterate over each query q within the given set and, for each query, generate queries that are less specific than q. We generate less specific queries in three different ways:

- Replace each symbol (variable or attribute value) within the query by the placeholder (line 5-11). For every replacement, a new non-descriptive query is added to the set of non-descriptive queries Q_n.
- Partially replace variables that appear at least four times within a query by a new variable that is not used in query q (line 13-15).
- Partially and completely replace attribute types that appear at least twice within the given query (line 16-18).

At the end, we calculate the set of descriptive queries Q_d by subtracting all queries in Q_n from the given set of queries Q (line 19).

The above approach relies on function NORMALFORM, which checks, if a variable occurs at least twice, and otherwise replaces it with the placeholder _. Second, it restores the order of the variables, such that the first occurrences of the variables appear in the same order in the query q as they do in $\mathcal{X}^{<}$.

EXAMPLE 5. *Let us consider stream S_2 from Example 1, the following queries per attribute, and their matching instances within the stream:*

Attribute	*Query*	*Positions*
Job Id	$\varepsilon, q_1 = \langle (2, \_, \_) \rangle$	$(e_{21}), (e_{23})$
Status	$\varepsilon, q_2 = \langle (\_, schedule, \_)(\_, schedule, \_) \rangle$	(e_{21}, e_{22})
Priority	$\varepsilon, q_3 = \langle (\_, \_, low) \rangle$	$(e_{21}), (e_{23})$

The combination of queries found for different attributes leads to the following set:

$$\{(q_1, q_2, q_3), (q_1, q_2, \varepsilon), (q_1, \varepsilon, q_3), (\varepsilon, q_2, q_3),$$
$$(q_1, \varepsilon, \varepsilon), (\varepsilon, \varepsilon, q_3), (\varepsilon, q_2, \varepsilon), (\varepsilon, \varepsilon, \varepsilon)\}.$$

The connection of the different position for the query tuple (q_1, q_2, q_3) leads to the following merged queries:

$$\langle (2, schedule, low), (\_, schedule, \_) \rangle$$
$$\langle (\_, schedule, \_), (\_, schedule, \_), (2, \_, low) \rangle$$
$$\langle (2, schedule, \_), (\_, schedule, \_), (\_, \_, low) \rangle$$
$$\langle (\_, schedule, low), (\_, schedule, \_), (2, \_, \_) \rangle$$

which then have to be matched against the complete stream database. This process would have to be repeated for all combinations of query tuples to get all possible merged queries.

Moreover, function GENERATEREPLACEMENTS takes as input a query q and a symbol s, i.e., an attribute value or a variable that

Algorithm 9: D-U-S

```
Input:  Stream database $D$, event schema $\mathcal{A}$, sequence of query var. $\mathcal{X}^<$.
Output: Set of descriptive queries $Q$.
   /* Set of queries and parent dict. per attribute */
1  $Q_\mathcal{A}, P_\mathcal{A} \leftarrow \emptyset$;
2  foreach $A \in \mathcal{A}$ do
3      $Q_\mathcal{A}(A), P_\mathcal{A}(A) \leftarrow \emptyset, \emptyset$;
   /* Use D-U-C to discover queries per attribute */
4  foreach $A \in \mathcal{A}$ do
5      $D_A \leftarrow \{\langle (e_1.A), \ldots, (e_l.A) \rangle \mid \langle e_1, \ldots, e_l \rangle \in D\}$;
6      $Q_\mathcal{A}(A), P_\mathcal{A}(A) \leftarrow$ D-U-C$(D_A, (A), \mathcal{X}^<, False)$;
7  $P \leftarrow \cup_{A \in \mathcal{A}} P_\mathcal{A}(A)$;
   /* Merge queries found per attribute */
8  $Q \leftarrow$ MergeAttributeQueries$(Q_\mathcal{A}, P, \mathcal{A}, D, \mathcal{X}^<)$;
9  $Q \leftarrow$ DescriptiveQueries$(Q, \Gamma_D, \mathcal{A}, \mathcal{X}^<)$;
10 return $Q$;
```

is to be replaced by a variable, which is not used in the query. The replacement routine first iterates through the number of symbols that can be replaced. In case of a variable (an attribute value) it is $[2, R(s) - 2]$ ($[2, R(s) - 1]$). Then, for each group size, it finds all combinations of possible replacements for the current query q.

For example, let s be a variable and $R(s)$=5. Let the positions of s within the query be $[1, 2, 3, 4, 5]$. Then the possible group sizes are 2 and 3. For group size 2, there are $\binom{5}{2} = 10$ combinations: $(1, 2), (1, 3), \ldots, (4, 5)$. For group size 3, there are $\binom{5}{3} = 10$ combinations: $(1, 2, 3), (1, 2, 4), \ldots, (3, 4, 5)$. For each of the calculated positions, s is replaced by the same variable x which is not used in q. The time complexity of the GenerateReplacements function is exponential, $O(2^{R(s)})$, due to the generation of all combinations of replacements. However, in practice, this complexity can be managed by typical constraints on the values of $R(s)$ in the dataset and by applying optimizations to limit the number of combinations generated.

The result is a set of queries which are less specific than query q and, therefore, not descriptive.

A.5 D-U-S & B-S-S

D-U-S: DFS, pattern-type unified, attribute separated. As mentioned, the D-U-S algorithm, presented in Alg. 9, is a variant of the D-U-C algorithm, which also employs DFS and constructs queries in a unified manner. It discovers queries separately per attribute, before merging them to obtain the final result. The sets of queries per attribute are maintained in a dictionary $Q_\mathcal{A} : \mathcal{A} \rightarrow 2^Q$, i.e., $Q_\mathcal{A}(A)$ is the set of queries found for attribute $A \in \mathcal{A}$. The algorithm first constructs the projections of the streams on the attribute (line 4), which are then used to run the D-U-C algorithm (line 5). Note that setting flag b to *False* means that the D-U-C algorithm will return all found queries, not only those that are descriptive. The queries discovered per attribute are then merged, as detailed above, before the non-descriptive queries are removed from the result.

B-S-S: BFS, pattern-type separated, attribute separated. The B-S-S algorithm is defined in Alg. 10. It is a variant of B-S-C, adopting BFS and the separated discovery of type queries and pattern queries. Yet, it first considers queries per attribute, which are again collected in a dictionary $Q_\mathcal{A} : \mathcal{A} \rightarrow 2^Q$, before merging them using the algorithm introduce above. As such, it adopts the strategy explained above for D-U-S, just with B-S-C as the base algorithm.

Algorithm 10: B-S-S

```
Input:  Stream database $D$, event schema $\mathcal{A}$, sequence of query var. $\mathcal{X}^<$.
Output: Set of descriptive queries $Q$.
   /* Set of queries and parent dict. per attribute */
1  $Q_\mathcal{A}, P_\mathcal{A} \leftarrow \emptyset$;
2  foreach $A \in \mathcal{A}$ do
3      $Q_\mathcal{A}(A), P_\mathcal{A}(A) \leftarrow \emptyset, \emptyset$;
   /* Use B-S-C to discover queries per attribute */
4  foreach $A \in \mathcal{A}$ do
5      $D_A \leftarrow \{\langle (e_1.A), \ldots, (e_l.A) \rangle \mid \langle e_1, \ldots, e_l \rangle \in D\}$;
6      $Q_\mathcal{A}(A), P_A \leftarrow$ B-S-C$(D_A, (A), \mathcal{X}^<, False)$;
7  $P \leftarrow \cup_{A \in \mathcal{A}} P_\mathcal{A}(A)$;
   /* Merge queries found per attribute */
8  $Q \leftarrow$ MergeAttributeQueries$(Q_\mathcal{A}, P, \mathcal{A}, D, \mathcal{X}^<)$;
9  $Q \leftarrow$ DescriptiveQueries$(Q, \Gamma_D, \mathcal{A}, \mathcal{X}^<)$;
10 return $Q$;
```

A.6 Completeness

While we highlighted several arguments regarding completeness of our algorithms already in §4.4, we now turn to a more detailed discussion. The functions that are relevant for an assessment of completeness, i.e., that determine that all potentially matching queries are generated at least once to be checked for matching, are mainly: The algorithms for generating query candidate, for merging pattern and type queries, and for merging attribute queries. We will discuss their completeness in dedicated subsections, i.e., A.6.1, A.6.2, and A.6.3.

A.6.1 Query Candidate Generation. Given a matching query (which, initially, is the empty query in all of our discovery algorithms), new queries are generated following a dedicated set of rules, which ensure that each potentially matching query is generated exactly once:

(1) **New variables** are added to a query in two locations. The first one concerns a placement after the first position of the last inserted variable. The second one concerns the position after the last inserted type.
(2) An **existing variable** is added to a query, only if this variable was the last inserted symbol. If this is the case, then it can be placed at any position after the last occurrence of this variable.
(3) A **new type** is added to the query after the first position of the last inserted variable, or after the last position of any type.

Recalling that the candidate generation always starts with the empty query, it follows directly that all candidates can be generated based on the above rules.

As such, the questions becomes if the above rules are correctly realized in Alg. 1. The three rules mentioned above are implemented as follows: When inserting a new variable, first the variable is instantiated. Then, the algorithm iterates over each attribute. For each attribute, we call the Next-Function which returns all helper queries with possible first positions for the newly added variable. For all the generated helper queries the Next-Function is called again to determine the new candidate queries which are added to the set of candidate queries.

To insert an existing variable again, we first check whether it was the last inserted symbol. Then, we determine the attribute of the variable and generate new query candidates by calling the Next-Function.

Finally, to generate queries adding a new type, we again iterate over all the attributes. For each attribute, we consider the supported attribute values. For each supported attribute value, the Next-Function is called, and the resulting queries are added to the set of candidates.

The Next-Function iterates over the query terms starting with the query term at position s until the last query term of the query. Then, per query term generates up to two new candidate queries: First it checks whether the current attribute in the query term is a placeholder. If this is the case, then it creates a new query in which the current symbol is added to the attribute of the current query term. Second it creates a new query by creating a new query term right after the current one which only contains the current symbol at the corresponding attribute and all the other attributes are set as placeholders.

A.6.2 Merge Pattern and Type Queries. To initalize the merging progress for all pairs of type and pattern queries, for each of their parent queries q. a 4-tuple is added to the queue of queries to be merged. The 4-tuple consists of a type query q_t, a pattern or mixed query q_p, a mixed query q_m and an evolved query q_e. For the initialization the tuple is set to $(q_t, q_p, \langle\varepsilon\rangle, q)$ For each such tuple the function MergeMixedQueries is called which is where the actual merging process takes place.

First the function calculates the starting position from which on the mixed query can be extended. If the evolved query is a type query then new merged queries are generated by inserting the query term after the last occurence of another type or attribute value, adding each such generated query to the set of mixed queries. It also checks whether the type to be added can be merged to an existing query term in q_m. If the evolved query is not a type query the function first checks whether all query terms for either the type query or the pattern query have already been incorporated into the mixed query. If this is the case then starting from that position, the remaining query terms of the eluded query are added to the end of the mixed query. In a second step the function tries insert the current last position of q_p into the current query term of q_m. If this can be done a new mixed query is generated which merges the query term and adds the remaining query terms of the evolved query q_e.

For the 4-tuples created in the intialization (line 2), The set of candidate queries will either contain a type query with one query term and one placed attribute value (if q_e is a type query) or q_e if it is a pattern query. The returned query candidates are matched and new 4-tuples are added to the queue accordingly. For the initializiation tuples, the matching is obviously *True*. The next 4-tuples added to the queue are (q_e, q_p, q_n, q), where q is either the empty query or one of the parents of q_p (q_t) if q_e is a type query (pattern query).

Since q_e is always a parent query we pass through all queries until reaching the empty query. This way it is assured that all possible queries are generated.

A.6.3 Merge Attribute Queries. The function first generates all combinations on n-tuples for the matching attribute queries, such that in each n-tuple there is a query from each attribute and n being the number of attributes. A valid query for each attribute is also the empty query.

For each n-tuple new possible mixed query candidates are generated using the following procedure: A function I is called for each attribute query which returns all the mappings of the query for each stream. For each stream a list of k-tuples is returned, where k is the number of query terms for the current attribute query and each k-tuple is a match of the query on that stream.

Then for one stream, we calculate all combinations of the different k-tuples of the n attribute queries. Each combination contains one k-tuple from each attribute query in the current n-tuple.

It is sufficient to consider the instances of one stream, since all matching queries necessarily need to match every stream. This also means that only those queries present in one stream are possible candidates to match the whole stream.

The resulting combinations of instance tuples are then translated (if possible) to mixed queries and if they match are added to the set of mixed queries.