Anomalies Detection in Software by Conceptual Learning From Normal Executions

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ABSTRACT Could we detect anomalies during the run-time of a program by learning from the analysis of its previous traces for normally completed executions? In this paper we create a featured data set from program traces at run time, either during its regular life, or during its testing phase. This data set represents execution traces of relevant variables including inputs, outputs, intermediate variables, and invariant checks. During a learning mining step, we start from exhaustive random training input sets and map program traces to a minimal set of conceptual patterns. We employ formal concept analysis to do this in an incremental way, and without losing dependencies between data set features. This set of patterns becomes a reference for checking the normality of future program executions as it captures invariant functional dependencies between the variables that need to be preserved during execution. During the learning step, we consider enough input classes corresponding to the different patterns by using random input selection until reaching stability of the set of patterns (i.e. the set is almost no longer changing, and only negligible new patterns are not reducible to it). Experimental results show that the generated patterns are significant in representing normal program executions. They also enable the detection of different executable code contamination at early stages. The proposed method is general and modular. If applied systematically, it enhances software resilience against abnormal and unpredictable events.

INDEX TERMS Anomaly detection, functional dependencies, formal concept analysis (FCA), data reduction, pattern generation, functional dependencies preservation.

I. INTRODUCTION
Data science and machine learning methods offer new methods for extracting knowledge and reducing big data while preserving the underlying main concepts in a summarized form. One may define a program by its preliminary specification, and then give a formal verification for its correctness through a mathematical analysis. But this is not sufficient. A program-testing step is necessary as the implementation may not accurately represent the theoretical algorithm because of programming errors. Even if the program, representing a mathematically proven algorithm, passes the testing step successfully, there is no guarantee about its permanent correct execution. In fact, the program environment might contaminate its state, by either transient or permanent errors, or by malicious external actors, which may cause an abnormal or unpredictable behavior of the program. In the case of critical systems, these errors, even if they appear once, might provoke human or environmental disasters. Waiting until the final execution to judge the correct behavior of such a program is not sufficient as it cannot undo wrong actions or remove the risk of unpredictable events. For example, due to damaged electrical signals or radiations, a robot may lose its equilibrium; an airplane may have a sudden direction change, a pressure valve may dangerously close in an industrial plant, etc.

During the last two decades, several researchers have built anomaly detection methods based on feature definition of the system parameters from which they learn how to recognize inconsistent or unstable states [1], [2]. On one hand, most empirical machine learning methods are able to provide limited accuracy in these methods. But on the other hand, strict mathematical specification of these systems [3] and their control states are not easy to handle completely. Some authors even tried to repair errors in the code [4], [5]. In this paper, instead of evaluating the state of the program on the basis of its mathematical specification, we adopt an original machine
learning approach by mining the features of a program’s execution traces to recognize future anomalies. First, we incrementally generate some knowledge $K$ containing consistent reduced conceptual sets of patterns associated with several correct executions of the program. For each random input, the program execution generates a set of traces $Tr$. These traces $Tr$ are then mapped to a formal context $FC$ that we include into the global set of patterns in a reduced form (the knowledge $K$). Implicitly, $FC$ represents the list of functional dependencies between all attributes of the traces generated by one program execution $K$ [6]–[8]. In this research, for the learning process, we try to find the minimum set of random inputs after which the gathered knowledge $K$ becomes stable enough to be used for discovering anomalies. The stability of $K$ is measured by the number of new patterns added to it over its total size after each program execution. In this work, we propose a novel approach to detect run-time program anomalies at the earliest stages, by first learning from its normal completed executions. We also validate the proposed method on several known algorithms such as sorting, searching, and minimum spanning tree extraction from a graph (i.e. Kruskal’s approach).

In the following section II, we present the state of the art about anomalies detection in a program and show to what extent it is similar to anomaly detection in data. In section III, we give some background on Formal Concept Analysis (FCA) as an important theoretical foundation for data analysis and for generating functional dependencies from formatted data [6], [7]. In section IV, we explain how we can represent functional dependencies in a formatted relational database with a formal context in reduced form. After considering case studies, in section V, we develop a methodology for anomaly detection in two phases. In the first phase, we collect the set of patterns $K$ reflecting the normal behavior of a program. This is built as the union of all conceptual patterns generated automatically by random inputs. In the second phase, we use the set of patterns $K$ as a reference to find anomalies in the program. In the same section V, we study the cases of sorting algorithms [9] and Kruskal algorithm for a minimal spanning tree in a graph [10]. These cases are used for evaluating our proposed approach. In section VI, we discuss the general validation of the proposed method. Section VII concludes the paper.

II. STATE OF THE ART ABOUT ANOMALIES DETECTION IN PROGRAMS AND DATA

In [11], the authors propose a solution for detecting anomalies in software during its execution, by controlling software invariant preservation. The method is interesting but suffers from the inconvenience that the number of invariants in a piece of software is high, and their manual extraction is very time consuming. Authors in [3] wrote: “…, the number of program invariants for large scale software is usually large, making it unfeasible to monitor all invariants online. Thus, an effective selection of invariants is essential. Existing selection approaches are mainly based on the types of invariants..., only invariants related to object read/write at each method invocation are selected, while … the models created from machine learning approaches are used to rank the relevance of the invariants to being fault-revealing based on their types”. In [12], Jianguang Lou et al proposed a log file analysis using learning method from data invariant relations. Recently, other authors proposed generating traces in a moderate way and checking some invariant, thus avoiding excessive splits of the program with too many checkpoints. In [4], Xi Cheng (2016) proposed anomaly detection and fault localization using run-time state models. In the literature, we also found research about feature extraction which constitutes a major problem to solve for the learning process [13]. In general, we could not find significant theoretical foundation for an automatic online analysis of software traces. In this paper, we mapped the problem of program anomalies detection to mining trace data sets anomalies either during the program execution or afterwards (i.e. by using a log file).

In an instance of a database, an abnormal object (i.e. row) is considered an outlier if it does not belong to any significant cluster, or does not respect some integrity conditions. In the context of supervised learning on formatted data, an object that we cannot classify in a particular category is an outlier. A more accurate definition of anomalies is associated to the state of the instance of the database as a whole. When incrementally updated, a database instance which changes its set of functional dependencies after each additional row is semantically unstable. It reaches a steady state if the pattern behind the list of satisfied functional dependencies becomes stable. This might serve as a measure for future abnormal states. This definition of a steady state in itself is not obvious and may only be approximate or used in some particular assumptions. By analogy, if we consider the list of structured traces of a program as an instance of a database, we can use existing machine learning methods for detecting anomalies in databases for finding corresponding anomalies in the program. However, these methods are not accurate enough because they are only based on correlations or statistics but not on exact dependencies as can be observed in the following two sections.

III. FORMAL CONCEPT ANALYSIS BACKGROUND

In this paper, during the learning phase, we use formal concept analysis for generating patterns from traces in a reduced form (i.e. knowledge $K$). An FCA-based algorithm checks the validity of a trace during the anomaly detection step with respect to the knowledge $K$. During the last three decennials, formal concept analysis theory emerged as a mathematical background for concepts structure representation of data, useful for extracting knowledge and finding concepts through “formal concepts” [14], [15]. Since its inception, we found an increasing number of applications for machine learning, data analysis, implications, and associations’ extractions. We use it to build features from texts, and to find some significant decreasing importance order of objects or attributes in a binary context. Recently, it has been applied for context.
reduction without losing implications corresponding to the functional dependencies defined between the attributes of pixels in the image [6], [7].

FCA starts from the philosophical view that a mapping of a context to a structured space of formal concepts may approximate real concepts representing texts or general structured or unstructured data mathematically. From the relativity of objects defined by conceptual clusters, and the logical structure behind the hierarchy of concepts, we can extract implications. It is possible to map most datasets, with different ways to a formal context by defining the spaces of objects, attributes, and a binary relation between these two spaces. This FCA structure is suitable for categorizing objects and attributes in a logical way.

Definition 1 (Formal Context): A formal context is a triplet \((O, A, R)\), where \(O\) is a set of objects, \(A\) is a set of attributes and \(R\), a binary relation linking some objects belonging to \(O\) to some attributes in \(A; R \subseteq O \times A\).

Example: Context “Divides”, is composed of objects \(O\) as numbers between 1 and 12, represented by the objects \(o_1, o_2\ldots, o_{12}\), and attributes \(A\) consisting of the numbers 1,2,..,6 represented by the attributes \(Attr_1, Attr_2, \ldots, Attr_6\) respectively. Where \(o_i\) and \(Attr_j\) represents integer \(i\) as an object and integer \(j\) as an attribute respectively.

Definition 2 (Galois Connection): Galois Connection is defined by two dual operators, \(\gamma\) and \(\lambda\):

\[X \subseteq O,\]
\[\gamma(X) = \{\alpha \in A \mid \forall o \in X : (o, \alpha) \in R\},\]
\[Y \subseteq A,\]
\[\lambda(Y) = \{o \in O \mid \forall \alpha \in Y : (o, \alpha) \in R\} \text{,} \]
\[\gamma(X) \text{ is the set of all attributes shared by all objects in } X \text{ while } \lambda(Y) \text{ is the set of all objects that share all the attributes in } Y.\]

The two operators \(\gamma\) and \(\lambda\) define the Galois connection between sets \(O\) and \(A\).

Definition 3 (Formal Concept): A pair \((X, Y)\) is a formal concept of the formal context \((O, A, R)\) if and only if: \(X \subseteq O, Y \subseteq A, \gamma(X) = Y \text{ and } \lambda(Y) = X\).

Remark: The closure operators \(\gamma\) and \(\lambda\) are important to build formal concepts, by either completing the set of objects \(X\), by calculating \(\lambda(Y)\) of \(X\), or a set of attributes \(Y\), by calculating \(\gamma(X)\).

Illustration: For the context in Fig. 1, we may find here below all formal concepts:

\[C_1 = \{o_1, o_2, o_3, o_4, o_5, o_6, o_7, o_8, o_9, o_{10}, o_{11}, o_{12}\} \times \{Attr_1\}\]
\[C_2 = \{o_3, o_{10}\} \times \{Attr_1, Attr_3\}\]
\[C_3 = \{o_4, o_{12}\} \times \{Attr_1, Attr_2, Attr_4\}\]
\[C_4 = \{o_3, o_6, o_{12}\} \times \{Attr_1, Attr_3\}\]
\[C_5 = \{o_6, o_{12}\} \times \{Attr_1, Attr_2, Attr_3, Attr_5\}\]
\[C_6 = \{o_{12}\} \times \{Attr_1, Attr_2, Attr_3, Attr_4, Attr_5\}\]
\[C_7 = \{o_{10}\} \times \{Attr_1, Attr_2, Attr_3\}\]
\[C_8 = \{o_2, o_4, o_6, o_8, o_{10}, o_{12}\} \times \{Attr_1, Attr_2\}\]
\[C_9 = \{x\} \times \{Attr_1, Attr_2, Attr_3, Attr_4, Attr_5, Attr_6\}\]

The total number of formal concepts is 9. In Fig. 2, we represent a line diagram of the lattice of concepts. Each circle represents a formal concept, and if two concepts are in the two extremities of a line, the concept at an higher position in the line diagram is "greater" than the one drawn at a lower position in the same path. Here we define the order relation between comparable two formal concepts. Let \((X, Y)\) be a formal concept as in Def. 3. We call \(X\) the extension (i.e.domain) of the formal concept, and set \(Y\) its intention (i.e. range). Formal concepts \(([X_1, Y_1], [X_2, Y_2], \ldots, [X_n, Y_n])\) mined from the formal context \((O, A, R)\) can be structured as a lattice of concepts. The sub-concept order relation naturally arranges the formal concepts of a given context into a lattice; the super-concept relationship is defined by \((X_1, Y_1) \subseteq (X_2, Y_2)\) if and only if \((X_2 \subseteq X_1) \text{ and } (Y_1 \subseteq Y_2)\).

Remark: Intentions of concepts in the same line diagram path increase, while their extensions shrink with respect to the inclusion order relation.

Definition 4 (Implication Extraction): If \((Y \subseteq A)\), then \(\lambda(Y) \text{ is included in } \gamma(\lambda(Y))\) if \(A \subseteq \gamma(\lambda(A))\) (i.e. \(\gamma(\lambda(A)) - A\) is an implication extracted from the formal context \((O, A, R)\)).

Illustration: We apply Galois Connection on the formal context in Fig. 1, here above, if we assume that \(Attr_1\) means that, an object is divisible by \(i\), then,

\[\text{Closure}([\{Attr_1, Attr_4\}]) = \{Attr_1, Attr_2, Attr_4\}\]
\[\text{Closure}([\{Attr_1, Attr_6\}]) = \{Attr_1, Attr_2, Attr_3, Attr_6\}\]
\[\text{Closure}([\{Attr_1, Attr_2, Attr_3\}]) = \{Attr_1, Attr_2, Attr_3, Attr_6\}\]

Consequently, we may derive the following implications:
\[Attr_1 \Rightarrow \{\}\]
\[\{\} \Rightarrow \{\}\]

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Premises of the rule. In this case, in formal concept to prove implication (1), first you search for the formal context. By following the line diagram of the lattice of concepts, between 1 and 12) divisible by 1, and 4, is also divisible while implication (1) means that any object (i.e. a number or object) satisfies attributes \( \{ \text{Attr}_1, \text{Attr}_2 \} \), satisfies \( \text{Attr}_3 \).

As the number of implications and formal concepts may grow exponentially in practice, it is not efficient to use the lattice of concepts for mining big data. In [4], we used the minimal conceptual coverage of a formal context for a new conceptual machine learning method, and in [5], we use “optimal concepts” to find the main topics in a piece of text. In this research, we used reduction algorithms that reduces a formal context without any loss of implications based on [16]. In the next section, we give a general definition of a formal context reduction operator.

IV. CONCEPTUAL PATTERN EXTRACTION FROM DATA

In [18], Ganter defined a clarified formal context as shown in Def. 5.

**Definition 5:** We say that a formal context is clarified if no two objects intentions are equal, and no two of its attributes extensions are equal.

In the next section, we give a general definition of a formal context reduction operator.

A. FORMAL CONTEXT REDUCTION OPERATOR

**Definition 6 (Formal Context Reduction):** An attribute \( m \) of a clarified context is said to be reducible if there is a subset of attributes \( S \subseteq A \), not containing \( m \), such that \( \lambda(S) = \lambda(m) \), otherwise it is irreducible. Similarly, an object \( o \) of a clarified context is reducible if there is a subset of objects \( \{ \text{Attr}_1, \text{Attr}_2 \} \Rightarrow \text{Attr}_3, (2) \), \( \text{Attr}_2 \Rightarrow \text{Attr}_3 \Rightarrow \text{Attr}_4; (3) \) \{ \} \Rightarrow \text{Attr}_3; (4) \).

Implication (4) means that any object is divisible by 1, while implication (1) means that any object (i.e. a number or object) between 1 and 12) divisible by 1, and 4, is also divisible by 2. Implication (2) means that any object divisible by 6, and 1, is also divisible by 2 and 3. Implication (3) means that any object divisible by 1, 2, and 3 is divisible by 6. By following the line diagram of the lattice of concepts, to prove implication (1), first you search for the formal concept with the smallest intention (i.e. range) containing the premises of the rule. In this case, in formal concept C3 (i.e. any object of the formal context satisfying attributes \( \{ \text{Attr}_1, \text{Attr}_4 \} \), satisfies \( \text{Attr}_2 \)).

In [18], Ganter defined a clarified formal context as shown in Fig. 3. R1 contains four objects \( \{ o_1, o_2, o_3, o_4 \} \) described by four properties \( \{ a_1, a_2, a_3, a_4 \} \) where the values have been set randomly.

**Definition 8 (Lukasiewicz Based Fuzzy Galois Connection):** Let \( R \) be a fuzzy binary relation defined on \( U \). For two sets \( X, Y \) such that \( X \subseteq Y \), there is a fuzzy set defined on \( A \), and \( \delta \in [0, 1] \). We define operators \( \gamma \) and \( \lambda_\delta \), where \( \lambda_\delta \) is generalization of \( \lambda \) to fuzzy context with precision \( \delta \):

\[
\gamma(X) = \{ d \in A | \alpha = \min\{ \mu_R(g, d) | g \in X \}, d \in A \} \quad (1)
\]

\[
\lambda_\delta(Y) = \{ g \in P | \mu_L(\gamma(Y) \rightarrow L \mu_R(g, d)) \geq \delta \} \quad (2)
\]

where \( \rightarrow_L \) stands for the Lukasiewicz implication i.e. for \( a, b \in [0, 1], a \rightarrow_L b = \min(1, 1 - a + b) \).

For the objects subset \( X \), \( \gamma(X) \) is the fuzzy set of their common properties since we use the min operator. Similarly, for the fuzzy subset \( Y \) of properties, \( \lambda_\delta(Y) \) computes the set of all objects that satisfy all properties in \( Y \) at a given level \( \delta \). Operators \( \gamma \) and \( \lambda_\delta \) represent a fuzzy Galois connection between the subsets \( X \) and \( Y \) as illustrated in Fig. 4.

**Definition 9 (Fuzzy Closure Operator):** For two sets \( X \) and \( Y \) such that \( X \subseteq Y \), \( \mu_L(\gamma(Y) \rightarrow L \mu_R(g, d)) \geq \delta \) where \( \rightarrow_L \) stands for the Lukasiewicz implication i.e. for \( a, b \in [0, 1], a \rightarrow_L b = \min(1, 1 - a + b) \).

For the objects subset \( Y \) of properties, \( \lambda_\delta(Y) \) computes the set of all objects that satisfy all properties in \( Y \) at a given level \( \delta \). Operators \( \gamma \) and \( \lambda_\delta \) represent a fuzzy Galois connection between the subsets \( X \) and \( Y \) as illustrated in Fig. 4.

**FIGURE 3. Fuzzy binary context R1.**

| \( o_1 \) | \( a_1 \) | \( a_2 \) | \( a_3 \) | \( a_4 \) |
|---|---|---|---|---|
| 0.5 | 1 | 0.7 | 0.5 |
| 0.6 | 0.7 | 1 | 0.5 |
| 1 | 0.9 | 1 | 0.1 |
| 1 | 0.9 | 0.9 | 0.1 |

**FIGURE 4. Fuzzy Galois connection schema.**

\( X \subseteq O \), such that \( \gamma(X) = \gamma(\{o_1\}) \). A formal context is called reduced if all of it’s objects and attributes are irreducible.

In [16] we extended it to a multi-level conceptual data reduction approach for fuzzy formal contexts, based on the Lukasiewicz implication definition. “Let \( U \) be a set, called the universe of discourse. Elements of \( U \) are denoted by lowercase letters. A fuzzy set \( E = \{ x_1/v_1, x_2/v_2, \ldots, x_n/v_n \} \) is defined as a collection of elements \( x_i \in U, i = 1 : n \) which includes a degree of membership \( vi = \mu_E(x_i) \in [0, 1] \) for each element \( x_i \). The membership degree may also be expressed by a membership function.

**Definition 7 (Fuzzy Binary Context):** A fuzzy binary context is a fuzzy set defined on the product of two sets \( O \) (set of objects) and \( P \) (set of properties).

**Example:** Let us consider the fuzzy relation \( R \) depicted in Fig. 3. \( R1 \) contains four objects \( \{ o_1, o_2, o_3, o_4 \} \) described by four properties \( \{ a_1, a_2, a_3, a_4 \} \) where the values have been set randomly.
As a second step, we try to remove attributes:

\[
\text{Attr} \text{ by: }
\]

we should remove the same effect.

\[
\text{S any superset of } \lambda \text{ that duplicate objects: }
\]

if there is a subset of attributes the full context. If the algorithm reduces an element from a subset of the formal context, it is incremental manner to a formal context. If the algorithm reduces an element from a subset of the formal context, it is also removed from any set containing it, and particularly from the full context.

An attribute \( m \) of a clarified context is said to be reducible if there is a subset of attributes \( S \subseteq A, \) not containing \( m \), such that \( \lambda(S) = \lambda([m]) \), then we may remove the attribute \( m \), and any superset of \( S \) satisfying the same condition would have the same effect.

Example: First we clarify the context by removing duplicate objects: \( \{07, 08, 09, 010, 011\} \). For reduction, we should remove \( o_1 \), replaced by \( \{o_2, o_3\} \) or any superset not containing \( o_1 \). We may also remove \( o_2 \), as might be replaced by: \( \{o_4, o_6\} \) or any superset not containing \( o_2 \).

Finally, we obtain the following set of remaining objects: As a second step, we try to remove attributes: \( \text{Attr} \) reducible because:

\[
\lambda(\{\text{Attr}\}) = \lambda(\{\text{Attr} 1, \text{Attr} 2, \text{Attr} 3\}) = \{o_6, o_12\}
\]

This reduction might be explained by the fact that any object dividable by 2 and 3 is dividable by 6, and vice versa. In Fig. 6, we find the irreducible context.

The irreducible context, should give exactly the same implications as the initial complete context, to which we should add:

\[
\text{Attr} 1 \text{Attr} 4 \Rightarrow \text{Attr} 2; (1)
\]

To which we should add:

\[
\text{Attr} 1 \text{Attr} 6 \Rightarrow \text{Attr} 2 \text{Attr} 3; (2)
\]

\[
\text{Attr} 1 \text{Attr} 2 \text{Attr} 3 \Rightarrow \text{Attr} 6; (3)
\]

B. MAPPING FUNCTIONAL DEPENDENCIES TO IMPLICATIONS

The suggested pattern-based reduction concentrates on the representation of conceptual data. First, the input dataset of the formatted program traces is converted into a binary association declared as a formal context. This association is mapped into binary patterns and then, a part of each pattern is computed and converted back to the original data. Next Fig. 7 demonstrates the main steps. The following discussion describes these steps in more details.

1) CONVERT DATA TO FORMAL CONTEXT

Data is transformed into the formal context by conducting pairwise comparisons between data rows representing serial traces as in [7]. Fig. 8 exhibits a database instance (DBI) that is converted into a formal context FC. As an example, Rows \( T_1 \) and \( T_2 \) are compared for attributes \( A, B, C \), and \( D \). This comparison is translated into a different object in the formal context FC with the same attributes, where “0” is used in case the values are different, and “1” otherwise. As an example, the value \( T_1(A) = 1 \) is not equivalent to \( T_2(A) = 4 \); consequently, \( T_1(T_2) \) \( A \) in the FC is “0”. However, \( T_1(B) = T_2(B) \), and therefore, \( T_1(T_2) \) \( B \) in FC is “1”. Every row is also compared to itself giving a same pattern containing only ones (“1”).

One disadvantage of this transformation approach is the precise matching between numbers, which causes information loss. To overcome this problem, a similarity measure is identified to process the pairwise comparison process as discussed in [33]. It is computed as follows: Similarity \( (n_1, n_2) = (1 - ((n_2 - n_1) / \max(n_2, n_1)) \), where \( n_1, n_2 \) are the two numbers to compare. If two numbers are equal then they are similar with a degree 1. Numbers \( (3, 4) \) are less similar than \( (1000, 1001) \), while they both differ by the same value 1. The reason is that relatively to the maximum

\[
\text{FIGURE 5.} \text{ Reduced objects in the context.}
\]

\[
\text{FIGURE 6.} \text{ Reduced attributes in the context.}
\]

\[
\text{FIGURE 7.} \text{ Proposed reduction method.}
\]

\[
\text{FIGURE 8.} \text{ Converting database instance into a formal context (set of patterns).}
\]
of the two values, 1000 and 1001 are judged more similar to each other than 3 and 4. Depending on the previous rule, the percentage of similarity is measured through the pairwise comparison. In case the similarity between the compared data values is greater than a defined threshold, then the FC object value is “1”. Otherwise, the value of the FC object is “0”.

2) MAP A DATABASE TO BINARY PATTERNS
From the format context FC, we generate the binary patterns. The number of features existing in FC is equal to the number of features in the dataset.

As an example, with a format context having M attributes, we obtain a binary pattern table of size $2^M$ patterns, where each tuple of the formal context is associated to one of these patterns. A counter is attached with each binary pattern, and it is incremented whenever an object of the FC is mapped with this pattern. A specific number of FC objects is preserved per pattern to reduce the memory consumption. Fig. 9 depicts an example of a binary pattern table (PT) and the counter table (CT) which are generated from FC with four attributes. As such, since objects $(T_3, T_6)$ and $(T_2, T_3)$ are associated with the pattern "0010", its corresponding counter value in the CT will be 2.

V. METHODOLOGY FOR ANOMALY DETECTION
In this section, we start by explaining our investigation concerning how to discover anomalies by using a formal context that abstracts the knowledge about generated traces in the program. After a preliminary analysis of generated traces, in section V-A, we develop our proposed method for detecting anomalies in a simple module by employing a learning step. In section V-B, we generalize it for complex software and for different number of features.

For anomaly detection, we start by saving the program traces for a specific input $I$ into a database $T$. Selected program state variables are used to represent the database features. Any anomaly occurrence in the trace is reflected as an anomaly in $T$. Therefore, any used method for detecting abnormal instances in a database becomes directly applicable for programs.

**Example:** Assume that a program, should calculate the sum of two numbers $X = 9$, $Y = 7$, then a possible algorithm is to increment $X$ by 1 and decrease $Y$ by 1, until the value of $Y$ becomes equal to 0, and getting the sum in $X$.

The execution trace $ET$ should be as in Fig. 10.

Traces in Fig. 10 are mapped to a formal context of patterns of Fig. 11a. From patterns in Fig. 11a, we find the only implications: $X \Rightarrow Y$ and $Y \Rightarrow X$.

An anomaly is detected as soon as we find a new pattern that could not be reduced to the correct ones in Fig. 11a.

Traces of Fig. 11b are not correct. We can see in Fig. 11c, the corresponding abnormal patterns containing row (0, 1).

In fact, we may only conclude implication $X \Rightarrow Y$, but not $Y \Rightarrow X$. 

FIGURE 10. Execution trace (ET).
In Fig. 11d, we get an abnormal formal context corresponding to \((Y \implies X)\).

We may even obtain the cases of no dependencies, as in Fig. 11e or Fig. 11f.

For the sum function, when we inject errors that contaminate the critical information of the program, we got the patterns of FC outputs as in Fig. 11g. Critical information is an invariant condition that the state of the program should preserve for a correct execution. In the case of function Sum, \(X + Y\) should remain unchanged at the beginning of each iteration. While increasing \(X\) by 1, \(Y\) is decreasing by 1, as shown in Fig. 10. We may notice that row \((1\ 0)\) does not belong to the correct FC pattern mentioned as in Fig. 11g.

If \((X \geq 0\text{ and } Y = 0)\) we only obtain the row \((1\ 1)\) included in the correct FC patterns.

A. A GENERAL ANOMALY DETECTION ALGORITHM

Anomaly detection is modular. Each module in a complex piece of software should go through two stages; first is the learning phase which generates some knowledge \(K\) describing regular patterns (see section V-A.1), and second is the regular utilization of \(K\) to discover some anomalies at run-time of the module, and in turn, alert owners about them (see section V-A.2). In section V-B, we give a general description of the method in the context of software engineering life cycle, and for complex software.

1) THE LEARNING PHASE

The learning phase involves a similar process for each module in the program. First, we should design the features for module tracing to be informative enough about the state of the program: it should contain whether the input state changed during execution or not, working variables that might include some input variables, and incremental solution construction as in most dynamic programming algorithms. Checkpoints used to generate the trace should reflect a state change, or invariant control. During this step, we run the current module \(M\), using a random data set \(T\), requiring no human effort. For each input test \(t\) belonging to \(T\), we run \(M\), generate the list \(Tr\) of several traces, and transform it to a reduced formal context \(FCt\) containing all dependencies between the different features of \(Tr\). Finally, by compiling incrementally all \(FCt\), for all traces \(t\) in \(T\), we generate the learnt knowledge database \(K\). The learning step is applied for correct executions of each module \(M\). During the learning step; we merge all generated patterns corresponding to all inputs into one set in reduced form. This sample then becomes our reference for detecting anomalies in the future regular life cycle of the module.

Let \(F\) be the selected set of tracing variables (i.e. features of the trace) of a module \(M\). Algorithm 1 shows the learning step.

After a sufficient number of module runs, having combined multiple patterns to set \(K\), it reaches some stability. Here, stability is measured as the percentage of non-reduced patterns with respect to the current size of \(K\) (i.e. reflecting a form of saturation). This constitutes an excellent criteria to assess the learning process completeness. In the sorting algorithm example that we use to evaluate our method, we are able to reach 100% saturation with only a few random input selections.

Below are several examples about identifying the features of the traces for some programs:

- In the module calculating the sum of two integers \(A\) and \(B\), the trace is featured by the set \(F\) including the two variables \(X\) and \(Y\). Variable \(X\) (respectively \(Y\)) contains initially the values that the program should add (i.e. respectively \(A\) and \(B\)). \(X\) and \(Y\) are also the only used variables in the program starting from the inputs (i.e. initial values of \(X\) and \(Y\)).

- For searching for the position of a value \(x\) in an array \(A\) of size \(n\), set trace feature \(F\) is composed of the input array \(A\), the searched value \(x\), and any browsing index. In fact, invariant as array \(A\), and value \(x\), or any constant in a program represent the most critical information in a running program. In case of linear search, the index \(I\) is used for comparing in each iteration \(A[I]\) with \(x\). For binary search, we add the lower and upper bounds limiting the search range.

- If we use an iterative or recursive binary search, the set of features \(F\) should contain the input \(A\), the search value \(x\), and the indexes, low and high bounding the search domain in \(A\). Fortunately, as constants and input \(A\) are invariant, during the learning step, they do not increase the number of patterns, but they are essential to detect anomalies.

- In sorting algorithms of an array \(B\) of size \(n\), we change \(B\) by consecutive swapping of its elements until obtaining a sorted array \(B\). Set \(F\) should contain all positions of the array (i.e. \(B_0, B_1, \ldots B_9\), if the size of array \(B\) is 10), a check of the right swap of two positions \(x\) and \(y\) using attribute \(S\) in Table 1, is added to the feature. In fact, if all swaps in an array are correctly executed, then "any array state is always a permutation of the initial array \(B\)"; this

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**Algorithm 1 Learning Step Algorithm for Building Knowledge Database of Patterns \(K\) for Detecting Anomalies in a Given Module \(M\)**

**Input:** a Module \(M\) With Input Size \(n\)

**Output:** the Knowledge Dataset of Patterns \(K\)

\[
K = \text{empty set;}
\]

**while \(K\) is still not stable do**

- Let \(S\) a new random input of size \(n\);

**while not end of execution of module \(M\) do**

- Generate Execution Trace \(Tr\) of \(M\) for input \(S\);
- Add formal context patterns (FC) corresponding to \(Tr\) into \(K\), using a reduction approach for checking consistency;

**end while**

**end while**
condition is not sufficient, but it is necessary for program correctness.

- In the case of Kruskal’s greedy algorithm for extracting a minimum spanning tree in a graph $G = (E, V)$, a trace is generated after each selection of an edge from the graph. The feature $F$ of the trace contains the weight of the selected edge, the number of edges in variable $e$, the number of nodes in variable $V$, and selected pairs of vertices so far. Weights of edges should not change in the program and their loss by contamination is fatal.

As Kruskal algorithm invokes function sorting of the list of edges in non-decreasing order of their weights, the control of anomalies should be done separately for the sorting step.

In general, traces should be generated, mostly inside repetitive statements at each potential change of at least one field of trace features. As examples, for adding two numbers $X$ and $Y$, using only an increment or a decrease by one, we generate a trace each time we execute an iteration in the loop.

For linear search algorithm, we generate a trace after each increase of an index by one. For binary search, we generate a trace after each update of either the lower or the higher bound of the searching range. For sorting, we trace after swapping any two elements of the array to sort.

Table 1 shows knowledge set $K$ for Quicksort, obtained incrementally from different $FC$ generated from training inputs. In fact, the number of patterns for sorting algorithms built that way, should be mathematically 46. This is what we obtained after only 10 random inputs, as by then, the set $K$ becomes stable.

2) DETECTING ANOMALIES

During the normal software life cycle, we discover an anomaly each time we generate an unknown pattern not reducible by knowledge $K$ built during the learning step. A trace is generated of a running module for some input and a formal context $FC$ is created from it. If a generated pattern of $FC$ is not reducible by $K$ then it is considered as abnormal. Users are alerted at real time about it.

In Table 2, we may see an example of Correct Formal Context corresponding to mined traces of Quicksort algorithm. We also notice that in each row we have only two “0”, or all “1” for one case. This means that any row with more than two “0” is reduced, because it may be replaced by a concept containing only rows with two “0”. This might be explained logically as well: in fact, pattern (1-2) reflects a swapping of two elements in the trace 1 giving trace 2. Pattern (2-3) reflects a swapping of two elements in the trace 2 giving 3, then pattern (1,3) represents the two consecutive swaps. Together patterns (1-2) and (2-3) represent the concept corresponding to (1,3) because it included all “1”s in (1-2) and (2-3) only.

In each row, we only have exactly two zeros or all ones in the last row of the Table 2. By generalization, as we have 10 elements in the array, we have 45 different possibilities to have only two zeros in a pattern, and one pattern with all features set to one. Thus, with an array of size $n$, we have $(n(n - 1)/2 + 1)$ total possible acceptable patterns after reductions. So all other patterns should either be reduced or correspond to some anomaly. Therefore, the program has some anomalies that we could detect online each time the two compared traces give a non-reducible pattern with more than two zeros or with only one zero. This result, may be applied to any sorting algorithm, where a trace is generated each time we swap two elements.

When the size $n = 10$, as the last column $S$ is always set to one, then we may code each pattern by only by the 10 first columns from $(B_0$ to $B_9$). The 46 binary patterns

| $B_0$ | $B_1$ | $B_2$ | $B_3$ | $B_4$ | $B_5$ | $B_6$ | $B_7$ | $B_8$ | $B_9$ | $S$ |
|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-----|
| 1     | 0     | 1     | 1     | 1     | 1     | 0     | 0     | 1     | 1     | 1   |
| 1     | 1     | 0     | 1     | 1     | 1     | 1     | 1     | 0     | 1     | 1   |
| 0     | 1     | 1     | 1     | 0     | 1     | 1     | 1     | 1     | 0     | 1   |
| 1     | 1     | 1     | 1     | 0     | 0     | 1     | 1     | 1     | 1     | 0   |
| 1     | 1     | 1     | 0     | 1     | 1     | 0     | 1     | 0     | 1     | 0   |
| 1     | 0     | 1     | 1     | 1     | 0     | 1     | 1     | 1     | 0     | 0   |
| 1     | 0     | 1     | 1     | 0     | 1     | 1     | 0     | 1     | 0     | 0   |
| 1     | 1     | 1     | 1     | 0     | 1     | 1     | 1     | 0     | 0     | 0   |
| 1     | 1     | 0     | 1     | 1     | 1     | 1     | 0     | 0     | 1     | 1   |
| 1     | 1     | 1     | 0     | 1     | 1     | 1     | 0     | 1     | 1     | 1   |

| $B_0$ | $B_1$ | $B_2$ | $B_3$ | $B_4$ | $B_5$ | $B_6$ | $B_7$ | $B_8$ | $B_9$ | $S$ |
|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-----|
| (1-2) | 1     | 1     | 1     | 1     | 1     | 0     | 0     | 1     | 1     | 1   |
| (2-3) | 1     | 1     | 1     | 1     | 1     | 0     | 1     | 0     | 1     | 1   |
| (3-4) | 0     | 1     | 1     | 1     | 0     | 1     | 1     | 1     | 1     | 1   |
| (4-5) | 1     | 1     | 1     | 0     | 1     | 0     | 1     | 1     | 1     | 1   |
| (5-6) | 0     | 0     | 1     | 1     | 1     | 1     | 1     | 1     | 1     | 1   |
| (6-7) | 1     | 1     | 1     | 1     | 0     | 1     | 1     | 1     | 1     | 1   |
| (7-8) | 1     | 1     | 1     | 1     | 1     | 0     | 0     | 1     | 1     | 1   |
| (8-9) | 1     | 1     | 1     | 1     | 1     | 1     | 1     | 1     | 1     | 1   |
TABLE 3. Reduced formal context corresponding to contaminated quicksort traces.

| 1-2 | 0 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 |
|-----|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2-3 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 1 | 1 | 1 |
| 3-4 | 0 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 4-5 | 1 | 1 | 1 | 0 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 5-6 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 6-7 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 7-8 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |

converted to decimal numbers correspond to the following set of codes:

Authorized patterns = \{255, 383, 447, 497, 495, 503, 507, 509, 510, 639, 703, 735, 751, 759, 763, 765, 766, 831, 863, 879, 887, 891, 893, 894, 927, 943, 951, 955, 957, 958, 975, 983, 987, 989, 990, 999, 1003, 1005, 1006, 1011, 1013, 1014, 1017, 1018, 1020, 1023\}.

In the current subsection, we presented some illustrations of how our method runs. In the next subsection, we will present the general methodology for anomalies detection of a program during run time.

B. THE GENERALIZATION OF ANOMALY DETECTION

In this section, we describe our approach from the software engineering life cycle perspective. The general method for anomalies detection is as structured as the software itself in a modular way. We can see in Fig. 12 the composition of the two different cycles: Learning step & Anomalies detection step. For each module of a given class, we extract all needed features for tracing it during its run-time. These features are mainly composed of inputs, outputs, and final constant values such as the size of an array, the number of nodes in a graph, or the value of an input that we are searching in a list, the number of days in April, or the days of the week if involved in the module. If the number of features is too high, it is recommended to select a limited number of features. This is important in order to get a solution that does not affect the program performance heavily. For each module, we perform the following actions for the learning step:

- Trace feature selection with limited size. Adequate features extraction should be designed carefully by the software designers. In fact, if a module calls another one, input arguments defined by the caller are generally included in the feature of the called module.
- Run the module with random inputs.
- For each trace, generate the corresponding formal context \(FC\).
- Reduce \(FC\) into the global consistent \(K\) of patterns using the same reduction algorithm, Integrating anomaly checking in the module.
- Incrementally generate traces with the same selected features as in the learning step for a new input.
- Generate the corresponding formal context \(FC\) incrementally during run-time, if a pattern in \(FC\) is not reduced by the global knowledge \(K\), we alert with an anomaly.

VI. VALIDATION OF THE METHOD AND ITS LIMIT

The presented method is limited to only finding contamination related to critical information in the program i.e. the part of code responsible for the loss of essential data is detected. For example, the method detects anomalies caused by the...
contamination of elements in an array during the sorting process, or the graph weights in the case of the minimum spanning tree program. However, as we assume that the program is correct, we cannot detect whether it is well designed or not, or if the solution is correct. In such cases, we might obtain a false positive due to some algorithm design deficiency. In fact, as a limit of the proposed approach, we only try to find anomalies about the program states through some selected features. We systematically obtain an alert in case of any sudden change in the controlled invariant data or in the list of saved partial solutions. As we observed in Table 4, in all tested cases, when we do not inject errors in the programs *Sum* or *Quicksort*, no anomaly is detected. When we inject errors contaminating the invariant in program *Sum*, we got 96% of anomalies detected. For *Quicksort*, incorrect swapping of two elements in an array gives 81.4% of real anomaly detected. If some values in the array are overwritten, we detect 100% of these anomalies. Added to the originality to the proposed learning method compared to other machine learning methods, it is giving very high accuracy in general. In [1], even not applied with our same tested programs, the learning-based run-time anomaly detection in software systems detects 70% of anomalies.

We could not observe a code or data change if it does not contaminate the state of the program. In that case the program might end with a correct output, as for *Kruskal* algorithm when the selected edge is not creating a cycle. The method only detects a change in the behavior of the program provoked by a code change or data loss. No alert occurs if the contamination makes a change in the algorithm which is not reflected in the generated patterns. Through realized experience, with
high probability, we recognize a non-reducible pattern in the proximity of the injected errors either in the code or in the data.

In Table 5, for Kruskal algorithm, we got very good accuracy (100%) with no injected errors, and 100% when we reversed some conditions. We can also see in Table 6 that accuracy is 96% when we incorrectly changed some values from 0 to 1 in partial results (i.e. selected edges in the spanning tree). In the last case, when we removed the condition checking if the selection of a new edge creates a cycle or not, and we did not add some invariant verification in the trace, we got only 23% of true anomalies detected. Fortunately, after inclusion of invariant preservation tracing, we got 100% of anomalies detected. Generally in all cases, the anomalies are recognized almost immediately after the damaged code or data. Anomalies detection method may be easily applied for any software in a systematic way, and give very good accuracy.

VII. CONCLUSION

In this paper, a novel method is presented for early discovery of program execution anomalies after learning from “initially correct” program executions. Such anomalies could be introduced by malicious or inadvertent code change, implementation bugs and software updates that might provoke regression errors, code security issues, and fatal or transient faults. The program starts by building conceptual patterns (i.e. knowledge K) as a reduced union set of formal concepts FCs generated from the program traces applied to random input sets. The process of building the patterns continues until stability is reached. Thereafter, the learned knowledge K is used throughout the program life cycle to find anomalies during execution. Validation of the method was performed on several well-known algorithms. The results demonstrate excellent accuracy either for detecting the normality of the program execution or anomalies when analysing the traces generated during program execution.

The modular approach introduced during the software life cycle gave encouraging results by successfully detecting several categories of errors. The design of the trace features for each module, containing variables representing its inputs, outputs, and intermediate working variables is important for accurate anomaly detection. We observed that the most important features to include are program invariant checks and permanent persistent data in the program. This study gives the designer another view about the software while preparing for featured trace generation. It links tracing to the software goals.

It is worthwhile for future work to focus on extending this research to the case of large features, corresponding to complex software with higher number of inputs and outputs.

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