# ANOMALY DETECTION ALGORITHMS IN BUSINESS PROCESS LOGS

Fábio Bezerra and Jacques Wainer
*IC-UNICAMP, Campinas, São Paulo, Brazil*

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Abstract: In some domains of application, like software development and health care processes, a normative business process system (e.g. workflow management system) is not appropriate because a flexible support is needed to the participants. On the other hand, while it is important to support flexibility of execution in these domains, security requirements can not be met whether these systems do not offer extra control, which characterizes a trade off between flexibility and security in such domains. This work presents and assesses a set of anomaly detection algorithms in logs of Process Aware Systems (PAS). The detection of an anomalous instance is based on the "noise" which an instance makes in a process model discovered by a process mining algorithm. As a result, a trace that is an anomaly for a discovered model will require more structural changes for this model fit it than a trace that is not an anomaly. Hence, when aggregated to PAS, these methods can support the coexistence of security and flexibility.

## 1 INTRODUCTION AND MOTIVATION

In some application domains, such as software development and hospital processes, the process control can not be normative as the control provided by workflow management systems. In these domains, the business process is not completely known before execution. For example, in a hospital process the system can not obligate the execution of a specific task during a care (e.g. administration of a drug). Even considering the similarity with other cases, such a care could be unique, which demands a flexible approach to its participants (e.g. physician) that could be the right to execute another task (e.g. request an examination).

On the other hand, a flexible system is vulnerable to fraudulent executions, which imposes a trade off between flexibility and security. Thus, it is important to develop methods that can support the adoption of such flexible systems without losing their security property. Since a BPMS (Business Process Management Systems) usually log the events (or tasks) executed during process execution, it would be interesting to aggregate into a BPMS a tool that can dynamically detect anomalous executions in the log. By and large, a log generated by such systems is comprised of process instances, referred in this work as traces, which are a stream view of process instances. For instance, a trace *abc* means that the task *a* was concluded before task *b*, and task *b* was concluded before task *c*.

A common intuition is to consider a fraudulent execution an infrequent or rare event. Nevertheless, this paper argue that although an anomalous trace is an infrequent event, an infrequent trace not necessarily indicates an anomaly, as will be shown later. This premise imposes a challenge: What infrequent trace could be classified as anomalous? This work will present some algorithms that collaborate in this mission, and it will asses the effectiveness of the proposed anomaly detection solutions.

Moreover, despite the motivation related to problems stated above, anomaly detection is becoming an exciting area within data mining arena, since many surprising and rare events are of interest in security, surveillance, epidemiology, fraud detection, among others. However, to our knowledge, little effort has been made with the investigation of anomaly detection algorithms in the context of process aware systems. The work in (van der Aalst and de Medeiros, 2005) represents an attempt to fulfill this gap, but it is a limited solution because it assumes that a process model is known or could be inferred from a known "normal" log.

In order to define an anomaly detection tool, we are interested in applying process mining techniques to discover anomalies or outliers in the log. *Process mining* were created to be used to discovery or mine process models from logs (Agrawal et al., 1998; Maruster et al., 2001; de Medeiros et al., 2003; van der Aalst et al., 2004). For example, process mining techniques can be used to discover how people work, to support business process modeling, and to diagnose the enterprise work practice (Hammori et al., 2006). Another usage of process mining techniques is to construct social networks as presented in (van der Aalst Minseok Song, 2004). In the anomaly detection algorithms of this work, the classification of an anomalous trace is based on the "noise" which a trace makes in a process model discovered by a process mining algorithm. These algorithms are based on the rationale that if a trace is not an instance of a process model, then the model will require some structural changes to the model fit the trace. In the case of an anomalous trace, such structural changes will be probably higher.

In the next section we report some related work. The process mining tool that is used to support the anomaly detection methods is presented in Section 3. Also in Section 3, we present the metric that is used to quantify the "noise" made by a trace for a model fit it. After that, three different approaches of anomaly detection in logs of PAS are presented in Section 4. Conclusions and future work are in Section 6.

## 2 RELATED WORK

Anomaly detection is an exciting area which has been applied in different application fields, and it has received a special attention of data mining community. For instance, in (Donoho, 2004) the author presents how data mining techniques can be used to early detect inside information in option trading. In (Fawcett and Provost, 1997) the authors present a system which is used to detect fraudulent usage of a cellular (cellular cloning). Moreover, disease outbreak detection has been proposed by detecting anomalies in the event logs of emergency visits (Agarwal, 2005), or the retail data for pharmacies (Sabhnani et al., 2005). There are solutions concerned with the intrusion detection in networks (eg. (Lee and Xiang, 2001; Noble and Cook, 2003)). Other efforts are concerned with the detection of fraudsters in auctions or e-commerce sites(e.g. (Pandit et al., 2007)).

Nevertheless, in the context of process aware systems, little effort has been done to the development of anomaly detection methods. To our knowledge, only the work in (van der Aalst and de Medeiros, 2005) is closer related to our research. In that work the authors present two methods whose support tool is a process mining algorithm, the α-algorithm (van der Aalst et al., 2004). In these methods, a known log comprised of "normal" traces is mined to define a classifier, whose function is audit a separated log. However, those methods are not suited in some domains of application because a "normal" log is not known or a "normal" model can not be known before execution. Differently, our approaches are applied directly over the audit log, and they do not consider the existence of a known model, nor do they consider the existence of a log without anomalous traces.

The accuracy of our anomaly detection algorithm can be related to three items: (i) the process mining algorithm; (ii) the metric used to quantify the modification in a model for fit a new trace ("noise" metric); and (iii) the process model representation. Therefore, it would be interesting to assess other process mining algorithms. For example, the algorithm described in (Schimm, 2004) mines a similar process model representation (block-structured models). Perhaps other process mining approaches could be used, e.g. α-algorithm (van der Aalst et al., 2004) or genetic mining (de Medeiros et al., 2006); however, these process mining algorithms utilize other process model representation, so they will demand another metric to evaluate the inclusion cost of a trace. In the context of "noise" metric, the set of conformance check metrics presented in (Rozinat and van der Aalst, 2005) could be assessed.

## 3 INCLUSION COST AND INCREMENTAL PROCESS MINING

The *inclusion cost* is a metric used to evaluate the amount of modifications done in an old process model in order to define a new process model which fits a merged trace. Thus, to cope with such a metric, it is important to use a process mining algorithm which incrementally define a process model. In this work we adopted the incremental *process mining algorithm* based on rewriting rules, presented in (Wainer et al., 2005). Such a mining algorithm discovers a model whose meta-model is based on a combination meta-models presented in (Agrawal et al., 1998; Cook and Wolf, 1998). The meta-model presented in (Cook and Wolf, 1998), which is based on selection structures (OR), define models that are syntactically more complex than the models defined by the meta-model presented in (Agrawal et al., 1998), which is based on parallel structures (AND). For example, while the

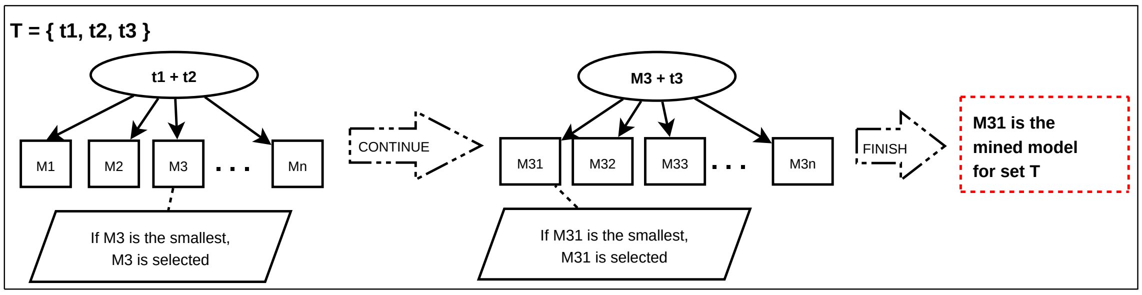

T = { t1, t2, t3 }
t1 + t2
M1
M2
M3
Mn
If M3 is the smallest, M3 is selected
CONTINUE
M3 + t3
M31
M32
M33
M3n
If M31 is the smallest, M31 is selected
FINISH
M31 is the mined model for set T

Figure 1: Greedy search for traces in set T.

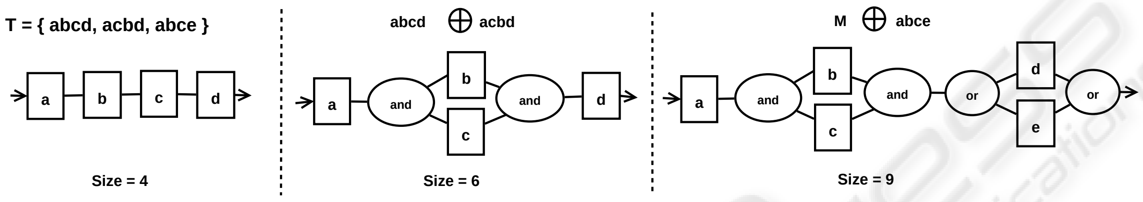


Figure 2: Mining example of a set of traces T.

parallelism between three tasks can be easily represented by an AND-Block, using an OR-Block it would demand six selection branches. On the other hand, the meta-model presented in (Cook and Wolf, 1998) defines models whose expressiveness is greater than the models defined by meta-model presented in (Agrawal et al., 1998). Therefore, a mix of these approaches represents a balance between complexity and expressiveness.

The model is a directed graph $M = (V(M), E(M))$ whose vertices $V(PM)$ are the tasks or AND/OR constructs (split and join), while the edges $E(PM)$ represent the play order of its vertices. For example, Figure 2 depicts three process models whose tasks are represented by a labeled rectangle while AND-Blocks and OR-Blocks are represented by a labeled ellipse. AND-Blocks indicate a parallelism, and OR-Blocks indicate a choice. The Equation 1 illustrates how the inclusion cost is evaluated for a trace $t \in T$, such that $T$ is a set of different traces of a log. It is based on two process models defined through the incremental process mining algorithm – an old model ($M_o$), which is created with the traces $T - t$, and a new model ($M_n$), which is created with the traces $T$.

$$IC(M_o, M_n) = |V(M_n)| - |V(M_o)| \tag{1}$$

Such an incremental mining algorithm constructs a model through the amalgamation of a trace over a model, which could be modified, generating another model. After that, another trace of log will be merged generating a new model, an so on. The procedure finishes when all unique traces were merged, resulting a process model. The incremental construction is based on a set of rules classified as (i) structural rules and (ii) introduction rules. The *structural rules* do not change a model, but they are used to identify the points of application of the introduction rule, whereas the *introduction rules* introduce structural blocks such as AND/OR Split/Join. The algorithm tries to amalgamate a trace into a model in different ways, either applying different sequences of rules, or merging the traces in a different sequence. Therefore, it has two drawbacks that imposes serious limitations of its usage on larger logs, which are the large search space generated by the rules and the amount of models generated at the end of mining.

To solve this limitation we added a greedy search for minimal models after the amalgamation of each trace. Figure 1 illustrates schematically how the process mining works on a log of three traces. Among all derived models, we select the smallest one. A model M is smaller than a model M' if M has less vertices than M'. The selection of the smallest model reduces the search space, so it improves the execution time of algorithm. In addition, such an algorithm returns a structured model that fits all traces and is likely minimal, which are requirements of completeness and minimality as stated in (Schimm, 2004; Rozinat and van der Aalst, 2005).

Figure 2 illustrate how a process mining works. The figure shows three models generated when mining a set of traces $T = \{abcd, acbd, abce\}$. The first trace *abcd* defines a sequential model whose size is four. Then, the second trace *acbd* is merged with the sequential model, and a bigger model of size six is generated for fitting the merged trace. Finally, the third trace *abce* is merged, generating a third model with size nine. Therefore, this simple example illustrates how the inclusion of a trace can produce a modification in the model.

## 4 ANOMALY DETECTION METHODS

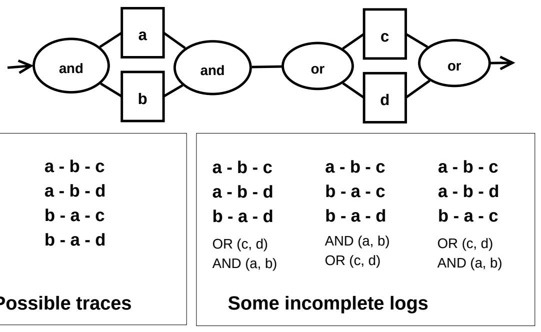


Figure 3: Mining of a process model with an incomplete log.

Despite the different semantics associate with an anomalous trace (e.g. noise, exception, or fraud), for the purpose of this work an anomalous trace is an irregular execution that differs from a process model which was dynamically discovery during anomaly detection process. This work adopts this approach because in some application domains a complete process model is not known before execution. Therefore, it is hard to adopt a precise definition of what an anomalous trace is. On the other hand, a common presupposition in literature is to consider an anomaly like a rare event. However, classifying a trace based only on its frequency in the log is not simple since it is probable that some "normal" traces be infrequent, for some "normal" operational procedures are preferable than others. Moreover, it would be very difficult to define a frequency which better describes an anomalous trace. For instance, it does not seem appropriate to classify as anomalous all traces whose frequency is inferior to 5%.

Figure 3 depicts a process model, its possible traces, and some subset of possible traces that can reconstruct the same model. A possible trace is an execution instance of a model, so the tasks *a* and *b* have to appear in a possible trace of model in Figure 3 while *c* and *d* do not. In the first incomplete subset, the first pair of traces ($[a-b-c]$ and $[a-b-d]$) inducts an "OR Block" to represent a choice (*OR (c, d)*), while the last pair of traces ($[a-b-d]$ and $[b-a-d]$) inducts an "AND Block" to represent a parallelism (*AND (a, b)*). In this example, the trace $[b-a-c]$ is an instance of original model although it has not been used to mine it. Thus, even if it was infrequent in the log, it would not be possible to classify it like an anomalous trace. Therefore, how to classify a (rare) trace in the log as an anomalous one?

The anomaly detection methods adopt the following hypothesis: most of the "normal" traces, if taken individually, will be more frequent than anomalous traces, and anomalies and a few "normal" traces will be rare in the log. The traces that are not anomalies when mined should generate a process model, and trying to fit the anomaly into this model will require a lot of structural changes in the models; therefore an anomaly is the trace whose inclusion produces a large modification to the model generated by other traces in the log.

```
1. $T$ is a list of all different traces of $L$;
2. For each $t \in T$ do
3.    Define a list $L' = \{L$ without one instance of $t\}$;
4.    Define a sampling $S$ with 50% of traces from $L'$;
5.    Create a model $M$ based on traces of $S$;
6.    If $t$ is not instance of $M$ then
7.       Add $t$ to list $A$;
```

Figure 4: Anomalous trace classifier based on sampling.

The algorithm of Figure 4 will consider each of the unique traces in the log as a possible anomaly, and each candidate will be an anomaly if it is not an instance of a process model created with a sampling of log. The sampling comprises 50% of traces from log, and it is redefined for each unique trace of log. The composition of sampling is crucial because if anomalies are rare as assumed, the set *S* will unlikely contain an anomaly itself. Thus it can be seem as a sampling of the "normal" traces, so it would reveal a approximation of the "normal" model.

Nevertheless, there are many things that can go wrong with such assumptions and thus with the algorithm. For example, the set *S* can comprise anomalies which "contaminates" the mined model *M*; thus, *t* could be an instance of *M* even though it may be anomaly. That danger can be lessen by reducing the size of the sample *S*. On the other hand, if the size of *S* is too small, it may not be a large enough sampling of the "normal" model because a too simple "normal" model will be mined, so a "normal" trace may be marked as anomalous.

The algorithm of Figure 5 classifies a trace as anomalous if such a trace has the highest inclusion cost, and its cost is higher than 2 (lines 4 and 9). This approach is called iterative because it is repeated until there is not such a trace in the log. The $select(C,F)$

```
1. $T$ is a list of all different traces of $L$;
2. $F$ is a list of frequent traces in log;
3. $C = T - F$ is a list of anomalous candidate traces;
4. $h \leftarrow select(C,F)$;
6. While inclusion cost of $h$ is higher than 2;
7.    Add $h$ to list $A$;
8.    Remove $h$ from list $C$;
9.    $h \leftarrow select(C,F)$;
```

Figure 5: Iterative anomalous trace classifier.

function returns nil or one trace that has the highest inclusion cost, and the inclusion cost of each candidate $t$ is evaluated based on a model constructed with the traces from $C \cup F - \{t\}$.

The step in line 2 select all frequent traces in the log. We say that a trace is frequent if its frequency is at least 10%. Such a step is used for optimization reasons, because the next (line 3) reduces the number of candidate anomalous traces. However, even with that optimization, the $select(C,F)$ function may compromise the execution time of whole algorithm.

The stop condition threshold represents our belief that even a “normal” trace may demand structural changes in a model mined with the remaining traces of a log, but possibly in a smaller scale. However, although such a threshold is a heuristic value, it was induced by an assessment done with 150 “normal” logs. We say that such logs are “normal” because they are based on traces of a know model that was randomly created for each log. In our intuition, knowing the values and frequencies of inclusion cost of traces in scenarios of “normal” logs, an inclusion cost threshold for a “normal” trace could be inferred. In this assessment, we collected the inclusion cost of each unique trace for each log, and we evaluates some statistic metrics of these costs, as follows: 1st quartile = 0; median = 0; 3rd quartile = 2; mean = 1.306; min = 0; and max = 7.

The algorithm of Figure 6 is similar to the iterative algorithm presented in Figure 5, but it selects all anomalous traces in a single step. Similarly, it uses a threshold value to classify the traces as anomalous or normal. Therefore, is has an execution time smaller

```
1. $\alpha$=2; {A threshold amount of modification}
2. $T$ is a list of all different traces of $L$;
3. $F$ is a list of frequent traces in log;
4. $C = T - F$ is a list of anomalous candidate traces;
5. For each $t \in C$ do
6.    $M$ is a model mined with traces from $T - t$;
7.    $c$ is the inclusion cost of trace $t$ over $M$;
8.    If $c \succ \alpha$ then
9.       Add $t$ to list $A$;
```

Figure 6: Anomalous trace classifier based on threshold.

than the iterative approach, because all anomalous traces are identified in the first and unique iteration.

Although we have used constant values for threshold and sampling factor in the algorithms, we know that a variance in these values could influence their accuracy. For example, if we increase these values, possibly the true (TPR) and false (FPR) positive ratios would decrease. Nevertheless, the values presented in each algorithm represent the best accuracy configuration of our preliminary tests.

## 5 ASSESSMENT OF ALGORITHMS

We have assessed the algorithms with a set of synthetic logs which have been created based on the traces of known process models. Two reasons influenced our choice for synthetic data. First, it is hard (perhaps inexact) to identify an anomalous trace in a real log, so it would impose some limitations on the assessment. For example, in (Pandit et al., 2007) the authors report some problems regarding the assessment of their anomaly detection system with real data. Last but not least, a real log is not available. Therefore, as we know the process model that was used to create a log, it is easy to identify the anomalous traces in the log since an anomalous trace is a trace that is not an instance of a known model.

### 5.1 Methodology

The experiments were based on 780 logs with different configurations. Initially, we randomly created 130 process models which were the matrix of logs. Such models could instance at least 8 unique traces and at most 15 unique traces. For each model, we instanced 80 traces that were used to compose the log and represent the normal traces to the experiment. In addition, the unique traces of each log were added in a non uniform frequency distribution. After that, we merged some anomalous traces to define six types of log, as follows: (i) a log A that has one single anomalous trace; (ii) a log B that has two single anomalous traces; (iii) a log C that has three single anomalous traces; (iv) a log D that has one double anomalous trace; (v) a log E that has two double anomalous traces; and (vi) a log F that has three double anomalous traces.

With regard to the anomalous traces, they were generated as instances of a process model created after shifting AND-Blocks to OR-Blocks, and vice versa. Such a process model is known only during log

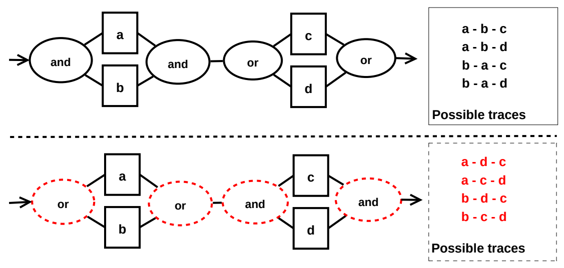


Figure 7: Example of definition of anomalous traces.

generation, but it is unknown during anomaly detection assessment. The instances of this new (shifted) process model are used to define the anomalous traces for the original model. Then, after an instance has been created some events could be removed of the trace, or two random events could be interchanged.

Figure 7 illustrates an example of definition of anomalous traces. The possible traces of upper model are anomalous for the lower model, and vice-versa. In this example, while the tasks *c* and *d* could not play together in the upper model, they are played together in the lower model. Moreover, while the tasks *a* and *b* would have to play together in the upper model, they are not played together in the lower model. Besides, the approach used to create the anomalous traces represents our intuition that anomalous traces are similar to "normal" traces, for they are based on the same set of tasks. In other words, we believe that in real scenarios a fraudster will not attempt to execute new tasks, but he will try to make "little changes" in a standard operational procedure, because it will be more difficult that his fraud be detected.

After the definition of logs, we carried out the experiments with the three algorithms described in Section 4. The results were organized in three classes: (i) logs with single anomalous traces (A, B, and C); (ii) logs with double anomalous traces (D, E, and F); and (iii) all logs (A, B, C, D, E, and F). The following subsection describes the results.

## 5.2 Results

Figures 8, 9, and 10 depict a graphical analysis tool (ROC graphs, (Fawcett, 2004)) utilized to compare the performance of the three proposed anomaly detection algorithms (or classifiers) in three different scenarios. Each point in those figures represent one of the three algorithms, labeled as follows: S for sampling approach; I for iterative approach; and T for threshold approach. In a ROC curve, the best classifier is that one closer to optimal point of coordinates (0, 100). The x-axis represents the ratio of false positives (FP rate), and the y-axis represents the ratio of true positives (TP rate). The diagonal line in the cen-

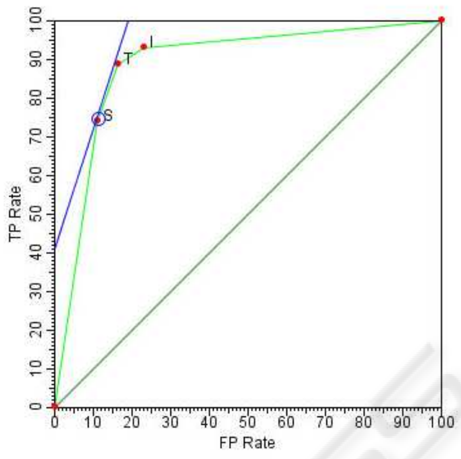


Figure 8: Logs with at most three single or three double anomalous traces.

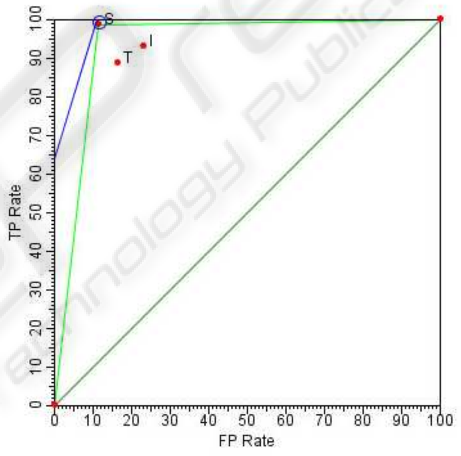


Figure 9: Logs with at most three single anomalous traces.

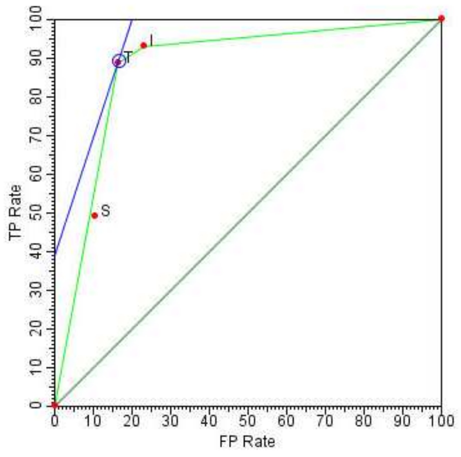
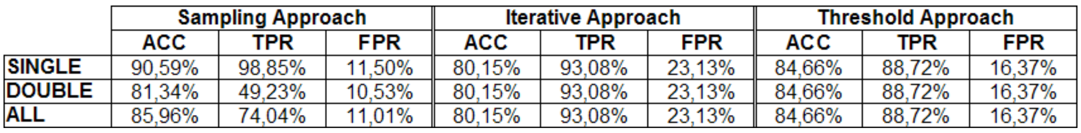


Figure 10: Logs with at most three double anomalous traces.



| | Sampling Approach | | | Iterative Approach | | | Threshold Approach | | |
|---|---|---|---|---|---|---|---|---|---|
| | ACC | TPR | FPR | ACC | TPR | FPR | ACC | TPR | FPR |
| SINGLE | 90,59% | 98,85% | 11,50% | 80,15% | 93,08% | 23,13% | 84,66% | 88,72% | 16,37% |
| DOUBLE | 81,34% | 49,23% | 10,53% | 80,15% | 93,08% | 23,13% | 84,66% | 88,72% | 16,37% |
| ALL | 85,96% | 74,04% | 11,01% | 80,15% | 93,08% | 23,13% | 84,66% | 88,72% | 16,37% |

Figure 11: Assessment Summary.

ter of graph is used to identify good or bad classifiers. Points above the diagonal line indicate good systems, while points below the line indicate bad systems. The figures illustrate a convex curve that is tangent to the iso-performance classifiers, that is, classifiers that are possibly optimal. Moreover, there is an upper line that is tangent to the curve, where it touches the optimal classifier. The inclination of line depends on the number of positives examples (anomalous traces) in the data, which in the case of this assessment were 25%.

Figure 11 shows a summary of results in the following scenarios: logs with single anomalous traces; logs with double anomalous traces; and logs with single or double anomalous traces. It presents three performance metrics, as follows: ACC indicates the accuracy of algorithm, that is, how many traces in the log were correctly classified; TPR, which is an acronym of True Positive Rate, indicates the ratio of anomalous (positive) traces that were correctly classified; and FPR, which is an acronym of False Positive Rate, indicates the ratio of normal (negative) traces that were incorrectly classified.

Among the algorithms, the sampling approach had the best accuracy either in the scenario of logs with single anomalous traces or in the scenario of all logs. However, such an approach was sensible to repetition of anomalous traces in the log; as one can notice in Figure 11, the threshold approach had the best accuracy rate in the scenario of logs with double anomalous traces. Also, the TPR of sampling approach was significantly smaller than the others in the scenario of logs with double anomalous traces. That performance difference is justified. The sampling approach is based on the instance traces, while iterative and threshold approaches are based the unique traces.

Considering the execution time of algorithms, the sampling approach had the best performance. The average time of execution for algorithms were as follows: 4.896 s for sampling approach; 9.016 s for threshold approach; and 16.275 s for iterative approach. In the worst case, the algorithms were executed in the following times: sampling = 466.422 s; threshold = 670.625 s; and iterative = 1145.160 s.

## 6 CONCLUSIONS

Normative information systems are not appropriate in application domains like software development and health care processes, because users needs a flexible support. On the other hand, such a flexibility in these systems can not be considered without improving security issues. Besides, little attention has been given to the anomaly detection area in the context of business process systems. To fulfill this gap this work presented three different approaches to detect anomalous traces in a log of process aware systems.

Despite the application context of algorithms has been presented for security in flexible environments, such algorithms are a proposal to detect anomalies, which have a larger semantic. For example, in the context of software development one could apply the algorithms to detect exceptions, while in process mining context one could use the algorithms to remove noise of logs before mining a model.

Several examples have been treated by our implementation. Considering the results, the sampling algorithm demonstrated to be a good solution, especially when applying it on logs without repeated occurrences of anomalous traces. Nearly 99% of anomalous traces were correctly identified, yet approximately 11% of “normal” traces were incorrectly classified (false positives). Thus, the accuracy rate can be improved reducing the cost of anomalous identification. To do so, we defined a research agenda to achieve such an improvement, either testing other process mining algorithms, or testing other metrics of model modification. Also, the sampling approach was less time consuming among the tested algorithms.

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