Linking Data and Process Perspectives for Conformance Analysis

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Abstract

The detection of data breaches has become a major challenge for most organizations. The problem lies in that fact that organizations often lack proper mechanisms to control and monitor users' activities and their data usage. Although several auditing approaches have been proposed to assess the compliance of actual executed behavior, existing approaches focus on either checking data accesses against security policies (*data perspective*) or checking user activities against the activities needed to conduct business processes (*process perspective*). Analyzing user behavior from these perspectives independently may not be sufficient to expose security incidents. In particular, security incidents may remain undetected or diagnosed incorrectly. This paper proposes a novel auditing approach that reconciles the data and process perspectives, thus enabling the identification of a large range of deviations. In particular, we analyze and classify deviations with respect to the intended purpose of data and the context in which data are used, and provide a novel algorithm to identify non-conforming user behavior. The approach has been implemented in the open source framework ProM and was evaluated through both controlled experiments and a case study using real-life event data. The

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results show that the approach is able to accurately identify deviations in both data usage and control-flow, while providing the purpose and context of the identified deviations.

1. Introduction

Large amounts of sensitive data (e.g., customer personal data, corporate secrets) are often collected and stored by organizations to carry out their businesses. Data are a valuable asset for organizations and, thus, need to be protected from unauthorized access and illegitimate usage. Organizations often use process models and security policies to describe the normative behavior of their IT systems and legitimate usages of data. However, in practice, organizations may allow users to deviate from the prescribed behavior in order to efficiently deal with unanticipated circumstances. For example, IT systems of hospitals often employ the "break-the-glass" functionality to deal with emergency situations. However, such a functionality can be abused, increasing the risks of harmful data breaches. Moreover, a user may exploit its credentials to access sensitive information for personal or financial gain.

Data breaches can have severe financial and legal consequences as well as decrease a company's competitive advantages over other companies. For instance, according to a study conducted by the Ponemon Institute in 350 companies in 2015, the average cost of data breaches is \$3.79 million per incident [42]. Many legal regulations and best practices such as HIPAA in healthcare, Basel III in finance, and COBIT for IT governance have been proposed to mitigate the risks of security incidents. These regulations require organizations to implement internal controls and constantly monitor their business processes to detect security incidents and respond to them. Moreover, organizations need to learn from earlier incidents to improve security policies and prevent data breaches in the future.

The continuous monitoring of processes has enabled the collection of event data that show, for example, which activities users performed, when users accessed certain data and which operations they executed on the data. Alongside process monitoring, several auditing solutions have been proposed to assist organizations in the analysis of user behavior (recorded in event logs) with respect to security policies and regulations. These solutions assess compliance of user behavior either *(i)* with respect to the access and usage of sensitive data (*data perspective*) or *(ii)* with respect to the activities performed by users (*process perspective*). Auditing techniques that operate at the data level [18, 24, 27, 45] analyze whether a user had the right to perform certain operations on the data. However, data operations are typically verified individually. This does not allow for the verification of data protection policies, such as purpose control, that require analyzing the observed behavior as a whole [39]. On the other hand, techniques that operate at the process level [11, 12, 19, 39, 46] usually analyze whether a user has performed the right activity as prescribed by the organization's processes. In particular, these techniques focus on the process control-flow and they do not analyze how data are used within the execution of the process.

Analyzing the observed behavior with respect to the data perspective or the process perspective alone has therefore two main drawbacks: *(i)* deviations can remain undetected and *(ii)* diagnostics may not provide an understanding of the deviations that occurred, thus making it difficult for a security analyst to take the measures necessary to respond to security infringements. These issues are even more critical when considering insider threats (i.e., security threats originating from within the organization being attacked or targeted). In fact, without knowing the context in which data are accessed and used, it is difficult, if not impossible, to discriminate between legitimate and illegitimate behaviors.

In this work, we propose an auditing approach that reconciles the data and process perspectives, thus enabling the identification of deviations that otherwise would remain undetected, and providing accurate diagnostics of those deviations. In particular, the usage of data is analyzed within both the context (defined with respect to the process control-flow) and the purpose (defined in terms of process activities) for which data were

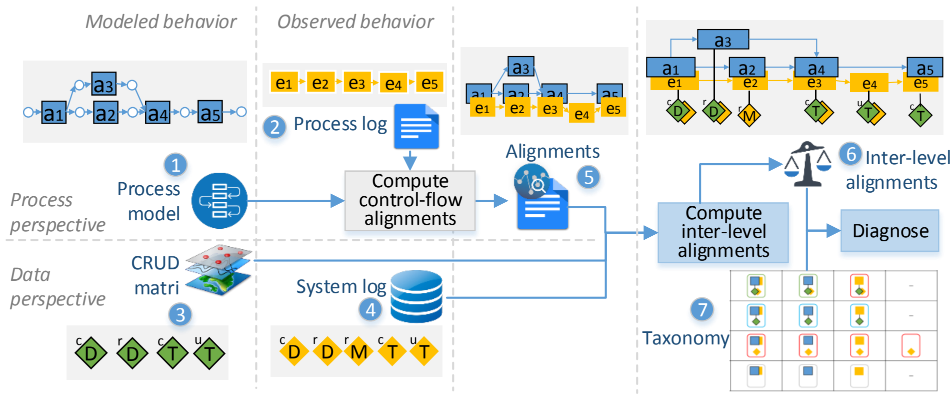


Figure 1: An overview of the proposed approach, showing how the data and process perspectives are reconciled.

used. Fig. 1 shows an overview of our approach together with its inputs and outputs. As shown in the figure, for the analysis of the process perspective, we rely on the notion of control-flow alignments (➎) and, in particular, partially ordered alignments [33], which provide a robust way to pinpoint the causes of non-conformity between a process execution recorded in a process log (➋) and a process model (➊). The diagnostics provided by control-flow alignments show the validity of the context in which operations on data are executed. Moreover, by linking data operations, recorded in a system log (➍), to control-flow alignments (➎), we can check whether the purpose (i.e., the activity) of a data operation is valid according to the intended usage of data (modeled using a CRUD matrix (➌) [23]).

By leveraging this reconciled view of the two perspectives, we introduce the notion of *composite moves*, representing pairwise matching between activities recorded in a log and activities in a process model along with the required operations on the data, and define a taxonomy of the different sorts of composite moves (➐). This taxonomy provides the basis for an analysis of the causes of non-conformity. Moreover, we propose an algorithm to construct *inter-level alignments* (❻), i.e. alignments consisting of composite moves, by linking the operations on data recorded in a system log to activities in the control-flow alignment. Such inter-level alignments enable the analysis of operations on the data with respect to the context in which those operations are executed. This way we can provide more accurate diagnostic information about non-conformity taking into account the purpose of data operations. To the best of our knowledge, this is the first work that proposes an auditing technique reconciling *both* the data and process perspectives.

It is worth noting that in this work we assume that the observed behavior is recorded at both the data and process level. We argue that this assumption is realistic as demonstrated by BPM platforms like FLOWer (now called Lexmark Case Management) [48] and Activiti (`http://activiti.org/`), which provide such functionality. Also in many other information systems both database updates and activity executions are recorded (see the change logs in ERP systems and the redo logs in database systems). Our technique has been implemented as a plug-in of the open source process-mining framework *ProM* and evaluated using both synthetic and real-life datasets.

The remainder of the paper is organized as follows. The next section presents the basic concepts used to represent the process and data perspectives and introduces background on alignments. Section 3 investigates data breaches and identifies types of insider threats relating to the data and process perspectives. Section 4 presents a taxonomy of composite moves and discuss how the identified threats can be captured in terms of composite moves. Section 5 formally defines inter-level alignments and presents our approach to construct such alignments. Experimental results are presented in Section 6. Finally, Section 7 discusses related work, and Section 8 concludes the paper and provides directions for future work.

2. Preliminaries

In this section, we introduce the main concepts and notation used to model the process and data perspectives of an IT system. An overview of these perspectives and their interconnections is shown in Fig. 1. Moreover, we introduce preliminaries on partially ordered alignments [33], which is the basis of the proposed approach.

2.1. Process Perspective

The normative behavior of a system is often described using *process models*. Intuitively, a process model describes the *activities* to be performed to reach a certain business goal. In this paper, we represent process models using Petri nets.

Definition 1 (Process model). *A process model $N = (P, T, F, \tau_i, \tau_f)$ is a marked Petri net where P is a set of places; T is a set of transitions; $F \subseteq (P \times T) \cup (T \times P)$ is the flow relation connecting places and transitions; τ_i is the initial marking; and τ_f is the final marking.*

The state of a process model is represented by a marking, i.e. a multiset of tokens on the places of the net. A process model has an initial marking τ_i and a final marking τ_f. A transition is *enabled* if each of its input places contains at least a token. When an enabled transition is fired (i.e., executed), a token is taken from each of its input places and a token is added to each of its output places. The set of transitions represents the set of activities in the business process.

Let $\mathcal{E}$ denote the universe of all identifiable *process-events*. A process-event can be endowed with attributes that provide additional information about the event. Hereafter, U denotes the universe of attribute names. Given an attribute $attr \in U$, we use partial function $\pi_{attr} : \mathcal{E} \nrightarrow Dom_{attr}$ to represent the value of $attr$ for a process-event from its domain Dom_{attr}. In this work, we assume that U includes at least the following attributes for a process-event $\varepsilon \in \mathcal{E}$: *case*, which denotes the process instance in which

ε was executed; *act*, which is used to represent the activity (transition) associated to ε; and *start* and *complete*, which denote the start and completion time of ε respectively. We assume that $\pi_{start}(\varepsilon) \leq \pi_{complete}(\varepsilon)$.[1]

A process model formally describes all possible runs (called *process-runs*) as intended by the model, whereas actual process executions (called *process-traces*) are recorded in process logs. Hereafter, we refer to a process-event in a process-run as *run-event* and to a process-event in a process-trace as *trace-event*. To distinguish these events, by convention, we use a to represent run-events and e to represent trace-events.

Definition 2 (Process run). *A* process-run *of a process model* $N = (P, T, F, \tau_i, \tau_f)$ *is a partial order*[2] $\varphi = (A_\varphi, <_\varphi)$ *of run-events* $A_\varphi \subseteq \mathcal{E}$ *such that, for each event* $a \in A_\varphi$*,* $\pi_{act}(a) \in T$ *and transition* $\pi_{act}(a)$ *is enabled after firing all its predecessors* $\{a' \in A_\varphi \mid a' <_\varphi a\}$*, starting in* τ_i*. After firing all* $a \in A_\varphi$ *following* $<_\varphi$*, the final marking* τ_f *should be reached. In addition, for all* $a, a' \in A_\varphi$*,* $\pi_{case}(a) = \pi_{case}(a')$*. Given a process model* N*, we use* $\Sigma(N)$ *to denote the (possibly infinite) set of all possible process-runs of* N*.*[3]

Fig. 2 shows a *process model* describing a healthcare process of a hospital for handling patients. In this net, $\tau_i = [p_0]$ and $\tau_f = [p_{11}]$ are the initial and final marking, respectively. The process starts with the identification of a patient (ip). Then, the patient is admitted to the hospital (ad). Next, the patient is visited by its treating doctor (vi). The doctor can request basic lab tests (bt) and advanced tests such as MRI scans (at),

[1]In a classical setting, events are assumed to be atomic. In this paper, however, a process event is used to represent an activity instance, which encompasses both the start and complete events of the activity performed.

[2]A partial order is a binary relation $\prec$ over a set S which is reflexive, antisymmetric and transitive.

[3]In this paper, we are only interested in non-isomorphic runs, i.e. the actual case ids are irrelevant and just used to group events.

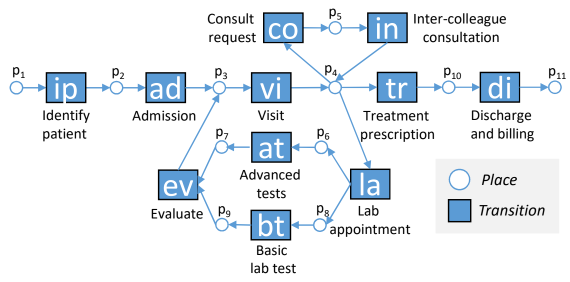
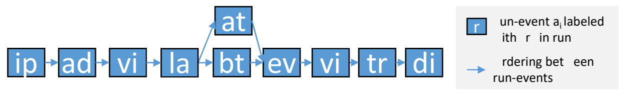
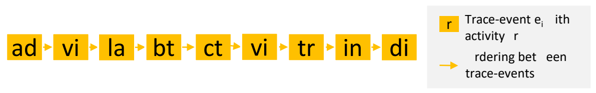


Figure 2: An example of healthcare treatment process.



(a) Process-run



(b) Process-trace

Figure 3: An example of process-run and process-trace.

for which the patient has to make an appointment (la). The results of the lab tests are evaluated by a specialist (ev). Based on this evaluation, the patient's treating doctor may request inter-colleague consultation (co followed by in), request more lab tests, or prescribe a treatment plan (tr). Finally, the patient is discharged, and a bill is created and sent to the patient's insurance company (di).

Fig. 3a shows a *process-run* $\varphi = (A_\varphi, <_\varphi)$ of the model, in which $A_\varphi = \{a_1, ..., a_{10}\}$ and the $<_\varphi$ relation is defined as follows: $a_1 <_\varphi a_2$, $a_2 <_\varphi a_3$, $a_3 <_\varphi a_4$, $a_4 <_\varphi a_5$, $a_4 <_\varphi a_6$, $a_5 <_\varphi a_7$, $a_6 <_\varphi a_7$, $a_7 <_\varphi a_8$, $a_8 <_\varphi a_9$ and $a_9 <_\varphi a_{10}$ (and their transitive closure). For example, transition $ev = \pi_{act}(a_7)$ is enabled after firing $\pi_{act}(a_5) = bt$ and $\pi_{act}(a_6) = at$, which in turn are enabled after firing $\pi_{act}(a_4) = la$. Note that in a process-run all choices have been resolved. Such a process run is also known as a *partially ordered run* of a marked Petri net [33].

The actual recording of a process execution is called a *process-trace*.

Definition 3 (Process trace, log). *A* process-trace $\sigma = (E_\sigma, <_\sigma)$ *is a partial order of trace-events* $E_\sigma \subseteq \mathcal{E}$ *related to a single process execution, i.e. for all* $e, e' \in E_\sigma, \pi_{case}(e) = \pi_{case}(e')$*, and if* $e <_\sigma e'$*, then* $\pi_{complete}(e) \leq \pi_{start}(e')$*. A* process log L_p *is a set of process-traces.*

We assume any two process-traces have disjoint sets of trace-events. Fig. 3b shows a process-trace $\sigma = (E_\sigma, <_\sigma)$, in which $E_\sigma = \{e_1, ..., e_9\}$ and the $<_\sigma$ relation is defined as follows: $e_1 <_\sigma e_2$, $e_2 <_\sigma e_3$, $e_3 <_\sigma e_4$, $e_4 <_\sigma e_5$, $e_5 <_\sigma e_6$, $e_6 <_\sigma e_7$, $e_7 <_\sigma e_8$ and $e_8 <_\sigma e_9$ (and their transitive closure). Note that a process-trace can deviate from the process model. We will discuss this in more detail in Section 2.3.

2.2. Data Perspective

Data are essential for the execution of business activities. In particular, the execution of an activity may require performing certain operations on data objects. In this work, we assume that operations on data objects are always executed in the context of process activities. This relation is often represented using a CRUD matrix [23]. Intuitively, a CRUD matrix relates the process logic to the data layer by indicating which operations on a given data object *must* or *may* be executed in order to complete a given activity.

Definition 4 (CRUD). *Let* T *be the set of transitions in a Petri net,* Obj *a set of data objects,* Op *a set of operations on data objects and* $Mode = \{mandatory, optional\}$ *the set of modes. A CRUD matrix* Θ *consists of a set of CRUD-entries; each entry* $q \in \Theta$ *is a tuple* $(t, obj, op, mode) \in T \times Obj \times Op \times Mode$*.*

It is worth noting that certain operations may be required to perform a certain activity while others may be optional. We capture this using the *mode*. In particular, the mode for a CRUD-entry indicates whether a given operation on a data object is "mandatory"

Activity	**Data object**					
	Demographics (D)	**Lab Test Results (T)**	**Medical History (M)**	**Treatment Plan (P)**	**Invoice (V)**	**Identity (I)**
Identify patient(ip)	–	–	–	–	–	R
Admission (ad)	crud	–	–	–	–	–
Visit (vi)	–	r	r	–	–	–
Lab appointment (la)	–	–	–	–	–	–
Basic lab test (bt)	–	Cru	–	–	–	–
Advanced tests (at)	–	Cru	–	–	–	–
Evaluate (ev)	–	ru	r	–	–	–
Consult request (co)	–	–	–	–	–	–
Inter-colleague consultation (in)	–	r	r	–	–	–
Treatment prescription (tr)	–	r	ru	Cru	–	–
Discharge and billing (di)	–	–	–	–	Cru	–
Clinical trial (ct)	–	–	–	–	–	–

Table 1: CRUD matrix showing the interaction between the activities of the net in Fig. 2 and data objects with respect to operations create (c), read (r), update (u) and delete (d). Capital letters indicate mandatory operations and small letters optional operations.

or "optional" to complete a certain activity. Hereafter, we extend the π notation to CRUD matrices to retrieve the elements of a CRUD-entry, i.e. given a CRUD-entry $q = (t, obj, op, mode)$, $\pi_{act}(q) = t$, $\pi_{obj}(q) = obj$, $\pi_{op}(q) = op$ and $\pi_{mode}(q) = mode$.

Table. 1 shows an example of CRUD matrix for the process model in Fig. 2. Four basic operation types are considered in this matrix, i.e. *create (c)*, *read (r)*, *update (u)* and *delete (d)*. Upper-case and lower-case letters indicate whether data operations are mandatory and optional respectively (i.e., the $mode$). For instance, when activity *discharge and billing* (di) is performed, an invoice must be created for the patient. This information can be (optionally) read and/or updated during the execution of di.

Operations on data objects are typically recorded by the IT system. Hereafter, we refer to a recorded operation as *system-event* and use $\mathcal{S}$ to denote the set of all possible

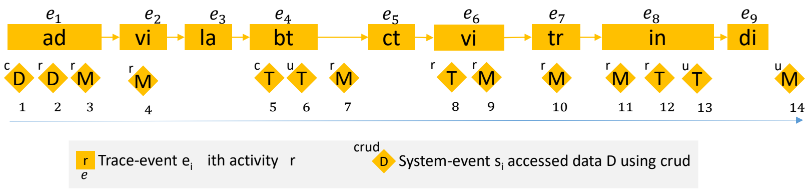


Figure 4: Example of the process-trace and system-trace recorded for a patient that undergoes the healthcare process in Fig. 2; the events of the two traces are ordered based on its time of execution.

system-events. System-events can be endowed with a set of attributes from the attribute universe U. In particular, for a system-event $s \in \mathcal{S}$, we consider the following attributes: pur, which is used to relate s to a purpose (in our case, to a process activity); $case$, which indicates the process instance in which s was executed; obj, which denotes the data object on which the operation was performed; op, which denotes the operation that was executed; and $time$, which indicates the time s was executed. Similarly to process-events, we use notation $\pi_{attr}(s)$ to represent the value of attribute $attr$ for a system-event s.

Definition 5 (System trace, log). *A* system-trace $\beta = \langle s_1, \ldots, s_n \rangle \in \mathcal{S}^*$ *is a sequence of system-events related to the same case, i.e., for all* $s, s' \in S_\beta$, $\pi_{case}(s) = \pi_{case}(s')$ *where* $S_\beta = \{s_1, \ldots, s_n\} \subseteq \mathcal{S}$ *denotes the set of system-events occurring in* β. *A* system event log L_s *is a set of system-traces.*

Fig. 4 exemplifies a process-trace and the corresponding system-trace. The sequence of diamonds, i.e. $\langle s_1, s_2, \cdots, s_{14} \rangle$, shows a system-trace consisting of fourteen system-events. System-event s_1 records that an instance of demographic information (D) has been created, i.e. $\pi_{op}(s_1) = c$ and $\pi_{obj}(s_1) = D$; s_2 records that D has been read, i.e. $\pi_{op}(s_2) = r$ and $\pi_{obj}(s_2) = D$; s_3 records that the corresponding medical history (M) has been read, i.e. $\pi_{op}(s_3) = r$ and $\pi_{obj}(s_3) = M$. These operations were executed while trace-event e_1 was performed, e.g. $\pi_{pur}(s_3) = \pi_{act}(e_1) = ad$. Similar information is visualized for other system-events and trace-events. It is worth noting that in the system-trace medical history (M) has been read and updated (s_7 and s_{14}, respectively), but no activity at the process level was executed concurrently.

2.3. Alignment-based Conformance Checking

Control-flow alignments provide a robust approach to conformance checking. In this work, we adopt partially ordered alignments [33]. We choose to use partially ordered alignments rather than sequential alignments [11, 15] because partially ordered alignments make it possible to explicitly represent concurrency. This allows us to choose the context for system-events more accurately.

Conceptually, a control-flow alignment relates the events in a process-trace $(E_\sigma, <_\sigma)$ to the events in a process-run $(A_\varphi, <_\varphi)$, thus pinpointing the deviations causing nonconformity. If a process-trace perfectly fits a Petri net, each "move" in the process-trace, i.e. an event observed in the process-trace, can be mimicked by a "move" in the model, i.e. an instance of a transition fired in the net. In cases where deviations occur, some moves in the process-trace cannot be mimicked by the net or vice versa. Hereafter, we explicitly denote "no move" by $\gg$ and use $X^{\gg} = X \cup \{\gg\}$ to include the no move in set X. Control-flow alignments consist of three types of process moves (hereafter called *legal moves*):

- (e, a) is a *synchronous move*, if $a \in A_\varphi$ and $e \in E_\sigma$;
- $(e, \gg)$ is a *move on log*, and $e \in E_\sigma$;
- $(\gg, a)$ is a *move on model*, and $a \in A_\varphi$.

Definition 6 (Control-flow alignment). *Let $\sigma = (E_\sigma, <_\sigma)$ be a process-trace and $\varphi = (A_\varphi, <_\varphi)$ a process-run of a process model N. A control-flow alignment $\gamma = (M_\gamma, <_\gamma)$ of σ and φ is a partial order, in which $M_\gamma \subseteq E_\sigma^{\gg} \times A_\varphi^{\gg} \backslash \{(\gg, \gg)\}$ is a set of process moves, such that*

(1) For all trace-events $e \in E_\sigma$, there is one and only one $(e', x) \in M_\gamma$ such that $e = e'$.

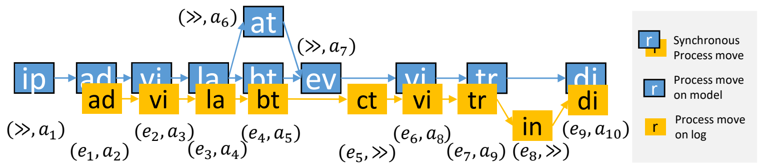


Figure 5: An example of control-flow alignment between the process-trace in Fig. 3b and the process-run in Fig. 3a.

(2) For all run-events $a \in A_\varphi$, there is one and only one $(y, a') \in M_\gamma$ such that $a = a'$.

(3) The ordering $<_\gamma$ respects both $<_\sigma$ and $<_\varphi$, i.e., for each pair of moves $(e, a), (e', a') \in M_\gamma$, $((e, a) <_\gamma (e', a')) \Leftrightarrow (((e <_\sigma e') \vee (a <_\varphi a'))$ and $(e <_\sigma e') \Rightarrow (a' \not<_\varphi a))$.

(4) For each synchronous move $(e, a) \in M_\gamma$, $\pi_{act}(e) = \pi_{act}(a)$.

A control-flow alignment between a process-trace and a process model is a partial order of legal moves such that, ignoring all occurrences of $\gg$, the projection on the first element yields the process-run and the projection on the second element yields the process-trace.

Fig. 5 shows an example of a control-flow alignment between the process-trace in Fig. 3b and the process-run in Fig. 3a. The alignment comprises: seven synchronous moves including (e_1, a_2) and (e_2, a_3); two model moves, namely $(\gg, a_6)$ and $(\gg, a_7)$; and two log moves, namely $(e_5, \gg)$ and $(e_8, \gg)$. In this paper, we assume that control-flow alignments correctly capture the deviations from the specifications and refer interested readers to [10, 14, 15] for heuristics to compute reliable alignments.

3. Threat Model

In the security research community and industry, there is consensus that a large percentage of data breaches that occur in organizations is caused by insider threats.

An insider is typically defined as an individual who has some privileged access to an organization's IT system [22, 30, 40]. Accordingly, an insider can be a current employee or officer of the organization but can also be a discharged employee whose system credentials have not yet been revoked, a masquerader who finds a computer logged in, or a business partner with access to the system. Malicious, negligent and accidental behaviors of these users are referred to as *insider threats*. By misusing their privileges, insiders can pose serious security threats to an organization driven by various motivations, e.g. for profit, revenge or curiosity. Insider threats are often considered more critical than external attacks because insiders have more knowledge about the IT system than external attackers and have direct access to the organization's sensitive information through the information systems they daily use. This makes insider threats more difficult to detect and prevent.

Several taxonomies have been proposed for insiders and insider threats [21, 31, 41, 43]. Bishop et al. [21] categorize insiders based on their access privileges and their ability to damage an organization. Predd et al. [43] propose four dimensions, namely the organization (expressed policy), the environment (laws, economics, ethics), the individual (perceived policy and intent), and the system (embedded policy) to understand and categorize the risk of insider threats. Phyo and Furnell [41] classify insider threats based on the system level (i.e., network, operating system, application, and data) these threats may be detected and/or monitored.

Based on a literature review and notable security incidents from the past, we have identified different types of insider threats relating to the process and data levels that can put an organization at risk:

1. *Unauthorized data access*: Insiders abuse their privileges and access data for curiosity or malicious purposes [17, 47]. A typical example of this type of threat is *insider snooping* into patient records.

2. *Unauthorized data modification*: Insiders replace or alter existing valid data, or introduce false data into a file or a database for personal or financial gain. An example of this type of threat is *medical fraud*, which involves the payment of treatment never rendered [29].
3. *Data update omission*: Insiders accidentally or intentionally do not update the data as required. This type of threat results in outdated data, which has an impact on the quality of data and, consequently, on the decisions taken based on these data.
4. *Security and privacy control bypass*: Insiders circumvent the security and privacy policies and controls currently in place to access sensitive information or to perform critical activities. These controls can be required to complete an activity or be a prerequisite for performing other activities; skipping such steps may indicate that the opportunity for a fraud or a privacy violation (e.g., processing personal data without the informed consent of the data subject involved) exists.
5. *Secondary usage of data* (also called *data re-purposing*): Insiders process data for purposes other than those for which the data were originally collected without data subject consent [28, 39]. Note that this threat differs from an unauthorized data access (insider threat type 1) because the user is authorized to access the data but uses these data in a way not allowed.

We now exemplify these threats using the healthcare treatment process in Fig. 2 and the CRUD matrix in Table 1. In order to handle a patient, healthcare workers involved in the treatment process should execute the prescribed activities and, in order to complete these activities, they must or may need to perform certain data operations as defined in the CRUD matrix. The processing of data should be performed according to security policies and controls in place. Insiders, however, can circumvent these policies and controls by misusing their privileges as illustrated by the representative scenarios below:

Scenario 1a. *A curious receptionist accesses the medical information of a high-profile* *patient such as a celebrity or a politician while the patient is being admitted to the hospital (insider threat type 1) [6]. This information might then be transmitted to the media, thus, violating the patient's privacy. This unauthorized access to data (typically called 'insider snooping') can be observed in Fig. 4 by noting that the reading of the patient's medical history (M), recorded by system-event s_3, is not allowed for patient admission (ad) according to the CRUD matrix.*

Scenario 1b. *A doctor is persuaded by a marketing or pharmaceutical company to sell medical information of patients. To this end, the doctor retrieves a massive amount of patient medical records (insider threat type 1) [7, 8]. To cover his actual intent and thus avoid detection, he accesses the data (M) for consultation purposes (in), which is allowed by the CRUD matrix in Tab. 1 and therefore does not raise any alarm from a data perspective. Nevertheless, this unauthorized access to data can be detected in Fig. 4 by observing that consultation happened (e_8) without being requested (i.e., a process-event recording the execution of activity 'in' can only occur after a process-event recording the execution of activity 'co').*

Scenario 2. *A nurse intending to harm a patient or obtain reimbursements alters the patient's medical record (insider threat type 2) [4]. For example, the nurse may change blood type and drug allergies or add medical services that were never received by the patient to the medical records. Such erroneous information could impact care quality or cause some problems to obtain medical, life or disability insurance. This unauthorized modification of data can be observed in Fig. 4 by noting that the nurse updates the medical history (M) of the patient (s_{14}) without an apparent reason (i.e., no process activities are executed concurrently).*

Scenario 3. *Hospitals usually require doctors to create a new treatment plan after visiting a patient, which is stored in the patient's medical record. A doctor negligently* *forgets to update a patient's medical record with the prescribed treatment (insider threat type 3) [47]. The missing information may cause other doctors to prescribe conflicting medication to the patient. This omission can be detected in Fig. 4 by observing that the treatment plan (P) has not been created when the treatment is prescribed (e_7) as required by the CRUD matrix of Table 1.*

Scenario 4. *A patient without medical insurance intending to get expensive medical care such as complicated surgeries or organ transplants impersonates a well-insured individual. A receptionist admits the patient to the hospital without verifying her identity (insider threat type 4) [5, 3]. The hospital provides full-service care and charges the victim for all the services obtained by the patient. Beyond financial losses, this can cause other personal consequences for the victim. In particular, the modification of its medical record with another patient's lab test results and prescribed treatments can be life threatening and difficult to erase, which resembles an insider threat of type 2. This threat can be detected in Fig. 4 by observing that the patient is admitted (ad) to the hospital (e_1) without being previously identified (ip) as required by the process model (Fig. 2).*

Scenario 5. *A doctor accesses patient information for providing medical treatment, but later uses this information to conduct a clinical trial (ct) without patients' consent and approval of the ethical medical committee of the hospital (insider threat type 5) [39]. This case of secondary usage of data can be detected in Fig. 4 by observing that, after some unjustified access to patient medical history (M), recorded by system-event s_7, the doctor performs a clinical trial (e_5), which among others does not contribute to the fulfillment of the treatment process as defined in Fig. 2.*

It is worth noting that the detection and diagnosis of the insider threats described in the scenarios above requires *both* control-flow and data perspectives together; one perspective alone is not sufficient. For instance, the threat in Scenario 1b can only be detected by relating the access to data (recorded by system-events s_{11} and s_{12}) to activity *in* (recorded by trace-event e_8). As shown in the next section, looking at control-flow and data together allows establishing a larger context for deviations, making it possible to identify richer patterns than when considering each perspective in isolation.

4. Taxonomy of Composite Moves

In order to detect deviations more accurately and provide contextual information for diagnosis, we relate the four basic elements discussed in Section 2, namely trace-events, run-events, system-events and CRUD-entries to each other. In particular, we introduce the notion of *composite move*, which connects these elements thus reconciling the process and data perspectives. A trace-event e and a run-event a constitute a control-flow alignment move (also called process move) that provides the *context* for a system-event s, while a CRUD-entry q associates a system-event to a process-event thus providing the *purpose* for data operations. Note that different system-events could be associated with the same context (process move). We define composite moves $((s,q),(e,a))$ as follows:

Definition 7 (Composite move). *Let A_φ be the set of run-events in a given process-run φ, E_σ the set of trace-events in a given process-trace σ, S_β the set of system-events in a given system-trace β and Θ a CRUD matrix. Let $\gamma = (M_\gamma, <_\gamma)$ be a control-flow alignment defined over E_σ and A_φ. A* composite move *is a tuple $((s,q),(e,a)) \in (S_\beta^{\gg} \times \Theta^{\gg}) \times M_\gamma^{(\gg,\gg)}$ (with $M_\gamma^{(\gg,\gg)} = M_\gamma \cup \{(\gg,\gg)\}$) such that:*

1. *if $(e,a) = (\gg,\gg)$, then $(s,q) = (x,\gg)$ with $x \in S_\beta$.*
2. *if $q \neq\gg$, then either ($a \neq\gg$ and $\pi_{act}(q) = \pi_{act}(a)$) or ($e \neq\gg$ and $\pi_{act}(q) = \pi_{act}(e)$).*
3. *if $s =\gg$ and $q \neq\gg$, then $\pi_{mode}(q) = mandatory$.*

Note that the first if-statement denotes system-events s that may be unrelated to any process move, for which we use $(\gg,\gg)$ (hereafter called *no process move*) in the definition of composite moves; thus, $((s, \gg), (\gg, \gg))$.

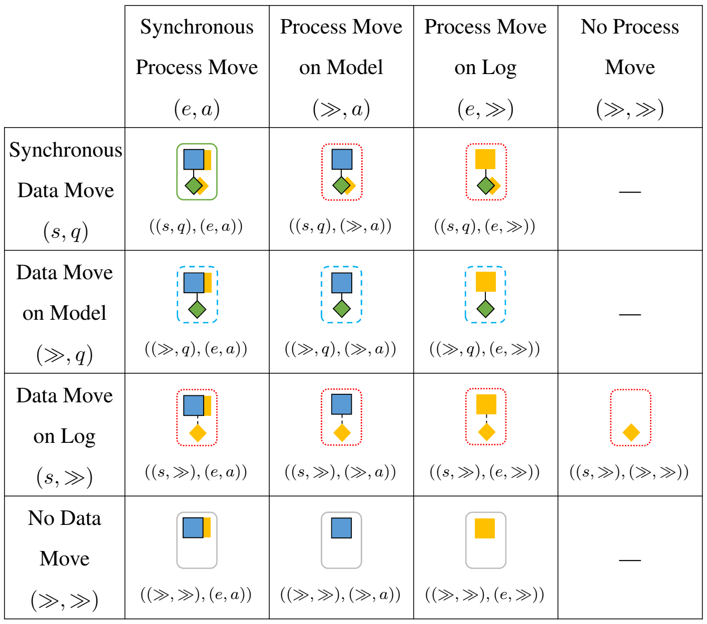
Given a composite move $((s, q), (e, a))$, we refer to process move (e, a) as the *context* in which s is executed. Moreover, we call the activity associated to the process move (i.e., $\pi_{act}(a)$ or $\pi_{act}(e)$) the *purpose* of the system-event s. Intuitively, the purpose denotes the activity for which the data operation is executed [39].

The purpose and context of an operation on data are used to assess its conformity with the specification. The (non)conformity at the process level provides contextual information for system-events. In particular, the context determines whether an operation on the data occurred in accordance with the expected control-flow as defined by the process model. On the other hand, the (non)conformity of a system-event with respect to the CRUD matrix is used to determine the validity of the purpose associated to an operation on the data, i.e. whether an operation is performed for the intended purpose.

Based on the definition of composite moves above, we can distinguish 13 types of composite moves. Fig. 6 shows a graphical representation of these moves. Hereafter, we use the row and column number to refer to move types (e.g., (1,2) refers to the move type located in row one and column two). It is worth noting that move types (1,4), (2,4), and (4,4) do not correspond to any legal composite moves, as is indicated by the dashes. Composite moves can be grouped in three categories with respect to data operations:

Legitimate Operations. This group of move types (denoted by a green full line rectangle in Fig. 6) indicates fully compliant behavior, i.e. an operation on the data was executed for a valid purpose under a valid context. This group comprises only moves of type (1,1).

Missing Operations. Move types in this group (denoted by a blue dashed line rectangle in Fig. 6) capture the cases where a mandatory operation on data expected to accomplish a certain purpose (activity) was not executed (i.e., a system-event is missing). The missing operation may correspond to a data update or a security check, indicating that an insider threat of type 3 or 4 (Section 3) occurred respectively. In particular, skipping a



	Synchronous Process Move (e, a)	Process Move on Model $(\gg, a)$	Process Move on Log $(e, \gg)$	No Process Move $(\gg, \gg)$
Synchronous Data Move (s, q)	$((s, q), (e, a))$	$((s, q), (\gg, a))$	$((s, q), (e, \gg))$	—
Data Move on Model $(\gg, q)$	$((\gg, q), (e, a))$	$((\gg, q), (\gg, a))$	$((\gg, q), (e, \gg))$	—
Data Move on Log $(s, \gg)$	$((s, \gg), (e, a))$	$((s, \gg), (\gg, a))$	$((s, \gg), (e, \gg))$	$((s, \gg), (\gg, \gg))$
No Data Move $(\gg, \gg)$	$((\gg, \gg), (e, a))$	$((\gg, \gg), (\gg, a))$	$((\gg, \gg), (e, \gg))$	—

Figure 6: Taxonomy of composite moves. Yellow diamonds represent system-events (s), green diamonds CRUD-entries (q), yellow squares trace-events (e), and blue squares run-events (a). The full line linking a process move to a CRUD-entry indicates that the operation is allowed by the CRUD matrix; the dashed line linking a process move to a system-event indicates that the operation is not allowed by the CRUD matrix. Composite moves enclosed in a green full line rectangle represent legitimate operations; composite moves enclosed in a blue dashed line rectangle represent missing operations; composite moves enclosed in a red dotted line rectangle represent illegitimate operations; composite moves enclosed in a grey rectangle represent composite moves not involving data.

security control can signal that the opportunity for a fraud exists, whereas skipping a data update indicates that data may not be reliable.

A move of type (2,1) indicates that the context, in which the missing operation should have been executed, is valid, i.e. the expected activity was performed. However, as the required operation was not executed, the corresponding activity has not been successfully accomplished. For example, consider the normative behavior defined in the net of Fig. 2 and the CRUD matrix of Table 1. As specified, whenever activity *discharge and billing (di)* is executed, an *invoice (V)* must be created. Skipping this operation may indicate that the provided treatment has not been paid. Moreover, move type (2,1) captures the threat described in Scenario 3. Here, the doctor executed activity *treatment prescription (tr)* as required by the net in Fig. 2 (represented by synchronous process move (e_7, a_9) in Fig. 5). However, at the data level, the *treatment plan (P)* is not created as demanded by the CRUD matrix in Table 1, resulting in a data move on model.

Move types (2,2) and (2,3) show that the context, in which the missing operation should have been executed, is also invalid. In particular, a move of type (2,2) indicates that the expected activity was not executed. This move type can be used to capture the threat described in Scenario 4. In this scenario, a receptionist may have skipped activity patient identification *(ip)* along with the required data operation (i.e., read *Identity (I)*). This behavior is captured as a move on log at both process and data level, which is encoded by move type (2,2). On the other hand, a move of type (2,3) indicates that the performed activity should not have been performed. In this case, even if we assume that the operation on data should have been executed to deal with an exceptional situation, the executed activity would not have been successfully accomplished, thus raising suspicion about the execution of that activity.

Illegitimate Operations. This group of move types (denoted by a red dotted line rectangle in Fig. 6) captures illegitimate data operations. A data operation is illegitimate if it is executed to accomplish an activity for which the operation is not allowed or it is executed within an invalid context (or a combination of the two). Move types in this group can be used to capture unauthorized data accesses (insider threat type 1), unauthorized data modifications (insider threat type 2) and secondary usage of data (insider threat type 5).

A move of type (3,1) indicates that an activity was executed as prescribed by the process model (i.e., the context is valid), but the executed operation on data is not allowed for that activity according to the CRUD matrix. This corresponds, for instance, to the situation described in Scenario 1a. The recorded behavior in Fig. 4 shows that the receptionist read the patient's *medical history (M)*, as indicated by system-event s_3, when admitting the patient to the hospital (trace-event e_1). While admission was performed as expected (denoted by synchronous process move (e_1, a_2) in Fig. 5), the data operation recorded by s_3 is not allowed for patient admission according to the CRUD matrix in Table 1. Thus, this move type can reveal cases of insider snooping, in which a user performs an unauthorized access to data within the execution of its duties.

Move types (1,2) and (1,3) indicate that the context is invalid and, thus, the operation on data is illegitimate. For example, move type (1,3) can be used to capture the situation described in Scenario 1b. As shown in Fig. 4, the doctor accessed the *medical history (M)* and *lab test results (T)* of several patients (recorded by system-events s_{11} and s_{12} respectively) for *inter-colleague consultation (in)*. These data operations are allowed for *inter-colleague consultation (in)* according to the CRUD matrix. However, activity *in*, recorded by trace-event e_8, was executed illegally as shown by log move $(e_8, \gg)$ of the control-flow alignment in Fig. 5. Therefore, the context of system-events s_{11} and s_{12} is invalid. The doctor may have faked (a portion of) the process execution, in this case *inter-colleague consultation (in)*, to justify the data access.

Move type (3,3) captures the cases in which both the context and the purpose of an operation on the data are invalid. Move type (3,2) is similar to move type (3,3), but in this case the expected activity has not been executed. In contrast, a move of type (3,4) indicates that the purpose of the executed operation on the data does not match any control-flow alignment move. Therefore, this operation was performed out of context. Move type (3,4) can be used, for instance, to capture what happened in Scenario 2. As shown in Fig. 4, a patient's *medical history (M)* was updated by a nurse (system-event s_{14}) after the patient was discharged (trace-event e_9). This operation cannot be linked to any process move and, thus, its execution cannot be justified. Move type (3,4) can also provide evidence of other threats like unauthorized data access and secondary usage of data. For instance, in Scenario 5 a doctor accessed a patient's *medical history (M)* without an apparent reason (i.e., out of context) while providing medical treatment, denoted by system-event s_7, and at a later time conducted a medical trial using those data (trace-event e_5).

It is worth noting that move types (4,1), (4,2) and (4,3) correspond to situations in which no operation on data is required to be executed according to the CRUD matrix. For these composite moves, the observed behavior at the data level coincides with the specification. At the process level, they correspond to control-flow alignment moves (see Section 2.3). Specifically, move type (4,1) is a synchronous move not involving data. Move types (4,2) and (4,3) represent the standard process moves on model and process moves on log (without any data access) respectively.

One can easily observe that some types of deviations identified in Fig. 6 may remain undetected if the data and process perspectives are not reconciled. Consider, for instance, moves of type (2,1). This type of moves encompasses a synchronous process move and, thus, complies with the specifications from the process perspective. On the other hand, auditing techniques operating at the data level only assess the compliance of operations on data that have been executed and are not able to detect that a certain operation was not executed. Therefore, moves of type (2,1) would remain undetected by considering the data and process perspectives independently. For similar reasons, the other types of missing operations (i.e., move types (2,2) and (2,3)) cannot be diagnosed properly and, in particular, cannot be distinguished from other deviation types (e.g., from move types (1,2) and (1,3) respectively). More in general, it is easy to observe that auditing techniques operating at the data level are not able to detect missing operations and some cases of illegitimate operations, namely moves of types (1,2) and (1,3). On the other hand, using auditing techniques operating at the process level moves of type (2,1), (3,1) and (3,4) may be considered as a legitimate behavior. We argue that, only through identifying the context and purpose in which operations on data are executed, one can gain a clear understanding of the infringements that occurred.

It is worth noting that there is not a one-to-one relation between the insider threats identified in Section 3 and the composite moves in Fig. 6. Different threat types might be captured by the same composite move, and a threat of a certain type might be captured by different composite moves. Moreover, threats can manifest as combination of composite moves (e.g., Scenario 5). Actually, composite moves pinpoint where the observed behavior differs from the specification and provide richer diagnostic information about deviations. The interpretation of non-conforming behavior and, thus, the identification of the type of threat that occurred, however, requires knowledge of the application domain and, in particular, of the activities and data operations involved in the composite moves. For instance, data update omission (insider threat type 3) involves the skipping of update operations, whereas security and privacy control bypass (insider threat type 4) requires the skipping of security and privacy controls. In essence, our approach does not aim to replace the role of the auditors in the auditing process. Rather, it aims to assist auditors in the analysis of non-conforming behavior by providing a better understanding of deviations and thus in choosing appropriate mitigation actions.

5. Inter-Level Alignments

Composite moves reconcile the process and data perspectives, thus enabling the identification of deviations that otherwise would remain undetected, and providing accurate diagnostics of those deviations. As discussed in the previous section, diagnostic information provided by composite moves provides a valuable support to analysts in the identification of several insider threats as the ones described in Section 3. However, determining which composite moves should be used to capture the actual usage of data requires knowledge of the process model and of the process execution at hand. To this end, as illustrated in Fig. 1, we assume that diagnostic information at the process level (in form of control-flow alignments) is available. Intuitively, this information is used to drive the analysis of system logs. This design choice is motivated by the fact that the context (represented by control-flow alignment moves) can help establish which data operations are expected to be executed in order to successfully complete the execution of the business process.

To check the compliance of system-traces with respect to control-flow alignments (thus verifying their contexts) and a CRUD matrix (thus verifying their purposes), we introduce the notion of *inter-level alignments* and then discuss the approach for computing them.

5.1. Defining Inter-Level Alignments

An inter-level alignment is a sequence of composite moves, associating the system-events in a system-trace to the moves of a control-flow alignment and entries in a CRUD matrix.

Definition 8 (Inter-level alignment). *Let β be a system-trace, S_β a set of system-events in β, Θ a CRUD matrix and $\gamma = (M_\gamma, <_\gamma)$ a control-flow alignment between a process-trace σ and a Petri net N. An* inter-level alignment *ψ is a sequence of composite moves $\langle (w_1, m_1), ..., (w_i, m_j), ..., (w_n, m_k)\rangle$, with $(w_i, m_j) = ((s_i, q_i), (e_j, a_j)) \in (S_\beta^{\gg} \times \Theta^{\gg}) \times M_\gamma^{(\gg,\gg)}$, such that*

1) *for each system-event $s \in S_\beta$, there is one and only one composite move $((s_i, q_i), (e_j, a_j)) \in \psi$ such that $s_i = s$;*
2) *for each process move $m \in M_\gamma$, there is at least one composite move $((s_i, q_i), (e_j, a_j)) \in \psi$ such that $(e_j, a_j) = m$;*
3) *for each mandatory CRUD-entry $x \in \Theta$, if there is a move $(e, a) \in M_\gamma$ such that $\pi_{act}(x) = \pi_{act}(e)$ or $\pi_{act}(x) = \pi_{act}(a)$, then there is $((s, q), (e, a)) \in \psi$ with $q = x$;*

4) *composite moves respect the ordering of system-events in β;*
5) *composite moves respect the ordering $<_\gamma$ of M_γ, i.e., for $1 \leq x < y \leq k$, $m_y \not<_\gamma m_x$.*

To properly link the data and process perspectives, we introduce a set of criterion functions Λ and a cost function κ: criterion functions are used to assess the legality of composite moves, whereas the cost function is used to assess their quality.

Definition 9 (Legal inter-level alignment). *A criterion function λ is a Boolean function of arity at least 1 where the first parameter is a composite move and the other parameters are additional inputs needed to verify the validity of the composite move against a given criterion. Let λ be a criterion function of arity $m+1$ (with $m \geq 0$); $\lambda((w,m), x_1, \ldots, x_m)$ returns $true$ if composite move (w,m) is legal according to the criterion defined by λ and $false$ otherwise. Let $\Lambda = \{\lambda_1, \cdots \lambda_n\}$ denote a set of criterion functions. An inter-level alignment $\langle (w_1, m_1), ..., (w_n, m_k)\rangle$ is* legal *if and only if each of its composite moves (w_i, m_j) is legal according to every criterion function in Λ, i.e., for all $\lambda_k \in \Lambda$, $\lambda_k((w_i, m_j), x_1, \ldots, x_m) = true$ (with $m+1$ the arity of λ_k).*

In essence, we use criterion functions to assess the legality of linked system-events and process moves. Note that, besides a composite move, a criterion function can rely on other artifacts (e.g., control-flow alignments) depending on the criterion used to determine the legality of composite moves. For example, if events have timestamps, we can define a criterion function λ_{time} to assess whether system-events are associated with trace-events that happened concurrently. This function takes two parameters: a composite move and a control-flow alignment. Let $w = (s, q)$ and $m = (e, a)$; $\lambda_{time}((w,m), \gamma) = true$ if $\pi_{start}(e) \leq \pi_{time}(s) \leq \pi_{complete}(e)$, otherwise $false$. Here, the control-flow alignment γ is needed to estimate the time attributes of process

	(e,a)	$(\gg,a)$	$(e,\gg)$	$(\gg,\gg)$
(s,q)	0	2	2	–
$(\gg,q)$	1	2	2	–
$(s,\gg)$	3	4	4	5
$(\gg,\gg)$	0	1	1	–

Table 2: An example of a cost function that assigns a cost to each composite move according to the move types in Fig 6.

moves on model. As no trace-event is associated to these moves, their start and completion time cannot be derived from any process-event directly. However, we can assume that these missing activities should have been executed after the previous trace-event and before the next trace-event. Using this assumption, criterion function λ_{time} determines the validity of potential links between system-events and these moves. Moreover, if system-events have attribute pur indicating the purpose (activity) for which a certain operation on data was executed, we can define a unary criterion function λ_{pur} where $\lambda_{pur}((w,m)) = true$ if $\pi_{pur}(s) = \pi_{act}(e) \vee \pi_{pur}(s) = \pi_{act}(a)$, otherwise $false$. Criterion functions will help us select legal composite moves while leveraging event attributes. The cost function is then used to define optimal inter-level alignments.

Definition 10 (Optimal inter-level alignment). *Let Ψ denote the set of all legal possible inter-level alignments between a system-trace β, a control-flow alignment γ and a CRUD matrix Θ. A cost function κ assigns a predefined cost to each type of composite move. An inter-level alignment $\psi \in \Psi$ is* optimal *if and only if for all $\psi' \in \Psi$, $\kappa(\psi) \leq \kappa(\psi')$.*

Table 2 exemplifies the standard cost function used in this paper. The number in each cell represents the cost assigned to the composite move in the same cell in Fig. 6. Let us consider the control-flow alignment in Fig. 5, the system-traces in Fig. 4 and the CRUD matrix in Table 1. Fig. 7 shows two inter-level alignments ψ_1 and ψ_2, proposing

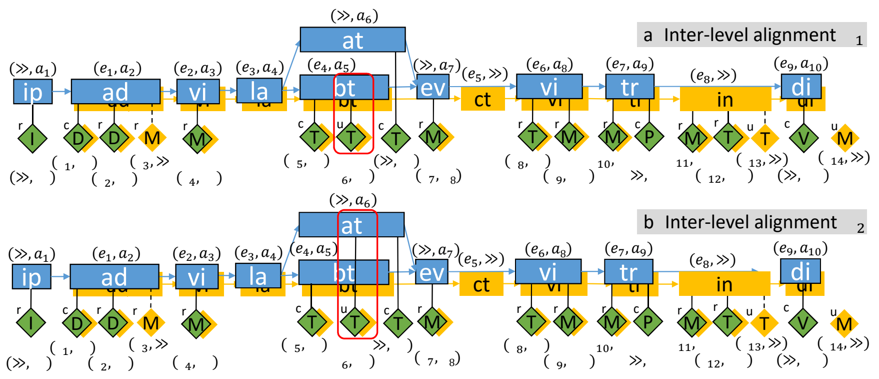


Figure 7: Construction of two inter-level alignments, each as a sequence of composite moves between the net in Fig. 2 and the recorded events in Fig. 4; the differences between the two are highlighted using red rectangles.

a sequence of composite moves.[4] For example, for ψ_1, system-event s_6 can be linked to synchronous process move (e_4, a_5) based on the timestamps and then associated with CRUD-entry $q_6 = (bt, T, u, optional)$, which results in $((s_6, q_6), (e_4, a_5))$, a synchronous composite move on both perspectives with cost 0 according to the cost function in Table 2. However, it is also legal to associate s_6 to model move $(\gg, a_6)$, resulting in composite move $((s_6, q_6), (\gg, a_6))$. The total cost of ψ_1 and ψ_2 is 25 and 27 respectively. Let assume $\pi_{pur}(s_6) = bt$, then criterion function λ_{pur} would make ψ_2 illegal.

Such inter-level alignments provide for each system-event its purpose and context, allowing for more accurate diagnosis. Consider, for example, composite move $((s_3, \gg), (e_1, a_2)) \in \psi_1$. This move shows that, although the read operation on M has a valid context, it is not allowed by the CRUD matrix and, thus was executed without a legitimate purpose. A possibly more severe deviation is composite move $((s_{13}, \gg), (e_8, \gg))$, which not only is performed for an illegitimate purpose, but also

[4]The number of the CRUD-entries in Fig. 5 reflects their order of appearance in the alignment and is not related to their appearance in the CRUD matrix of Table 1.

in an invalid context (process move on log). The fact that the activity of e_8 (in) was not allowed during that phase of the process makes s_{13} more suspicious. In addition to more accurate diagnosis, leveraging the context, our approach can detect deviations that otherwise would remain undetected. For example, if we consider composite move $((s_{12}, q_{14}), (e_8, \gg))$, the read operation on T was allowed by the CRUD matrix; without considering the context $(e_8, \gg)$, one may consider such an operation to be legitimate. However, the process move on log $(e_8, \gg)$ shows that the context, in which s_{12} was executed, is actually invalid as the activity should not have been performed.

5.2. Computing Inter-Level Alignments

This section presents our approach to construct an optimal inter-level alignment of a system-trace and a control-flow alignment with respect to a given cost function, a set of criterion functions and a CRUD matrix. Similarly to [11], we translate the problem of finding an optimal inter-level alignment into a shortest path problem and employ the A^* algorithm [26] to find the path with minimum cost. A^* is a search algorithm widely used in graph traversal. A^* aims to efficiently compute the shortest path using a heuristic function, which under some condition (see below) guarantees that the actual shortest path is found.

Hereafter, we indicate that a sequence σ' is a prefix of a sequence σ, denoted $\sigma' \in \mathit{prefix}(\sigma)$, if there exists a sequence σ'' such that $\sigma = \sigma' \oplus \sigma''$, where $\oplus$ denotes the concatenation operator.

Let $G = (V, D)$ be a directed graph with V a set of nodes and D a set of weighted edges. The A^* algorithm aims to find the path with the minimum cost from the source node $v_0 \in V$ to a node v in target nodes $TN \subset V$. A cost is assigned to each node $v \in V$ using an *evaluation* function $f(v) = g(v) + h(v)$ where

- $g : V \to \mathbb{R}_0^+$ is a function that returns the cost of the smallest path from v_0 to v;

- $h : V \to \mathbb{R}_0^+$ is a heuristic function that estimates the cost of the path from v to its preferred target node.

Function h is said to be *admissible* if it returns a value that is guaranteed to underestimate the cost of a path from a node $v' \in V$ to any target node $v'' \in TN$, i.e. $g(v') + h(v') \leq g(v'')$. If h is admissible, then A^* guarantees that the path found by the algorithm has the minimum cost.

The algorithm also requires that the number of paths with zero cost between nodes in the graph to be finite. To solve this problem, we use a pragmatic approach to ensure that each edge in the graph has cost greater than zero along the lines suggested in [9]. Given a cost function κ_1, a new cost function κ_2 is generated by adding a negligibly small constant $\epsilon > 0$ to every cost as defined in κ_1. Then, the algorithm uses κ_2 to find the path with minimum cost. Note that ϵ should be significantly lower than all non-zero costs in the original cost function, otherwise the obtained path may not be the one with minimal cost. Once the path ν with minimal cost is found, its cost with respect to κ_1 can be simply obtained by subtracting the additional cost introduced by κ_2, i.e. $|\nu| \times \epsilon$, from the obtained cost. For the sake of clarity, hereafter, we omit ϵ and use the cost function in Table 2 in the example. However, our implementation of the approach automatically transforms this cost function as described above to find optimal inter-level alignments.

Employing A^* to find the optimal inter-level alignment between a system-trace and a control-flow alignment requires defining an appropriate search space:

Definition 11 (Search space). *Let β be a system-trace, $\gamma = (M_\gamma, <_\gamma)$ the control-flow alignment between a process-trace σ and a Petri net N, Θ a CRUD matrix and Ψ be the set of all possible legal inter-level alignments between β and γ. The search space is a graph $G = (V, D)$ where V is the set of all prefixes of inter-level alignments:*

$$V = \{\mu \mid \psi \in \Psi \wedge \mu \in \mathit{prefix}(\psi)\}.$$

and D is the set of edges $(\mu', \mu'') \in V \times V$, where μ'' is obtained by adding one *composite move to μ' such that μ'' is a prefix of an inter-level alignment:*

$$D = \{(\mu', \mu'') \mid \exists (w, m) \in ((S_\beta^{\gg} \times \Theta^{\gg}) \times M_\gamma^{(\gg,\gg)}) \textit{ s.t. } \mu'' = \mu' \oplus \langle (w, m) \rangle \wedge \psi \in \Psi \wedge \mu'' \in \textit{prefix}(\psi)\}.$$

In this search space, the source node is the empty sequence $v_0 = \langle\rangle$ and the target nodes are all possible legal inter-level alignments, i.e. $TN = \Psi$. As each node in the graph is associated with a prefix of an inter-level alignment and vice versa, we use this prefix to refer to that node. The cost associated to a path leading from the source node to $\mu \in V$ is defined as follows:

$$g(\mu) = \sum\nolimits_{(w,m)\in\mu} \kappa((w, m)).$$

where κ denotes the cost of each composite move according to the given cost function (see Table 2).

To guide the state space exploration of the A^* algorithm, a heuristic function needs to be defined. We can observe that each system-event in a system-trace must appear in some composite move associated to a target node. Thus, the number of steps required to reach an inter-level alignment from a certain state is lower bounded by the number of system-events that have not been considered in the sequence of composite moves associated to that state. These remaining system-events may appear in various move types, i.e. the move types shown in the first and third rows of Fig. 6. The heuristic function employed in this work estimates the cost of reaching a target node by multiplying the minimum cost associated to these moves (according to a given cost function) by the number of system-events that still need to be replayed. (Recall that a heuristic function is only admissible if it underestimates the cost of a path from a node to a target node.)

Algorithm 1 represents how the A^* algorithm computes an optimal inter-level alignment. The algorithm keeps a priority queue of nodes to be visited: higher priority is given to nodes with lower costs. First, the queue is initialized with the

Algorithm 1: Compute an optimal inter-level alignment

```
Input  : control-flow alignment $\gamma$, system-trace $\beta$, CRUD matrix $\Theta$, set of criterion
         functions $\Lambda$, cost function $k$
Output : inter-level alignment with the lowest total cost
1  $priorityQueue.enqueue(\langle\rangle, 0)$;
2  while $priorityQueue.size \neq 0$ do
3      $\mu \leftarrow priorityQueue.dequeue()$;
4      if $\mu \in \Psi$ then
5          return $\mu$;
6      foreach $\mu' \in successor_{\gamma,\beta,\Theta,\Lambda}(\mu)$ do
7          $f(\mu') \leftarrow g(\mu') + h(\mu')$;
8          $priorityQueue.enqueue(\mu', f(\mu'))$;
9      end
10 end
```

source node (line 1). Then, in each iteration, the node μ with the lowest cost is taken from the priority queue (line 3). If μ belongs to the target set, the algorithm ends returning node μ (lines 4-6). Otherwise, its direct successors are explored. We use function $successor_{\gamma,\beta,\Theta,\Lambda}(\mu)$ to identify the set of all successors of node $\mu = \langle((s_1, q_1), (e_1, a_1)), \ldots, ((s_m, q_m), (e_m, a_m))\rangle$. This set consists of all nodes μ' that can be obtained by adding one composite move $((s_n, q_n), (e_n, a_n)) \in (S_\beta^{\gg} \times \Theta^{\gg}) \times M_\gamma^{(\gg,\gg)}$ to μ such that:

1) the sequence $\langle s_1, \ldots, s_m, s_n\rangle$, ignoring all occurrences of $\gg$, is a prefix of β;
2) $(e_n, a_n) = (\gg, \gg)$ or, for each $((s, q), (e, a)) \in \mu$, $(e_n, a_n) \nless_\gamma (e, a)$ and for all $(e, a) \in M_\gamma$, if $(e, a) <_\gamma (e_n, a_n)$ then $(e, a) \in \{(e_1, a_1), \ldots, (e_m, a_m)\}$;
3) $(e_n, a_n) = (\gg, \gg)$ or, for each $((s, q), (e, a)) \in \mu$ such that $(e, a) <_\gamma (e_n, a_n)$ and for each mandatory CRUD-entry $q \in \Theta$ such that $\pi_{act}(q) = \pi_{act}(e)$ or $\pi_{act}(q) = \pi_{act}(a)$, there exists at least one $((s_i, q_i), (e, a)) \in \mu$ with $q_i = q$;

4) for all $\lambda \in \Lambda$, $\lambda(((s_n, q_n), (e_n, a_n)), x_1, \ldots, x_k) = true$.

Intuitively, the direct successors of a node is the set of nodes μ' that can be obtained by adding one (legal) composite move to μ according to a given set of criterion functions. After associating a cost to each of these nodes, they are inserted into the priority queue (lines 7-10) and the search continues until a target node is reached.

Fig. 8 shows the portion of the search space that Algorithm 1 constructs to find the optimal inter-level alignment of the system-trace in Fig. 4 and the alignment in Fig. 5 according to the cost function in Table 2. Each node, represented by a circle, represents the cost assigned to the node itself. The nodes are also associated with an index, i.e. $\#0, \ldots, \#12$, indicating the order in which they are visited. An edge between two nodes μ' and μ'' is labeled with the move $((s, q), (e, a))$ with which μ' has been extended, i.e. $\mu'' = \mu' \oplus \langle((s, q), (e, a))\rangle$.

To speed up the computation, we prune the search space. This optimization follows from the observation that the same composite moves but with different ordering may appear in different constructed inter-level alignments. In particular, this happens when the sequence contains composite moves corresponding to missing operations. In fact, composite moves indicating missing operations can be observed before, between or after other composite moves with the same alignment moves. This re-ordering does not change the cost of inter-level alignments. Hence, it is not necessary to consider all these cases when we search for the shortest path. Thus, we only consider one of these possibilities, i.e. the case where the composite moves corresponding to missing operations appear after other composite moves in a certain order. For instance, consider the search space in Fig. 8. According to our optimization, as the node associated with $\#11$ contains $((\gg, q_7), (\gg, a_6))$, it is not allowed to be extended with $((s_6, q_6), (\gg, a_6))$. A node with these composite moves is explored if and only if $((s_6, q_6), (\gg, a_6))$ appeared before $((\gg, q_7), (\gg, a_6))$ in the sequence. This way, we avoid exploring the paths

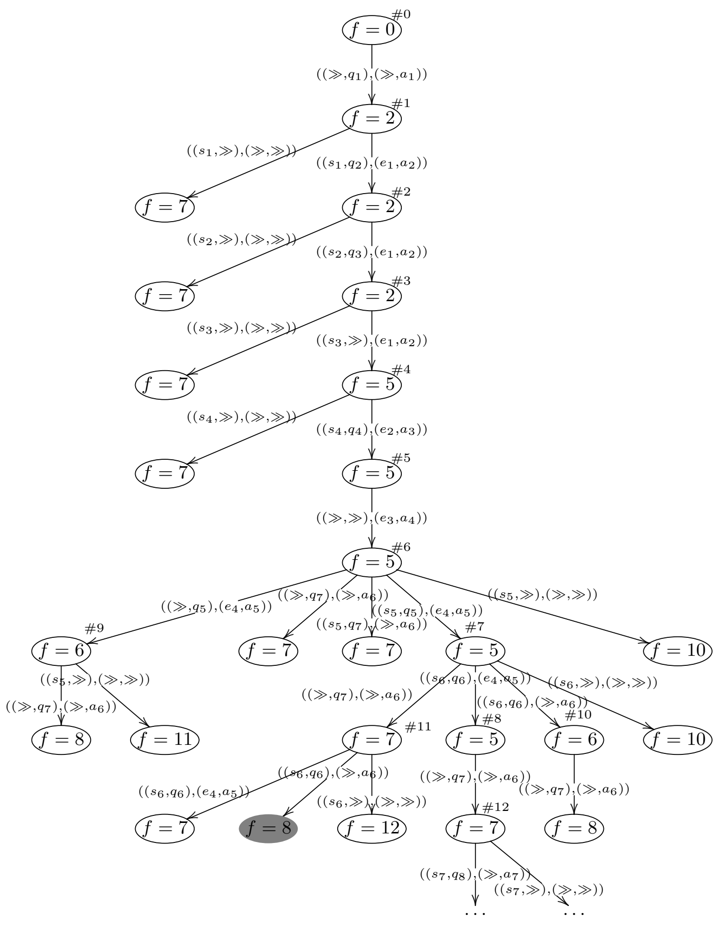


Figure 8: Portion of the search space constructed to find an optimal inter-level alignment of the system-trace in Fig. 4 and the control-flow alignment in Fig. 5 based on the cost function in Table 2. Nodes in the search space are represented by circles, which are labeled with the cost assigned to them by the evaluation function f. Numbers associated to nodes represent the order in which they are visited. Gray circles represent pruned nodes.

consisting of the permutations of composite moves that have already been considered, speeding up the search for the shortest path.

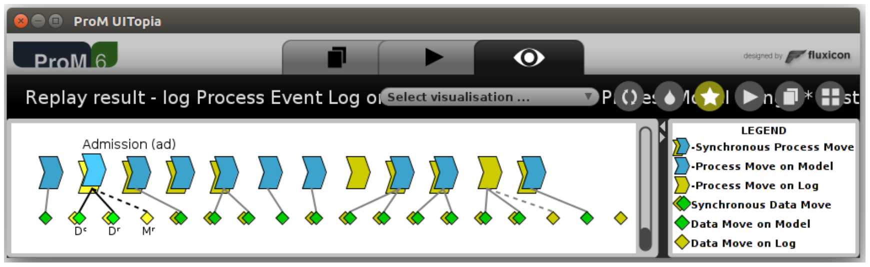


Figure 9: Screenshot of the implemented approach in ProM, showing the inter-level alignment constructed between the control-flow alignment in Fig. 5 and the system-trace in Fig. 4

6. Evaluation

We implemented the approach illustrated in Fig. 1 as a plug-in named *Inter-Level Replayer* for the *Security* package within the ProM framework (`http://www.promtools.org`). The plug-in takes as input control-flow alignments, a system event log and a CRUD matrix, and computes an inter-level alignment for each system-trace and its corresponding control-flow alignment. The output of the plug-in consists of the computed inter-level alignments and can be used by other plug-ins for visualization or further analysis. Fig. 9 shows a screenshot of the ProM plug-in.

We evaluated the proposed approach using both synthetic and real-life logs. The aim of the evaluation with the synthetic data is to perform controlled experiments with a known ground truth and assess the accuracy of the obtained diagnostics. We used a real-life case study to show that the approach provides useful insights into deviations and is robust to logs and models with real-life complexity. The experiments were performed using a machine with 3.4 GHz Intel Core i7 processor and 16 GB of memory.

6.1. Synthetic Data

For the experiments with synthetic data, we designed the process model in Fig. 2 using CPN tools (`http://cpntools.org`) and generated 10000 process-traces and 10000 system-traces consisting of 96994 trace-events and 140999 system-events

Case 1 **P**: 0% **R**: 0%		**Case 7** **P**: 10% **R**: 0%		
		Case 8 **P**: 10% **R**: 5%		
Case 2 **P**: 0% **R**: 10%	**Case 3** **P**: 5% **R**: 10%	**Case 4** **P**: 10% **R**: 10%	**Case 5** **P**: 15% **P**: 10%	**Case 6** **P**: 20% **R**: 10%
		Case 9 **P**: 10% **R**: 15%		
		Case 10 **P**: 10% **R**: 20%		

Figure 10: Experiment Settings. **P** indicates the percentage of attack patterns and **R** the percentage of random noise.

respectively (available at [1]). Trace- and system-events both carry timestamps (according to the same global clock in the simulation). Moreover, for system-events we also recorded the activity of the generating trace-event (i.e., the pur attribute of Section 5.1). In order to assess the capability of detecting deviations and the accuracy of the obtained diagnostics, we manipulated the generated process-traces and system-traces. In particular, we inserted attack patterns corresponding to the threat scenarios 1a, 1b, 2,. . . , 5 described in Section 3 along with random noise (i.e., adding or removing some events). In a series of experiments, we varied the percentage of attack patterns in the traces (denoted by **P**: 0%, 5%, 10%, 15%, 20%) while leaving the random noise constant (denoted by **R**: 10%). In a second series of experiments, we increased the percentage of random noise (**R**: 0%, 5%, 10%, 15%, 20%) while leaving the percentage of attack patterns unchanged (**P**: 10%). We also considered the case where no attack patterns and random noise were introduced in the log, which will serve as the reference case. In total, we analyzed ten cases, which are illustrated in Fig. 10.

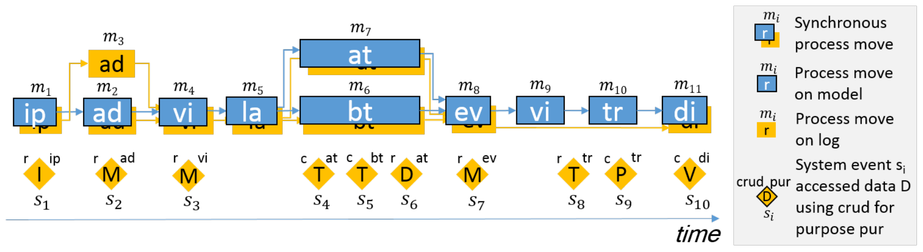
Control-flow alignments reflecting the noise introduced in the process-traces were constructed. We computed the inter-level alignments for every constructed control-flow alignment and its corresponding system-trace. To determine the legality of composite moves, we considered the two criterion functions described in Section 5.1. The first criterion function (λ_{time}) links system-events to alignment moves using the *time* attribute of system-events ensuring that they fall between the start and completion time of process moves. The second criterion function (λ_{pur}) uses the pur attribute of system-events to ensure that the purpose of system-events coincides with the activity associated to the process move. For the experiments, we used two sets of criterion functions: $CF_1 = \{\lambda_{time}, \lambda_{pur}\}$ and $CF_2 = \{\lambda_{time}\}$. In the experiments, we used the cost function described by Table 2.

To assess the approach's capability of detecting deviations and the accuracy of the obtained diagnostics, we computed precision, recall and the F_1-measure. Following standard practice [38], precision is computed as the fraction of the detected deviations that are actual deviations, whereas recall is computed as the fraction of the inserted deviations (which is known since deviations were introduced artificially) that are detected. The F_1-measure is the harmonic mean of precision and recall. For each case, the percentage of the detected attack patterns was assessed. We also measured the time needed to construct an inter-level alignment (after the control-flow alignment had been computed).

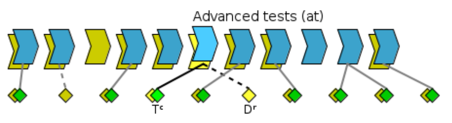
Table 3 reports the results of the experiments for different levels of noise. Overall, the results show a high precision and recall, varying between 0.98 and 0.99 for CF_1 and between 0.93 and 0.95 for CF_2. We can observe that using both the $time$ and pur attributes (CF_1) provides more accurate results compared to using only the $time$ attribute (CF_2). The main reason is that, in the presence of concurrent process moves, the $time$ of system-events can fall between the start and completion time of more than one process move. Without the pur attribute, it is easy to establish incorrect links between system-events and process moves. For example, consider the control-flow

	CF_1 (*time* and *pur*)					CF_2 (*time*)				
Noise (**P**,**R**)	Precision	Recall	F_1-Measure	Detected Patterns (%)	Computation Time (ms)	Precision	Recall	F_1-Measure	Detected Patterns (%)	Computation Time (ms)
Case 1 (0%, 0%)	1.00	1.00	1.00	-	0.28	0.97	0.97	0.97	-	0.80
Case 2 (0%, 10%)	0.99	0.99	0.99	-	0.58	0.95	0.95	0.95	-	1.97
Case 3 (5%, 10%)	0.99	0.99	0.99	99	0.36	0.95	0.95	0.95	95	3.08
Case 4 (10%, 10%)	0.99	0.99	0.99	99	0.45	0.94	0.95	0.94	94	4.24
Case 5 (15%, 10%)	0.99	0.99	0.99	99	0.40	0.94	0.95	0.94	94	9.01
Case 6 (20%, 10%)	0.99	0.99	0.99	99	0.46	0.94	0.94	0.94	94	15.12
Case 7 (10%, 0%)	0.99	0.99	0.99	99	0.25	0.97	0.97	0.97	97	1.41
Case 8 (10%, 5%)	0.99	0.99	0.99	99	0.31	0.95	0.96	0.95	96	2.35
Case 9 (10%, 15%)	0.98	0.98	0.98	99	0.42	0.94	0.94	0.94	94	9.80
Case 10 (10%, 20%)	0.98	0.98	0.98	99	0.54	0.93	0.94	0.93	93	16.47

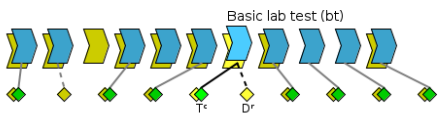
Table 3: Results of experiments on synthetic data.



(a) An example of a control-flow alignment and a system-trace.



(b) Inter-level alignment that can be obtained using CF_1 and CF_2



(c) Inter-level alignment that can be obtained using CF_2

Figure 11: An example of the constructed inter-level alignments using two different criterion functions.

alignment and process-trace in Fig. 11a. We can observe that s_6 occurred between the start and completion time of m_6 and m_7. Thus, this event can be linked to either of these process moves according to CF_2 (Fig. 11b and Fig. 11c). On the other hand, as the pur attribute of s_6 matches with the activity associated to m_7, this event can only be linked to m_7 using CF_1 (Fig. 11b). It is worth mentioning that, even if CF_1 is used, a system-event can be linked to different concurrent process moves with the same activity name. For instance, in Fig. 11a, CF_1 allows linking s_2 to either m_2 or m_3. In addition to concurrent process moves, the presence of process moves on model may also increase the complexity of finding actual links between system-events and process moves. As discussed in Section 5.1, the start and completion time of process moves on model cannot be derived from any process-event directly. Criterion function λ_{time} finds potential links between system-events and these moves using the control-flow alignment. For instance, in Fig. 11a, suppose that we want to identify the purpose of s_8 using CF_2. In this case, as s_8 occurs after the completion of m_8 and before the start of m_{11}, either m_9 or m_{10} can be chosen as the purpose of this system-event. This uncertainty plays an important role when identifying the purpose of system-events and is the reason that in some cases the approach was not able to identify all the deviations correctly.

Table 4 shows an in-depth analysis of the results for Case 3 (**P**:5%,**R**:10%) with respect to attack patterns representing the threat scenarios presented in Section 3. We can observe in the table that the threat described in Scenario 1a may not be detected when CF_2 is used. This is due to the fact that, if a data operation falls between the start and completion time of two process moves, the system-event may be linked to either of these process moves. A similar observation applies to the attack pattern corresponding to the threat of Scenario 1b. We can observe in Table 4 that the recall for Pattern 1b is lower than for Pattern 1a. This is because moves on log are penalized more than synchronous moves (i.e., the cost assigned to a move on log is higher than the one assigned to synchronous moves). Therefore, if another activity expected according to the process model is executed concurrently (thus resulting in a synchronous process move) and the CRUD matrix allows the execution of the data operation for that activity, the system-event is linked to the synchronous move, thus not detecting the violating move type (1,3) described in Section 4 which reveals Pattern 1b. Moreover, threats involving operations executed out of context

	CF_1 ($time$ and pur)			CF_2 ($time$)		
Pattern #	Recall	Precision	F_1-Measure	Recall	Precision	F_1-Measure
1a	1.00	1.00	1.00	0.99	0.99	0.99
1b	0.98	1.00	0.99	0.89	0.99	0.94
2	1.00	1.00	1.00	0.98	1.00	0.99
3	1.00	1.00	1.00	1.00	1.00	1.00
4	1.00	1.00	1.00	1.00	1.00	1.00
5	1.00	1.00	1.00	0.98	1.00	0.99

Table 4: Analysis of detected attack patterns corresponding to the threat scenarios 1a, 1b, 2,. . . , 5 in Section 3 for Case 3 (**P**:5%,**R**:10%)

may not be detected when the *pur* attribute is not used as a criterion function. According to the cost function in Table 2, operations executed out of context have the highest cost. Therefore, system events are linked to process moves whenever it is possible, i.e. the employed criterion functions allow linking the system event to a process move. In particular, if a system event falls between the start and completion time of a process move, the event is linked to that move. Finally, we can observe that missing operations, which characterize the threats described in Scenarios 3 and 4 are always detected correctly.

Table 5 presents an overview of the composite moves identified in Case 3 (**P**:5%,**R**:10%) when the criterion functions in CF_1 were used. It is worth noting that several deviations would not have been detected or accurate diagnostics obtained using control-flow alignment techniques (see Section 2.3) like [11, 12, 15, 33]. For instance, these techniques are not able to distinguish move types (2,1) and (3,1) from (1,1) and (4,1), and would mark all of them as legal moves. As a consequence, 5714 missing operations and 5166 illegitimate operations would remain undetected. Moreover, control-flow alignments are not able to capture moves of type (4,4),[5] leaving additional 3078 illegal operations undetected. The deviations corresponding to the remaining six

[5]As discussed in Section 2.3, “no process moves” $(\gg, \gg)$ cannot occur in control-flow alignments.

	Synchronous Process Move (e, a)	Process Move on Model $(\gg, a)$	Process Move on Log $(e, \gg)$	No Process Move $(\gg, \gg)$
Synchronous Data Move (s, q)	125507	8087	8512	—
Data Move on Model $(\gg, q)$	5714	1925	105	—
Data Move on Log $(s, \gg)$	5166	509	232	3078
No Data Move $(\gg, \gg)$	19587	1129	3073	—

Table 5: Overview of identified composite moves data for Case 3 (**P**:5%,**R**:10%) and CF_1 as the criterion functions.

move types can also be identified by only observing the process perspective. However, this perspective alone provides limited diagnostics on these deviations. For instance, let us consider deviations involving process moves on model (second column in Table 5). In this case, we cannot distinguish whether an operation on data was illegitimate (8596 cases), missing (1929 cases) or not required (1129 cases). Similarly for deviations involving process moves on log (third column in Table 5), looking only at the process perspective we are not able to distinguish whether an operation on data was illegitimate (8744 cases), missing (105 cases) or not required (3073 cases). Overall, 23579 cases would have incomplete diagnostics using control-flow alignments.

The diagnostic information obtained using our plug-in can assist a security analyst in the analysis and understanding of deviations. Table 6 presents an example of such diagnostic information indicating the number and type of different operations executed on *Lab Test Results (T)* in Case 3 (5%, 10%) and the two criterion functions in CF_1

Activity	**Lab Test Results (T)**											
	Create			**Read**			**Update**			**Delete**		
	LO	**IO**	**MO**	**LO**	**IO**	**MO**	**LO**	**IO**	**MO**	**LO**	**IO**	**MO**
Identify patient (ip)	0	25	0	0	29	0	0	30	0	0	17	0
Admission (ad)	0	22	0	0	21	0	0	17	0	0	19	0
Visit (vi)	0	41	0	7752	753	0	0	37	0	0	43	0
Lab appointment (la)	0	27	0	0	12	0	0	20	0	0	13	0
Basic lab test (bt)	5688	753	840	3142	411	0	3173	417	0	0	20	0
Advanced tests (at)	5743	745	796	3172	372	0	3200	401	0	0	18	0
Evaluate (ev)	0	18	0	3145	399	0	0	19	0	0	21	0
Consult request (co)	0	12	0	0	8	0	0	10	0	0	15	0
Inter-colleague consultation (in)	0	20	0	3030	416	0	0	13	0	0	21	0
Treatment prescription (tr)	0	31	0	4587	580	0	0	22	0	0	35	0
Discharge and billing (di)	0	28	0	0	24	0	0	32	0	0	22	0
Clinical trial (ct)	0	3	0	0	5	0	0	2	0	0	5	0
No activity (out of context)	0	9	0	0	9	0	0	14	0	0	5	0
Total	11431	1734	1636	24828	3039	0	6373	1034	0	0	254	0

Table 6: Analysis of the operations executed on *Lab Test Results (T)* for Case 3 (5%, 10%) and CF_1 as the criterion functions. **LO** indicates legitimate operations; **IO** indicates illegitimate operations; and **MO** indicates missing operations.

were used. The results indicate that 1636 expected operations were skipped and 6061 illegitimate operations were executed on this data object. Recall that an operation is considered illegitimate if it is executed to accomplish an activity for which the operation is not allowed or it is executed within an invalid context (or a combination of the two). That is why we still observe illegitimate operations, even though they are allowed by the CRUD matrix (e.g., 753 *Lab Test Results (T)* were created with purpose *Basic lab test (bt)* within an invalid context). Among these illegitimate operations, 37 of them were executed out of context or for accomplishing a purpose for which they are not allowed to be executed. For example, 24 times *Lab Test Results (T)* were read for the purpose of *discharge and billing (di)*, which is not allowed according to the CRUD matrix in Table 1. It is worth noting that missing operations and operations with invalid or no context

(4473 operations in this case) may remain undetected if system-events are analyzed without considering their contexts. This again demonstrates that the combination of both levels helps revealing problems that would otherwise remain undetected.

On average, the construction of optimal inter-level alignments required 0.36 ms per case (i.e., a system-trace and the corresponding control-flow alignment) when CF_1 is used, so in total 3.6 s. When CF_2 is used, the construction of optimal inter-level alignments required on average 3.32 ms per case, so in total 33.2 s. As CF_2 allows more linking between system-events and process moves in comparison to CF_1, its search space is typically much larger. This explains why finding optimal inter-level alignments using CF_2 required more time than using CF_1. We, thus, conclude observing that both the accuracy and performance of the approach depend on the information used to link the process and data perspective together.

6.2. Real-life Logs

For the experiments with real-life logs, we used a dataset taken from a road traffic fine management system of the Italian police (available at [2]). As we aim to analyze only cases that are complete, we used the heuristic proposed in [35] to filter out incomplete cases. Then, by splitting activities and data operations from the original dataset, we obtained a process event log and a system event log. The resulting process event log and system event log contain 550021 trace-events and 917693 system-events respectively. These log data were recorded for managing 145800 road traffic offense cases. Each case starts by recording a traffic fine, followed by sending it to the offender. After receiving the notification, the offender may appeal against a fine to prefecture and/or judge. If the appeal is successful, the case ends. Otherwise, the offender is notified about the result of the decision. The fine has to be paid within 180 days. Otherwise, a penalty is added. If the fine is not paid fully by the offender, the case ends by asking for credit collection. The execution of these activities may require performing

Activity	**Data object**					
	Points	**Amount**	**Expenses**	**Payment Amount**	**Total Payment Amount**	**Dismissal**
Create Fine	U	C	–	–	C	C
Send Fine	–	–	C	–	–	–
Notification	–	–	–	–	–	–
Payment	–	–	–	U	U	–
Add Penalty	–	U	–	–	–	–
Appeal to Judge	–	–	–	–	–	U
Send for Credit Collection	–	–	–	–	–	–
Appeal to Prefecture	–	–	–	–	–	–
Send Appeal	–	–	–	–	–	U
Receive Result	–	–	–	–	–	–
Notify Offender	–	–	–	–	–	–

Table 7: CRUD matrix showing the interaction between the activities of the road traffic fine management process and data objects.

certain operations on data objects. The relationship between activities and operations on data was obtained from the insights reported in [35] and is shown in Table 7.

To construct the control-flow alignments between process-traces and the process model, we used the work presented in [33], which is implemented as a plug-in named *Partial-Order Aware Replayer* in the ProM framework. Then, we applied our approach to compute inter-level alignments of the constructed control-flow alignments and the system event log using the CRUD matrix in Table 7, the cost function in Table 2 and the set of criterion functions CF_1. On average, the construction of optimal inter-level alignments from the system logs and control-flow alignments required 1.17 ms per case.

Table 8 reports the number of different composite moves identified in the analysis of the log. In total, we identified 139 missing operations and 3306 illegitimate operations. All missing operations correspond to potential cases of data update omission (insider threat type 3). In 33 cases, we observed that the amount of the fine was not recorded when activity *create fine* was executed. In 21 cases, after applying the penalty, the amount

	Synchronous Process Move (e, a)	Process Move on Model $(\gg, a)$	Process Move on Log $(e, \gg)$	No Process Move $(\gg, \gg)$
Synchronous Data Move (s, q)	914391	0	3298	—
Data Move on Model $(\gg, q)$	85	50	4	—
Data Move on Log $(s, \gg)$	0	0	0	4
No Data Move $(\gg, \gg)$	143883	87347	170	—

Table 8: Results of experiments on real-life data.

of the fine was not updated. Among the others, this is in conflict with the Italian law that requires the *total payment amount* to be increased in these cases [35]. Moreover, the value of *total payment amount* and *payment amount* were not updated in 32 and 3 cases respectively when activity *payment* was performed. This data update omission should be investigated to determine why it happened. In particular, it is not plausible that, when the fine was paid by the offender, the total payment amount was not updated. The results also show that 50 times activity *send appeal* and its required operation (*dismissal* update) were skipped (i.e., a composite move of type (2,2)). This suggests that process participants do not always adhere to the prescribed behavior when the appeals are processed.

Illegitimate operations are mainly related to the illegal execution (i.e., a process move on log) of activity *add penalty* and the corresponding data update (3115 times). In particular, the amount value of the fine was increased as required by the activity, but the activity should not be executed (i.e., a composite move of type (1,3)), providing evidence that unauthorized data modifications (insider threat type 2) could have happened.

Moreover, 4 system-events recording an update operation on the amount value were executed out of context, i.e. they were not linked to any process moves (composite move of type (3,4)). These operations were executed for the purpose of adding a penalty (i.e., their *pur* attribute is equal to *add penalty*) but the order in which they were recorded in the system event log does not make it possible to link them to any alignment move. This could indicate some synchronization issues in the recording of events at different levels, but it could also indicate an unauthorized modification of data (insider threat type 2).

Our work is not the first that analyze the traffic fine management dataset. Alizadeh et al. [14] analyze this dataset using control-flow alignments. However, as discussed in Section 6.1, control-flow alignments only consider the process perspective. Thus, they are unable to capture moves of type (2,1), (3,1), and (3,4) and cannot provide accurate diagnostics for moves of types (1,2), (2,2), (3,2), (4,2), (1,3), (2,3), (3,3) and (4,3). Specifically, if control-flow alignments are used for the analysis, in total, 89 illegitimate operations would remain undetected and the diagnostics obtained for 90869 deviations would not provide additional information on the use of data.

Another work that analyzes the traffic fine management dataset is the one by Mannhardt et al. [35], who use data-aware alignments. Similarly to our work, Mannhardt et al. consider the data perspective in the analysis by treating system-events as data attributes of trace-events. However, although some of the conclusions obtained using our approach are similar to the ones that can be obtained using data-aware alignments, these two approaches have different goals and underlying assumptions. In particular, data-aware alignments assume that the link between the process and data perspectives is available and detect deviations in the control-flow based on the modification of attribute values of trace-events. In contrast, our approach aims to discover such a link and exploits this information to diagnose the usage of data and provide insights into the detected deviations. In addition, the inability of analyzing data operations independently from process activities makes data-aware alignments unable to capture a number of move types identified in Figure 6, namely (1,2), (3,2), and (3,4). One may observe in Table 8, that only few composite moves of these types were identified in our experiments. The main reason lies in the way the dataset used for the experiments was constructed. In the original log [2], data operations are attributes of trace-events, which were then extracted to create a system event log. By doing so, all operations on data can be potentially linked to trace-events, which was, for instance, not ensured for the synthetic log of Section 6.1. The results in Table 8 show that our approach is capable to reconstruct the links between system-events and trace-events.

7. Related Work

Existing auditing techniques can be classified in three categories based on the layer(s) in which they operate: data layer, process layer or both.

Data Layer. Several auditing approaches have been proposed to detect illegitimate data access and usage (see [44] for a survey). Agrawal et al. [13] propose an auditing framework to verify whether a database system complies with privacy policies. Differently from our work, the focus of this framework is on minimizing the information to be disclosed and identifying suspicious queries rather than verifying data usage. Other researchers have proposed methods for a-posteriori policy compliance [18, 20, 24]. For instance, Cederquist et al. [24] present a framework that allows users to construct justification proofs for their actions. Azkia et al. [18] propose an auditing framework to check the compliance of recorded actions with respect to security policies that may depend on contextual conditions. However, these frameworks can only deal with a limited range of policies and do not consider the purpose for which a data operation is executed. Moreover, these frameworks usually analyze each data operation individually and do not take into account the order in which data operations are executed to determine their context. Kveler et al. [32] consider the purpose for which a data operation is executed in order to detect policy infringements. However, in this work the purpose is treated as a label and, consequently, it does not make it possible to analyze the context in which a data operation is executed. Petković et al. [39] address this issue by linking the intended purpose of data to the business processes of an organization and detect privacy infringements by determining whether the data have been processed for their intended purposes. However, this technique is only able to detect whether a deviation from the specifications occurred and does not explicitly identify which deviation occurred. In contrast, this work uses the purpose and context of data operations to provide fine-grained diagnostic information capable of pinpointing the deviations that occurred.

Process Layer. From a process perspective, several researchers developed techniques to check compliance between normative behavior of a process and the recorded behavior in a process log [11, 12, 15, 33, 35, 46]. Rozinat et al. [46] propose to replay observed behavior by firing recorded events in the process model and count the number of remaining tokens and missing tokens to assess deviations. However, this approach is not able to pinpoint the exact deviating behavior in a model. Banescu et al. [19] extend the work in [46] to identify and classify deviations by analyzing the configuration of missing and remaining tokens using deviation patterns. However, token-based approaches may allow behavior that is not allowed by the model and thus may provide incorrect diagnostics. Adriansyah et al. [11] propose an approach based on the so-called alignment notion relating observed events in the process event log to runs of the model. This approach has been extended in various ways. For example, the work in [33] generalizes sequential alignments to partial orders handling concurrency between trace-events and process moves, which is used in this work to derive process moves. Alizadeh et al. [15] propose to use historical data to derive probable alignments. The work in [12] extends alignments to detect high-level deviation patterns. However, all the aforementioned techniques only focus on the process perspective. Our work extends and complements those techniques by taking into account other perspectives than only the control-flow, i.e. the name of activities and their ordering, and, thus, providing richer diagnostics. As discussed in Section 6, only considering a process perspective does not allow distinguishing move types (2,1), (3,1) from legitimate operations (i.e., move type (1,1)) and identifying illegitimate operations of type (3,4). Moreover, it does not make it possible to discriminate and provide detailed diagnostics for a number of move types such as (1,2), (2,2), (3,2) and (4,2) (and similarly for (1,3), (2,3), (3,3) and (4,3)).

Similarly to our work, de Leoni et al. [25] extend the alignment approach to handle the data perspective in which control-flow is aligned first and then data are considered. Mannhardt et al. [35] propose a more balance approach in which data-aware Petri nets and process logs are aligned to find violations with respect to data-related business rules and guards. Specifically, these approaches analyze the executed activities and the data values written by these activities to determine whether case variables are set correctly and activities are executed as prescribed by the model. This allows the verification of routing decisions during process executions, time related constraints and user restrictions on the execution of activities. However, data-aware alignments require that the link between the process and data perspective is already established. In contrast, our approach aims to discover such a link and exploits this information to diagnose the usage of data and provide insights into the detected deviations. Even if the link between the process and data perspectives is provided, the techniques in [25, 35] are not to identify all the composite moves presented in Figure 6. The main problem lies in the fact that these approaches analyze violations only from a process perspective where system-events are treated as data attributes of process events. As a result, data-aware alignments are unable to consider the data perspective separately and diagnose system-events independently from trace-events. For example, these techniques fail to identify move types (1,2), (3,2) and (3, 4) as they neglect data accesses executed outside of trace-events.

Inter-Data-Process Layer. A large body of research has focused on modeling interactions between processes and data to align IT implementations and business strategies. One popular approach is the use of a CRUD matrix to relate process activities to data accesses [34, 36, 37]. However, to the best of our knowledge, no approaches have been proposed to check compliance between recorded and modeled behavior from both process and data perspectives in a reconciled way. The work in this paper leverages the CRUD artifact and proposes a novel way to reconcile the process and data perspectives to obtain more comprehensive diagnostics of data misuse.

8. Conclusion

In recent years, many auditing techniques have been proposed to analyze the observed behavior recorded by information systems. These techniques typically focus on either the process or data perspective. Focusing on a single perspective, however, may not be sufficient to detect threats posed by insiders who have knowledge of the information system and security controls in place and can misuse their privileges and this knowledge for malicious purposes. In addition, diagnostics obtained using these techniques may not provide fine-grained insights required to understand the detected deviations. This makes it difficult to decide appropriate mitigation actions. In this paper, we propose a novel auditing approach that analyzes the observed behavior with respect to both the data and process perspectives. We have illustrated how the obtained diagnostics can assist auditors in the detection and identification of common insider threats that can only be revealed by analyzing deviations in-between both perspectives. Moreover, experiments have shown that our approach can detect such deviations accurately and is able to provide valuable insights into deviations.

In practice, a (possibly infinite) number of control-flow alignments may exist between a process-trace and a process model. In this work, we used the control-flow alignment that is preferable from the process perspective for the analysis of data operations. However, by considering other control-flow alignments, we may able to find an inter-level alignment with lower total cost than the one we constructed using the selected control-flow alignment [35]. An interesting research direction for future work is to develop techniques that efficiently consider all possible control-flow alignments in the analysis and provide diagnostics with respect to them.

Similar to the existence of multiple control-flow alignments, several inter-level alignments may exist between a system-trace and a control-flow alignment. These inter-level alignments provide different explanations for non-conformity and the quality of the provided explanations typically is evaluated using a cost function. Following common practice in control-flow alignment techniques [11, 12, 15, 33, 35], among possible explanations of non-conformity we have considered the explanation that is optimal with respect to the given cost function. However, an optimal inter-level alignment may not necessarily represent what actually happened in the system. To this end, various heuristics have been proposed to compute probable control-flow alignments [15] or to handle also non-optimal control-flow alignments in the analysis [16]. However, the study of these heuristics and methods is orthogonal to the scope of this work and represent an interesting direction for future work.

In this work, we showed that reconciling the data and process perspectives allows for a more fine grained analysis of the observed behavior. Considering other process perspectives in the auditing process can enhance detection capabilities even further and provide even more accurate diagnostics of deviations. For instance, accounting for the user perspective (i.e., which user/role performed a certain activity and data operation) can enable the verification of separation of duty and binding of duty constraints. Therefore, in future work, we plan to extend our auditing framework by incorporating other perspectives and, in particular, the user perspective to provide auditors with more comprehensive diagnostics for the investigation of security incidents.

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