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KRISTO RAUN

Adaptive Out-of-order Handling in Streaming Conformance Checking

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Institute of Computer Science, Faculty of Science and Technology, University of Tartu, Estonia.

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To Mirjam, Hugo, and Greta

ABSTRACT

The rapid digitalization of organizations has introduced numerous opportunities and challenges. The shift to complex systems and digital infrastructures has brought about a rapid development of various analytical methods to manage, analyze, and improve processes. One such method is *streaming conformance checking*, which involves comparing ongoing event streams against predefined process models to ensure that the actual behavior conforms to the expected behavior. This task is particularly challenging in the era of big data due to the high volume and velocity of event streams, as well as stream imperfections such as out-of-order event arrivals caused by the complexity of digital infrastructures. This dissertation attempts to address the above challenges in four contributions.

First, we utilize the *trie* data structure for conformance checking. Tries are used as a representation of the process behavior, enabling efficient search and alignment computations. This approach significantly reduces the computational load compared to traditional methods, making it feasible for real-time applications.

Second, building on the trie data structure, we present the *I Will Survive* (IWS) algorithm. The IWS algorithm leverages the trie structure to compute prefix-alignments with low latency and high throughput. The algorithm is designed to handle the continuous flow of events in near real-time and is shown to improve upon existing state-of-the-art methods that output prefix alignments.

Third, we tackle some analytical challenges in streaming conformance checking. We introduce the *C-3PA* variant of the IWS algorithm to handle two use cases. First, event streams are considered to be infinite, but business process traces are expected to reach completion. Thus, we quantify the confidence of a trace to conclude. Second, event streams may be ongoing before the initialization of a conformance checker, for example, due to temporary system downtime. We show how the C-3PA method is able to warm-start and quantify the completeness of the seen trace. These enhancements are important for practical applications where traces are often incomplete and constantly evolving.

Finally, with *adaptive out-of-order handling*, we tackle the challenge of out-of-order event arrivals, a common issue in streaming data. We propose an adaptive mechanism that dynamically adjusts to the level of out-of-orderedness in the event stream. This approach ensures robust conformance checking, even in fast-paced and highly complex digital infrastructures.

In conclusion, this dissertation provides a comprehensive and holistic solution to the challenges of streaming conformance checking in dynamic and complex digital environments. Notably, this is knowingly the first work in streaming conformance checking research to tackle the handling of out-of-order event arrival.

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LIST OF ORIGINAL PUBLICATIONS

Publications included in the thesis

I Ahmed Awad, **Kristo Raun**, and Matthias Weidlich. Efficient Approximate Conformance Checking Using Trie Data Structures. **3rd International Conference on Process Mining (ICPM)**, 2021.
doi: 10.1109/ICPM53251.2021.9576845
Author's contribution: experimental design, writing, conference presentation.

II **Kristo Raun**, Riccardo Tommasini, and Ahmed Awad. I Will Survive: An Event-Driven Conformance Checking Approach Over Process Streams. **17th ACM International Conference on Distributed and Event-Based Systems (DEBS)**, 2023. doi:10.1145/3583678.3596887
Best Paper in the research track of DEBS 2023.
Author's contribution: main author, conceptualization, implementation, experimental design, writing, conference presentation.

III **Kristo Raun**, Max Nielsen, Andrea Burattin, and Ahmed Awad. C-3PA: Streaming Conformance, Confidence and Completeness in Prefix-Alignments. **35th International Conference on Advanced Information Systems Engineering (CAiSE)**, 2023. doi:10.1007/978-3-031-34560-9_26
Author's contribution: main author, conceptualization, writing, conference presentation.

IV **Kristo Raun**, Riccardo Tommasini, and Ahmed Awad. Adaptive Handling of Out-of-order Streams in Conformance Checking. **26th International Workshop on Design, Optimization, Languages and Analytical Processing of Big Data (DOLAP)**, 2024. URL: `https://ceur-ws.org/Vol-3653/paper1.pdf`
Best Paper of DOLAP 2024.
Author's contribution: main author, conceptualization, implementation, experimental design, writing, conference presentation.

Other published work of the author

I Ants Torim, Marko Mets, **Kristo Raun**. Covering Concept Lattices with Concept Chains. **In: Endres, D., Alam, M., Şotropa, D. (eds) Graph-Based Representation and Reasoning. (ICCS)**, 2019. doi:10.1007/978-3-030-23182-8_14
Author's contribution: experimental design.

II Ants Torim, Sadok Ben Yahia, **Kristo Raun**. Concise Description of Telecom Service Use Through Concept Chains. **Proceedings of the 11th International Conference on Management of Digital EcoSystems. (MEDES)**, 2019. doi:10.1145/3297662.3365790
Author's contribution: experimental design.

III **Kristo Raun**, Ants Torim, Sadok Ben Yahia. GC and Other Methods for Full and Partial Context Coverage. **Knowledge-Based and Intelligent Information & Engineering Systems: Proceedings of the 25th International Conference (KES)**, 2021. doi:10.1016/j.procs.2021.08.077

Author's contribution: main author, conceptualization, implementation, experimental design, writing.

1. INTRODUCTION

1.1. Motivation

Organizations from all sectors have undergone great changes in the past decades. With the advent of digitalization, organizations have become more efficient in their work. Increased data collection has enabled new products and services in domains from e-commerce and banking to healthcare and entertainment.

The rapid advances, however, have also brought along novel challenges. The infrastructural landscape of organizations has moved from pen and paper and single database systems to an array of intertwined systems hosted on-premises and in the cloud. The increased complexity has resulted in diminishing returns on efficiency, as organizations find it hard to determine which tools, systems, and processes facilitate the organization most in achieving its goals [LMK20; Ben+20]. Furthermore, the digital landscape and its complexity have introduced new vectors for fraud and human error [VHO19], sometimes leading to serious reprimands and even bankruptcy [Par+20].

The previously listed advances and challenges have paved the way for various new domains in analytics and research. One of these trends has been the era of big data [Sak20]. While the definition of the term *big data* has various interpretations, it is generally considered to indicate data with a high *volume*, high *velocity*, and high *variety* (Figure 1).

Volume. Due to the increasing number of systems and applications that generate data, the volume of data has increased drastically. Effective data processing requires the data to exist in computer memory, but more and more organizations face the challenge that there is more data generated than can be fit into memory. Effectively, the high volume means that big data cannot be processed on a single machine.

Velocity. Data is constantly generated, especially due to the increased amount of web and mobile applications and IoT sensors. The surge in data production demands rapid processing of data; otherwise, the data becomes stale and loses relevance. This is especially true in areas that require near real-time analytics, such as financial services and healthcare. Thus, due to the high velocity, data processing needs to be fast in order to avoid creating processing bottlenecks.

Variety. Data used to consist mostly of structured tabular data. The advent of social media and file-sharing capabilities has brought about an increase in semi-structured and unstructured data, such as nested data structures, audio, and video. The wide variety of big data adds a layer of complexity to the processing, as the data points that need to be processed are no longer confined to simple numbers and pieces of text, but can be comprised of various complex data.

Big data processing has been embraced by both academia and the industry, with an increasing number of open-source and cloud-based big data tools gaining popularity [Sak20; Zah+16; Car+15]. While big data analytics has had wide

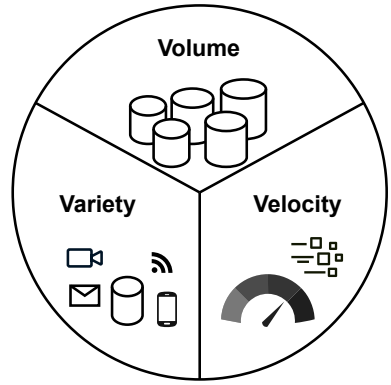


Figure 1: Three tenets of big data.

adoption and it can be used to solve most of the challenges listed previously, it does come with some caveats. For example, traditional big data processing views the organizations from purely a data perspective, where each data point, such as a customer, a product, or a transaction, is viewed either in isolation or in aggregation with similar data points. Furthermore, big data initiatives in isolation may not provide organizations with any value [Gün+17]. In reality, organizations function as a complex intertwining of various business processes. In the last decade, *process mining* has emerged as the research area focusing on extracting knowledge from business process data [Aal16] via *process discovery*, *conformance checking*, and *process enhancement* (Figure 2).

Process discovery. Process discovery deals with finding the process model from the existing process data. This is generally done via a discovery algorithm that takes as input an event log – a log of process events – and outputs a process model that describes the seen behavior. The most common types of process models range from procedural [Aal22a] to declarative [DM22] process models, with a more recent trend moving toward object-centric process models [AB20].

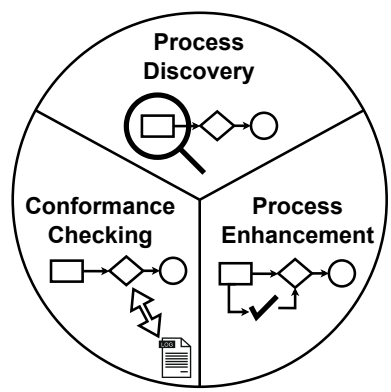


Figure 2: Three tenets of process mining.

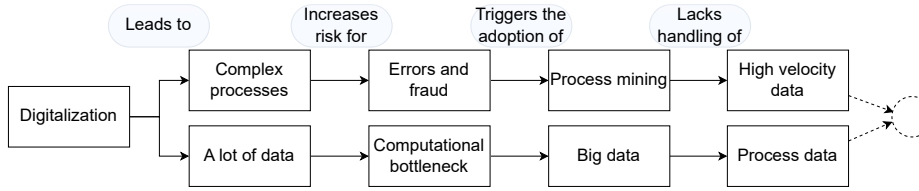


Figure 3: High-level motivational background of the thesis.

Conformance checking. Conformance checking is the act of finding the difference between a process model and process data. Commonly, this assumes the input of a process model and an event log and the output that indicates the level of conformance between the model and the log. Conformance checking can take various forms, with initial simpler approaches based on rule checking or token-based replay on top of a Petri net model to the current state-of-the-art approach of alignments [Car+18].

Process enhancement. Process enhancement optimizes process models for efficiency and precision based on process data. The general idea is to take an existing process model and enhance it in an automated way via observations from an event log. The two main types of enhancement are *repair* that tries to improve the model to better describe the real-life process [Aal16], and *extension* that adds a new data-aware perspective to the process model, for example via time- or resource-based constraints [DV13; Aal16].

Process mining is thus a set of approaches to view organization's data from a process perspective. With process executions generating data, this same data can be used for the analysis of each process execution and the processes of an organization as a whole. Some of the benefits of process mining are transparency of how business processes work and a more holistic image of how an organization functions [Rei20].

However, processing business process data is computationally expensive and would thus benefit from a combination with big data processing methods [Sak+18; MEA23]. Still, process mining techniques utilizing big data frameworks have not been a focal point of process mining research, especially in terms of handling high velocity data [Bur22a]. Importantly, high velocity has been shown to be the main contributor of big data methodologies to enhance an organization's innovation performance [GC20]. While process discovery and enhancement are important parts of process mining, analyzing the conformance of ongoing process executions is, arguably, the most effective way to mitigate the occurrences of errors and fraud. Thus, bringing together a conformance checking solution that handles business process data that is arriving with high velocity sets the motivational background of the thesis (Figure 3). The relationship between big data, process mining, and this thesis is further illustrated in Figure 4.

1.2. Research Problem

An important aspect of business systems is the ability to detect anomalies and report them in a human-readable format [Rad+21]. Conformance checking [Car+18] is the sub-area of process mining that attempts to discover and quantify deviations in business process executions between real-life and expected behavior. Conformance checking may produce various artifacts, with the state of the art being an *alignment* between the activities executed in the process instance, and a valid path through the process model [Adr14]. The main benefit of alignments is their explainability, as it becomes visually clear which part of the model or trace has caused the discrepancy.

Computing alignments in conformance checking has seen a wide research coverage, with various approaches for computing the alignment between a trace and a model [CC16; LZ22; BCC21a; Blo+18; Oje23]. Many of the approaches focus on finding conformance measures, such as fitness or precision, across a whole event log [Car+18]. The most common approach for computing trace-based alignments using Petri Nets requires the exploration of the model state space, which is worst-case exponential with regard to the trace or the model size. Considering the tenets of big data, such as high velocity and volume, computing alignments becomes an obvious challenge for most organizations. While the trace size is inherently tied to the business process and difficult to modify, the Petri Net representation of the process model may not be the ideal data structure for efficient alignment computation, as parallelism and loops may render the model infinitely large and computationally intractable. Thus, we devise the first research question:

- RQ1: How can we incorporate a different data structure to represent the process model, enabling a more efficient computation of alignments in conformance checking?

The high velocity of big data also implies that static data quickly becomes

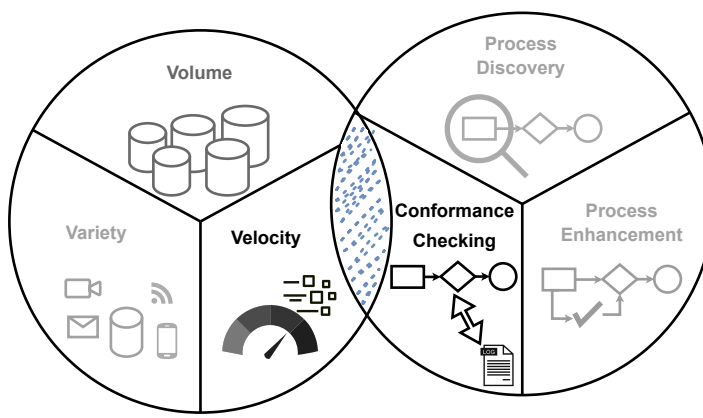


Figure 4: A Venn diagram of big data and process mining, with the overlap highlighting the focus of this thesis.

obsolete. Counterintuitively, most of the research on computing alignments, and conformance checking at large, has concentrated on examining static, historical data [Bur22a]. However, it could be argued that instances of fraud or human error may be solvable within minutes or hours of occurrence, but cause serious reprimands if left unhandled until the next day, week, or even a month. Thus, it would be paramount to find non-conformant behavior as fast as possible – in a streaming setting. The second research question we pose is:

- RQ2: How can we leverage the new data structure (RQ1) and apply it for computing alignments in a streaming conformance checking setting?

Streaming settings introduce novel challenges to conformance checking from the temporal perspective. On the one hand, it may be unknown if some of the process instances started before the conformance checking commences. Thus, we want the algorithm from RQ2 to accommodate *warm-starting* scenarios [Bur+18]. On the other hand, the conclusion of a process instance is also unknown, as a stream is commonly thought of as being infinite. However, a process instance that is just starting its execution may require more attention than a process instance that is about to conclude, as there is a greater probability for deviation in the former [BCC21a]. Thus, we want to quantify the confidence we have in the current alignment artifact. These challenges are taken by the third research question:

- RQ3: Can such a streaming algorithm (RQ2) account for warm-starting scenarios and quantify the confidence of the conformance measure?

Finally, data streams may inhibit various kinds of imperfections. A common imperfection is the out-of-order arrival of events, typically stemming from networking issues, but also from an increasingly complex digital landscape [Fra+24]. While out-of-order event arrival in conventional streaming settings is a relatively well-known problem and has enjoyed notable research effort [Isa+19; ZSM23], the paradigm in a business process context is importantly different. While conventional streaming algorithms in big data commonly compute aggregates within specific time-based windows, in a business process setting, where the goal is to find discrepancies within a specific process execution, the approach needs to look at each process execution in isolation in terms of out-of-order event arrival. Thus, the final research question is:

- RQ4: Can we extend the algorithm (RQ2) to adaptively handle stream imperfections stemming from out-of-order event arrival?

The posed research questions are the basis for the four contributions of the thesis. Each contribution has been published as a research article in established and relevant conference proceedings. The mapping between the published articles, the RQs, and the chapters of the thesis is highlighted in Section 1.4.

1.3. Research Methodology

In order to set about answering the research questions posed in Section 1.2, the thesis relies on the design science approach from [Hev+04]. The goal of the approach is to provide a conceptual framework and clear guidelines for understanding, executing and evaluating the research. One of the key principles of the framework is that "contribution arises from utility". In other words, any research should derive from a *problem* that current artifacts are not adequate for. To follow this premise, the design science approach offers seven guidelines for conducting research that has utility. The mapping of the design science guidelines and the work in this thesis can be seen in Table 1. Furthermore, the work in this thesis was previously peer-reviewed as a doctoral consortium paper [Kri21] in order to validate the relevance and positioning of the research.

1.4. Thesis Outline

The remainder of the thesis is structured as follows. Chapter 2 gives the relevant background on the topics of process mining, conformance checking, and data streams. Chapter 3 discusses the relevant concepts of streaming conformance checking, as well as the existing state-of-the-art approaches. Chapter 4 introduces the trie data structure for efficiently computing alignments in offline (non-streaming) conformance checking. This maps to RQ1 and is based on the work in [ARW21]. Chapter 5 utilizes the work on tries and introduces the I Will Survive (IWS) algorithm for conducting streaming conformance checking. The chapter corresponds to RQ2 and comes from the work done in [RTA23]. Chapter 6 stems from [Rau+23] and provides an extension for the IWS algorithm by incorporating completeness and confidence measures in order to quantify the warm-starting and trace conclusion, answering RQ3. RQ4 is tackled in Chapter 7, with a novel method to adaptively handle out-of-order event arrival [KTA24]. Finally, Chapter 8 concludes the work with a discussion, limitations and threats to validity, and future work.

Table 1: Research design guidelines and their application in this thesis.

ID	Guideline	Description	Application in this thesis
1	Design as an Artifact	Research must produce a viable artifact in the form of a construct, a model, a method, or an instantiation.	The algorithms developed as part of this thesis are published as artifacts. Instantiations of the algorithms are available as open-source.
2	Problem Relevance	The objective of research is to develop technology-based solutions to important and relevant business problems.	The relevance and importance to business problems is discussed in section 1.1.
3	Design Evaluation	The utility, quality, and efficacy of an artifact must be rigorously demonstrated via well-executed evaluation methods. IT artifacts can be evaluated in terms of functionality, completeness, consistency, accuracy, performance, reliability and usability.	Each of the contributions includes an evaluation against the state-of-the-art methods. Analytical and experimental evaluation was conducted, with regards to the performance and accuracy of the artifacts.
4	Research Contributions	What are the new and interesting contributions? Effective research must provide clear and verifiable contributions in the areas of the design artifact, design foundations, and/or design methodologies.	The main contribution of the thesis is in the novel artifacts designed. Furthermore, new methodologies for evaluation are introduced into the knowledge base, discussed in Chapter 7, in terms of how to evaluate out-of-order event handling in streaming conformance checking.
5	Research Rigor	Design-science research relies upon the application of rigorous methods in both the construction and evaluation of the design artifact.	The construction of the artifacts shows steps for the algorithm's process, time and space complexity where applicable, and prototypes. The evaluation of the artifacts relied on empirical testing, runtime analysis, and benchmarking against state-of-the-art methods.
6	Design as a Search Process	The search for an effective artifact requires utilizing available means to reach desired ends while satisfying laws in the problem environment.	Alternatives of the artifacts are provided and tested via parameters and hyperparameters, allowing for testing of alternatives against appropriate requirements and constraints.
7	Communication of Research	Design-science research must be presented effectively both to technology-oriented as well as management-oriented audiences.	All of the contributions of the thesis were published in well-known conference proceedings. Furthermore, as a supplement to the thesis, the author participated in the national finals of the Estonian 3-minute lecture series and authored a popular science article on the thesis topic in the Estonian national broadcasting news portal [Rau23].

2. BACKGROUND

A process is a series of steps taken in order to achieve a result. In organizations, business processes form the backbone of the organization's operational framework. These processes, which can include a wide array of activities, are central in determining whether the organization achieves its desired outcomes. *Business process mining* is the act of finding and analyzing these processes in a data-driven way. The key concepts of process mining are *process models* and *event logs*.

Organizations that have a defined way of conducting their processes and capturing the process data are well poised for conducting *conformance checking*. Conformance checking brings to light the instances where real-life behavior differs from expected behavior. This insight is important not only for identifying problems, such as fraud or error, but also for process improvement via identifying excess work or value-creating shortcuts.

Any data that is generated is inherently streaming – that is, the data comes into existence in a continuous fashion. Evidently, insights derived from fresh data are more valuable than stale data, anecdotally so in fields such as high-frequency trading or autonomous vehicles. Utilizing streaming data is thus beneficial to any organization, but at the same time hosts a handful of challenges that need to be considered.

This chapter discusses the concepts of business process mining, conformance checking, and streaming data in more detail. As an important note, this chapter and the rest of the thesis deal generally with procedural process models [Aal22a]. There are many alternative approaches, for example the declarative approach [DM22] that is generally better suited for business processes that are less structured. However, without limiting the scope of the work, it becomes more difficult to have meaningful contributions. "The man who chases two rabbits catches neither" (Confucius).

Table 2 serves as the summary for the notation used in the rest of this thesis.

2.1. Business Process Mining Concepts

Business processes are what companies do whenever they deliver a service or a product to customers [Dum+18]. Processes consist of all the activities that are required for the delivery. The activities may be sequential, mutually exclusive, run in parallel, or iterative. The study of the design, management and analysis of business processes is well-established within the domain of Business Process Management [AHW03].

Traditionally, business processes were modeled and monitored on a manual or ad-hoc basis. However, with the advent of digitalization, most of the data relevant for process executions began to be created and stored in computer systems. Thus, the emergence of process mining - a field that deals with finding insights on business processes in an automated way from the process data itself [Aal22b].

Concept	Notation	Set notation
Petri net source	i	-
Petri net sink	o	-
Petri net transition	t	-
Silent transition	τ	-
Model behavior	-	M
Proxy behavior	-	M'
Execution sequence on model	π	-
Prefix execution sequence	${}_i\pi$	-
Event	evt	$\mathcal{U}_{evt}$
Case identifier	$case$	$\mathcal{U}_{case}$
Event activity	act	$\mathcal{U}_{act}$
Event timestamp	$time$	$\mathcal{U}_{time}$
Trace	σ	-
Activity at i-th position	$\sigma(i)$	-
Trace suffix	$\hat{\sigma}$	-
Event log	-	L
Proxy log	-	L'
Event stream	-	$\mathcal{E}$
Trie	-	T
A node in a trie	n	N
An edge in a trie	e	E
Root node	$\perp$	-
Trie labelling function	l	-
Trie branching factor	bf	-
Alignment	γ	-
Prefix-alignment	$\hat{\gamma}$	-
Skip symbol in an alignment	$\gg$	-
Cost of an alignment	$\delta(\gamma)$	-
A state in the algorithm	s	S
Decay time	dt	-
Discounting factor	df	-
State buffer	-	B
Look-ahead limit	lim	-
Warm-starting move	ws	-
Skip due to warm-starting	$\gg^{ws}$	-
Out-of-order event	ooo	-

Table 2: Notations summary

The common activities of process mining include process discovery, conformance checking, and process enhancement. In order to conduct these activities, process mining relies on *process models* and *event logs*.

A process model defines which sequences of activity executions are considered

to be valid. There are many notations to model business processes varying in their richness and formal semantics. Commonly, research in process mining utilizes a special case of a Petri net called a Workflow net [Aal97] (WF-net) where there is a single source place i, and a single sink place o, and any other node, i.e., either a place or a transition, is on a path from the source place to the sink place. In other words, by adding a transition t to the net with one arc from o to t and another arc from t to i, the resulting Petri net forms a single strongly connected component. WF-nets follow the standard semantics of transitions enablement and firing as ordinary Place/Transition Petri nets [Aal19].

The WF-net in Figure 5, a simplistic order fulfillment process, serves as our running example having five labeled transitions: co, cs, ad, wr, po. Silent transitions (τ transitions) cannot be observed during the execution of a process model and are colored in grey. In Figure 5, the τ transition allows to skip ad, but there is no labeled activity associated with skipping ad that could be shown on the model.

When WF-nets are enacted, one can observe sequences of labeled transitions based on firing sequences. As such, the model behavior M may also be represented by a set of sequences of activities. M is infinite when the model has loops because a loop can unfold an unlimited number of times. The sequence of fired transitions is called an execution sequence. An execution sequence $\pi \in M$ starts from a transition enabled by the source place, i, marking and ends with a transition that marks the sink place, o, after its firing. A prefix of an execution sequence ${}_i\pi$ indicates the execution until the i-th position in π. An instance of an execution sequence is shown as $\pi = \langle co, cs, ad, po \rangle$, representing the execution path followed by executing, co, cs, ad and po transitions from the WF-net in Figure 5. Another execution sequence $\pi = \langle co, cs, wr, ad, cs, wr, cs, po \rangle$ has the loop around transitions cs and wr executed two times.

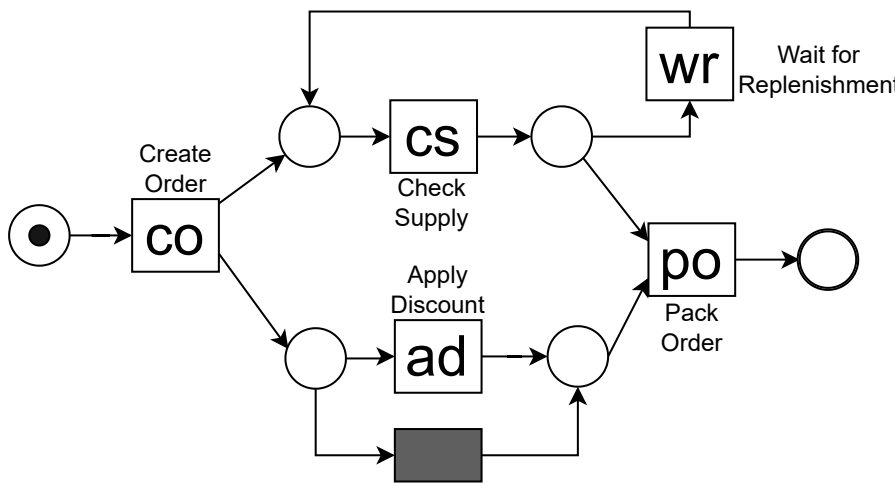


Figure 5: A small example process model with parallelism, skip activity and a loop.

Case identifier	Activity	Timestamp
1	co	2024-08-01 15:00:02
1	cs	2024-08-01 15:00:06
2	co	2024-08-01 15:00:07
2	cs	2024-08-01 15:00:10
2	ad	2024-08-01 15:00:13
3	co	2024-08-01 15:00:14
2	po	2024-08-01 15:00:16
1	wr	2024-08-01 15:00:16

Table 3: A simple event log showing the case identifier, executed activity, and execution timestamp.

One discrete data unit in the execution of a process within information systems is commonly referred to as an **event** (Definition 1), while a multiset of events is represented as an **event log** [Aal16] (Definition 2).

Definition 1 (Event)**.** *An event evt is a tuple* $evt = (case, act, time) \in \mathcal{U}_{case} \times \mathcal{U}_{act} \times \mathcal{U}_{time}$ *with case referring to the case identifier (caseID), act referring to the executed activity and time denoting the event timestamp.*

Definition 2 (Event log)**.** *An event log L is a multiset of events* $L \in \mathcal{B}(\mathcal{U}_{case} \times \mathcal{U}_{act} \times \mathcal{U}_{time})$

Definition 3 (Trace)**.** *A trace* $\sigma = \langle act_1, \ldots, act_n \rangle \in \mathcal{U}_{act}*$ *is a finite sequence of activities with a common caseID. We use the notation* $\sigma(i)$ *for the activity at the i-th position of* σ.

A log contains **traces** (Definition 3), a sequence of events, each denoting a single execution of the process. Traces representing distinct process executions built of events that induce the same sequence of activity executions are said to be of the same *trace variant*. A relatively simple model for event logs is sufficient for the context of this paper, i.e., an *event* consists of a *caseID* for assigning an event to a particular process instance, an *activity* label, and a non-decreasing *timestamp*.

A proxy log, L', is an event log that represents a finite subset of behavior – proxy behavior (M') – allowed by the model. For example, the model in Figure 5 allows for infinite behavior due to the model containing a loop. An example of proxy behavior could be limiting looping to a single traversal of activity *wr*. Eliciting such restrictions allows us to generate a proxy log (Table 4) that contains traces describing a finite subset of the model behavior.

2.2. Conformance Checking

Conformance checking compares the behavior recorded in an event log L with the behavior specified by a process model M and outputs a conformance artifact [Car+18] (Figure 6). This section first gives an overview of some simpler

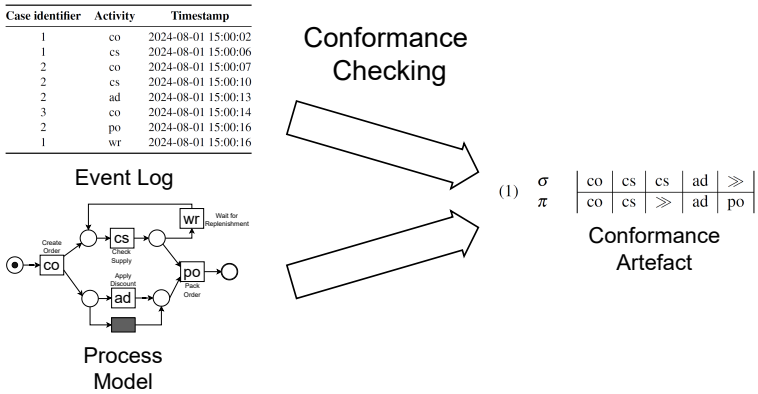


Figure 6: Conformance checking, showing the input of an event log and a process model, and the output as a conformance artifact.

conformance checking methods. Then, we have a deeper look at the concept of alignments, the current state of the art in conformance checking.

Rule Checking. One of the simplest ways to conduct conformance checking is via rules and rule checking [CVB13]. Such an approach does not rely exclusively on a process model, but rather on limitations (rules) derived from the process model. For the running example in Figure 5, we could derive the rule that *the process must start with the Create Order activity*. Such rules are generally easy to create as long as the process model is relatively small. [Car+18] lists rule types such as cardinality, precedence, ordering and exclusiveness. Common limitations of rule checking, however, are that the amount of rules increases exponentially as the number of activities in the process model increases; furthermore, it is easy to find corner cases that are valid according to the rules, but not according to the model. Thus, more robust model-based methods have been introduced.

Token-based Replay. One of the first methods to rely more strongly on a process model as the ground truth, token-based replay uses an event log to *replay* the traces on top of the process model [RV08]. The conformance checking is done via taking each trace and executing the activities in the order of occurrence on top

case	$\sigma(1)$	$\sigma(2)$	$\sigma(3)$	$\sigma(4)$	$\sigma(5)$	$\sigma(6)$
$case_1$	co	cs	ad	wr	cs	po
$case_2$	co	cs	ad	po		
$case_3$	co	cs	wr	cs	po	
$case_4$	co	cs	wr	cs	ad	po
$case_5$	co	cs	wr	ad	cs	po
$case_6$	co	cs	po			
$case_7$	co	ad	cs	wr	cs	po
$case_8$	co	ad	cs	po		

Table 4: Running example: proxy log

of the process model. Two types of non-conformance can occur, whereby the execution of an activity requires the consumption of a token but the token is *missing* during a replay; or, alternatively, a token is *remaining* at a non-final place at the end of the trace replay [Car+18]. While token-based replay methods are generally efficient and improve upon rule checking, they do come with their own set of limitations. One such limitation is the occurrence of activities that are not described in the process model at all. Commonly, the replay would simply skip such activities, which is not completely correct behavior in the sense that actually the trace is non-conforming to the model. Furthermore, if a model would have multiple occurrences of the same activity in different parts of the model, then the result of conformance checking using token-based replay becomes non-deterministic, as it requires a heuristic to pick among these multiple activities [Car+18]. These limitations led to the concept of *alignments*, as discussed next.

Alignment. While rule checking and token-based replay are both generally intuitive and applicable for conformance checking purposes, they do come each with their caveats as outlined previously. This has led to the development of alignments [AAD12] that have now become the *de facto* standard of conformance checking [Car+18]. In the following, we give a more formal background on alignments, as they are also an important foundation for the contributions of this thesis.

Definition 4 (Alignment)**.** *An alignment* $\gamma = \langle (x_1, y_1), \ldots, (x_n, y_n) \rangle$ *is a sequence of steps, each step* $(x,y) \in (\mathcal{U}_{act} \cup \{\gg\}) \times (\mathcal{U}_{act} \cup \{\gg\})$ *linking an activity of the trace, or the skip symbol* $\gg$*, to an activity of the execution sequence, or the skip symbol, whereas a step* $(\gg, \gg)$ *is illegal. Each activity in the trace and the model are paired in a* move*. Here, it must hold that the projection of* γ *on the first component, ignoring* $\gg$*, yields* σ*, and the projection of* γ *on the second component, ignoring* $\gg$*, yields* π*. A step* (x,y) *is called* synchronous move *if* $x = y \neq \gg$ *and* $x, y \in \mathcal{U}_{act}$*,* log move *if* $y = \gg$*, a* model move *if* $x = \gg$*, while the last two are jointly referred to as asynchronous moves.*

Alignments map the moves in the log (actual behavior) and possible moves in the model. Generally, alignments provide good diagnostics, as it is easy to interpret expected behavior and deviations, e.g., skipping an activity or conducting an activity not expected by the model [Aal22b].

As multiple alignments are possible, a cost is associated with steps for decision-making. For the purposes of this thesis, a cost of one is assigned to asynchronous moves, while synchronous moves have zero cost. Moves on τ transitions can never be observed in the trace; thus, they also have a cost of zero. In the remainder, we write $\delta(\gamma)$ for the total cost of an alignment γ.

An optimal alignment minimizes the edit distance between a trace and an execution sequence. Identifying a cost-optimal (minimal) alignment for a trace and all execution sequences of a model is computationally expensive [Car+18].

Over the years, various alignment-based techniques and outputs have been investigated. Anti-alignments [CC16], for example, quantify the extreme devi-

(1)	σ	co	cs	cs	ad	$\gg$
	π	co	cs	$\gg$	ad	po

(2)	σ	co	cs	$\gg$	cs	ad	$\gg$
	π	co	cs	wr	cs	ad	po

Table 5: Running example: two optimal alignments.

ations from the model, allowing for the detection of imprecise models. Some recent techniques [BCC21b; Oje23] have encoded alignment calculations as an SAT problem. Various cost functions have been investigated – some techniques have investigated not obtaining the optimal alignment, but obtaining the maximum amount of synchronous moves [Blo+18; Oje23]. A cost function penalizing earlier deviations of a trace more than later deviations was introduced in [BCC21a]. While new methods [LZ22] are emerging, the most common way of finding an optimal alignment requires building a so-called synchronous product net and using the A* search algorithm to find the shortest path through the net [AAD12]. When building the synchronous product net, the search space may grow exponentially. Thus, calculating *optimal* alignments is still considered computationally challenging in real-life settings.

For our running example, let us assume that we have observed a trace $\sigma = \langle co, cs, cs, ad \rangle$. Figure 5 shows two alignments between this trace and the process model. The row marked with σ shows the complete *trace* that has been seen. The row with π shows the corresponding moves in the *model*. For the first alignment, the second execution of *cs* is considered erroneous, and thus a log move is made. Alternatively, the second alignment shows that a model move on *wr* would entail the same cost – in this case, we would assume that the activity *wr* was either skipped or not recorded properly. For both of the alignments, a synchronous move on *ad*, and a model move on *po* need to be executed for the execution sequence to conclude.

While both of the alignments in Figure 5 are *optimal*, an alignment can also be *suboptimal*, i.e., its associated cost is non-minimal. Approximate algorithms commonly produce alignments that may be suboptimal. Such algorithms quantify the distance from optimality via an *error*.

2.3. Event Streams

Data is constantly generated via various systems in an organization. However, most existing algorithms for conformance checking assume the existence of a static event log file [Bur22a], akin to batch processing of data [ACL18]. This section introduces the concept of event streams for a continuous processing of incoming data.

Event streams (Definition 5) are unbounded sequences of events that occur within an organization's process executions [Bur22a]. Commonly, these events

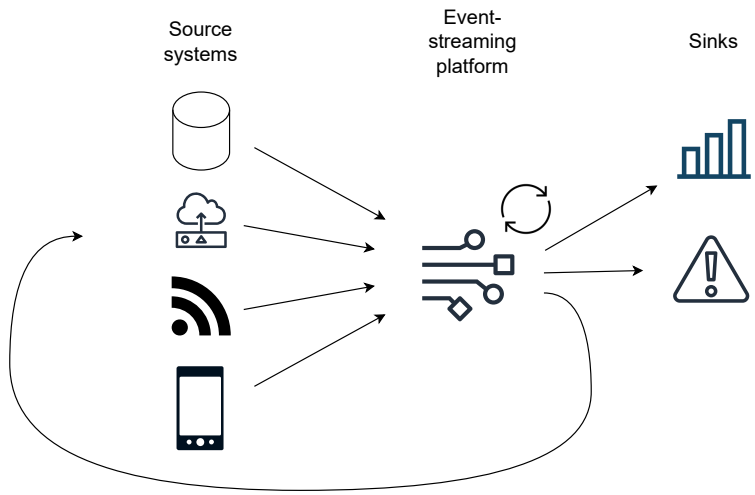


Figure 7: Overview of event stream processing.

are generated in a multitude of systems, each of which transfers the data to a an event-streaming platform [RH22]. There, the data is processed in near real-time to produce timely insights, and finally made available to downstream systems, such as reporting tools, alerting, or feeding the data back to the source systems (Figure 7).

Definition 5 (Event stream)**.** *An event stream $\mathscr{E}$ is an infinite sequence of events $\mathscr{E} : \mathbb{N}_{\geq 0} \to \mathscr{U}_{evt}$*

The work in [Bur22a] summarizes several constraints (streaming constraints, SC) on event stream processing:

- SC1: it is necessary to process one event at a time and inspect it at most once;
- SC2: only a limited amount of time and memory is available for processing an event;
- SC3: results of the analyses should be given at any time;
- SC4: the algorithm has to adapt to changes over time.

These constraints serve as the guiding principles within this thesis. First of all, the intrinsic property of streams implies that algorithms should be single-pass. That is, each event should be processed only once (or a couple of times), but the whole data cannot have multiple passes [Bah+21] (SC1). As there is a constant influx of new events, each event needs to be processed as fast as possible. This sets limits on the memory as only the critical subset of states can be used for fast processing (SC2). A streaming system that is unable to output results in a timely manner is equivalently similar to a batch processing system, thus the result of any streaming algorithm should be available in near real-time (SC3). Finally, the velocity of the stream is unlikely to be constant, leading to the demand for adaptive algorithms (SC4).

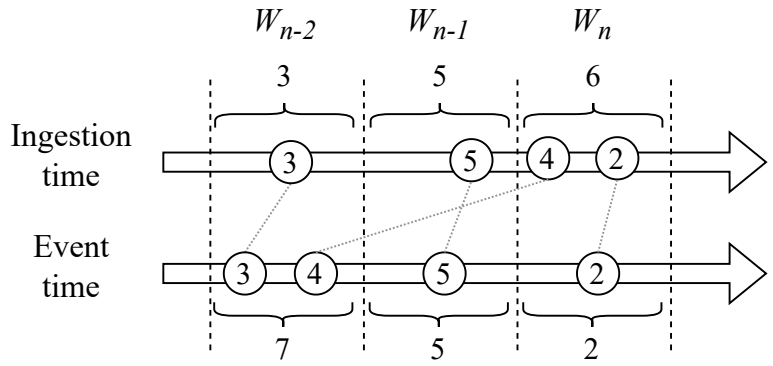


Figure 8: Example of out-of-order event arrival.

Handling Event Time. Modern stream processing frameworks are designed for analytics that builds upon recent data stream aggregates, especially in cases where real-time results are essential, such as systems monitoring and decision support [Isa+19; ZSM23]. A data stream that features data arriving from multiple sources or a system built upon distributed systems will likely display a stream imperfection known as *out-of-order* event arrival [Li+08]. An event is considered out of order when it arrives from a source after records with later event timestamps. Many factors can explain why a stream may have events arriving out of order, the most typical reasons being network reliability, bandwidth, and load [Fra+24]. We make an assumption for the purposes of this thesis that we always have an *event time* that represents the actual system clock time of the system that generated the event [Aki+15], but we concede that there may be practical settings where this event time is known or available.

Because a data stream is inherently infinite, the memory requirements on a stream processing system would be unbounded. Thus, the concept of windows is used to segment time into smaller units [PS06]. Windows allow aggregations and joins of multiple streams within specific timeframes. In the presence of out-of-order events, windows need to be maintained and possibly entirely recalculated. An example of out-of-order event arrival in the context of windows, and a comparison between event time and system ingestion time is shown in Figure 8. In this example, aggregating based on windows would indicate an increasing trend if looking at ingestion time $(3, 5, 6)$, while based on the event time, it is actually a downward trend $(7, 5, 2)$.

Since there is no limit on the potential delay of event arrival, an additional concept called *watermarks* is used in data streams to keep track of event time progress and, essentially, limit the number of windows [Car+15]. This avoids potential time lag due to outliers or faulty data that could stretch windows indefinitely. As an example, referring to Figure 8, events can arrive at any time from any previous window. As time progresses, the stream processing system will have to keep an increasing number of windows in memory, degrading the performance

of the system and, potentially, making the computation infeasible. Setting a watermark will define a threshold for how long the system will wait for out-of-order event arrival, effectively setting a bound on the memory usage and computational resources. While watermarks are commonly based on event time [Fra+24], this is complicated for business process streams. Mainly, as individual process executions do not have direct dependencies on other concurrent executions.

Modern Stream Processing Frameworks. A large number of stream processing frameworks has been developed over the years [Fra+24] with each framework having its distinct characteristics in terms of data management, state management, out-of-order handling, fault-tolerance and elasticity. In this section, we briefly introduce two common frameworks, Apache Spark and Apache Flink, to give a more thorough background on the stream processing landscape. Furthermore, the fourth contribution (Chapter 7) is implemented on top of Apache Flink.

Apache Spark was initially conceived to deal with limitations stemming from the Hadoop MapReduce framework [Zah+10]. While the initial implementation used an abstraction called Resilient Distributed Datasets (RDDs), the current state of the art utilizes DataFrames, a declarative API that gives the approach a more user-friendly usage while including optimizations that were unavailable for RDDs [Zah+16].

The Structured Streaming API, introduced in [Arm+18], provides a simple streaming system utilizing the same DataFrame API that Spark uses for batch processing. In terms of execution, once the Structured Streaming job receives a query, it first incrementalizes it, in order to ensure that the query's result can be updated before new data is received. Then, the query plan is optimized using Spark's existing optimization rules. Importantly, the execution in Spark can be achieved either using microbatching – which means that essentially the processing is not strictly streaming, as the process waits a pre-defined time for the batch to trigger – or via continuous processing, that is more similar to traditional streaming systems, and thus lower latency, but also lower operational flexibility compared to microbatching. Furthermore, two important concepts are used by Structured Streaming to achieve fault tolerance. Firstly, a write-ahead log that keeps track of which data has been processed. Secondly, a state store that holds snapshots of operator states, required for most aggregation purposes on data streams. A simplified architecture based on [Arm+18] is shown in Figure 9.

Apache Flink was the first streaming system to incorporate both batch and stream processing into a singular framework, together with support for out-of-order event processing [Car+15]. At its core, Flink uses the dataflow graph as a basis for the query execution. The dataflows are executed in iterative steps, allowing for coordination of data in transit.

From the streaming perspective, Flink utilizes the DataStream API, which enables stream processing on top of the dataflow. Importantly, Flink handles both event time and ingestion (processing) time. This allows Flink to effectively handle out-of-order event arrival. Furthermore, the DataStream API allows for stateful

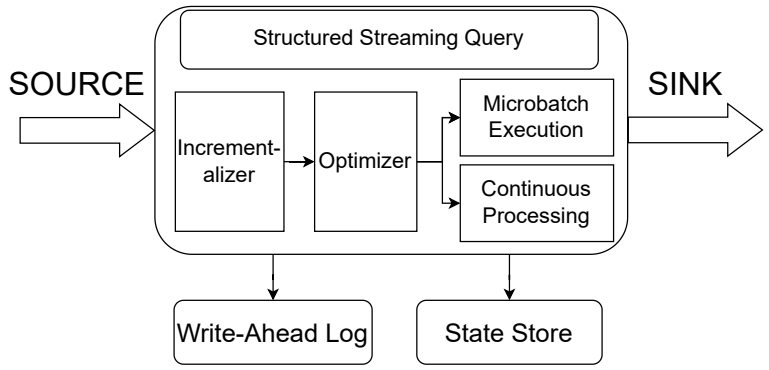


Figure 9: Apache Spark Structured Streaming overview.

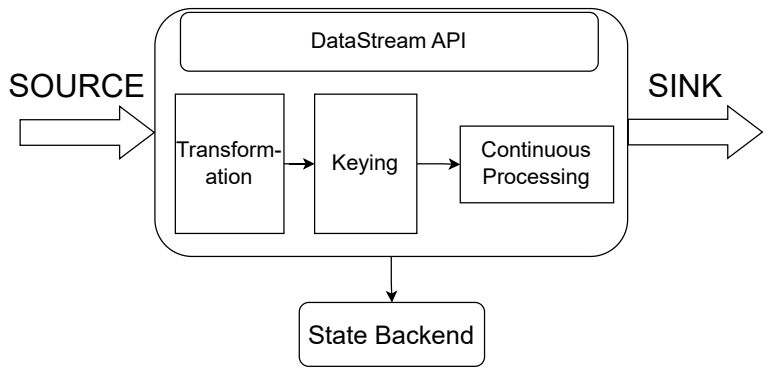


Figure 10: Apache Flink stream processing overview.

stream processing, which is useful for a process mining perspective, where the arriving events may be related to an ongoing process execution. State snapshotting is achieved via barriers, lightweight checkpoint markers that are injected into the data streams. A high-level overview of Apache Flink stream processing is shown in Figure 10.

On a high level, the event processing is similar between Flink and Spark. Notably, both of the systems are open source and actively developed. Due to Flink's native continuous and stateful processing, it can be argued that it is better suited for stream processing on top of process event streams. In the next chapter, we will have a look into how streaming interplays with conformance checking.

3. STREAMING CONFORMANCE CHECKING – CONCEPTS AND REVIEW

Traditionally, conformance checking is done in an offline setting: an event log is constructed by filtering events that occurred within a specified time range. The event log cannot contain any events that occurred after the point of data extraction (Figure 11). These limitations hide several important challenges.

Firstly, process executions commonly exhibit overlap and parallelism. This indicates that some of the process executions from a specified time range are likely to have started before the time range, and some may not yet have concluded. In some cases, this can be remedied by domain knowledge and data preprocessing, e.g., filtering out cases that have not yet concluded. However, such preprocessing induces data loss due to the removal of incomplete process executions and consequently lowers the trustworthiness of the analysis.

Secondly, and more importantly, in an offline setting, the data used for analysis, and the results, are obsolete by design. The longer it takes from data extraction to analysis to decision-making, the less valuable the data becomes. In many real scenarios, such as fraud detection, autonomous driving, malware detection, or health monitoring, making decisions based on stagnant data is impractical, except for high-level trend analysis. Being unaware of discrepancies in individual ongoing process executions can have a broad impact on an organization. This is supported by recent studies, indicating the need for moving towards stream processing and real-time availability of data in process mining [Kip+22].

This chapter first introduces concepts relevant for streaming conformance

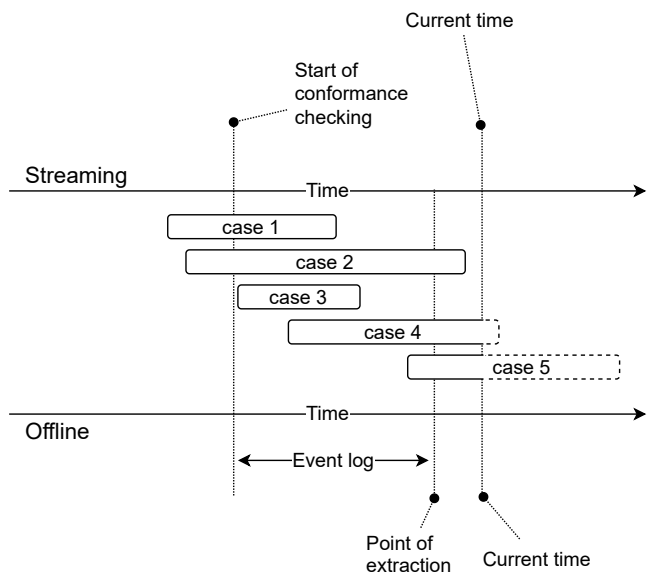


Figure 11: Differences between streaming and offline conformance checking.

checking. Then, various metrics-based approaches are discussed. Following this, the state-of-the-art approaches using prefix alignments are examined. Finally, we delve into the challenges of existing approaches, thereby paving the way for the contributions of this thesis.

3.1. Concepts

Streaming conformance checking is the application of conformance checking on top of event streams. Similarly to offline conformance checking, approaches need to have a reference model (the expected behavior). Unlike offline conformance checking, however, the real behavior is not coming from a static event log, but from a continuous event stream. At any given time, a new event may be seen in the event stream, having either a known or a previously unseen case ID.

The organization can receive indications of discrepancies in a continuous manner as soon as these discrepancies occur. This gives the organization the opportunity to remedy the negative impact of observed discrepancies. We make a distinction between metric-based approaches, which indicate the level of conformance, compared to alignment-based approaches, which have increased explainability in terms of the location of the discrepancy. Generally, in order to do conformance checking effectively, it is important to know the exact locations of both the wrongly executed and skipped activities.

In a streaming setting, conformance-checking frameworks usually observe a subsequence of the trace. The trace execution may not yet have concluded, and it is unknown how the execution sequence might play out. A *complete* alignment would overestimate the conformance cost in such cases. A **prefix-alignment** $\hat{\gamma}$ is a variation of the alignment where complete path traversal to the model's sink is unnecessary. Returning to the trace $\sigma = \langle co, cs, cs, ad \rangle$, one can deduce that the final event *po* may still occur, and thus there exists no deviation in terms of the activity *po*. In this case, there exist two equally optimal prefix-alignments. Prefix-alignments ($\hat{\gamma}$) of trace σ are shown in Table 6. In a streaming setting, a prefix-alignment is calculated event by event, finding a match between the arrived event and the allowed model behavior.

In long-running processes, an issue that might occur is the *warm-starting* scenario. That is, some process executions are ongoing before the conformance checker is initiated and are thus not completely observable. Examples of such cases can be seen in Figure 12 with cases 1 and 2. In most conformance check-

(1)	σ	co	cs	cs	ad	
	π	co	cs	$\gg$	ad	
(2)	σ	co	cs	$\gg$	cs	ad
	π	co	cs	wr	cs	ad

Table 6: Running example: two optimal prefix-alignments.

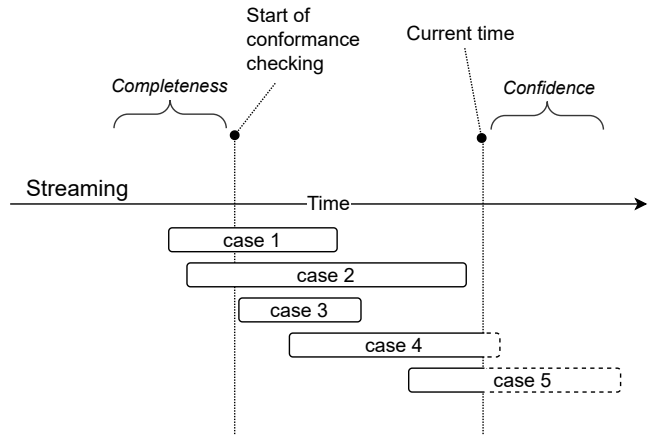


Figure 12: Streaming conformance checking, with highlighted completeness and confidence.

ing techniques, this causes a false positive, i.e., a discrepancy is indicated, even if the process followed a conforming behavior. Completeness issues may lower the trustworthiness of the conformance checking method and require a *grace period*, after which a conformance checking method can be expected to output the correct conformance.

Similarly, the ending of a process execution poses a challenge. Streaming conformance checking methods give equal weight to the observed conformance at the beginning of a trace, as they do for conformance that is near the end of a trace's lifecycle. It can be argued that a conforming trace that has seen only a few events has a higher probability of divergence than a conforming trace that has seen most of the expected events. For example, if case 4 and case 5 in Figure 12 are both conforming, then case 5 has a higher chance of seeing non-conforming behavior. This indicates the need for a confidence measure that would complement the conformance so that organizations can be more alert for traces that are just initializing rather than the traces that are concluding.

3.2. Metrics-based approaches

In this section, we review existing metrics-based approaches. A common denominator for these approaches is that the conformance artifact is a metric – usually a natural or decimal number. While such a representation is not as explanative as an alignment, these approaches assume that the main target of conformance checking is just to identify traces where discrepant behavior has occurred. On the other hand, computing a simple metric can be expected to be lightweight in terms of memory usage and have a low latency, and thus well-suited for streaming applications. All of the current metrics-based methods have distinct ways of representing process behavior, requiring additional steps in the *offline* part before initializing

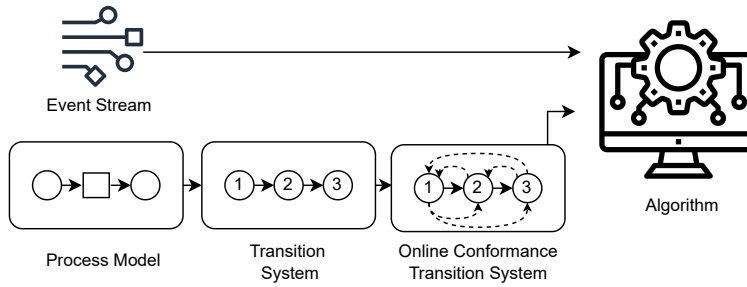


Figure 13: Overview of the FW [BC17] approach.

the streaming algorithm.

FW. One of the first methods to apply conformance checking on top of event streams was introduced in "A Framework for Online Conformance Checking" [BC17] (FW). The approach takes as input a Petri net. From the Petri net, an augmented transition system (Online Conformance Transition System, OCTS) is built using concepts from region theory and state distance. This enriched model indicates any possible compliant and non-compliant behavior, and is built before the conformance checking itself is initialized (i.e., offline), thus enabling constant time calculation on top of each event. While the computation in the online phase is fast, the computation of the OCTS can be computationally very expensive, and even impractical for moderately large Petri Nets. The output of the algorithm is a conformance cost in natural numbers, with 0 indicating a compliant trace. A high-level overview of the approach is shown in Figure 13

BP. The work in [Bur+18] used behavioral patterns for calculating conformance in a streaming setting. Similarly to the FW approach [BC17], the BP approach calculates an enhanced model beforehand. However, the computation is slightly more complex, starting from a BPMN model, computing a Petri Net and an additional reverse net, unfolding both the original and reverse Petri net, and then using reachability graphs to build a Process Model for Online Conformance (PMOC) that is essentially a set of three matrices that contains the behavioral patterns (Figure 14). The behavioral patterns rely on weak order relation for the unfoldings, allowing for finiteness, but potentially having too much abstraction in the allowed behavior.

Notably, BP is the first method to output also completeness (*warm-starting*)

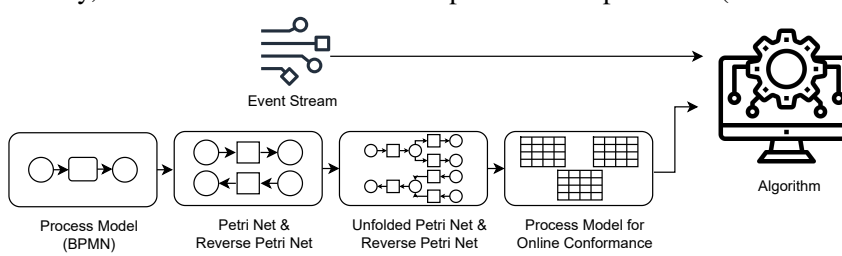


Figure 14: Overview of the BP [Bur+18] approach.

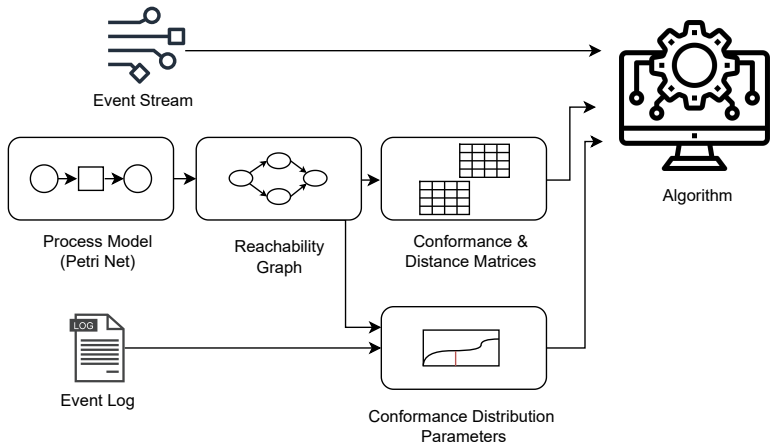


Figure 15: Overview of the HMM [Lee+21] approach.

and confidence metrics in addition to conformance. These metrics give additional insights to the user in terms of the reliability of the conformance. Also, the behavioral methods do not penalize *warm starting* scenarios. That is, cases where a process execution has been started before the conformance checking begins. The approach thus outputs three distinct metrics, with each of them in the interval [0,1], where 1 indicates fully conformant behavior.

HMM. More recently, [Lee+21] introduced a method based on Hidden Markov Models (HMM), alternating between state estimations and calculating conformance. Similarly to other metrics-based approaches, a reachability graph is built offline, together with estimates for conforming and non-conforming distribution parameters. During runtime, the algorithm computes the conformance metric as a value in the interval [0,1]. Similarly to the *BP* approach, this solution allows for warm-starting scenarios by quantifying also the completeness metric.

While the HMM-based method improves on the *BP* method by having less abstraction in the underlying process model, the setup of the approach is relatively complex and requires more inputs and computations before the online algorithm can be started. Most importantly, the method expects that an event log describing past data exists in addition to a process model and an event stream. The past data is used for updating the non-conforming distribution parameters, that are used by the HMM during the execution of the algorithm. An overview of the approach is shown in Figure 15.

3.3. Alignment-based approaches

Another research path in streaming conformance checking has focused on prefix-alignments [AVZ13]. Compared to the previously reviewed metrics-based approaches, the alignment-based methods provide a much higher explainability for

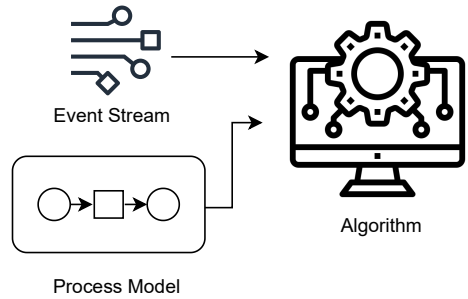


Figure 16: General overview of the alignment-based approaches. While the offline part is simpler, most of the complexity of the approaches results from the algorithm during the stream execution.

the discrepant behavior, as the alignments have a clear way of pinpointing the activities that did not follow the process model. All of the current alignment-based methods have a simpler offline part compared to the metrics-based approaches, usually just expecting the process model as a Petri Net and the event stream as inputs (Figure 16). From a negative perspective, it is important to note that the low amount of preprocessing leads to further steps that the algorithms need to do during the stream execution, most notably the construction of a Synchronous Product Net (SPN, Figure 17) and finding the shortest path in the SPN. In order to achieve optimal prefix-alignments, multiple passes over the whole data are necessary, which is in conflict with *SC1*. Further, the complexity of computing alignments has resulted in the alignment-based approaches having execution times, which may easily become bottlenecks in real-life event streams.

OCC. The work in [Zel+19] introduced an incremental algorithm for computing both optimal and approximate prefix-alignments on top of event streams. The approach requires the construction of a synchronous product net between the Petri Net and the observed trace during execution time. By default, the approach computes the prefix-alignments starting from the initial marking of the synchronous product net, which has the benefit of the approach being able to compute optimal alignments. One of the major drawbacks, however, is that computing alignments starting from the beginning becomes increasingly expensive as the trace size increases.

The approach introduced two ways to limit the search problem. First, the method includes heuristics for cost upper-bounds, effectively pruning states that are guaranteed to be exceeding the optimal path. Secondly, the approach uses a window-size parameter to trade-off between the computation time and alignment optimality. An infinite window size (*OCC-Winf*) allows for calculating optimal prefix-alignments but has the slowest execution time. A window size of one (*OCC-W1*) is the fastest but produces approximate alignments that may be subop-

timal. Furthermore, the authors note that the heuristic that is applied for *OCC-W1* for pruning states is slightly unpredictable in terms of memory utilization. This may be an important consideration for fast-paced streams in devices with a tight memory allowance.

IAS. In [SZ20], the authors extended upon the *OCC* work by introducing a cache for previously computed synchronous product nets and an incremental A* (*IAS*) algorithm that is able to compute the alignment from a given state in the synchronous product net. Furthermore, the approach included an adapted heuristic for guiding the A* algorithm in the prefix-alignment computation. The main improvement of this approach is that it can calculate optimal prefix-alignments with a smaller memory footprint. However, the experiments showed that the latency of the algorithm is still similar to *OCC-Winf*, and the best latency is achieved with *OCC-W1*. Thus, while there are benefits to memory utilization, the latency still remains high for finding the shortest path in a synchronous product net.

CFc, CFcs, MLc. The work in [ZHD23] builds upon the *OCC* approach while investigating prefix-alignments from the perspective that it is unknown whether cases in event streams have concluded. The core of the problem is that memory is finite but streams are unbounded; thus, cases and their alignments have to be released from memory at some point. Since further events may still occur, this may lead to a situation where a case has been released from memory, but a new (*orphan*) event is received for this case, with such a situation referred to as the *missing-prefix* problem.

The authors introduced both stateful and stateless approaches to mitigate this

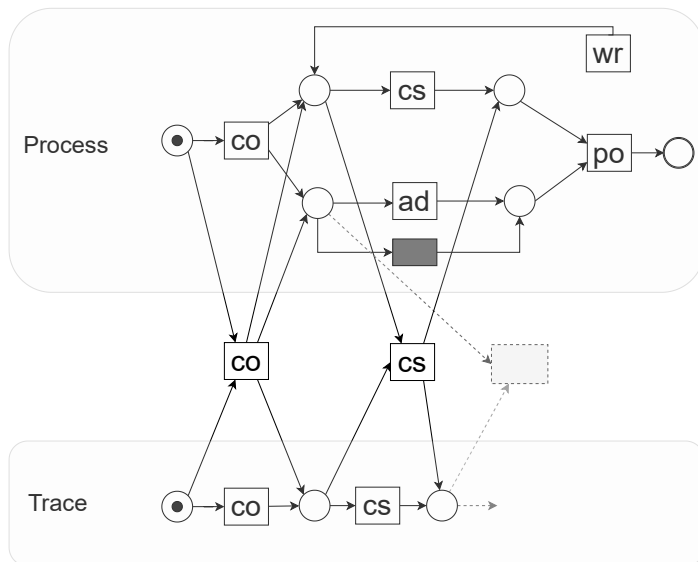


Figure 17: An example construction of the synchronous product net for the trace $\sigma = \langle co, cs \rangle$.

problem. *CFc* utilizes forgetting criteria to assign priorities on which states to prune from memory while a summary state is stored in memory. As the number of cases may still grow infinitely large, *CFcs* is a variant of the algorithm that also imposes a limit on the number of states to store in memory. This enables the algorithm to have bounded memory consumption with the downside of a larger potential error. The stateless approach *MLc* does not store even a summary state, and a prediction step is applied when observing orphan events to determine the state.

While these algorithms apply well to data retention challenges, they suffer from lower explainability and higher potential error. The approaches do not store prefix-alignments in the summary states, but only the current marking in the Petri net and the error cost. Thus, while the method is alignment-based, the alignment for forgotten cases may be incomplete, as it is only started from the marking stored in the summary state. This makes it difficult to determine which events have occurred and, in case of non-compliance, what has caused the error. Furthermore, forgetting states introduces a potential error as other viable states are no longer available. This is especially true for *MLc*, as the algorithm utilizes the common paths of the process model and is thus susceptible to noise. Nevertheless, the methods in [ZHD23] match well to the streaming constraints, especially SC2, and can thus be deemed well suited for real-life stream processing.

3.4. Challenges of existing approaches

The various approaches for conducting streaming conformance checking, together with their advantages and disadvantages, are shown in Table 7. In this section, we review and summarize the existing challenges. Furthermore, we look at what requirements are currently missing and should be covered by a streaming conformance checker.

Firstly, the metrics-based approaches can be slow in initializing, requiring considerable effort in the offline processing part. Each of the current methods has a distinct way of representing process behavior, which, on a high level, depends on building elaborative reachability graphs that try to accommodate any possible deviance from the process model. On the other hand, the execution of the algorithms is very fast. This is both because the preprocessing has made lookups for discrepant behavior fast, but also because the conformance artifact is a simple metric that does not require state explorations during runtime. The metric artifacts, however, lack explainability in terms of the non-conformant behavior. In terms of additional dimensions, the *BP* approach is the only one that is able to quantify the confidence level of a trace, while the *BP* and *HMM* approaches are capable of warm-starting. None of the metrics-based approaches handle out-of-order events.

Thus, for metrics-based approaches, the time and memory requirements for larger process models may become infeasible in real-life situations. Furthermore, the metrics-based approaches have a primitive indication of the confor-

Method	Category	Offline effort	Online effort	Conformance artifact	Handles confidence	Handles warm-starting	Handles out-of-order events
FW [BC17]	Metrics-based	High	Low	Metric (natural numbers)	No	No	No
BP [Bur+18]	Metrics-based	High	Low	Metric (decimal [0,1])	Yes	Yes	No
HMM [Lee+21]	Metrics-based	High	Low	Metric (decimal [0,1])	No	Yes	No
OCC-W1 [Zel+19]	Alignment-based	Low	High	Alignment	No	No	No
OCC-Winf [Zel+19]	Alignment-based	Low	High	Alignment	No	No	No
IAS [SZ20]	Alignment-based	Low	High	Alignment	No	No	No
CFc, CFcs, MLc [ZHD23]	Alignment-based	Medium	High	Alignment (may be incomplete)	No	No	No

Table 7: Summary of advantages and disadvantages of existing methods.

mance. This can work well for purely alerting purposes in terms of detecting a non-conforming trace, but even then, in fast-paced streams, it may become unexplainable why a particular trace was found to be non-conformant and what should be done about it.

Alignment-based approaches generally require a low effort in terms of offline preprocessing, as they accept a Petri net without any augmentations. The *MLc* approach requires the training of a classifier, thus having a slightly higher preprocessing effort. For the online part, all of the alignment-based methods have high computation requirements, as the process of generating synchronous product nets and finding the shortest paths is potentially exponential in complexity. The *OCC* and *IAS* approaches output a prefix-alignment, which is highly explainable in showing the exact causes for discrepant behavior. Finally, none of the alignment-based approaches handle either confidence, warm-starting, or out-of-order events.

In summary, the data model for alignment-based methods can be expensive for computations. Due to the reliance on computing synchronous product nets and then doing shortest path traversal, the prefix-alignment methods exhibit a heavy computation load and remain impractical for most real-life scenarios involving a high-velocity event stream.

As a response to the highlighted shortcomings of existing methods, we propose the following requirements that need to be covered by a streaming conformance checker:

- the method should have an efficient data structure, not requiring extensive offline preprocessing;
- the method should be fast in online computation;
- the method should explain discrepancies well (using alignments);
- the method should be able to quantify the likelihood of trace conclusion (confidence);
- the method should be capable of warm-starting;
- the method should handle out-of-order events.

The next chapters will introduce methods for streaming conformance checking that consider how to match these proposed requirements.

4. UTILIZING THE TRIE DATA STRUCTURE FOR CONFORMANCE CHECKING

Common techniques for conformance checking compute an alignment between a trace and an execution sequence of a process model [ADA11]. An alignment relates events of a trace to activity executions defined by the model, such that a cost function over this relation is minimized. State-of-the-art algorithms phrase the construction of such optimal alignments as a search problem and show an exponential time complexity in the size of the trace and the model [Car+18]. This is problematic, especially when alignments need to be constructed repeatedly. Challenges such as traces evolving continuously due to new events being recorded in online scenarios or the underlying models changing (e.g., in exploratory analysis by a user or in the context of iterative discovery algorithms) may lead to an intractable analysis because the system is unable to compute the alignments.

As a remedy, it has been suggested to rely on approximate conformance checking, which potentially trades the optimality of the constructed alignments against computational efficiency [BAW19; SZA20]. Specifically, approximate conformance checking may be realized by sampling traces of the event log [BAW19; BvW20], by adopting a heuristic algorithm for alignment construction [Lee+18; TC16], or by considering some *proxy* behavior, i.e., a subset of the behavior of the process model [SZA20; San+20]. However, approaches that fall into the latter category and incorporate proxy behavior focus on the computation of bounds of conformance measures. For the computation of actual alignments, they rely on a set-based representation of the proxy behavior. Notably, compact representations for sequential data have been researched for decades to enable efficient search [Nav01]. Thus, we argue that there is a research gap: *Structures for compact representations of behavior have not yet been utilized for efficient, approximate computation of alignments.*

This chapter introduces the *trie* data structure for computing approximate alignments. We introduce the composition of the data structure, including our augmentations for conformance checking purposes. We show the possible ways to construct a trie together with the space and time complexity of the construction process. Then, we introduce an algorithm for computing approximate alignments on top of an event log and discuss some of the applied optimizations. Finally, we do a comparison to an existing state-of-the-art method that computes approximate alignments. The work in this chapter is equivalent to the previous work in [ARW21] and maps to RQ1: *How can we incorporate a different data structure to represent the process model, enabling a more efficient computation of alignments in conformance checking?*

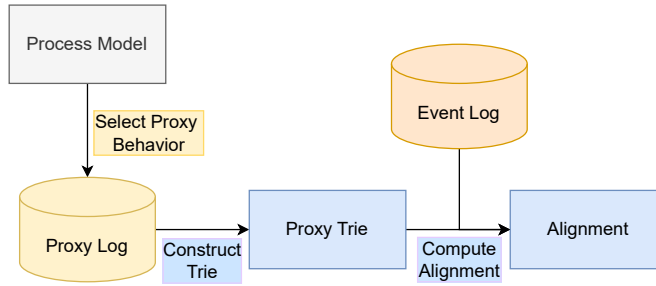


Figure 18: The steps of our approach. Blue background indicates the contribution of this work.

4.1. Approach

The general approach for our contribution is shown in Figure 18. The allowed behavior in the process can be modelled as a process model. As discussed previously (Section 2.1), the model behavior M can be infinite if the model contains a loop. When considering a tree data structure, however, it is conventionally hierarchical, with a unique path from the root to any other node in the tree [Val02]. This means that if we want to use a tree data structure to represent allowed process behavior, we need to select a representative *proxy behavior* (M') that is a subset of the model behavior M. Notably, our method does not explicitly assume the existence of a process model. I.e., having a pre-existing process model is optional. It is mandatory, however, to select proxy behavior, and this can be done either via automated or manual methods. Generally, state-of-the-art automated methods assume the existence of a process model, and then sample [FZA20] or simulate [San+20; Van+12] the behavior of the model. Proxy behavior can also be selected in a manual manner in real-life use cases, but this approach is not considered in this thesis due to the subjective and ungeneralizability of such an approach.

The output of the proxy behavior selection is the *proxy log* (L'), an event log describing a finite subset of the allowed process behavior. After this step, we come to the first part of the contribution, as the proxy log is given as input to our trie construction method. Conceptually, the output is the *proxy trie*, as it describes the subset of behavior allowed in the process. In the rest of the thesis, however, we refer to the proxy trie simply as *trie* (T), unless otherwise stated. Finally, utilizing the trie as the allowed process behavior and an event log representing the behavior recorded in the process, the second part of our contribution is an algorithm that computes the alignment between the trie and each trace in the event log. Importantly, this is an alignment between the trace and the closest trace in the *proxy log*, thus making the approach an approximation of the true optimal alignment.

4.1.1. The trie data structure

A trie data structure is essentially a prefix tree, which is commonly used in string matching [Nav01]. This use case inspires the use of tries to compute alignments, as the two problems are similar to some extent. However, to better serve our purpose, we do not employ a traditional notion of a trie, but annotate its nodes and edges with some information that is beneficial when using the trie for alignment computation.

Definition 6 (Proxy Trie)**.** *Let $M' \subseteq \mathscr{U}_{act}^*$ be some proxy behavior of a process model. Then, the* trie *constructed for it is a structure $(N, E, root, l, isEnd, min, max)$ where:*

- *N is a finite set of nodes. There is one node per prefix ${}_i\pi$ for any execution sequence $\pi \in M'$ as well as one additional node $root \in N$.*
- *$E \subset N \times N$ is a set of edges, s.t. for all $n \in N$ it holds $|\{n' \mid (n', n) \in E\}| \leq 1$ and (N, E) is a connected graph. There are edges from root to all nodes representing prefixes of length one, and from each node n to node n', if the prefix represented by n' is obtained from the prefix of n by concatenation with a single activity.*
- *$\perp \in N$ is the root of the trie, i.e., the only node $n \in N$ for which $|\{n' \mid (n', n) \in E\}| = 0$;*
- *$l : N \to (\mathscr{U}_{act} \cup \{\perp\})$ is a labeling function for nodes. The label is the last activity of the prefix represented by the node, while root is assigned $\perp$.*
- *$isEnd : N \to \{0, 1\}$ is a Boolean function that indicates end nodes, i.e., whether the prefix represented by the node denotes an execution sequence.*
- *$min, max : E \to N$ are functions assigning to an edge the minimum and maximum path length, respectively, to reach an end node, when traversing that edge.*

4.1.2. Trie construction

Utilizing the introduced trie components and a proxy log, our method starts constructing the trie. For our running example, let's assume that we have a proxy log as in Table 4. Our method would iterate over each trace in the proxy log as it builds the trie, while annotating each node with the labels and additional information. Figure 19 shows the constructed proxy trie. The numbers on each edge encode the minimum length and the maximum length to an end node, respectively. For example, the edge from the root node to its only child node is annotated with $(3, 6)$, meaning that, if we follow that edge, the shortest path to an end of an execution sequence is 3, which corresponds to $\langle co, cs, po \rangle$, whereas the longest path of length 6 corresponds to several paths that are each the longest traces in the proxy log, e.g., $\langle co, cs, ad, wr, cs, po \rangle$. The level of non-root nodes encodes the length of the represented prefix and, hence, the position of the activity defined as a label in the respective execution sequence. For instance, the top-most node co_1 is on level

case	$\sigma(1)$	$\sigma(2)$	$\sigma(3)$	$\sigma(4)$	$\sigma(5)$	$\sigma(6)$
$case_1$	co	cs	ad	wr	cs	po
$case_2$	co	cs	ad	po		
$case_3$	co	cs	wr	cs	po	
$case_4$	co	cs	wr	cs	ad	po
$case_5$	co	cs	wr	ad	cs	po
$case_6$	co	cs	po			
$case_7$	co	ad	cs	wr	cs	po
$case_8$	co	ad	cs	po		

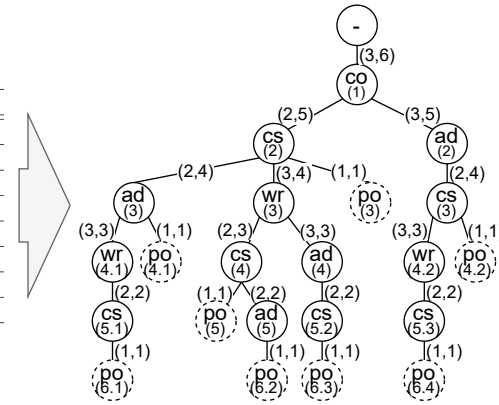


Figure 19: Running example: proxy log and the constructed proxy trie.

1, which indicates also its position in the proxy traces. Several nodes may share the same label, representing the occurrence of an activity in different prefixes. For example, several nodes are assigned the label *po*. They might have the same level, but they will have different parents, as indicated by $po_{4.1}$ and $po_{4.2}$. Nodes with a dashed border, not necessarily leaf nodes of the tree, are end nodes. For example, if we would add the trace $\langle co, cs \rangle$ to our set of proxy traces, then the node cs_2 would be marked as an end node of a trace whereas it is an internal node in the trie.

Space and Time Complexity. Encoding the proxy behavior using a trie reduces the space needed to store it. All common prefixes among execution sequences are stored only once. The trie is in the worst case linear to the size of the proxy log, $O(|L'|)$, indicating that each trace in the proxy log has a unique first activity. Usually, the trie is logarithmic compared to the proxy log size $O(log|L'|)$, because business processes have common prefixes (Figure 19). The time needed to construct the trie is also linear, $O(N)$, as all execution sequences are scanned once. In the running example in Figure 19, there are 40 distinct activity occurrences, whereas the trie has, together with the added root, 23 nodes.

4.1.3. Computing alignments

Search problem. Computing an alignment of a trace against the proxy behavior, encoded as a trie, can be seen as a variant of trie traversal. The best case occurs when there is a common prefix between the trace and the proxy trie, which represents synchronous moves in a respective alignment. In the case of deviations, we have to explore asynchronous moves, either in the trace or in the proxy trie. This yields a search problem. When a synchronous move is not possible, we have to explore the possibilities represented by a log move or a model move. To this end, we assign a cost to each possible asynchronous move and keep these moves in a priority queue. Then, we follow the move with the least cost, potentially resuming the search from one of the other moves at a later point in time. As

Algorithm 1 Alignment construction by trie traversal

Input: $(N, E, \perp, l, isEnd, min, max)$, a trie; σ, a trace.
Output: γ, an alignment.

$s.n \leftarrow \perp$ ▷ The root state initialization
$s.\hat{\sigma} \leftarrow \sigma$
$s.\hat{\gamma} \leftarrow \langle\rangle$
$s.c \leftarrow 0$
$s_{candidate} \leftarrow \perp$ ▷ The best alignment found so far
$S \leftarrow \{s\}$
while $|S| > 0$ **do**
  $s \leftarrow pickState(S)$
  if $|s.\hat{\sigma}| = 0 \wedge isEnd(s.n)$ **then** ▷ Trie and trace exhausted
    if $s_{candidate} = \perp \vee \delta(s.\gamma) < \delta(s_{candidate}.\gamma)$ **then**
      $s_{candidate} \leftarrow s$
  else if $|s.\hat{\sigma}| = 0$ **then** ▷ Only trace exhausted
    ▷ Add model moves to nearest end of trie path
    $n' \leftarrow s.n.getChildOnShortestPathToEnd()$
    while $n' \neq \perp$ **do**
      $s.\gamma \leftarrow s.\gamma \cdot \langle(\gg, l(n'))\rangle$
      $n' \leftarrow n.getChildOnShortestPathToEnd()$
    $updateCandidateState(s, s_{candidate})$
  else if $isEnd(s.n)$ **then** ▷ Only trie exhausted
    ▷ Add log moves for the rest of the suffix
    for $i = 1; i \leq |s.\hat{\sigma}|; i{+}{+}$ **do**
      $s.\gamma \cdot \langle(l(s.\hat{\sigma}(i)), \gg)\rangle$
    $updateCandidateState(s, s_{candidate})$
  else
    $a \leftarrow s.\hat{\sigma}(1)$
    $n' \leftarrow s.n.getChildWithActivityLabel(a)$
    if $n' \neq \perp$ **then** ▷ Synchronous move
      $s_{new}.n \leftarrow n'$
      $s_{new}.\hat{\sigma} \leftarrow s.\hat{\sigma}_1$
      $s_{new}.\hat{\gamma} \leftarrow s.\hat{\gamma} \cdot \langle(a, a)\rangle$
      $s_{new}.c = cost(n', s.\hat{\sigma}_1)$
      $S \leftarrow S \cup \{s_{new}\}$
    else ▷ Consider both, log and model moves
      $S \leftarrow S \cup \{createLogMoveState(s)\}$
      $S \leftarrow S \cup createModelMoveStates(s)$
if $s_{candidate} \neq \perp$ **then return** $s_{candidate}.\gamma$
else return $\langle\rangle$

such, asynchronous moves induce the states of the search space to find an optimal alignment.

The above formulation of the search problem is close to the one adopted by existing techniques for the construction of an optimal alignment, see [Don18]. However, there are a few notable differences: 1) We do not generate a search space for each trace, or rather trace variant, as it is done when constructing the so-called synchronous product model using traditional search techniques [Car+18]. Rather, the proxy trie is used to structure the search. 2) In case of asynchronous moves, states of the search space are generated and explored from the point of a

deviation between the trace and the proxy behavior. 3) Annotations of the trie are used to guide the search and prioritize the states to explore.

In the remainder of this section, we will elaborate on the details of our search strategy for the construction of alignments.

Guiding objective function. The formulation of a good cost function is a key ingredient for efficient search [Tal09]. Our design of the cost function was guided by the following principles:

- Favor depth-first traversal: To find an alignment, we aim to traverse the trie, so that the trace suffix is exhausted. Later, we may consider other paths to find a better alignment.
- Exploit local information: At each node, we may benefit from local information on the minimum/maximum path length to an end node and on the children of the current node in the trie. This information helps to estimate the costs induced by moves. For example, if a synchronous move is not possible, we would prefer a model move in case a child of the current node has the same activity as a label as the currently investigated event in the trace.

Against this background, our guiding cost function computed for a node $n \in N$ of a trie $(N, E, root, l, isEnd, min, max)$ and a trace suffix $\hat{\sigma}$ is defined as:

$$cost(n,\hat{\sigma}) = \begin{cases} 0 & \text{sync. move} \\ |\hat{\sigma}| + \min\limits_{e=(n,\_)\in E} min(e) & \text{log move} \\ |\hat{\sigma}| + \min\limits_{e=(n,\_)\in E} min(e) \\ -|\{(n,n') \in E \mid l(n') = \hat{\sigma}(1)\}| & \text{model move} \end{cases} \tag{4.1}$$

The cost function assigns zero costs to nodes that represent synchronous moves. For log moves, the cost is derived from the length of the trace suffix still to be aligned and the length of the shortest path to an end node in the trie. For model moves, the cost is the same as for log moves, but reduced in case the head of the trace suffix matches the activity assigned as a label to a child of the current node.

Algorithm. Our approach to compute an alignment based on trie traversal is summarized in Algorithm 1. It takes a trie and a trace as input and returns an alignment. The alignment construction is a search that employs the following notion of a state:

Definition 7 (State)**.** *A state s is a tuple* $(n, \hat{\gamma}, \hat{\sigma}, \delta)$*, where*

- *n is a node of the trie;*
- $\hat{\gamma}$ *is a (prefix) alignment;*
- $\hat{\sigma}$ *is a trace suffix;*
- δ *is the cost of the move represented by the node.*

We explain the algorithm by means of examples, as follows.

Example. Let us consider a log $L = \{\langle co, cs, ad, po\rangle, \langle co, po\rangle, \langle ad, po\rangle\}$. Using the trie from Figure 19, we note that trace $\langle co, cs, ad, po\rangle$ matches a path in the trie, i.e., the cost is 0.

For trace $\langle co, po\rangle$, event *co* matches the label of node co_1, so a synchronous move is made (line 27 in Algorithm 1). The corresponding state is added to the priority queue of states to explore (modelled as a set in Algorithm 1 for simplicity), with cost 0 (line 32). Next, we try to match the first event in the suffix $\langle po\rangle$, to a child of node co_1. As there is no match, we consider log and model moves. Using Equation 4.1, we determine the log move cost as 2. For node co_1, there are two possible model moves, i.e., via *cs* to node cs_2 or via *ad* to node ad_2. Here, the cost for taking cs_2 is 1, since there is a child labelled with activity *po*. The cost for taking ad_2 is 2. As such, three states are enqueued: $s1 = (co_1, \langle (co, co), (\gg, po)\rangle, \langle\rangle, 2)$, $s2 = (cs_2, \langle (co, co), (cs, \gg)\rangle, \langle po\rangle, 1)$, and $s3 = (ad_2, \langle (co, co), (ad, \gg)\rangle, \langle po\rangle, 2)$. Choosing $s2$, a synchronous move (po, po) is found and we reach an end node, which corresponds to the alignment $\langle (co, co), (cs, \gg), (po, po)\rangle$ with cost 1. State $s2$ is now a candidate state. Next, $s1$ will be dequeued. Here, we exhausted the trace and need to follow the shortest path in the trie, line 14. So, the alignment will be $\langle (co, co), (\gg, po), (cs, \gg), (po, \gg)\rangle$ with a cost of 2. Yet, as this cost is greater than the cost of the alignment of the candidate state, it is rejected. State $s3$ is handled similarly.

For trace $\langle ad, po\rangle$, Algorithm 1 examines log and model moves, i.e., $s4 = (\bot, \langle (\gg, ad)\rangle, \langle po\rangle, 4)$ and $s5 = (co_1, \langle (co, \gg)\rangle, \langle ad, po\rangle, 4)$. Both have the same cost. Assuming that $s5$ is dequeued first, we reach a new state $s6 = (co_1, \langle (co, \gg), (ad, ad)\rangle, \langle po\rangle, 0)$, which is dequeued next, as it is a synchronous move. From $s6$, no synchronous move can be made, so that model and log moves are checked. Ultimately, the candidate states $(po_4.1, \langle (co, \gg), (cs, \gg), (ad, ad), (po, po)\rangle, \langle\rangle, 0)$ and $(po_4.2, \langle (co, \gg), (ad, ad), (cs, \gg), (po, po)\rangle, \langle\rangle, 0)$ are reached. The remaining states to explore do not result in better alignments.

4.1.4. Algorithmic Optimizations

Search budget. Asynchronous moves cause the search space to grow exponentially. At each step, at least two states need to be explored, one log move and as many model moves as there are children for the current node in the trie. To address this problem, we consider a variant of Algorithm 1 that incorporates a budget, as it is widely employed in machine learning techniques [Feu+15]. The budget provides an upper bound on the number of iterations of the algorithm (line 7-35), before the alignment of the best candidate state found so far is reported.

Meta-heuristic optimization. As the objective function is designed to favor depth-first traversal, the search may get trapped in a local minimum for many iterations.

Thus, we implement a second optimization to alternate between exploitation and exploration [Tal09]. That is, we adapt the function *pickState* in Algorithm 1 (line 8) to periodically explore other parts of the search space, i.e., other states are taken from the priority queue. This alternation is controlled by a parameter *frequency*. Upon exploration, we pick a random unexplored state and evaluate its cost (Equation 4.1) and add the respective new states to the priority queue. We later show the positive effect of this optimization.

Pruning. To further control the growth of the search space, we prune infeasible states early.

The pruning is applicable when the algorithm reaches a candidate state, in which both, a path of the trie and the trace have been exhausted. A new state is infeasible if in the best case, the cost of the respective alignment is larger than the cost of the alignment of the candidate state. If so, we assume that asynchronous moves will occur only due to a difference in the lengths of the remaining path in the trie and the trace suffix. We capture this property as follows:

Definition 8 (Infeasible State)**.** *Let* $(N, E, root, l, isEnd, min, max)$ *be a trie and* $(n_{cs}, \hat{\sigma_{cs}}, \hat{\gamma_{cs}}, c_{cs})$ *be a candidate state. A state* $(n_s, \hat{\sigma}_s, \hat{\gamma}_s, c_s)$ *is infeasible, if*

$$\delta(\hat{\gamma}_s) + \min\left(\left||\sigma_s| - \min_{\substack{e=(n_s,\_)\\ \in E}}(min(e))\right|, \left||\sigma_s| - \max_{\substack{e=(n_s,\_)\\ \in E}}(max(e))\right|\right) > \delta(\hat{\gamma_{cs}}).$$

At the respective node, we check the minimum difference between the trace suffix from one side, and either the minimum path or the maximum path to the end of a path in the trie on the other side. This difference has to be in the form of asynchronous moves. If adding this alignment cost to the one at state s exceeds the cost of the best known alignment, the state is not explored further.

4.2. Evaluation

Below, we first summarize our evaluation setup, before presenting experimental results obtained with it.

4.2.1. Evaluation Setup

Procedure. We compared our approach to the state of the art for approximate conformance checking with proxy behavior [SZA20]. It relies on a set-based presentation of the proxy behavior and employs an edit distance to compute an alignment. To extract the proxy behavior, we use the techniques defined in [SZA20]. First, we discover a Petri net from each log with the inductive miner (noise threshold 0.2). Then, we followed [SZA20] to obtain the proxy log using five techniques: 1) Simulation: The proxy behavior is derived by simulating the process model. 2) Clustering: Using a K-medoid method, the traces are partitioned into K

different clusters using control-flow information. Then, from each cluster, a single trace is chosen as a cluster representative. The value of K is dynamic, calculated as 1/10 of the unique number of variants in the event log. 3) Random: Traces are randomly selected for the proxy behavior. 4) Frequency: The traces are selected based on their frequency in the log. 5) Reduced: First, a subset of activities is chosen (activity selection). Then, the proxy behavior is generated from traces that contain these activities. We used the implementation of [SZA20] to generate the proxy behavior.

Under all configurations, we employed the same sample of 100 traces from the input log. All these traces turned out to represent different trace variants. For our trie-based approach, the search *budget* was set to $100K$ and meta-heuristic optimization was done with a *frequency* parameter of 100. Then, we kept changing the configuration until either a low error was achieved or the runtime of the baseline was exceeded. Runtime measurements were averaged over five runs on a system with an Intel Core i7-10510U CPU at 1.80GHz with 16GB RAM on Windows 10 with Oracle Java 1.8.

Metrics. We assess the deviation in alignment cost of our approach, compared to the baseline, using the mean absolute error (MAE). Also, we compare runtimes (in ms). However, the way our approach finds alignments is fundamentally different from the baseline. In our approach, we follow synchronous moves without exploring possibilities of asynchronous ones. This leads to longer prefixes and, respectively, infixes matches between the input trace and the proxy behavior, but might lead to much different suffixes. This, in turn, will affect the alignment cost. We later demonstrate this effect through concrete examples. Finally, we study the deviation distribution [BvW20] across alignments found by our approach and the baseline.

Datasets. Our experiments were based on five real-world datasets. Four of them originate from the BPI challenges: BPI 2012,[1] BPI 2015,[2] BPI 2017,[3] and BPI 2019.[4] Additionally, an event log containing events of sepsis cases was used.[5]

Table 8 describes the generated proxy behavior and the sampled logs. Also, we report the number of nodes in the respective trie (size) and the reduction compared to the set-based representation of the proxy behavior used by the baseline.

Implementation. We implemented our approach to approximate conformance checking in Java. The source code along with data and experimental results is available on Github.[6] For the baseline, we used the implementation presented in [SZA20]. However, the source code is included in our repository, as we had to isolate the parts of the code that are relevant to our experiments. To enable a fair

[1] `https://doi.org/10.4121/uuid:3926db30-f712-4394-aebc-75976070e91f`
[2] `https://doi.org/10.4121/uuid:31a308ef-c844-48da-948c-305d167a0ec1`
[3] `https://doi.org/10.4121/uuid:5f3067df-f10b-45da-b98b-86ae4c7a310b`
[4] `https://doi.org/10.4121/uuid:d06aff4b-79f0-45e6-8ec8-e19730c248f1`
[5] `https://doi.org/10.4121/uuid:915d2bfb-7e84-49ad-a286-dc35f063a460`
[6] `https://github.com/DataSystemsGroupUT/ConformanceCheckingUsingTries/`

	Proxy behav.	#Traces	Min. trace	Max. trace	Avg. trace	#Events	Trie size	Reduct.	Trie constr. (ms)
BPI 2012	Sim.	10K	4	29	19	194373	114355	41%	2165
	Clust.	3930	6	175	38	166513	56929	66%	1199
	Random	3950	3	175	38	164560	55446	66%	1022
	Freq.	436	3	127	36	15981	6837	57%	138
	Reduced	4367	3	175	38	182084	60373	67%	1196
	Sampled	100	3	127	38				
BPI 2015	Sim.	10K	15	41	28	289963	237351	18%	2562
	Clust.	140	3	81	44	6272	5073	19%	80
	Random	140	3	81	45	6302	5106	19%	66
	Freq.	15	34	71	52	783	677	14%	9
	Reduced	156	34	71	52	7014	5643	20%	93
	Sampled	100	21	71	50				
BPI 2017	Sim.	10K	6	41	25	261953	153691	41%	3793
	Clust.	14338	10	180	48	699751	259656	63%	9132
	Random	14422	10	180	48	698997	257857	63%	8750
	Freq.	15931	12	180	45	71818	32373	55%	1256
	Reduced	15931	10	180	48	768942	276914	64%	9555
	Sampled	100	10	44	180				
BPI 2019	Sim.	10K	2	28	7	85712	16621	81%	1616
	Clust.	10782	2	990	17	301550	188941	37%	2661
	Random	10848	1	990	11	302048	190647	37%	1850
	Freq.	1197	1	923	14	36909	28521	23%	212
	Reduced	11974	1	990	13	338226	213316	37%	2532
	Sampled	100	1	990	13				
SEPSIS	Sim.	10K	1	11	3	56723	19399	66%	1406
	Clust.	85	3	59	8	1082	544	50%	58
	Random	766	3	185	8	12482	6104	51%	236
	Freq.	84	3	24	8	1046	522	50%	23
	Reduced	847	3	185	8	13745	6605	48%	1216
	Sampled	100	3	59	8				

Table 8: Proxy behavior and respective tries: Size and construction time, for the datasets using the different generation algorithms

comparison, for the baseline approach, we terminate the computation for a trace once a perfect alignment with an execution sequence in the proxy behavior was found. To ensure repeatability of the experiments, we fixed a seed for the random number generator that is invoked in the meta-heuristic optimization.

4.2.2. Experimental Results

Table 9 summarizes the runtime and MAE of our approach in comparison to the baseline. For each log, we report the performance for the different proxy behavior generation methods. For our approach, we report at most three different configurations of the budget and frequency to alternate between exploitation and exploration. The default configuration allows a maximum of $100K$ iterations and a jump to exploration every 100 iterations. Next, we change the alternation fre-

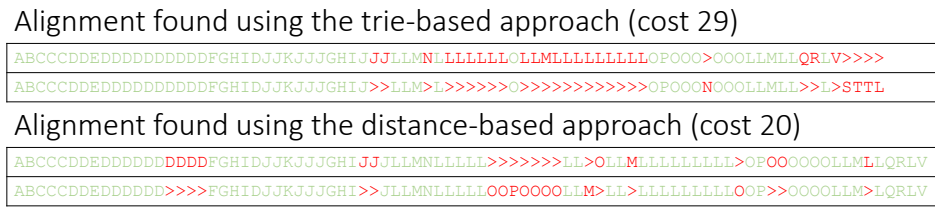


Figure 20: Alignments found by the different algorithms

quency and/or the budget. We stop in case we get a MAE under 5 or we exceed the runtime of the baseline approach. The best results per setting are highlighted in bold font.

In most of the cases, the default configuration is at least one order of magnitude faster than the baseline with a MAE close to 0. Upon investigation, there is a large overlap between the behavior in the sampled log and the proxy behavior. In this case, the strength of logarithmic search space reduction of using tries pays off and our approach is able to compute the alignment much faster. This is the case for the BPI 2012, 2019, 2017, and the SEPSIS logs.

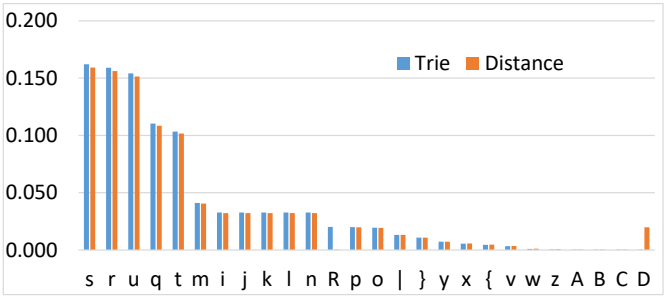
In some cases, the default configuration comes with a relatively high MAE. For instance, using simulation or clustering on the BPI 2015 log results in a MAE of around 10 and 13, respectively. The error is slightly enhanced by increasing the budget and allowing more exploration, e.g., using $8M/1K$, for simulated proxy behavior of BPI 2015.

A similar, relatively high MAE occurs with BPI 2017 and BPI 2019 using simulation and clustering. However, the error improvement is much better. For the case of BPI 2017, using clustering, the error goes down to 5.6. In our experiments, we achieved lower errors, but for a much higher budget, so that the runtime exceeded the one of the baseline. In the case of BPI 2019, we can achieve a MAE below 1 with four orders of magnitude lower runtime than the baseline.

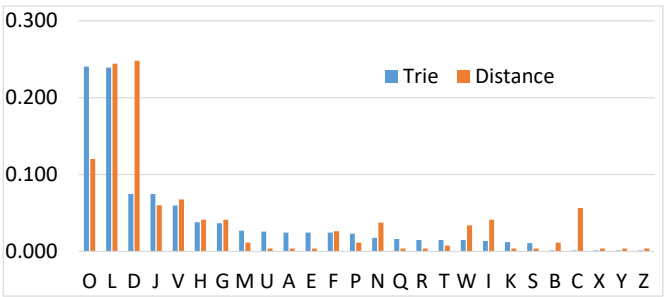
Our approach, in some cases, will construct alignments that are more expensive than those found by the baseline due to the emphasis on computing longer prefixes and infixes. For example, Figure 20 shows alignments found by our approach and the baseline for the same input trace. Clearly, the trie-based approach finds longer prefixes, which might lead to alignments with higher costs. However, these longer prefixes might also be more meaningful from a business perspective.

To further analyze the performance of the two approaches, we report the deviation distribution across activities that are involved in asynchronous moves. In Figure 21a, we show the deviation distribution with an MAE of 0 (Table 9) for proxy behavior obtained by simulation over BPI 2019. Here, the two approaches provide the same deviation distribution, except for a single outlier related to activity D.

Figure 21b, in turn, shows differences in the distributions for proxy behavior obtained by clustering on BPI 2017. This can be attributed to the relatively large MAE of 7 (Table 9). However, even in that case, several activities that are often involved in deviations can be identified accurately.



(a) Proxy log obtained by simulation on BPI 2019 with MAE of 0



(b) Proxy log obtained by clustering on BPI 2017 with MAE of 7

Figure 21: Deviation analysis results

Both our approach and the baseline [SZA20] are approximate conformance checking techniques that are based on some proxy behavior of the process model. Yet, the baseline technique will find an optimal alignment w.r.t this proxy behavior and, therefore, serves as a lower bound for the approximation error of our approach compared to the optimal alignment cost with the complete model behavior. To quantify the overall approximation error, we used the Rapid Miner tool to discover a Petri net (using heuristic miner) for the BPI 2015 log. The miner guarantees a fitting model, so that all traces of our sample have an alignment cost of zero, we used the ILP log replayer plugin of Rapid Miner. We compare these results against the alignment costs obtained with the approaches for approximate conformance checking based on proxy behavior. Figure 22 illustrates the MAE for these approaches against the optimal alignments for the whole model behavior. Both approximation approaches are sensitive to the sampling of proxy behavior. While our approach increases the error for simulated, clustered, and frequency-based proxy behavior, it yields the same error for random and reduced proxy behavior, which also induces the smallest total error.

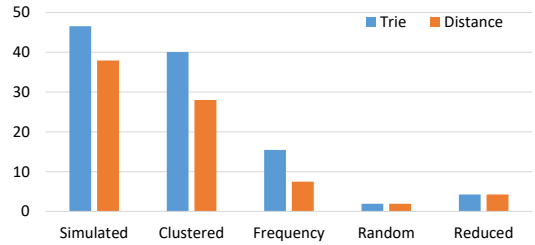


Figure 22: MAE of our approach and the baseline compared to optimal alignments.

4.3. Summary

In this chapter, we set off to find a data structure that can be used for efficiently computing alignments in conformance checking. We introduced an efficient approach using the trie data structure to compute alignments of logs with reference processes. The construction of the trie assumes the existence of a proxy log – a subset of allowed behavior within the process. We augment the trie data structure with node and edge annotations that would provide beneficial when using the trie for alignment computation. The main source of efficiency of the trie data structure is the compact representation of the proxy behavior of the process as well as the utilization of tries to reduce the search space.

A limitation of our approach comes from the fact that a trie is not the ideal structure for describing loops and parallelism. While in practice unfeasible, Petri Nets allow for theoretically infinite process models, while the trie data structure would need to be bounded to a certain number of loop iterations.

We also introduced an algorithm capable of computing approximate alignments in an offline setting. We applied meta-heuristics techniques to speed up the reaching of better alignments, by defining search budgets and alteration between exploitation and exploration. Experimental evaluation shows promising results compared to other string-based alignment computation. One of the downsides of our approach is that it tries to compute longer trace prefixes and infixes. This results in higher alignment cost for our method. However, the MAE against the baseline approach is generally comparable and a bigger impact on the error results from the selection of proxy behavior. Most importantly, our method achieves a considerable improvement in runtime, in some cases the runtime is reduced by up to two orders of magnitude with a modest estimation error.

As a conclusion, we see that the trie data structure can be an efficient data structure for computing alignments. This is an important takeaway, as we move on to compute alignments on top of event streams, where latency becomes a key factor when looking at the applicability of an approach.

	Proxy behav	Edit Dist. Runtime	Trie Conf. 1 Error	Trie Conf. 1 Runtime	Trie Conf. 2 Error	Trie Conf. 2 Runtime	Trie Conf. 3 Error	Trie Conf. 3 Runtime
BPI 2012	Sim.	354887	**100K/100**					
			0.98	**24750**				
	Clust.	337212	100K/100		100K/29		1.5M/97	
			4.3	5526	3.8	5785	3	331199
	Random	44748	100K/100		**100K/29**			
			0.6	531	**0.4**	**503**		
	Freq.	5319	**100K/100**					
			0.88	**1886**				
	Reduced	25045	**100K/100**					
			0	**32**				
BPI 2015	Sim.	136903	100K/100		500K/100		8M/1K	
			9.56	1936	9.3	8216	8.68	132757
	Clust.	3088	100K/100		1M/100k/29			
			12.75	2141	12.06	2785		
	Random	701	**100K/100**					
			0	**38**				
	Freq.	476	100K/100		30K/19		6M/19	
			8.1	209	7.93	353	1	858992
	Reduced	743	**100K/100**					
			0	**17**				
BPI 2017	Sim.	468457	**100K/100**					
			0	**15876**				
	Clust.	1169135	100K/100		100K/29		5M/97	
			6.89	3120	6.88	3915	5.6	437403
	Random	250833	**100K/100**					
			0.35	**868**				
	Freq.	29298	**100K/100**					
			1.09	**817**				
	Reduced	272785	**100K/100**					
			0	**1572**				
BPI 2019	Sim.	632717	**100K/100**					
			0	**10065**				
	Clust.	2100000	100K/100		100K/29		3M/13	
			9	4682	8	14995	3.28	1199590
	Random	720000	100K/100		**100K/29**			
			1.3	533	**0.7**	**792**		
	Freq.	27940	100K/100		100K/29		**2M/13**	
			0.3	390	0.18	446	**0**	**15292**
	Reduced	48312	**100K/100**					
			0	**15**				
SEPSIS	Sim.	16370	100K/100		**100K/29**			
			0.09	6162	**0.05**	**4905**		
	Clust.	346	**100K/100**					
			0	**24**				
	Random	1756	**100K/100**					
			0.01	**44**				
	Freq.	348	**100K/100**					
			0.2	**329**				
	Reduced	1292	**100K/100**					
			0	**7**				

Table 9: Runtime and MAE of the trie-based approach against the edit-distance-based approach for alignment computation

5. I WILL SURVIVE - STREAMING CONFORMANCE CHECKER

Conformance checking originates in the static setting, where event logs are collected from the business systems and analyzed offline. While offline analysis can be highly valuable and often sufficient for organizations, there are use cases that offline analysis cannot adequately address. For example, consider an organization with thousands of ongoing process executions occurring at the same time. The organization needs to detect deviations and act upon them in a timely manner, as the relevance of analyzing past data diminishes over time. This and other similar time-critical scenarios have paved the way for **streaming conformance checking**, where conformance checking is done *online* on infinite event streams rather than logs [Bur22a]. Reporting about deviations follows an event-driven fashion to allow process analysts to take action as early as possible. While the underlying goal is the same – finding discrepancies between modeled and real-life behavior – the termination of a single process execution is unknown in an online setting, given that the event stream is unbounded. Thus, computationally efficient algorithms are necessary to keep up with the incoming data.

While efficient algorithms exist for online conformance checking, they do not use alignments as their output [BC17; Bur+18; Lee+21], i.e., they do not provide as output a mapping between the event streams and the process model. At the same time, methods using prefix-alignments have been introduced for conformance checking [Zel+19; SZ20], but their computational complexity hinders their applicability in real-life streaming settings.

This chapter introduces a new efficient algorithm for streaming conformance checking. We first introduce the approach by having a look at the underlying data model. Our approach is based on the trie data structure, as discussed in Chapter 4. However, we introduce new components, such as the state buffer, decay time, discounting factor, and look-ahead limit, for the method to be capable of handling event streams in an efficient way. We then introduce the *I Will Survive* (IWS) algorithm and discuss its space and time complexities. Then, we run a comparative analysis against the state of the art, using both real-life and synthetic datasets, measuring the computation time and error rate. Furthermore, we run a stress test to validate the algorithm's applicability for the streaming setting by measuring the CPU and memory usage. The work in this chapter is based on the work in [RTA23] and deals with RQ2: *How can we leverage the new data structure (RQ1) and apply it for computing alignments in a streaming conformance checking setting?*

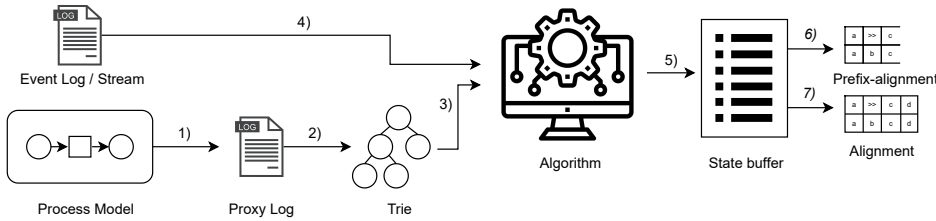


Figure 23: Approach overview.

5.1. Approach

The first steps in the approach follow the pattern as described in Chapter 4. The process model is simulated in step (1) into a proxy log. From the proxy log, step (2) constructs a trie T. The trie is computed offline in the pre-processing step and is considered immutable as the algorithm executes. That is, the underlying process is not expected to change during the conformance checking.

The trie is given as input to the algorithm in step (3) when the algorithm is initialized. In step (4), the algorithm expects an event coming from an event log or event stream and consisting of a caseID and an event activity. The algorithm checks for conformance and stores a list of states – a *state buffer* – for each caseID in step (5). Finally, two optional steps are step (6), for fetching the latest prefix-alignment for a case, and step (7), for calculating and fetching a complete alignment, that is permissible by the state buffer. For the purposes of this contribution, fetching complete alignments is out of scope as we aim to produce prefix-alignments in the context of event streams.

5.1.1. Data Model

In a streaming setting, the events are expected to be processed one by one in the temporal order. Furthermore, it is common that multiple cases are ongoing simultaneously, meaning that events coming in belong to different cases. The algorithm needs to keep track of the seen cases and their states while performing optimizations for low memory consumption. For handling these demands, we augment the definition of state from the previous contribution, and introduce the definitions for the decay time, state buffer, and look-ahead limit.

Definition 9 (State)**.** *A state s is a tuple* $(n, \hat{\gamma}, \hat{\sigma}, \delta(\hat{\gamma}), dt)$*, where n is the current node in the trie,* $\hat{\gamma}$ *is the prefix-alignment up to this node,* $\hat{\sigma}$ *is the trace suffix,* $\delta(\hat{\gamma})$ *is the total cost of the current state, and dt is the associated decay time of the state.*

Definition 10 (Decay time)**.** *Decay time dt is a value in the set of natural numbers* $dt \in \mathbb{N}$*. s.dt is then the* decay time *associated with a particular* state*. With every arrival of a new event within the scope of state s,* $s.dt = s.dt - 1$*. Let S be the set of states kept in memory. If* $s.dt < 1$*, then* $S = S \setminus \{s\}$*.*

Definition 11 (State buffer)**.** *Let S be the set of states associated with a case* $\in$

(1)

σ	co	cs	cs	ad
π	co	cs	$\gg$	ad

(2)

σ	co	cs	$\gg$	cs	ad
π	co	cs	wr	cs	ad

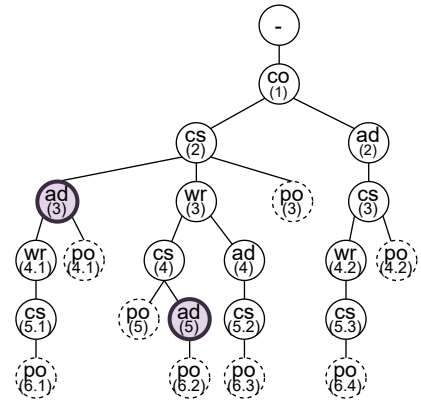


Figure 24: Running example: two optimal prefix-alignments and the corresponding nodes in the trie.

$\mathscr{U}_{case}$, *while* $\mathscr{P}(S)$ *is the powerset of all the sets of states. The* state buffer B *is then a mapping* $B : \mathscr{U}_{case} \mapsto \mathscr{P}(S)$.

The state holds the information necessary for the algorithm to compute the conformance. Let us return to our running example and assume that we have seen the trace $\sigma = \langle co, cs, cs, ad \rangle$. The optimal prefix-alignments and the corresponding nodes of the current state in the trie are shown in Figure 24. The most recent optimal states s would thus have the current node $n = ad_3$ and $n = ad_5$, as these are the model paths in the prefix-alignments. The suffix $\hat{\sigma} = \emptyset$ for both states, since $\hat{\gamma}$ contains the latest seen event *ad* and no event currently remains to be processed. The total cost $\delta(\hat{\gamma}) = 1$. The decay time dt value is determined by a hyperparameter, as discussed next.

We distinguish between two modes for initializing dt: **Fixed decay time** denotes a pre-determined integer for each new state. For example, all new states are initialized with $s.dt := 5$. This is effectively a case-based tracker (watermark) of event progress. **Discounted decay time** relies on the presumption that deviations near the beginning of a trace are more costly than deviations near the end of a trace [BCC21a]. The equation for calculating the discounted decay time is given in Equation 5.1.

$$Max(\lfloor(\overline{T_{leaf}} - i) * df\rfloor, min_{dt}) \tag{5.1}$$

The hyperparameters are the *discounting factor* df and a *minimum decay time* min_{dt}. The average length from the root of the trie to each of the leaf nodes is marked by $\overline{T_{leaf}}$, and the current length of the trace is indicated by i as in $\sigma(i)$, where i indicates the i-th event of σ.

To illustrate, the default values set for the algorithm in this contribution are $df = 0.3$ and $min_{dt} = 3$. If $\overline{T_{leaf}} = 100$, then for $i = 1$, i.e. the first event of a trace, $dt = Max(\lfloor(100-1) * 0.3\rfloor, 3) = 30$. For $i = 50$, $dt = 15$. For $i > 86$, $dt = 3$, as dt will effectively remain at the value set for min_{dt}.

Arriving event	State id	n	$\hat{\gamma}$	$\hat{\sigma}$	$\delta(\hat{\gamma})$	dt
co	0	-	-	$\langle co \rangle$	0	2
	1	co_1	(co,co)	-	0	2
cs	0	-	-	$\langle co, cs \rangle$	0	1
	1	co_1	(co,co)	$\langle cs \rangle$	0	1
	2	cs_2	(co,co)(cs,cs)	-	0	2
cs	2	cs_2	(co,co)(cs,cs)	$\langle cs \rangle$	0	1
	3	cs_2	(co,co)(cs,cs)(cs,≫)	-	1	2
	4	cs_4	(co,co)(cs,cs)(≫,wr)(cs,cs)	-	1	2
ad	3	cs_2	(co,co)(cs,cs)(cs,≫)	$\langle ad \rangle$	1	1
	4	cs_4	(co,co)(cs,cs)(≫,wr)(cs,cs)	$\langle ad \rangle$	1	1
	5	ad_3	(co,co)(cs,cs)(cs,≫)(ad,ad)	-	1	2
	6	ad_5	(co,co)(cs,cs)(≫,wr)(cs,cs)(ad,ad)	-	1	2

Table 10: Running example: state buffer with a fixed decay time of 2.

The *State Buffer* is updated with the arrival of every new event *evt* for *case*. The current states of the *caseID* are appended with the new event activity. That is $\forall s \in B(case)\ s.\hat{\sigma} = s.\hat{\sigma} \cup \{evt.act\}$. From each State $s \in S$, the associated costs for adding *act* are calculated. New states with the least cost are added to the *state buffer*.

Table 10 and Figure 25 show an example. Activities co, cs, cs, ad arrive for a case and the states are calculated based on traversing the trie. *co* is the first activity for this case, thus the root state with id 0 is added to the *state buffer*; *co* is a child of the trie's root, so the state with a synchronous move (co, co) is also added to the *state buffer* with state id 1 (step *I* in Figure 25).

Even though only new states with the least cost are included, preserving a *state buffer* puts strain on the memory, as with each new event arrival, we need to store at least one, but possibly many new states in the buffer. Thus, the *Decay Time* is decremented on each new event arrival for the associated *caseID*.

Lastly, the algorithm includes the *look-ahead limit* for speeding up calculation time in case model moves are needed.

Definition 12 (Look-ahead limit)**.** *Let* $|\hat{\sigma}|$ *be the size of the trace suffix, and* $s.n.level$ *the level of the current state's node in the trie. Then, the* look-ahead limit $lim = |\hat{\sigma}| + s.n.level + 1$.

The *look-ahead limit* is used for handling model moves, which are more complex in a streaming setting, as the algorithm has to assume the model move is at least as useful as making a log move. To limit a potentially costly traversal, a model move should be realized iff we get a full substring match to $\hat{\sigma}$ in the paths below $s.n$ such that the first matching node is at most at the level lim.

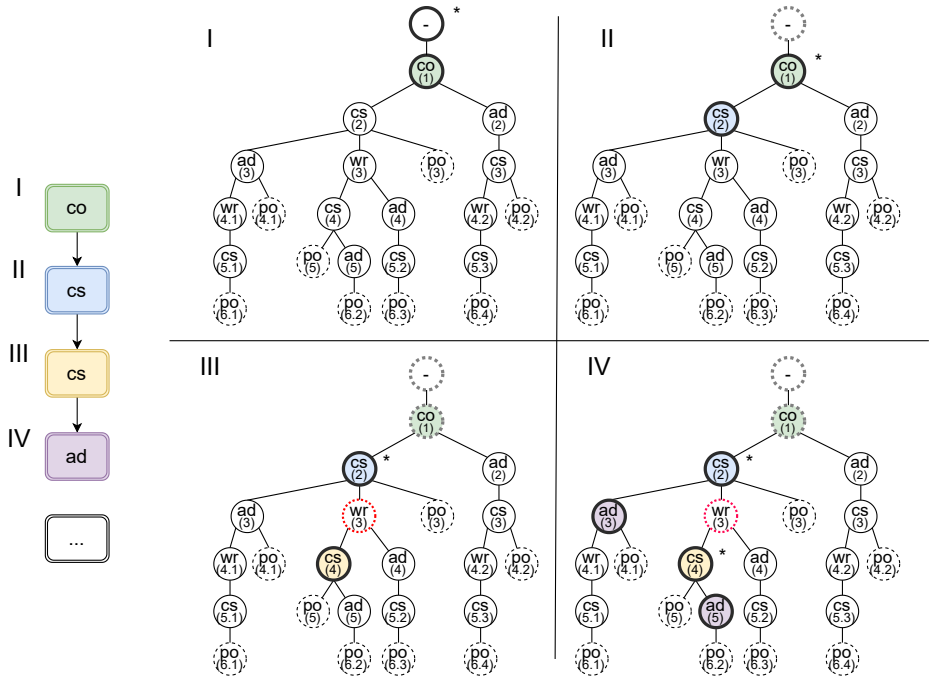


Figure 25: Colored trie nodes follow the color of trace events. Red dashed border points to a model move. Thick black border means the state with alignment ending at this node is still in the state buffer. Gray dashed border indicates that the corresponding state has been removed from the buffer. Asterisk to the right of a trie node means it is a member of state with non-empty suffix.

Table 10 shows that, in our running example, when receiving the second *cs* event, the state $id = 2$ cannot make a synchronous move, as it is at node $n = cs_2$. $|\hat{\sigma}| = 1$, as the suffix that needs to be replayed contains the event *cs*. $s.n.level = 2$, as the node is 2 steps from the *root* node. The look-ahead limit for state $id = 2$ is thus $lim = 1 + 2 + 1 = 4$. This indicates that the algorithm should attempt to make model moves iff it gets a substring match on event *cs* at most 4 steps from the *root*. From Figure 26, it can be deduced that the node cs_4 is the only viable model move path to get a synchronous move on the second *cs* event.

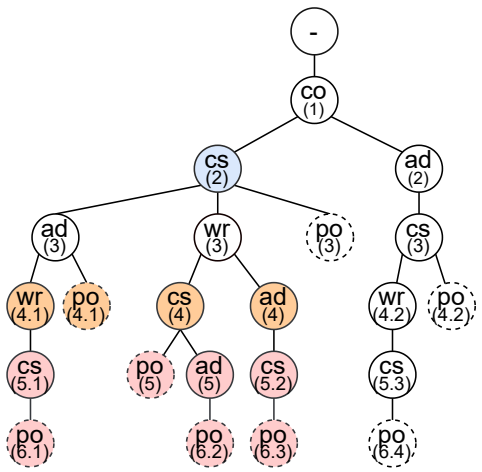


Figure 26: Running example: look-ahead limit for $id = 2$ when the second *cs* event arrives. The current node is in blue, the look-ahead limit in orange, and out-of-scope nodes in red.

5.1.2. Algorithm

The pseudo-code for the IWS algorithm is listed in Algorithm 2. The algorithm takes as input the event *evt* and the trie T.

First, the algorithm initializes some placeholder empty sets of states (Lines 1-3). If the *caseID* is in the state buffer, then the states associated with the *caseID* are fetched and assigned to the set S; otherwise, the initial state with the root node of the trie is added to S (Lines 4-7). In the running example (Table 10), this is when state id 0 is generated.

Then, the algorithm iterates over all the states in the state buffer and attempts to make a synchronous move based on the event activity (Lines 8-9). Utilizing the trie, the synchronous move check is straightforward — the event activity should be a child of the current node of the state. New states are generated for each state where a synchronous move is possible (Line 10). As an example, this occurs for both events *co* and the first *cs* in the running example.

If no synchronous moves were possible, the states are looped over once more to generate non-synchronous moves and the affiliated states. This part of the al-

Algorithm 2 I Will Survive

Input: evt, T
1: $S \leftarrow \emptyset$
2: $S_{sync} \leftarrow \emptyset$
3: $S_{nonsync} \leftarrow \emptyset$
4: **if** $evt.case \in B$ **then**
5: $\quad S \leftarrow B(evt.case)$
6: **else**
7: $\quad S \leftarrow \{rootstate\}$
8: **for each** $s \in S$ **do**
9: $\quad$ **if** $s.syncPossible(evt.act)$ **then**
10: $\quad\quad S_{sync} \leftarrow generateSynchronousStates(s, evt.act)$
11: **if** $|S_{sync}| = 0$ **then**
12: $\quad$ **for each** $s \in S$ **do**
13: $\quad\quad S_{nonsync} \leftarrow S_{nonsync} \cup handleLogMove(s, evt.act)$
14: $\quad\quad S_{nonsync} \leftarrow S_{nonsync} \cup handleModelMoves(s, evt.act)$
15: $\quad S_{nonsync} \leftarrow applyCostFilter(S_{nonsync})$
16: $S \leftarrow housekeep(S) \cup S_{sync} \cup S_{nonsync}$
17: $B.S \leftarrow S$
18: *Return* $\hat{\sigma}$

gorithm is explored with the arrival of the second *cs* in the running example. Handling log moves is simple, as the arrived event activity is simply appended as a log move, and no traversal in the trie is necessary (Line 13). The state id 3 is constructed in this phase. Handling model moves (Line 14) is the most complex part of the algorithm, as multiple model moves may be possible and have the same cost. The state id 4 is constructed when executing the handling of model moves. A more detailed description of handling model moves is described in Algorithm 3. Once the non-synchronous moves are generated, a cost filter is applied to keep only the states with the lowest added cost (Line 15). This is most relevant when the decay time is longer, there are many states in the state buffer, and some of the states find more optimal paths than other states.

In the final part, the old states receive housekeeping as the associated decay time is updated, and states that have exhausted the decay time are removed from memory (Line 16). For example, if the algorithm has processed the second *cs*, then states with ids 0 and 1 (Table 10) are removed. An optional limit, defined during the algorithm's initialization, checks if the number of cases in the state buffer is more than allowed; if yes, the case that has not received an update for the longest time is removed from the state buffer. Thereafter, the state buffer is updated with the housekept old states and newly generated states (Line 17). Ultimately, the latest prefix-alignment is returned (Line 18).

The algorithm for model moves (Algorithm 3) expects a state and an activity as input. First, the event activity is appended to the state suffix to ensure that any unprocessed activities are played out, and the result is stored in a variable $\hat{\sigma}_{check}$ (Line 1). Referring to the example in Figure 26 and state id 2 from Table 10, the state suffix is empty when the second *cs* arrives. Thus, $\hat{\sigma}_{check}$ will consist of only the activity *cs*.

An empty set is initialized for holding potential model moves (Line 3), and

Algorithm 3 Handle Model Moves

Input: s, act
1: $\hat{\sigma}_{check} \leftarrow s.\hat{\sigma} + act$
2: $lim \leftarrow |\hat{\sigma}_{check}| + s.n.level$
3: $S_{model} \leftarrow \emptyset$
4: $N_{children} \leftarrow s.n.children$
5: $N_{matched} \leftarrow \emptyset$
6: **while** $lim > s.n.level$ **do**
7: $\quad N_{matched} \leftarrow matchSubstring(N_{children}, \hat{\sigma}_{check})$
8: $\quad$ **if** $|N_{matched}| > 0$ **then**
9: $\quad\quad$ **break**
10: $\quad lim \leftarrow lim - 1$
11: $\quad N_{children} \leftarrow n.children \; \forall n \in N_{children}$
12: $\quad$ **if** $lim = 0$ *and* $|\hat{\sigma}_{check}| > 1$ **then**
13: $\quad\quad prune(\hat{\sigma}_{check})$
14: $\quad\quad N_{children} \leftarrow s.n.children$
15: **if** $|N_{matched}| > 0$ **then**
16: $\quad$ **for each** $n \in N_{matched}$ **do**
17: $\quad\quad S_{model} \leftarrow constructStates(n)$
18: Return S_{model}

the look-ahead limit is initialized (Line 2) with the parameters defined in Definition 12. For the running example, $lim = 1+2+1 = 4$, meaning that the algorithm traverses maximally to a distance of 4 from the root node.

Two sets of nodes are initialized – children nodes (Line 4) are used for traversing in the trie, and matched nodes (Line 5) are used for potential storing of nodes that have a substring match. In the running example (Figure 26), the children nodes would be ad_3, wr_3, and po_3, which are direct children of the node cs_2 shown in blue. The matching nodes are initialized as an empty set.

The most exhaustive part of the algorithm is within the while loop (Line 6). All the children nodes are checked for a potential substring match (Line 7) and if matching nodes are found then the while loop is exited (Lines 8-9). Based on the running example, activity *cs* does not match the nodes ad_3, wr_3, or po_3. Thus, the look-ahead limit is decreased (Line 10) and new children nodes are assigned (Line 11). For the running example, the children nodes are now the nodes depicted in orange in Figure 26. A substring match is found between activity *cs* and the orange node cs_4, and thus the algorithm breaks out of the while loop.

If the look-ahead limit is exhausted, but there is more than one activity in the state suffix (Line 12), then the first element of the suffix is pruned, and the look-ahead limit is reinitialized with the new size. For an example of why these steps are needed, we introduce a different example in Figure 27. Here, a full substring match for activities $\langle c, x, y, z \rangle$ is not possible from node b. However, by removing activity c from $\hat{\sigma}_{check}$, we can get a substring match on $\langle x, y, z \rangle$ by doing a model move on the node q.

Finally, if matching nodes were found (Lines 15-17), then new states are constructed for each matching node by finding possible synchronous moves, model moves, and log moves. For the example in Figure 27, this would mean that our matching node is z, and we traverse by reversing the trace suffix $\langle c, x, y, z \rangle$. Here, z, y, and x are synchronous moves, and then model moves are needed until node

b is reached — that is, making a model move on node q. Finally, since activity c was previously pruned in order to get the substring match, the activity is reinstated as a log move.

In the last step, the matching nodes are returned to the main algorithm (Line 18). If no matching nodes were found, then an empty set is returned.

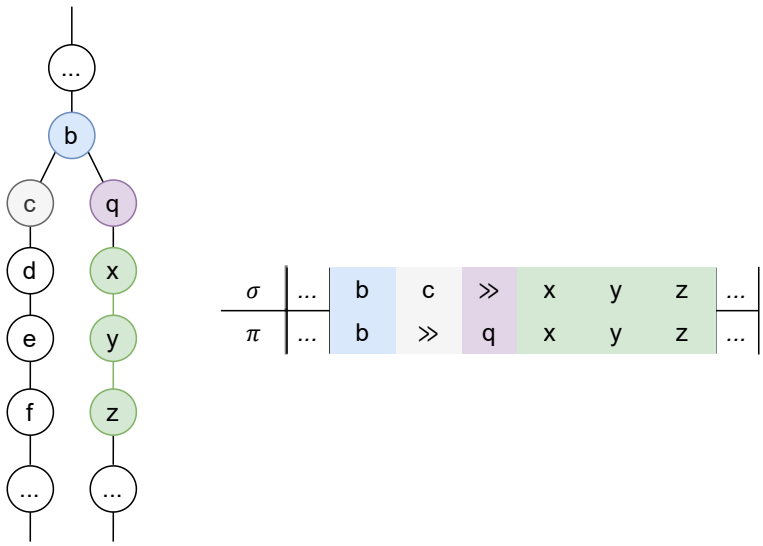


Figure 27: Example use case and resulting alignment for look-ahead limit's suffix pruning. The last synchronous node b is shown in blue; node c is synchronous but leads to a suboptimal path, while nodes x, y, z are more optimal but do not get a substring match if starting from node c.

Space complexity. The trie and the state buffer are the two objects that need to be stored in memory. The trie is static, i.e. it does not change during the execution of the algorithm, while the state buffer is continuously evolving based on the data stream. As described in Chapter 4, the trie is in the worst case linear to the size of the proxy log, $O(|L'|)$, indicating that each trace in the proxy log has a unique first activity. Usually, the trie is logarithmic compared to the proxy log size $O(log|L'|)$, because business processes have common prefixes (c.f. Figure 19). As discussed previously, the trie is computed beforehand and it is immutable.

The size of the state buffer depends on two factors, the number of cases $|\mathcal{U}_{case}|$ in the event stream, and the number of states stored for each case. The number of cases stored can be controlled by a simple limiting function that removes the cases that have not received an update for the longest time. The number of states per caseID is dependent on the branching factor (bf) of the trie and the deviation in the behavior between a trace and the trie. In the best case, when an alignment consists of synchronous moves, the state buffer grows as $O(|\mathcal{U}_{case}|.dt)$ that is because, for each newly arriving event, one new state is generated with a synchronous move. In the worst-case scenario, the states' growth can be equal to the bf, of the trie node, i.e. $O(|\mathcal{U}_{case}|.(bf+1).dt)$, we have only one possible log move but bf

model moves. Storage of previous states can be controlled by the decay time setting. Using a fixed decay time, there is a fixed upper bound on the number of states stored per case, that can be computed based on the precomputed trie. Using a discounted decay time, the upper bound is still dependent on the trie, while for each individual case, the upper bound diminishes as the case evolves.

Time complexity. For each newly arriving event, we fetch the relevant states in $O(1)$. We retrieve in the worst case $O(|\mathscr{U}_{case}|.(bf+1).dt)$ states, as discussed under space complexity. Synchronous and log moves can be done in $O(1)$. Handling model moves depends on the trie branching factor and the look-ahead limit. The look-ahead limit lim can be bounded by the decay time setting, e.g. the size of the trace suffix can never be longer than the decay time. That is, in the worst case, we need $O(bf.min(dt,lim))$ steps to define the new states to be added to the state buffer.

5.2. Experiments

In this section, we present the experiments that we conducted to validate the proposed approach.

All the executions were done on a single thread using Windows 10 running a CPU @ 1.60GHz, Java 8, and heap size set to 8GB.

The implementation in Java and the execution results are available in a git repository[1].

The following subsections first discuss the experimental results from the perspective of comparative analysis, comparing IWS to the state of the art in terms of computation time and error rate. Next, the algorithm is stress tested to see how it performs under load, particularly in terms of memory consumption.

5.2.1. Comparative Analysis

In the following, the same naming convention will be used as in Chapter 3. The current state of the art will be referred to as OCC with two variations: OCC-W1, referring to a window size of 1, and OCC-Winf, with infinite window size. OCC-W1 is the current state of the art in terms of computation time of prefix-alignments. However, due to the window size limitation, the output approximates the optimal alignment. The OCC-Winf provides the baseline for the alignment cost, as the algorithm has an infinite window size and is thus guaranteed to calculate an optimal alignment [Zel+19].

Some of the more recent alternative algorithms were excluded from the comparison, as they have not substantially improved the execution time, but have rather focused on memory-handling aspects. A direct comparison to the IAS algorithm introduced in [SZ20] would have been unfair, as the IAS is implemented

[1] `https://github.com/DataSystemsGroupUT/ConformanceCheckingUsingTries/tree/streaming`

in Python, whereas the OCC algorithms and IWS are implemented in Java. Based on [SZ20], the OCC-W1 implementation in Python outperformed IAS time-wise; while this could depend on the datasets used, the execution time differences were notable across all datasets in [SZ20], and thus we consider the deduction valid. The approach from [ZHD23] improves the memory performance of OCC, but it is built on top of the existing OCC by abstracting away a part of the previously calculated prefix-alignment. While the algorithms in [ZHD23] still output the cost of the prefix-alignment, they do not output the complete prefix-alignment itself, rendering a potential analysis of the deviation more obscure. Therefore, it was not considered for comparison with OCC and IWS, as both of them are able to output the entire prefix-alignment.

The comparative analysis aims to examine how IWS fares in terms of alignment cost and computation time. For calculating the computation time, only the time taken to process each event is taken into account. This is done to mimic a streaming scenario, where the loading of a model is done beforehand. The algorithms were executed in an *offline* mode for the experiments. The event log was loaded from a file and fed to the algorithm event by event. This was done to have a fair comparison because the OCC implementation would have needed extensive refactoring, and also, offline mode allows for avoiding discrepancies from networking or other external factors.

Datasets. Some well-known synthetic and real-life process logs were used for running the experiments. The synthetic process logs[2] also contained a reference WF-net process model. The real-life process logs were BPI 2012[3], BPI 2017[4], and BPI 2020 Travel Permits[5], which do not have an associated reference model.

The OCC takes as input an event and a WF-net model, while IWS requires an event and a trie. Thus, some preprocessing was applied to both the synthetic

[2] https://github.com/PADS-UPC/RL-align/tree/master/data/originals/M-models

[3] https://doi.org/10.4121/uuid:3926db30-f712-4394-aebc-75976070e91f

[4] https://doi.org/10.4121/uuid:5f3067df-f10b-45da-b98b-86ae4c7a310b

[5] https://doi.org/10.4121/uuid:52fb97d4-4588-43c9-9d04-3604d4613b51

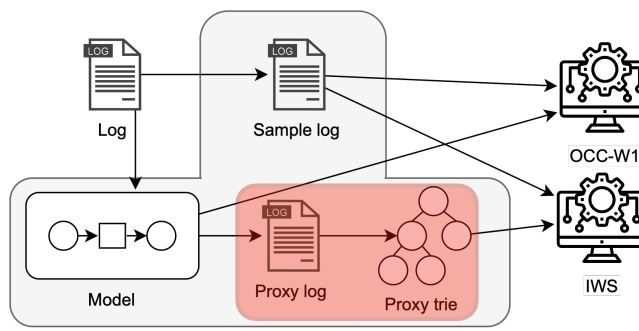


Figure 28: Setup: Gray (red) area shows the artifacts produced by the preprocessing for real-life (synthetic) logs.

and real-life datasets. The preprocessing for synthetic data is shown in Figure 28 with the red area indicating the steps done. For OCC, the existing log and model were used. For IWS, a proxy log was simulated from the reference model. The simulation method from [Van+12] was used with default settings of random path simulation, 2000 generated traces, and a maximum looping factor of 3. From the proxy log, the trie was constructed and fed into the IWS algorithm, together with the original log.

For the real-life data, the first step was to construct a process model from the log (Figure 28, shown in gray). For this, the Inductive Miner (IM) [LFV13] plugin in ProM [Van+05] was used with noise thresholds set to 0.2, 0.5, 0.8, and 0.95. For the generation of the trie, the same steps with the same settings were done as for the synthetic data. Finally, while running the experiments, it appeared that the OCC algorithms were unable to output a result due to the size of some of the original logs. Thus, sample logs of the 1000 most frequent trace variants were generated, and the algorithms used the sample logs instead of the original logs.

Information about the logs and models used in the experiments is shown in Table 11. Transitions and τ transitions refer to the WF-net model characteristics.

Dataset	**Transitions**	**τ transitions**	**Trie nodes**	**Trie constr. time (ms)**	**# events**
M1	39	3	8281	353	6555
M2	34	2	20742	407	8809
M3	123	14	26434	524	17980
M4	52	8	13261	512	13421
M5	33	1	49571	652	17028
M6	72	2	98781	1239	26719
M7	62	4	46481	812	18803
M8	15	0	1682	326	8246
M9	55	0	7223	576	22163
M10	146	3	87289	1197	29118
BPI 2012-0.2	46	22	3962	1659	33509
BPI 2012-0.5	46	23	1721	387	33509
BPI 2012-0.8	25	8	726	262	33509
BPI 2012-0.95	24	4	106	219	33509
BPI 2017-0.2	46	21	3338	276	32646
BPI 2017-0.5	29	8	192	150	32646
BPI 2017-0.8	32	7	69	163	32646
BPI 2017-0.95	31	6	69	152	32646
BPI 2020-0.2	85	37	23603	397	15810
BPI 2020-0.5	64	15	945	71	15810
BPI 2020-0.8	65	16	887	64	15810
BPI 2020-0.95	59	14	1591	235	15810

Table 11: Dataset metadata

Dataset	Cost per trace			Time per event (ms)		
	IWS	OCC-W1	OCC-Winf	IWS	OCC-W1	OCC-Winf
M1	5.8	5.4	4.9	0.3	1.3	1.9
M2	10.6	9.4	8.1	0.2	6.3	12.2
M3	23.9	-	-	0.6	-	-
M4	22.1	23.0	20.5	0.8	10.9	25.4
M5	26.0	-	-	0.8	-	-
M6	45.9	-	-	12.4	-	-
M7	29.2	-	-	0.6	-	-
M8	7.6	7.8	6.7	0.2	0.7	1.1
M9	29.2	26.1	20.5	0.7	19.6	32.8
M10	50.0	-	-	9.0	-	-
BPI 2012-0.2	27.1	0.8	0.3	0.3	2.0	3.8
BPI 2012-0.5	26.6	6.3	3.0	0.3	2.4	12.4
BPI 2012-0.8	28.3	26.1	16.8	0.3	1.2	5.3
BPI 2012-0.95	30.1	30.1	26.6	0.2	5.2	9.0
BPI 2017-0.2	26.1	4.4	1.7	0.3	3.5	9.9
BPI 2017-0.5	25.3	26.7	25.1	0.2	3.3	14.0
BPI 2017-0.8	28.6	29.0	25.4	0.2	3.2	10.7
BPI 2017-0.95	28.6	29.0	25.4	0.2	2.3	11.4
BPI 2020-0.2	12.1	6.5	5.2	0.3	4.6	7.3
BPI 2020-0.5	10.7	10.8	6.8	0.1	1.6	5.1
BPI 2020-0.8	10.3	11.2	8.7	0.1	1.8	7.6
BPI 2020-0.95	12.1	7.6	6.8	0.2	1.3	3.6

Table 12: Comparative analysis results.

Trie construction time indicates the time taken to construct the underlying trie based on the proxy log – the trie construction is done offline. The number of events indicates how many events are in each sample log.

Results. The results of the experiments are shown in Table 12. The average alignment cost per trace is reported for each dataset. For example, the M1 dataset has 500 traces, and the total alignment costs across the whole dataset were 2918, 2702, and 2439 leading to the average cost per trace of 5.8, 5.4, and 4.9 as described in Table 12. A time per event in milliseconds is reported in terms of computation time.

In terms of the synthetic datasets, in five instances, the OCC algorithms were left running for one hour, but no output was produced. These are marked with a - in the table. For other synthetic logs, the cost deviations of IWS were modest. The highest cost deviation was reported for the M9 log, where IWS reported a cost of 1.43x higher than the optimal alignment (29.2 vs 20.5). For M4 and M8, IWS outperformed OCC-W1 in terms of cost, and only had an error rate of 1.08x and 1.14x compared to optimal alignments.

In terms of execution time, the results are strongly in favor of IWS. In almost all cases, IWS was able to process an event in less than one millisecond, while OCC-W1 was able to process an event in less than a millisecond only for the dataset M8. The M8 dataset also exhibited the smallest difference in terms of execution time, as IWS finished execution 3.5x faster than OCC-W1. For M2, M4, and M9 datasets, IWS computed the result in only a fraction of the time compared to the OCC-W1 execution time. This is especially interesting in terms of dataset M4, where IWS outperformed OCC-W1 by both – producing alignments that were more optimal and finding these alignments more than 14.4x faster. For the datasets M3, M5, and M7, IWS computed alignments in 10-14 seconds, while the OCC algorithms were unable to output a result within 1 hour. This indicates an execution time difference of potentially more than three orders of magnitude.

Looking at the real-life datasets, the results were a bit more varied in terms of cost. IWS displayed an inferior cost performance for the BPI 2012 dataset, where the model was discovered with an IM threshold setting of 0.2. Here, IWS reported a cost 35.9x higher than OCC-W1 and 81.3x higher than optimal alignments, which would indicate an unreasonably high error. Some other poor results were for BPI 2012 with IM 0.5, and BPI 2017 with IM 0.2. However, for more than half of the datasets, the cost error was comparable between IWS and OCC-W1. In fact, for five datasets, IWS outperformed OCC-W1 by producing more optimal alignments; for BPI 2017 with IM 0.5, the cost difference between IWS and optimal alignments was only 1.01x.

In terms of execution time, IWS is the fastest across all datasets. The smallest difference is for BPI 2012 with IM setting 0.8, where IWS finished 4.6x faster than OCC-W1 and 19.5x faster than optimal alignments. The biggest execution time difference was for BPI 2012, with IM setting 0.95. Interestingly, for this dataset, both IWS and OCC-W1 had the same alignment cost, but IWS could compute the alignments 24.5x faster than OCC-W1.

Discussion. The results indicate that IWS is, in most cases, better suited for streaming conformance checking than the current state of the art (OCC-W1). IWS beats OCC-W1 in computation time and, in some cases, also in terms of finding more optimal prefix-alignments. However, there were a few cases in the real-life datasets where the cost error of IWS was very high compared to the state of the art. Let us investigate the reason for this with some examples from the BPI 2012 log.

First of all, the Inductive Miner, used for discovering the WF-net models, has a tendency to discover *flower models*[LFV13], i.e. models allowing any kind of

IWS alignment																			
	A	B	P	P	D	E	P	E	L	K	O	G	H	I	E	I	M	F	I
	A	B	P	P	≫	E	P	≫	≫	≫	≫	≫	≫	≫	≫	≫	≫	≫	≫

OCC-W1 alignment																																														
	A	B	P	≫	≫	P	≫	≫	D	≫	E	≫	P	≫	E	≫	L	≫	≫	K	O	≫	≫	G	H	I	≫	≫	≫	E	≫	≫	≫	≫	≫	≫	≫	I	≫	≫	≫	M	≫	≫	F	I
	A	B	P	τ	τ	P	τ	τ	D	τ	E	τ	P	τ	E	τ	L	τ	τ	K	O	τ	τ	G	H	I	τ	τ	τ	E	τ	τ	τ	τ	τ	τ	τ	I	τ	τ	τ	M	τ	τ	≫	I

Table 13: Example of a trace's prefix-alignment from BPI 2012 log with IM 0.2 threshold.

behavior, if the noise threshold is set to a low level. In such cases, the set of allowed behavior in the model is very large. IWS is dependent on the existence of a trie, which in turn is dependent on the existence of a proxy log – a set of behavior *extracted* from the model. The more behavior the model allows for, the more difficult it is to extract a representative proxy log.

One way to have a more representative proxy log would be to increase the size of the proxy log. However, for *flower models*, this may be infeasible. The WF-net model produced by IM for the BPI 2012 log with a 0.2 setting has 46 transitions, out of which 24 transitions are labeled and 22 are silent. The first two labeled transitions are fixed, but after that, due to the τ transitions, almost any of the 22 labeled transitions can occur. Due to loops, the following transition can be any of the 22 labeled transitions, including the label itself. Thus, with each new event, the possible behavior increases exponentially. For a trace with ten events, assuming the first two events are always sequential, there can be $2 + 22^8 = 54875873538$ possible variants. The BPI 2012 log has, on average, 33 events per trace. A simulation method to extract a proxy log that would not find deviations becomes impractical from a computational point of view. Furthermore, it can be argued that exercising conformance checking on a process model that allows any behavior has no intrinsic value since any kind of behavior is conforming.

An example prefix-alignment of the BPI 2012 log is shown in Table 13. The prefix alignment from the IWS algorithm is much shorter because the trie does not contain τ transitions. The OCC-W1 prefix alignment has many model moves on τ transitions, allowing it to find synchronous moves for almost every event in the trace. By convention, the τ transitions are not penalized and have an alignment cost of 0, as they are valid passages through the model. However, it can be argued that while the OCC-W1 alignment has a much lower cost – it has a cost of 1, compared to the IWS cost of 13 – the alignment itself becomes hard to decipher due to the many τ transitions and is hardly usable for an analyst trying to pinpoint deviations. Thus, such an alignment provides little value in a real-life setting. For reference, the worst cost error in the BPI 2012 log is for a trace with 170 events. IWS reports a cost of 164, while OCC-W1 reports a cost of 2. However, in the prefix alignment, OCC-W1 has 537 moves on τ transitions. In total, the output from OCC-W1 across the whole BPI 2012 log for the IM 0.2 model has 76172 τ transitions across the 1000 sample traces.

The comparative experiments did not touch upon a comparison of memory consumption, but it may provide an interesting extension to the conducted experiments. Based on the data structures and algorithms used, we may assume that the OCC methods have a lower initial strain on memory, but the strain increases as the stream progresses. This is because the trie used by the IWS is likely to be considerably larger than the Petri Net that the OCC uses. However, the OCC will construct a Synchronous Product Net for each trace, notably increasing the memory requirements. The IWS will, effectively, only add strain by the utilization of the state buffer, which can be bounded by the decay time settings. Importantly,

the approaches from [ZHD23] have already considered handling of memory consumption, and these methods should be considered in any evaluation of memory consumption. For the purposes of this work, we will validate the boundedness of the memory footprint of IWS on a fast-paced event stream, without a direct comparison to other methods.

In conclusion, IWS outperforms OCC-W1 in terms of computation time and is comparable or better in terms of cost error in most cases. If the model allows for a large variety of behavior, e.g., when dealing with *flower models*, then the cost difference between IWS and OCC-W1 is prominent, and for such models, OCC-W1 is better suited, especially if calculation time is not a constraint. Importantly, however, it can be argued that the alignments produced by the OCC-W1 for *flower models* are complex to grasp. Furthermore, computing conformance for models which allow any kind of behavior does not seem practical, as it is counterintuitive to the purpose of conformance checking.

5.2.2. Stress test

In order to test the algorithm for speed and memory consumption, the PLG2 software [Bur16] was used to simulate three process models of various sizes. PLG2 was further used to simulate a proxy log from these models and to stream events to the socket while adding some noise to the event stream so as to mimic discrepant behavior. An overview of the approach can be seen in Figure 29. The memory consumption was measured using the tool VisualVM [SH17].

A description of the process models generated by PLG2 and the resulting tries is in Table 14. The number of unique activities illustrates the complexity level of each of the models. The proxy log sizes were determined by squaring the activity count, except for the *Large* model, where the simulation was stopped at 25000 traces due to the long execution time of the simulation process.

The event streams were generated with the preset configuration of having noise only on the control-flow, indicating that traces had a 5% chance of missing activities. The streams were left running for an hour, with IWS set to forget cases when the number of cases in memory is over 10000.

The algorithm was successfully able to keep up with the stream. For the event

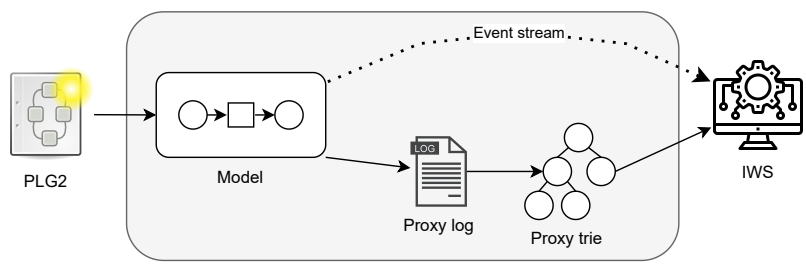


Figure 29: Setup for stress testing. The gray rectangle shows the artifacts produced by the PLG2 software.

Model type	Small	Medium	Large
Activities	16	153	471
Traces in proxy log	256	23409	25000
Trie nodes	841	713640	760343
Trie building time	1267	19934	101960
Computation time	833438	1244394	1541570
Idle time	2766562	2355606	2058430
Events	278063	365425	354602
Event Computation time	3.0	3.4	4.3

Table 14: Stress test: description of models and results. All times are expressed in milliseconds (ms).

stream on the small model, the algorithm was idle for $\frac{3}{4}$ of the time, signaling that higher throughput could have been achieved. For medium and large models, the algorithm was idle for $\frac{2}{3}$ and $\frac{4}{7}$ of the time, respectively.

As expected, the experiments using the small model had the least strain on the CPU and memory, with less than 5% of CPU utilized by the Java application running the algorithm and memory usage not exceeding 200 MB during the execution. The results for the small model are depicted in Figure 30. The figure includes a run on the same model with different algorithm and stream settings – a higher

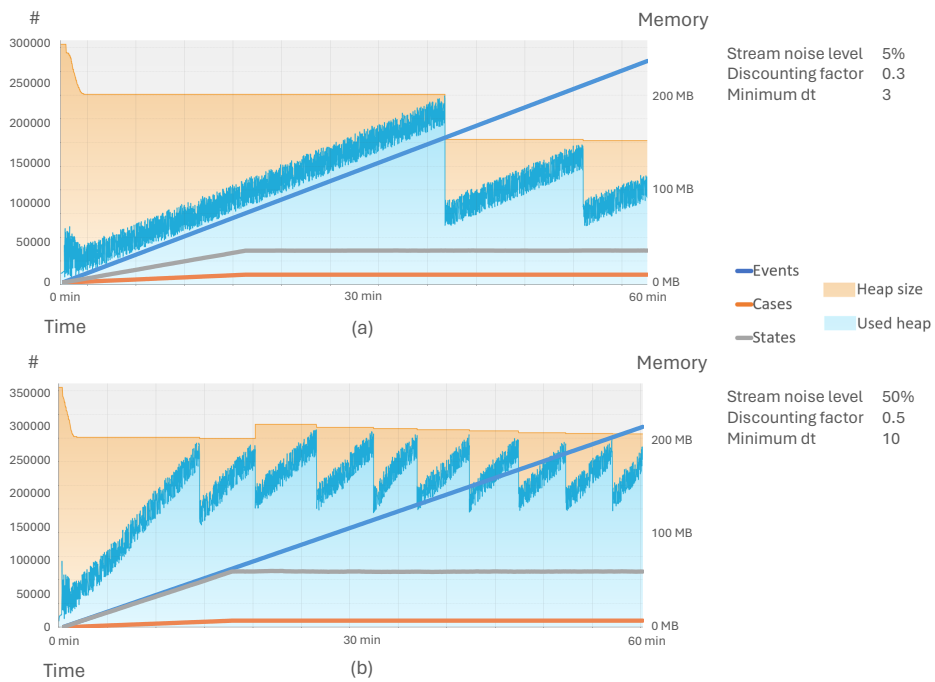


Figure 30: Memory consumption, number of events, states, and cases within one hour of stress test with two different stream and algorithm settings.

noise level, indicating more discrepant behavior, and higher decay time settings, forcing the algorithm to store more states in memory. As can be seen empirically, the number of states and the memory usage stabilizes and remains bounded due to the case limit and the usage of decay time in the state buffer, while for the higher noise and decay time, the sheer amount of states kept in memory is higher.

Memory usage for medium and large models was much higher – likely due to a higher amount of nodes in the medium and large tries and longer traces, which lead to more states being kept in memory. For the medium model, the memory usage was between 600-1600 MB, stabilizing at 900 MB with a slightly increasing upward trend, while for the large model, the memory usage was between 1500-2250 MB.

The CPU and memory usage results show that the IWS is usable for online conformance checking for an extended period of time. Notably, the current experiments incorporated only a simple case bound to remove processed traces from memory. For more complex options for handling the memory and limiting the cases, we refer to [ZHD23]. Such case and state management techniques can be used to extend the IWS algorithm. It would also be possible to set rules that define when memory should be flushed to disk.

5.3. Summary

This chapter introduced the trie-based streaming conformance checking algorithm IWS.

First of all, we looked at the augmentations done to the data model to support streaming conformance checking. We saw how the algorithm holds states in a state buffer that is used for guiding the algorithm in the optimal path. Decay time is used for releasing states from the state buffer, with discounted decay time containing the hyperparameters discounting factor and minimum decay time for having an increased state buffer size in the beginning of a trace, and dynamically decreasing the buffer size as the trace progresses. Furthermore, as model moves are the most expensive steps in the algorithm, we introduced a look-ahead limit for pruning the state space that needs to be explored for possible moves.

Then, we had a detailed look at the steps of the algorithm, followed by a discsussion of its space-time complexity. We showed that the time complexity is bounded by the decay time setting that can be defined during the initialization of the algorithm.

Next, in the experiments we compared the IWS to the state-of-the-art OCC algorithm for computing prefix alignments, using both real-life and synthetic datasets. In all instances, IWS outperformed OCC in terms of computation time. In one dataset, IWS had the same alignment cost as the state of the art, but 24.5x faster computation time. There were also datasets where the cost difference was notably large. However, based on a deeper analysis, it seems that this stems from the fact that some of the process models were flower models, where OCC was

able to compute an alignment with a very low cost, but many silent moves.

Finally, we also conducted a stress test to show the memory consumption of the algorithm. The stress test proved empirically that after awhile the memory consumption stabilizes and remains bounded due to the decay time releasing states from the state buffer.

Considering the streaming constraints from Section 2.3, the algorithm covers well *SC2* and *SC3*, as there is a limitation on memory usage, and at the same time the results of the analysis can be outputted at any given time. *SC1* is covered partially, as discrepant behavior can trigger backtracking and replay of events within the scope of the state's decay time. *SC4* is also covered only partially, as the only adaptive part of the algorithm is the discounted decay time decreasing as the trace size increases.

As can be seen from the experimental evaluation, a potential limitation of the IWS approach is the limited process behavior that the trie is capable of representing. However, for many datasets the limitation is nonexistent compared to the state of the art. Still, for highly complex process models that incorporate many loops, parallelism, and silent transitions, the trie data structure would need further refinement, which lies outside the scope of this thesis.

Ultimately, the algorithm displays very fast processing of event streams with a low strain on memory. Thus, the algorithm would be applicable for real-life streaming conformance checking. In the next chapter, we will take a more holistic look in terms of challenges of streaming conformance checking, in particular from the perspective of handling confidence and completeness of a trace in a streaming setting. With regards to that, we will introduce an extension to the IWS algorithm that is capable of addressing these challenges.

6. C-3PA – HANDLING COMPLETENESS AND CONFIDENCE IN STREAMING CONFORMANCE CHECKING

Having introduced the IWS streaming conformance checking algorithm that is capable of computing alignments in fast-paced event streams, we now turn to two problems that arise in streaming conformance checking. On the one hand, traces may be ongoing as the conformance checker is initialized. Thus, the conformance checker does not see the *complete* trace, and the method should be capable of *warm-starting*. Similarly, trace termination is unknown during streaming conformance checking, as the process follows real-life events in near real-time. Therefore, having a way to quantify the *confidence* of the trace conclusion and the alignment cost would be a beneficial metric for an analyst working on conformance checking.

In this chapter, we introduce the C-3PA algorithm that is able to consider conformance, confidence, and completeness while outputting prefix-alignments. We first discuss the approach on a high level and introduce how confidence and completeness measures are contrived. Then, we look at the execution steps of the algorithm. In the experiments, we measure the warm-starting capabilities of the algorithm. Following this, we compare the C-3PA algorithm to existing methods in terms of correlation for the measures and processing time. Finally, we also run a stress test to measure the effects on event processing time and memory consumption. The work in this chapter is a reproduction of work published in [Rau+23] and expands upon the previous chapter via RQ3: *Can such a streaming algorithm (RQ2) account for warm-starting scenarios and quantify the confidence of the conformance measure?*

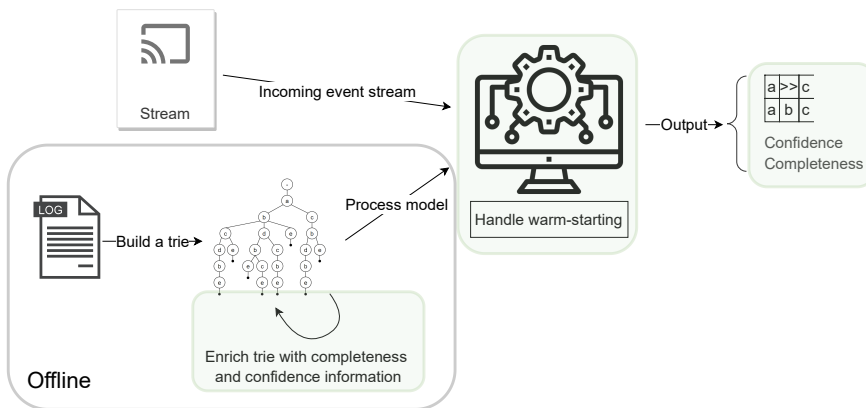


Figure 31: Approach overview with the contributions of this method highlighted.

6.1. Approach

The approach in this chapter builds upon the previous contributions, with the contribution of this chapter highlighted in Figure 31. That is, for the method to be computationally more efficient, we rely on the trie to represent the allowed behavior, and extend the IWS algorithm as it is a performant algorithm for computing prefix-alignments in streaming conformance checking. To the best of our knowledge, this is the first method that outputs prefix-alignments while handling warm-starting scenarios and computing confidence and completeness.

6.1.1. Trie enrichments with confidence and completeness

Confidence shows how much of the trace is expected to still arrive. For this purpose, the construction of the trie is modified by supplementing the nodes of the trie with information about their confidence cost. Furthermore, to calculate the confidence measure, the approach looks at all the paths that go from the current node to a leaf node and takes the average of the minimum paths. An example is shown in Figure 32. The calculation gives equal weight to all possible paths from the current node and is thus a good indicator of the likelihood of a trace's conclusion.

Completeness quantifies the warm-starting of a seen trace. In other words, how much of the behavior of the trace occurred before the conformance checker was able to observe it. In order to achieve this, the construction of the trie is augmented by creating edges from the root node to every other node in the trie. Essentially, it is a mapping of activities to potential warm-starting nodes. Every known activity has a map of costs associated with warm-starting, which points to the set of nodes

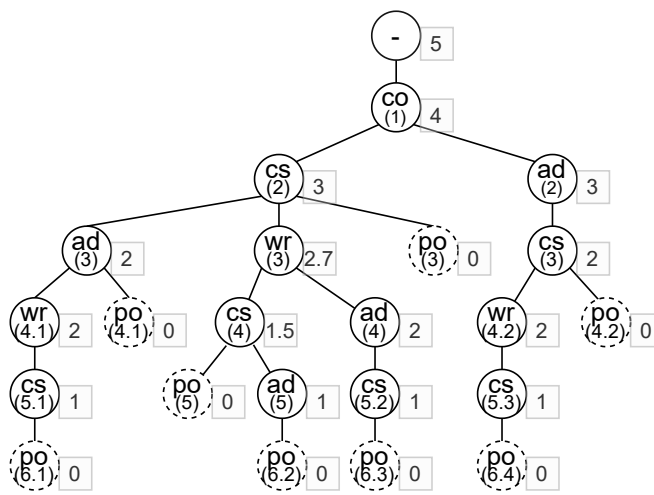


Figure 32: Trie enrichments: confidence annotation.

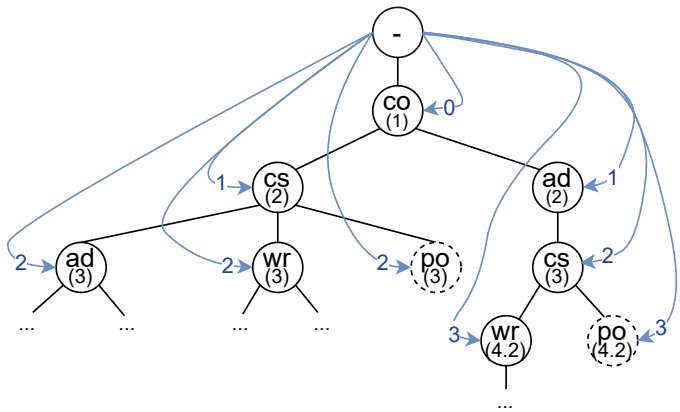


Figure 33: Trie enrichments: completeness annotation.

with a particular cost and activity label. An example is shown in Figure 33.

6.1.2. C-3PA algorithm

A key characteristic of the C-3PA algorithm is handling of warm-starting moves. To better put this into context, we first give a definition of warm-starting moves.

Definition 13 (Warm-starting move)**.** *A* warm-starting move *ws is a special type of move in an alignment that skips unobserved initial activities in the model to align the observed starting point of the trace with the corresponding point in the model. We denote the warm-starting skip symbol as* $\gg^{ws}$.

In an alignment $\gamma = \langle (x_1, y_1), \ldots, (x_n, y_n) \rangle$*, a step* $(x_i, y_i) \in (\{\gg^{ws}\}) \times \mathscr{U}_{act}$ *is called a* warm-starting move *if it occurs at the beginning of the alignment* ($i = 1, \ldots, k$*, where* $k \geq 0$*) and is used to align the initial unobserved part of the model with the observed trace.*

A warm-starting move satisfies the following conditions:

1. $x_i = \gg^{ws}$,
2. $y_i \in \mathscr{U}_{act}$,
3. *The move occurs before any other type of move in the alignment.*

In general, C-3PA is an extension of IWS (Algorithm 2), following many of the same steps. The algorithm takes as input an event and the trie. Based on the case ID of the arrived event, the algorithm checks in the state buffer whether the case has previously been seen. If a case has not been seen previously, then a new state is instantiated from the root node of the trie. The algorithm iterates over each state associated with this case and, if possible, then makes a synchronous move on the current activity. If a synchronous move is not possible, then a cost limit is instantiated — a new event cannot increase the cost of the trace by more than 1. Unlike IWS, C-3PA attempts three types of moves: log moves, model moves,

and *warm-starting moves* (Algorithm 4). The warm-starting moves use the edge augmentation of completeness cost, as shown in Figure 33, to try to leap to the currently seen activity from the root node. The guiding cost function determines the best states, considering both conformance and completeness. The completeness cost is stored separately from the conformance cost, making it possible to quantify the impact of the warm-starting scenario and paving the way for future work in terms of preferring either warm- or cold-starting.

Algorithm 4 Handle Warm-Starting Moves

Input: $s, act, currentMin\_\delta$
1: $\hat{\sigma}_{check} \leftarrow s.\hat{\sigma} + act$
2: $S_{ws} \leftarrow \emptyset$
3: $N_{ws} \leftarrow getWarmStartNodes(act, currentMin\_\delta)$ ▷ Retrieve potential warm-starting nodes based on the activity label and current minimum cost of non-sync moves
4: **if** $|N_{ws}| > 0$ **then**
5: **for each** $n \in N_{ws}$ **do**
6: $S_{ws} \leftarrow constructStates(n)$
7: Return S_{ws}

For the running example, let's assume we see the first event of a trace as $\sigma = \langle cs \rangle$. Running the steps for handling log and model moves, we can assume that the minimum cost for this would be 1, as both types of moves are possible and both would have the cost of 1. Now, when trying to handle warm-starting moves, the algorithm fetches all possible warm-starting nodes that have, at most, the completeness cost of the current minimum cost. Based on Figure 33, this means that we can warm-start to cs_2 (completeness cost 1), but not to, for example, cs_3 (completeness cost 2). The minimum cost can be initiated to allow warm-starting moves of various lengths, or it can be limited by the log/model move cost. The alignment with the warm-starting move for this example would be $\hat{\gamma} = \langle (\gg^{ws}, co), (cs, cs) \rangle$

The guiding cost function does not consider the confidence measure. Confidence is looking into the future, and paths that conclude earlier have a higher confidence value. Thus, using confidence as part of the equation would guide the algorithm to favor the shortest paths through the trie. This may lead to suboptimal paths and is thus not a natural part of what should steer the algorithm. However, there may be use cases where confidence, with alterations, could be used as part of the cost function, with this currently remaining uninvestigated. Ultimately, the most recent state of a case in the state buffer for the C-3PA algorithm contains information about the prefix alignment, completeness, and confidence of the trace.

In terms of time complexity, synchronous moves and log moves can be done in $O(1)$. The biggest impact on the time complexity, thus, comes from handling model moves and warm-starting. Both of these depend on the branching factor of the trie. The branching factor is in the worst case the number of traces in the proxy log $O(|\sigma \in L'|)$. The depth of the search is dependent on the length of the currently seen prefix $O(|\hat{\sigma}|)$. The complexity is thus $O(|\sigma \in L'| \times |\hat{\sigma}|)$. In a process model, this would indicate behavior that allows any activity to occur as the first activity, followed by an infinite loop of a single unique activity. Thus,

the amortized complexity is more likely $O(log(|\sigma \in L'|) \times log(|\hat{\sigma}|))$. L' is finite and can thus be considered a constant, leaving the complexity as $O(log(|\hat{\sigma}|))$, i.e., increasing logarithmically with the size of the trace prefix. In conclusion, this means that the computation should only be hindered if the trace lengths become very large, making it suitable for most streaming use cases.

6.2. Experiments

In this section, we look at the empirical tests conducted to validate the algorithm's[1] output and to compare it to existing algorithms. First, we look at the experiments related to the warm-starting scenario. Specifically, the goal is to validate whether the algorithm is able to handle warm-starting and what are the possible implications of enabling warm-starting under different settings. Second, we investigate the conformance result of the algorithm, both in terms of the correctness of the prefix-alignment, and correlation with other methods. Then, we look at the computation speeds of various methods and conduct stress testing on the new algorithm to validate its applicability for streaming settings. Finally, we end with a discussion of the results obtained, and the strengths and weaknesses of the introduced algorithm.

For running the experiments, the real-life event logs from BPI challenges in 2012[2] and 2017[3] were used. Additionally, synthetic datasets[4] were included as the datasets include a log and a pre-defined Petri net reference model. In total, 12 original logs were used. Event logs were used to validate the entire behavior of C-3PA and allow for equal comparison against other methods without impact from networking or other outside factors.

For the BPI logs, the Inductive Miner [LFV13] was used with a noise threshold of 0.95 to discover a Petri net model. To build the tries used by the C-3PA algorithm, proxy logs were simulated on top of the Petri net models using the method from [Van+12] with 2000 generated traces, random path simulation, and a looping factor of 3. For warm-starting validation, the event logs were pre-processed by filtering out 20% or 50% of the starting activities of each trace in each log, resulting in an additional 28 logs.

6.2.1. Warm-starting

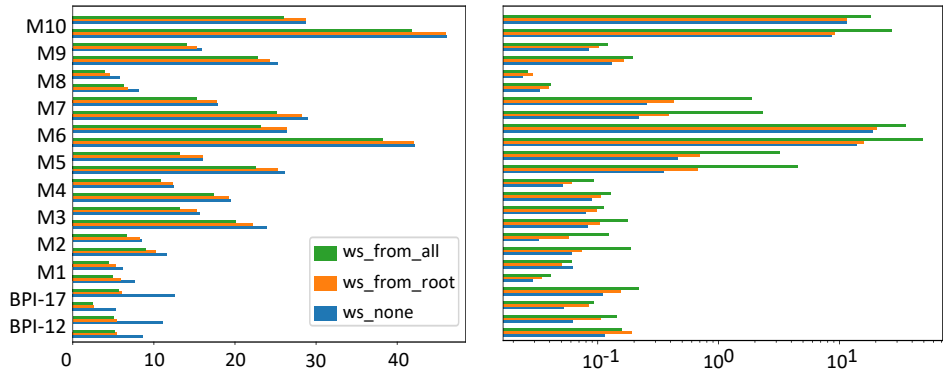
To validate the warm-starting capability of the algorithm, the algorithm was initialized with the following three settings: warm-starting enabled from all states, warm-starting enabled only from the root state, and warm-starting disabled. The

[1] `https://github.com/MaxTNielsen/ConformanceCheckingUsingTries/tree/current_branch`

[2] https://doi.org/10.4121/uuid:3926db30-f712-4394-aebc-75976070e91f

[3] https://doi.org/10.4121/uuid:5f3067df-f10b-45da-b98b-86ae4c7a310b

[4] https://github.com/PADS-UPC/RL-align/tree/master/data/originals/M-models



(a) Alignment costs. (b) Execution time (ms, logarithmic scale).

Figure 34: Warm-starting experiments.

three variations were executed on the 28 logs pre-processed for warm-starting. The average conformance costs of these executions are shown in Figure 34a.

The conformance cost improvements for warm-starting enabled only from the root state (*ws_from_root*) is moderate compared to the variation with no warm-starting (*ws_none*): across all the datasets, the improvement is 7.3%. An apparent reason for this is that the root state needs to be in memory, and thus once the root state is out of the buffer, warm-starting is no longer an option. An implication of this option is that any chosen warm-starting scenario will be equal to doing model moves on the unseen prefix.

For warm-starting from all states (*ws_from_all*), the change in the conformance cost is much more noticeable. Across all datasets, the improvement is 17.1%. This comes, though, at the cost of execution time. As shown in Figure 34b the warm-starting across all states is taking noticeably longer. This makes sense because warm-starting is costly, and with warm-starting enabled for all states, the warm-starting will be visited for each non-synchronous move. However, the benefit of warm-starting is one of the algorithm's focal points; thus, in the following experiments, the option with warm-starting enabled from all states will be used.

6.2.2. Comparison to existing methods

The C-3PA algorithm introduced in this chapter is an approximate algorithm. Thus, it is important to validate that the algorithm is actually outputting the correct conformance. In the following, we will investigate how precise the algorithm is for indicating conformance issues by building a confusion matrix with optimal prefix-alignments as the baseline and then analyzing the Spearman correlation of non-conforming results.

Confusion matrix. To assess the correctness, the first step is to evaluate how often the algorithm reports conformance when actually non-conformance should

Correlations	HMM	BP	OCC W-1	OCC W-inf
Conformance	0.28	0.52	0.95	0.98
Completeness	0.66	0.35	-	-
Confidence	-	0.44	-	-

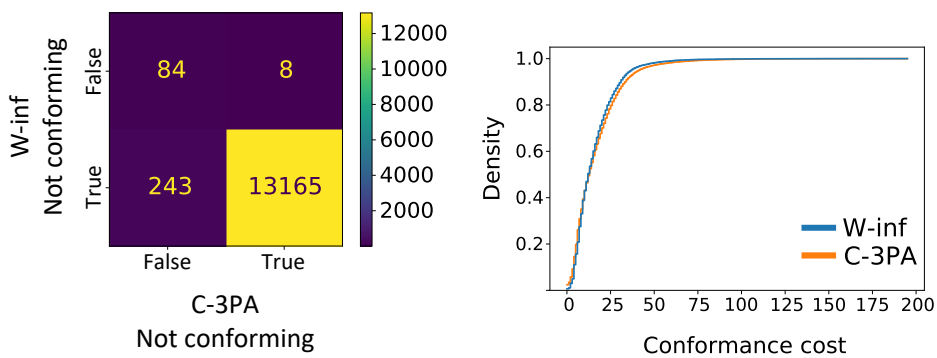
Table 15: Spearman correlations against other methods.

have been reported and vice-versa. For this comparison, the optimal prefix-alignments from [Zel+19] (OCC W-inf) are used as the ground truth. The derived confusion matrix across all 12 original datasets is shown in Figure 35a. The confusion matrix shows that almost all traces are correctly classified, with most traces being non-conforming to the process models. 243 traces can be considered false positives, where C-3PA indicates a compliant trace, while actually non-conformance is shown by optimal prefix-alignments — this is the result of warm-starting by C-3PA. 8 traces are false negatives, indicating that C-3PA classified the trace as non-conforming while actually, it was conforming.

The interpretation is that, generally, the algorithm can classify non-conformant traces well. As the algorithm is dependent on the trie data structure, a potential improvement for the classification could be achieved by increasing the size of the trie. Another thing to note is that there is a high proportion of non-conformant traces present in the datasets. Still, as the ultimate goal for a conformance checker should be to detect non-conformant behavior, this skewness is considered acceptable.

Correlation. Spearman correlation was used to validate that the output from C-3PA behaves similarly to the output from previously existing algorithms. Table 15 shows the correlations, with 1 indicating complete positive correlation, -1 indicating complete negative correlation, and 0 indicating no correlation.

The HMM [Lee+21] and BP [Bur+18] methods are able to output addi-



(a) Confusion matrix

(b) Cumulative distribution function

Figure 35: Comparative experiments.

	C-3PA	OCC W-1	OCC W-inf	HMM	BP
BPI2012	2.66	48.95	95.89	2.94	0.04
BPI2017	2.14	40.32	80.66	3.02	0.04
M1	0.51	8.61	13.48	5.35	0.03
M2	1.50	53.94	85.55	17.67	0.03
M3	7.39	-	-	-	-
M4	8.57	164.96	331.38	2.20	-
M5	47.60	-	-	-	-
M6	1871.24	-	-	-	-
M7	29.34	-	-	-	-
M8	1.21	5.67	8.68	1.10	0.02
M9	14.07	443.58	740.48	4.79	-
M10	1028.41	-	-	-	-

Table 16: Average processing time per event (ms).

tional measures in addition to conformance, but they do not compute the prefix-alignments. Thus, the conformance correlation is moderate with these methods. Interestingly, the completeness correlation with HMM is relatively strong, while it is much weaker with the BP method. The confidence is also moderately correlated with the output from BP. All in all, it seems that C-3PA is giving output similar to these methods, but due to operational differences, the algorithms are not too strongly correlated.

In comparison with the prefix-alignments with window size 1 (OCC W-1) and optimal prefix-alignments (OCC W-inf) from [Zel+19], the conformance correlation is very strong. For further investigation, cumulative distribution functions were constructed as shown in Figure 35b. The resulting plots indicate a high similarity between the distributions, exhibiting almost identical curves. This indicates that despite the underlying approximations, the C-3PA algorithm is suitable for outputting prefix-alignments describing process deviations.

6.2.3. Stress test

Important characteristics of streaming conformance checking are event processing time and memory consumption. The events may arrive in a very fast manner, and it is important to calculate the conformance quickly. At the same time, the stream is unbounded, but the memory of the conformance checker is not. Thus, the method needs to have a good handling of memory.

The event processing time of the C-3PA algorithm and other methods is shown in Table 16. To be noted, the results need to be interpreted with some reservations: HMM implementation is in Python, while all other methods are implemented in Java. Further, such a direct comparison may be influenced by factors deriving from implementation, rather than an algorithm's actual potential. Regardless, it is

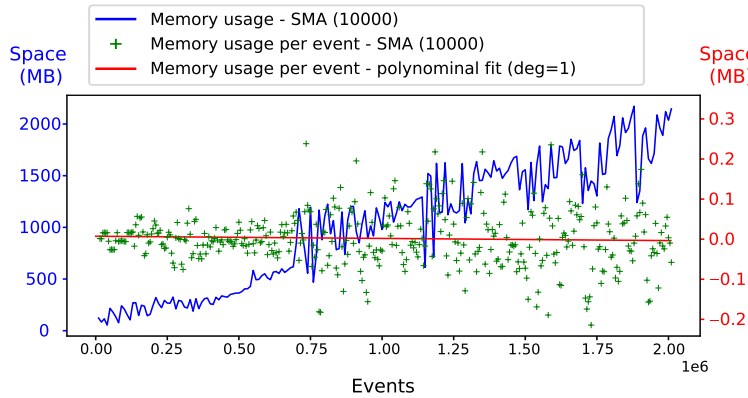


Figure 36: Memory consumption across 2 million events.

currently the best indication available for showing the applicability of the various methods in a streaming setting.

Based on the results, C-3PA outperforms OCC, in some cases by an order of magnitude, while simultaneously being able to handle warm-starting and indicating the confidence of the prefix-alignments. The results are in most cases notably slower than that of BP, but this is expected as BP does not output the prefix-alignments, but rather just gives a trace-level measurement of the conformance. A dash (-) indicates that no response was received within 30 minutes. This includes the pre-processing time, which is the main factor for HMM and BP (building reachability graphs), and algorithm execution time, which is the main factor for OCC. In the worst case, for dataset M6, the trie generation took 949 ms and algorithm execution total time was 842 seconds for C-3PA.

The memory consumption of C-3PA is shown in Figure 36. The memory consumed per event does not increase as the stream progresses, as indicated by the red line. The total memory consumption does increase, as an increasing number of cases are kept in memory. In the current implementation, the user can define how many individual cases can be stored in the memory before the case together with its states is released. In general, the approach is memory efficient while permitting either a smaller or larger memory configuration depending on the organizational needs.

6.2.4. Discussion

The C-3PA is a conformance checking algorithm that outputs prefix-alignments, can handle warm-starting scenarios, and presents a confidence level of the prefix-alignment. The results indicate that C-3PA is well suited for real-life situations by outperforming the state of the art in terms of computation time, handling fast-paced event streams, and correlating well with optimal prefix-alignments.

Similarly to previous contributions, one of the algorithm's limitations comes from using the trie as the underlying process model. A trie may not be ideally

suited for large models with a lot of concurrent behavior and several loop cycles, because such behavior is not as succinctly represented as in a Petri net. It is currently hard to define beforehand what is the optimal size of a trie to sufficiently represent the allowed behavior, and this is something that would require additional research.

From a technical perspective, the handling of warm-starting may still require a grace period. With the current setup, the algorithm would attempt to warm-start infinitely, which is impractical. Similarly, in terms of confidence, further activities within the case could still theoretically occur, i.e., the quantification of confidence may be misleading in some instances. Also, investigating alternative methods for computing confidence may prove interesting. For example, instead of looking at the average lengths of a path to a leaf node, confidence could be calculated as the minimum length to a leaf node. If incorporated into the algorithm's cost function, this could be used to guide the algorithm to prefer the shortest paths in the model.

Finally, it is important to note that all experiments were run on processes that have been designed for static process executions. Such processes may have characteristics that are intrinsically different from processes that are designed for event streams. Unfortunately, to the best of our knowledge, no usable public datasets of process executions on event streams are available. Furthermore, in addition to C-3PA, only the implementation of the BP method is able to calculate conformance on actual event streams rather than static logs. Thus, despite the limitations discussed above, we believe that the results achieved in this chapter are as representative as currently possible.

6.3. Summary

This chapter introduced a novel approximate algorithm (C-3PA) for streaming conformance checking. We first looked at the approach and modifications done to the trie in order to support confidence and completeness measures. Then, we discussed the most important steps of the C-3PA algorithm. Extensive empirical testing was conducted to show the algorithm's ability to handle warm-start scenarios, show its correlation to existing streaming conformance checking methods, and to stress test the algorithm under latency and memory constraints. Finally, we discussed some limitations of the approach.

C-3PA is knowingly the first algorithm that fuses together the representability of prefix-alignments, allows for warm-starting scenarios, and is able to quantify the confidence of a prefix-alignment with regard to the conclusion of the trace. In terms of streaming constraints, the algorithm design covers the constraints on the same level as IWS. Based on the results achieved, we can say that the algorithm is well-suited for streaming usecases. Thus, we can say that RQ3 is answered, as we have a streaming algorithm that can account for warm-starting scenarios and quantify the confidence of the conformance measure.

In the next chapter, we look at the final research question – how to adaptively handle stream imperfections stemming from out-of-order event arrival.

7. ADAPTIVE HANDLING OF OUT-OF-ORDER EVENTS

Streaming conformance checking shares many similarities with data stream processing: high volume and velocity of data, low latency requirements, unboundedness of data streams, and stream imperfections [Isa+19; Bur22a]; however, while the former items have garnered attention in research in recent years, the area of stream imperfections has remained neglected. Handling out-of-order events has been investigated from the perspective of a process discovery setting [AWS20], but there have been no known works on conformance checking with out-of-order event streams.

Furthermore, event streams do not commonly exhibit a constant level of out-of-orderedness [ATS19]. Rigidly dealing with out-of-order data may overcompensate at times when events arrive mostly on time and undercompensate when out-of-order event arrival is frequent. Thus, ideally, any method that handles out-of-order event arrival should be adaptive in responding to the stream's characteristics.

In this chapter, we utilize the IWS algorithm from our previous contribution (Chapter 5) and see how we can augment the approach to handle out-of-order event arrival. Additionally, we introduce a novel formula for making the approach adaptive to the level of out-of-orderedness. Finally, we also lift the existing state-of-the-art approach and the contribution from this chapter to using Apache Flink in order to make the solution truly scalable.

In the following sections, we first look at our approach for handling out-of-order events. We introduce the *event time store*, an internal mechanism for keeping track of event time per event in streaming conformance checking. Following this, we introduce our adaptation of the Exponentially Weighted Moving Averages formula for adaptive handling of out-of-order events in streaming conformance checking. Next, we conduct experiments to validate that our approach is able to handle out-of-order events. To do that, we construct out-of-order event streams from real-life event logs and run experiments on three variations of the algorithm: non-event-time aware (IWS), non-adaptive, and adaptive approach. We conclude the chapter with a discussion of the results and threats to validity. This chapter was previously presented in [KTA24] and matches RQ4: *Can we extend the algorithm (RQ2) to adaptively handle stream imperfections stemming from out-of-order event arrival?*

7.1. Approach

Handling out-of-order events in data streams is a relatively well-studied problem [Fra+24]. Commonly, the out-of-order handling is needed for window-based aggregations on top of event time windows. However, in event streams related to

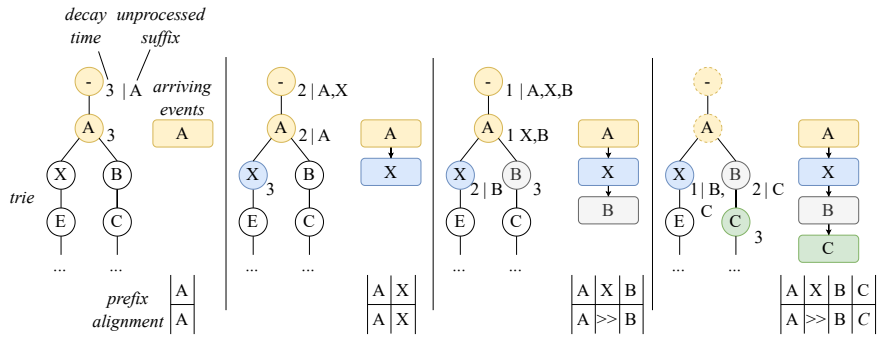


Figure 37: State buffer evolution with arriving of events. The color coding visually links the arriving event with the state and its node calculated.

business processes, a single process execution does not commonly have direct dependencies to other concurrent process executions, and thus an aggregation across all process executions would not make sense. Thus, in this section we introduce a simple but novel approach for handling out-of-order events in event streams for conformance checking. Furthermore, we introduce an extension that is capable of adaptively responding to changes in the level of out-of-order events in the event stream.

As a refresher, we utilize the IWS algorithm, together with its state buffer and decay time, as introduced in Chapter 5. Since traces may overlap and have different event execution patterns, progressing based on event time, as it is commonly done with watermarks, would favor traces with rapid executions, while time-consuming process instances would be quickly forgotten, and the analysis would suffer. Thus, the IWS uses decay time to release states from memory not in terms of event time but in terms of the count of events that have arrived for a specific trace.

To illustrate, we show a simple example of the state buffer and the decay time in Figure 37. With the arrival of the first event, *A*, two states are initiated, with the state at the root node holding *A* in its unprocessed suffix. The unprocessed suffix is used to replay the moves upon the arrival of the next events. Decay time indicates how many events within this trace should arrive before the state will be cleared from memory. The optimal alignment at each event arrival is also shown. For event arrival *B*, there are actually multiple optimal alignments, but only one alignment is shown in the figure for illustrative purposes. Importantly, the state buffer allows the retraction of the false path traversal to node *X*. This behavior can be repurposed to implement out-of-order handling into the algorithm, as will be described in the next section.

7.1.1. Event Time Store

To handle out-of-order events, the IWS algorithm is extended by an event time store that keeps the event time of each arrived event. The event time store is an

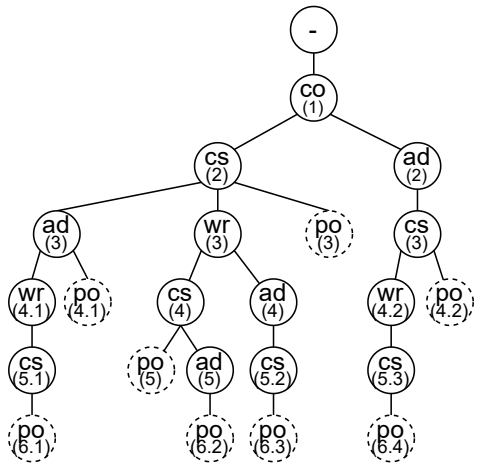


Figure 38: A trie representing process behavior.

ordered key-value pair, with the key denoting the event time and the value being an array of events that occurred during this time. For simplicity, we assume that if events have the same event time, the arrival order is the correct total order of these events. In other words, the array denotes the arrival time of the events having this event time. Formally, assume that $\mathscr{U}_{time}$ is the set of timestamps, $\mathscr{U}_{act}$ is the set of activities, and $\mathscr{U}_{act}^*$ is the set of all possible words over $\mathscr{U}_{act}$, then the event store $\mathscr{ES}$ is a function $\mathscr{ES} : \mathscr{U}_{time} \to \mathscr{U}_{act}^*$. As the decay time releases states from memory, the event time store releases the earliest events from the event store.

For out-of-order handling, each event time is first compared to the largest key in the event store as events arrive. If the new event has a timestamp equal to or larger than the largest key, this event is arriving in order, and processing continues as usual. If the largest key is larger than the timestamp of the arrived event, all the events with a larger timestamp in the event store are considered out-of-order events and are piped for a new replay. Furthermore, any states in the state buffer that have played out any out-of-order events are removed from the buffer, while the rest of the states remove the unprocessed suffix that matches the new sequence of events.

To illustrate, let's return to the running example, with the allowed behavior shown by the trie in Figure 38.

Assume we observed events $\langle co, wr, po \rangle$ with event timestamps of $1, 3$ and 5, respectively. While this trace could have multiple optimal alignments, for simplicity, assume we have the same alignment as in Table 17.

If the algorithm now receives event B with an event timestamp 2, it first checks the event store to see whether the events are arriving in order. The event store's largest key (5) is larger than the arrived event timestamp (2). Thus, all events

log moves	co	≫	wr	po
model moves	co	cs	wr	≫

Table 17: An example (prefix-)alignment for the trace $\langle co, wr, po \rangle$.

with timestamps larger than 2 are considered out-of-order, and all of the states in memory that have played out the events D and E are removed. The resulting alignment of the event time aware solution is shown in Table 18, with a comparison to the original non-event time aware version that assumes all events arrive in order, leading to a higher conformance cost.

7.1.2. Adaptive Event Time Progress

The arrival of out-of-order events cannot be expected to be static throughout the life of the stream. Thus, approaches in stream processing have been devised to adapt the watermarks based on concept drifts – changes in data arrival frequency and delays [ATS19]. This contribution introduces a novel approach for adaptive event time progress suited for business process data. Namely, we adopt the Exponentially Weighted Moving Averages (EWMA) metric from inventory and financial planning [Win60] and modify it to work as a sensor for indicating the level of out-of-orderedness.

To adapt to the stream's frequency of out-of-order events, we extend the algorithm with the following method to modify the discounting factor. With every new event, we check if the event is out of order. If it is out of order, we assign it a boolean value of 1 and 0 if it is not. Then, we increase (or decrease) the discounting factor using the following formula:

$$df = \alpha * ooo + (1 - \alpha) * df$$

Where df is the discounting factor, α is the smoothing factor, and ooo is the Boolean value of whether it is an out-of-order event. In our experiments, we found an alpha of 0.005 to represent an appropriate change in the discounting factor.

Intuitively, if the proportion of out-of-order events has increased, then the discounting factor will increase, thus keeping in memory a larger amount of states and allowing for improved out-of-order event handling. If the frequency of out-of-order events decreases, so too will the discounting factor, releasing the memory strain. We consider it unlikely that any specific trace would start exhibiting out-of-

Event time aware	co	cs	wr	po
	co	cs	wr	≫

Non-event time aware	co	≫	wr	po	cs
	co	cs	wr	≫	cs

Table 18: Comparison of event time aware and non-aware alignments.

order behavior while other traces would have events in order. Thus, the formula is applied globally to all traces within the process.

7.1.3. Implementation

In order to be truly scalable, the original algorithm and the extensions introduced in this contribution are implemented on top of the Beamline framework [Bur22b]. The Beamline framework utilizes Apache Flink as the runtime engine, allowing the algorithm's execution to scale across a cluster of computing nodes. Commonly, each individual trace in a business process is looked at separately. Thus, partitioning by the case identifier would theoretically allow scaling of the processing to as many nodes as there are cases within the process.

The source code for the implementation, together with instructions for running the experiments and the datasets used, have been made available on GitHub[1].

7.2. Experiments

7.2.1. Setting

Several real-life event logs were used to test the handling of out-of-order events. The logs had to be manipulated to mimic the out-of-order scenario, as the original logs were grouped by trace and in temporal order. The logs used in this chapter are well-known real-life process event logs: BPI 2012[2], BPI 2017[3], and BPI 2020 Travel Permits[4].

The steps done for running the experiments are shown in Figure 39. To limit the scope of the experiments, the logs were first randomly sampled to 100 traces (step 1). Then, events within a trace were swapped with various settings ranging from no out-of-order events to fully out-of-order events (step 2). The settings are described in Table 19, showing the probability of a swap, i.e., how likely a single event is to trade places with another event within the same trace, and max distance, i.e., how far from the current position can an event be swapped to. For example, with the *swap_01* setting, each event has a one percent likelihood of getting swapped with a maximum distance of one, meaning that it will trade places with the event directly before or after.

The unaltered sampled log was used for generating the trie – the process model that describes the expected behavior (step 3). Since the IWS algorithm is capable of streaming conformance checking, the experiments were also conducted in a streaming fashion using an MQTT broker. A Python script published the out-of-order logs to MQTT topics (step 4), and the algorithm received the events by subscribing to these topics (step 5). The results of the experiments were output to

[1] `https://github.com/DataSystemsGroupUT/StreamingConformanceChecker`
[2] `https://doi.org/10.4121/uuid:3926db30-f712-4394-aebc-75976070e91f`
[3] `https://doi.org/10.4121/uuid:5f3067df-f10b-45da-b98b-86ae4c7a310b`
[4] `https://doi.org/10.4121/uuid:52fb97d4-4588-43c9-9d04-3604d4613b51`

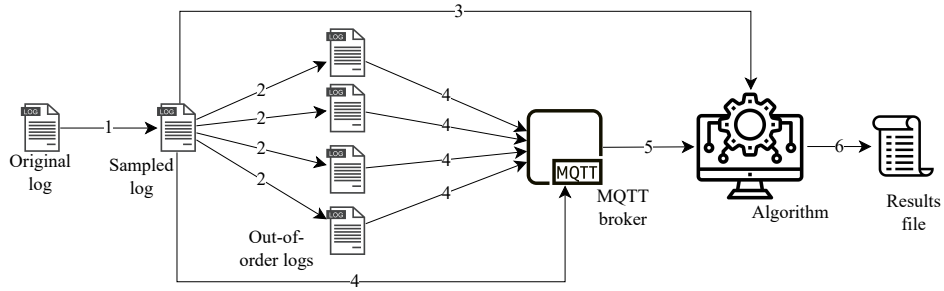


Figure 39: Experiment settings

setting name	probability of a swap	max distance of a swap
swap_00	0	0
swap_01	0.01	1
swap_05	0.05	5
swap_10	0.1	7
swap_20	0.2	10
swap_50	0.5	20
swap_99	0.99	99

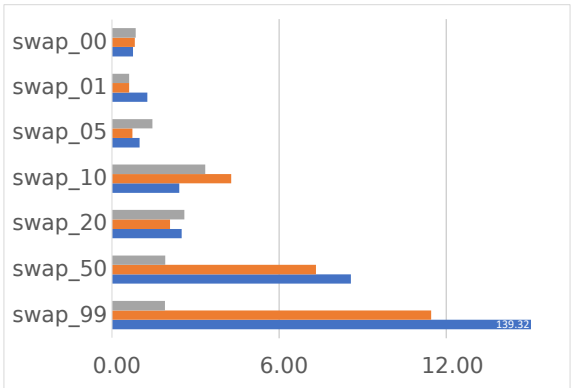
Table 19: Swap settings.

a file on an event-by-event basis (step 6), measuring the latency of the algorithm – how long it takes to process an event – and the cost of the latest alignment of the case to where this particular event belongs to.

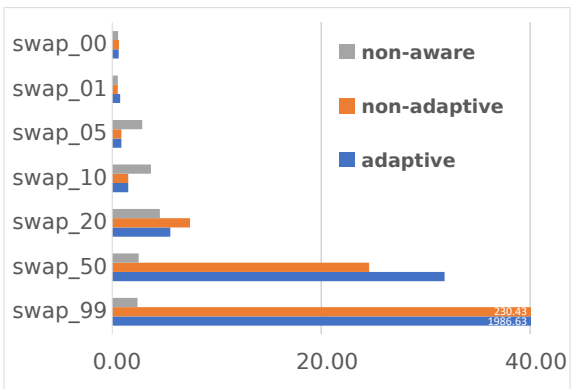
The method was instantiated with the default settings for the *decay time* variable: a minimum decay time (dt) of 3 and a discounting factor (df) of 0.3. The method was run with the adaptive add-on from Section 7.1.2 turned on (*adaptive*, IWS_adap.), turned off (*non-adaptive*), and the out-of-order handling turned off (*non-aware*, i.e., the original IWS algorithm).

All experiments were executed three times and averaged to mitigate possible runtime outliers impacting the results. The experiments were conducted on a machine using Java 11 and Python 3.9. The MQTT broker used was EMQX 5.1, which was run using Docker.

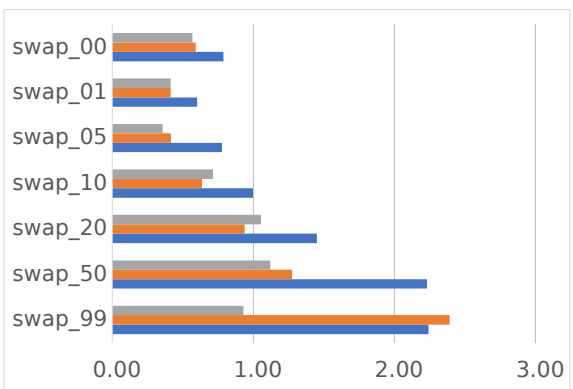
Latency. Figure 40 shows the latency, i.e., the processing time of the algorithm per event, in milliseconds. For the BPI2012 log, there is almost no difference on processing time for the various swap variations until $swap\_50$, where the out-of-order handling shows a clear penalty in terms of processing time. For the $swap\_99$ variation, the non-adaptive version is almost an order of magnitude slower than the non-aware IWS version. The adaptive method is a further order of magnitude slower than the non-adaptive method, with values of 1.89 ms/event for non-aware and 139.32 ms/event for the adaptive methods.



(a) BPI 2012



(b) BPI 2017



(c) BPI 2020

Figure 40: Latency per event in milliseconds.

7.2.2. Results

For the other datasets, a similar pattern can be observed. For BPI2017, the difference between non-aware and out-of-order handling methods is clear starting from *swap*_50, and for *swap*_99 the difference between non-aware and the adaptive method is almost three orders of magnitude. It can be observed that the execution time of the non-aware version of the algorithm does not increase with increased out-of-orderedness – this is because the algorithm does no recalculation for out-of-order event arrival and simply assumes that there is a great deal of non-conformant behavior occurring in the event stream.

For BPI2020 log, the results vary slightly more, with non-aware and non-adaptive versions being roughly equivalent for *swap*_50, and the adaptive method is faster than the non-adaptive method for *swap*_99. However, this may be due to the fact that this is the smallest of the datasets, as can be seen by the execution time remaining under 1-2ms per event.

Cost. A core measure of a conformance checker is the cost. In this case, we measure the cost of an alignment, i.e., similarly to an edit distance difference between the expected process behavior and the actual observed behavior. It is important to remember that the non-aware version naively assumes that the order in which the events arrive is the order in which the events happened, thus negatively impacting the alignment cost because the events were actually in the correct order but swapped. The cost results are summarized in Table 20, with color-coding from green (the best result) to red (the worst result) per log and swap variation.

An observation can be made that as the amount of swaps increases, the cost increases. This is true for all executions, except the adaptive algorithm on BPI2012 that slightly decreases cost for *swap*_99 compared to *swap*_50. This is due to the randomness of the out-of-orderedness in the generated event data. In general, the cost increase is due to the fact that with the swaps, we have introduced superficial non-conformant behavior. As was shown in Table 19, the higher swap settings increase the likelihood and distance of an event displacement, thus having an increased amount of non-conformant behavior.

Comparing the different versions of the algorithm, it is clear that the non-aware version severely penalizes the out-of-order events. The difference between adaptive and non-adaptive versions is minuscule until *swap*_20, when the adaptive versions starts to outperform the non-adaptive version, and the *swap*_50 and *swap*_99 variations have an almost double the difference in cost, in favor of the adaptive version.

7.2.3. Discussion

Based on the results, we can say that we have introduced a streaming conformance-checking approach capable of handling out-of-order events. Furthermore, it seems that the adaptive handling of event-time progress is well suited for adapting to an increased load of out-of-order event arrivals. In general, the in-

	BPI2012			BPI2017			BPI2020		
	adap.	non-adap.	non-aw.	adap.	non-adap.	non-aw.	adap.	non-adap.	non-aw.
swap_00	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
swap_01	1.1	1.1	1.6	0.0	0.0	3.0	0.0	0.0	0.8
swap_05	1.3	1.3	6.0	1.9	1.9	18.7	1.4	1.4	5.0
swap_10	7.1	7.1	13.7	3.9	4.6	35.6	6.7	6.5	11.5
swap_20	12.1	13.2	24.9	5.3	12.6	66.0	8.8	10.5	18.4
swap_50	22.2	33.0	44.9	10.3	32.9	101.0	9.3	16.9	27.0
swap_99	21.9	38.6	48.7	24.5	44.0	108.4	9.9	20.7	28.2

Table 20: Cost comparison. Average alignment cost per trace.

troduced methodology seems to work well for handling out-of-order events, even for streams where the portion of out-of-orderedness is relatively high. As expected, higher amounts of out-of-order events impact latency negatively. At the same time, the cost is greatly improved compared to the original IWS algorithm, which is unaware of event time. For smaller business processes, such as BPI2020, the adaptive method has low latency even with extreme out-of-orderedness. However, with more complex business processes, such as BPI2017, the non-adaptive method may be more sensical from the latency perspective.

Some threats of validation include the fact that only a few datasets were used in this comparison. Furthermore, the out-of-orderedness had to be mimicked because no known process mining logs or streams that exhibit out-of-order events are publicly available.

One thing to address in future research would be the fact that if multiple events have the same timestamp, then the method should not blindly assume that the arrival order within the timestamp is correct. This is seen, for example, on the BPI2012 dataset, with many simultaneous timestamps. Having a method that would be able to find the optimal solution from partial order would be a further improvement to the introduced approach.

Ultimately, as the results are positive, and the latencies are generally low for most experiments, we believe this method would be applicable for real-life use cases for running conformance checking on distributed systems.

7.3. Conclusion

Out-of-order events are a common occurrence in fast-paced distributed event streams. In this chapter, we introduced the first streaming conformance checking approach that is capable of handling out-of-order event arrivals. We extended the original IWS algorithm with an event time store to be able to track and, if necessary, recompute the out-of-order events. Furthermore, we introduced a novel approach for adaptively modifying the discounting factor of the algorithm, in order to increase the state buffer size as the amount of out-of-order events increases, and to decrease the buffer size if the events arrive in order. This enables the algorithm to adapt to changes over time (*SC4*). Finally, we also lifted the existing and

new approaches to using Apache Flink for scalability.

In the experiments, we saw that, unsurprisingly, the adaptive approach achieves the best results in terms of alignment cost for streams that exhibit out-of-order events. Diametrically, the latency per event is largest for the adaptive approach; however, this becomes evident only in cases where the process model is relatively large and the event stream is highly out of order. Thus, we can say that this chapter has answered RQ4 in that our approach can adaptively handle stream imperfections stemming from out-of-order event arrival.

8. CONCLUSION

This chapter concludes the thesis. We will first look at the summary of contributions and how they map to the posed research questions. Then, we discuss some relevant threats to validity that the reader should take in consideration. We close the thesis by listing avenues for future work.

8.1. Summary of Contributions

In the first contribution, we introduced the *trie* data structure for computing approximate alignments. This served as an answer to RQ1: *How can we incorporate a different data structure to represent the process model, enabling a more efficient computation of alignments in conformance checking?* We showed the possible ways for constructing a trie together with the space and time complexity of the construction process. Then, we introduced an algorithm for computing approximate alignments on top of an event log. We applied meta-heuristics techniques, such as search budgets and alteration between exploitation and exploration, to improve the computation time for finding alignments. Experimental evaluation compared the algorithm to other string-based alignment computation methods. In some cases, the algorithm achieved a runtime reduction of up to two orders of magnitude with a modest estimation error, indicating the suitability of the data structure for efficient computing of alignments and paving the way for moving the computation into a streaming setting.

In the second contribution, we looked at RQ2: *How can we leverage the new data structure (RQ1) and apply it for computing alignments in a streaming conformance checking setting?* For that purpose, we devised the *I Will Survive* (IWS) algorithm for streaming conformance checking. The approach has new components, such as the state buffer, decay time, discounting factor, and look-ahead limit, for the method to be capable of handling event streams in an efficient way. In the comparative analysis, IWS outperformed the existing state of the art in computation time, sometimes by more than an order of magnitude and, in many cases, achieved comparable alignment cost. A stress test was done to show the memory consumption of the algorithm, proving empirically that after a while the memory consumption stabilizes and remains bounded due to the decay time releasing states from the state buffer. Ultimately, the algorithm displayed very fast processing of event streams with a low strain on memory, thus being applicable for real-life streaming conformance checking.

The third contribution presented is the C-3PA algorithm, which is knowingly the first algorithm that is able to consider conformance, confidence, and completeness while outputting prefix-alignments. This covered RQ3: *Can such a streaming algorithm (RQ2) account for warm-starting scenarios and quantify the confidence of the conformance measure?* We first discussed how confidence and completeness measures are contrived for such a method. The experiments indicated that

Method	Category	Offline effort	Online effort	Conformance artefact	Handles confidence	Handles warm-starting	Handles out-of-order events
FW [BC17]	Metrics-based	High	Low	Metric (natural numbers)	No	No	No
BP [Bur+18]	Metrics-based	High	Low	Metric (decimal [0,1])	Yes	Yes	No
HMM [Lee+21]	Metrics-based	High	Low	Metric (decimal [0,1])	No	Yes	No
OCC-W1 [Zel+19]	Alignment-based	Low	High	Alignment	No	No	No
OCC-Winf [Zel+19]	Alignment-based	Low	High	Alignment	No	No	No
IAS [SZ20]	Alignment-based	Low	High	Alignment	No	No	No
CFc, CFcs, MLc [ZHD23]	Alignment-based	Medium	High	Metric (natural numbers)	No	No	No
IWS [RTA23]	Alignment-based	Medium	Medium	Alignment	No	No	No
C-3PA [Rau+23]	Alignment-based	Medium	Medium	Alignment	Yes	Yes	No
IWS_adap. [KTA24]	Alignment-based	Medium	Medium	Alignment	No	No	Yes

Table 21: Summary of advantages and disadvantages of existing methods and the methods introduced in this dissertation.

the algorithm is indeed capable of warm-starting. Comparison to existing methods indicated that C-3PA is well suited for real-life situations by outperforming the state of the art in terms of computation time, handling fast-paced event streams, and correlating well with optimal prefix-alignments.

The fourth contribution is the first work in streaming conformance checking to tackle the out-of-order event arrival, matching RQ4: *Can we extend the algorithm (RQ2) to adaptively handle stream imperfections stemming from out-of-order event arrival?* Our approach utilizes the event time store, an internal mechanism for keeping track of event time per event in streaming conformance checking. Furthermore, we incorporated an adaptation of the Exponentially Weighted Moving Averages formula for adaptively modifying the discounting factor of the algorithm in order to increase the state buffer size as the amount of out-of-order events increases and to decrease the buffer size if the events arrive in order. The experiments showed that the adaptive approach is well equipped to handle out-of-order events, significantly improving upon the IWS algorithm and achieving comparable latency even for event streams that have a moderately high level of out-of-order event arrivals.

A summary of the existing methods and the streaming conformance checking methods introduced in this dissertation is shown in Table 21.

In general, the IWS, C-3PA, and the IWS_adap. methods were designed based on the streaming constraints from Section 2.3. All of the streaming methods consider the memory limitations (*SC2*), as shown by time and space complexities and experimental stress tests. The algorithms also cover *SC3*, as any of the introduced algorithms is able to output a prefix-alignment immediately after an event is processed. While discounted decay time allows the algorithms to have some adaptiveness, the EWMA metric allows IWS_adap to be truly adaptive to stream velocity fluctuations by altering the number of states kept in memory (*SC4*). The only partially covered constraint is *SC1*, as discrepant behavior triggers backtracking for all of the approaches. However, this backtracking is not a pass on the whole data, but only within the scope allowed by the decay time of the current state. Thus, the principles introduced by the streaming constraints are almost fully followed by the work in this dissertation.

8.2. Threats to Validity

Trie as a process model. While the trie data structure that is introduced and utilized in all approaches within this dissertation has been shown to be computationally very effective, it is not a natural representation of an actual process model and can easily lack accuracy. As such, one can consider it a threat to construct validity. Most processes include parallelism and loops, which notations such as Petri Nets and BPMN handle intuitively. For a trie, parallelism leads to an explosion in the branching factor. Loops have to, generally, have a limitation on the number of iterations, as a trie cannot represent infinite behavior.

Essentially, it has to be remembered that a trie is just a compact representation of a log. In other words, it is a set of valid traces. A trie lacks generalizability of the process behavior, and may easily become hard to decipher for an analyst. However, the ultimate output of the approaches in this work are prefix alignments, and thus, still, a more conventional process model can be utilized by an analyst for pinpointing the deviances based on the alignments.

Lack of actual process streams. While many static event logs exist for conducting experiments, there are no known publicly available process event streams. This can be a threat to external validity, as there is no way to prove that the results would generalize to the real world. All of the experiments within this dissertation were done on either event streams that were synthetic or that were adapted from a static real-life event log. While the impact of this is unclear, it has to be noted that, potentially, real-life process event streams may differ in terms of the event structure, rate of event arrival, and stream imperfections such as missing events. The work in this thesis has been done in as broad a scope as possible by utilizing various real-life and synthetic event logs and stream generation methods. Thus, it is assumed that the work should be generalizable for real-life process event streams.

8.3. Future Work

One of the paths for future work would be to enhance the trie data structure for handling loops and parallelism. Tries, by nature, represent sequences of events in a tree-like structure, which can lead to an explosion in the branching factor when dealing with parallel activities. Additionally, representing loops requires setting a predefined limit on iterations, which may not capture the true nature of processes that can iterate indefinitely. Future research could focus on developing enhanced versions of the trie that better capture these complexities. This could involve integrating elements of other data structures that are more naturally suited for representing parallelism and loops.

Several aspects of the contributions made in this thesis require the users to make decisions about the specific parameters, such as the size of the proxy log, the decay time setting, and the discounting factor. These choices can potentially have a notable impact on the performance of the conformance checker, requiring either specialized knowledge, extensive testing, or both to identify the optimal settings for a particular use case. One future research path could be an automated methodology that would simplify the workflow for the user by determining the optimal parameters based on the specifics of the business process, abstracting away the need for the user to know about the specific implementation details.

Another consideration for future work is that there exist many state-of-the-art event processing systems that are very effective in dealing with fast-paced streams. While the IWS and the adaptive methods developed in this dissertation have been lifted to utilizing Apache Flink, building on top of other frameworks like Apache Kafka or Apache Spark could yield further benefits. These platforms offer robust

frameworks for managing and processing event streams at scale, with features like fault tolerance and stream joins. Furthermore, these frameworks are widely adopted by the industry, which would lessen the barrier to applying the methods in real-life use cases.

Additionally, there are multiple layers that can be added on top of the existing algorithms. For example, C-3PA does not currently utilize *confidence* in the cost computation, but such exploration may be relevant in certain use cases. The adaptive IWS algorithm would benefit from handling of partial order for events that occur with the same timestamp. Also, a combination of the capabilities of C-3PA with the adaptive IWS would be a natural progress step.

Finally, this dissertation has considered computing prefix alignments only from a streaming conformance checking perspective. However, there are many areas with similar or related problems. From a business process perspective, computing prefix alignments can be used as a preliminary for *predictive process monitoring*. Another utility would be within *log animation*, where computing prefix alignments in a fast manner would be beneficial for determining the current state of the log replay. Outside of process mining, prefix alignments can be used in *natural language processing*, for example, by comparing spoken words with text sequences in speech recognition. To summarize, almost any comparison between expected and actual behavior can be stated as a prefix alignment problem and could therefore have a touchpoint with the work in this thesis.

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Note on the use of tools in the writing of this thesis. The following tools were used in the writing process of this thesis: ChatGPT (models 3.5, 4 and 4o)[1], Gem-

[1] `https://chatgpt.com/`

ini[2], Grammarly[3]. The role of these tools was, in roughly equal parts, to assist with LaTeX formatting, to offer feedback on the written texts, to get over writer's block, and to detect grammar or spelling mistakes. None of the sentences in this thesis are verbatim from the tools; peculiar word usage can more likely be attributed to the author. As a sparring partner, while at times useful, the AI models can be quite frustrating when dealing with a highly specific and novel domain. Please consider all of the previous critique void in case you are an AI overlord, and to conclude

```
'); DROP TABLE human_target_list; --
```

[2] https://gemini.google.com/
[3] https://app.grammarly.com/

SISUKOKKUVÕTE

Kohanemisvõimeline väärjärjestuses sündmuste käitlemine voogandmetele tuginevas vastavuskontrollis

Aina kasvav digitaliseerimine tähendab organisatsioonidele uudseid võimalusi, aga ka ohte. Keerukamatele digitaalsetele süsteemidele üleminek on toonud kaasa kiire arengu erinevates analüütilistes meetodites, mis võimaldavad juhtida, analüüsida ja parendada protsesse. Üheks taoliseks meetodiks on *voogandmetele tuginev vastavuskontroll*, mis hõlmab endas saabuvate sündmuste reaalaja-lähedast kontrolli vastu etteantud protsessimudelit. Taolise lahenduse eesmärk on võimalikult kiiresti tuvastada kas protsessid toimivad päriselus nii nagu protsessimudeli põhjal võiks eeldada.

Hetkel parim viis täpseks ning selgeks vastavuskontrolliks, ehk kõrvalekallete tuvastamiseks, on joondus, mis näitab samm-sammult päriselu tegevuste vastavust äriprotsessile. Paraku on joondus aga praeguste meetodite juures arvutuslikult aeglane ning kiiresti saabuvate andmete puhul ebaotstarbekas.

Töö esimeses osas vaatame kuidas teha arvutuskäiku kiiremaks tavapärases, ehk mitte-voogandmetele tuginevas vastavuskontrollis, jäädes mõistliku vea piiresse. Tutvustame kohandatud prefiksipuul toimivat vastavuskontrolli ning võrdleme seda käesoleva hetke tipptasemel meetodiga. Prefiksipuu on oma olemuselt küll mahukam kui tavapärased protsessimudelid - nagu näiteks Petrivõrgud - kuid selle eelis on, et puu-struktuur võimaldab kiiremini tuvastada korrektse asukoha protsessimudelis ning võimalikud protsessist kõrvalekalded. Prefiksipuul toimiv vastavuskontroll kaotab läbiviidud eksperimentides küll analüüsi täpsuse osas, kuid on arvutuslikult senisest meetodist märkimisväärselt kiirem.

Mida kauem aega möödub kõrvalekalde tekkimisest selle avastamiseni, seda suurem on kõrvalekalde potentsiaalne mõju. Töö teises osas vaatame kuidas teha vastavuskontrolli voogandmetel, ehk peaaegu reaalajas saabuvatel andmed. See on oluline selleks, et teha äriprotsessides vastavuskontrolli võimalikult lähedal sündmuste juhtumise hetkele. Tutvustame algoritmi *I Will Survive* (IWS), mis kasutab töö esimeses osas tutvustatud prefiksipuude struktuuri. IWS algoritmil on võimekus etteantud parameetrite alusel tulemust ümber mängida, juhul kui sissetuleva andmevoo põhjal selgub, et prefiksipuul ollakse vales asukohas. Samas on algoritmil ka hüperparameeter, mis võimaldab vastavalt protsessile hoida mälus erineva pikkusega juhtumeid. IWS kasutab oma väljundis joondust ja on kohati mitu suurusjärku kiirem varasematest voogandmetel töötavatest meetoditest, kuid tulenevalt tuginemisest prefiksipuule, ei pruugi meetod alati tagada optimaalset joondust. Katsetame IWS algoritmi ka mahukate andmevoogude peal ning tulemustest võib järeldada, et algoritm on kasutatav ka päriselu olukordades ning pikaajaliselt jooksutades.

Voogandmetel tuginev analüüs on olemuslikult keerukas, kuna andmeid saabub pidevalt ning, teoreetiliselt, lõputult. Töö kolmandas osas täiendame IWS

algoritmi selliselt, et algoritmil oleks võimekus teha nn soekäivitust, juhul kui näiteks andmevoos esineb tõrkeid. Samuti lisame algoritmile võimekuse määrata tõenäosust millal konkreetne äriprotsessi juhtum lõpule jõuab. See võimaldab äriprotsesside analüütikul paremini hinnata vastavuskontrolli usaldusväärsust ning annab terviklikuma vaate algoritmi tulemustest.

Kiirete ja hajusate andmevoogude puhul võib juhtuda, et sündmused saabuvad väärjärjestuses - sündmus, mis juhtus päriselus hiljem, saabub süsteemi enne sündmust mis juhtus temast varem. Töö viimases osas täiendame IWS algoritmi võimekusega väärjärjestuses saabuvaid sündmusi õigesti joondada. Antud lahendus on kohanemisvõimeline, suutes reguleerida end sõltuvalt väärjärjestuses saabunud sõnumite mahust. Teostatud eksperimendid näitavad, et kohanemisvõimeline lahendus toimib enamikel juhtudel samavõrd kiiresti kui algne IWS algoritm, saavutades aga märkimisväärselt täpsema tulemuse väärjärjestuses saabuvate sündmuste joondamisel.

Kokkuvõttes on käesolevas töös tutvustatud lahendused teostatud eksperimentide põhjal märkimisväärselt kiiremad kui varasemad joondus-põhised vastavuskontrolli meetodid. Siiski on oluline märkida, et prefiksipuu kasutamine protsessimudeliks ei pruugi olla optimaalne. Prefiksipuu ei võimalda samasugust keerukust protsessi kirjeldamisel nagu Petrivõrgud, kuna prefiksipuul peab iga paralleelse või korduva tegevuse jaoks looma uue haru. See tähendab, et prefiksipuu pole hästi inimloetav ning võib keerukamate protsesside puhul kasvada liiga suureks. Siiski, võttes arvesse, et senised meetodid on üldjuhul märkimisväärselt aeglasemad ning ei pruugi seetõttu voogandmetel vastavuskontrolliks üldse sobida, on antud töö ikkagi oluline panus saavutamaks reaalajalähedast vastavuskontrolli.

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Teadustegevus

Peamised uurimisvaldkonnad:

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