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Improved Artificial Negative Event for Process Model: Precision and Generalization

Sonali Sonavane, Megha Garud, Neha Pawar, Mansi Patil, Harpreet Kaur

Assistant Professor, Dept. of I.T., G.H.R.I.E.T, Savitribai Phule Pune University, Maharashtra, India

BE Student, Dept. of I.T., G.H.R.I.E.T, Savitribai Phule Pune University, Maharashtra, India

BE Student, Dept. of I.T., G.H.R.I.E.T, Savitribai Phule Pune University, Maharashtra, India

BE Student, Dept. of I.T., G.H.R.I.E.T, Savitribai Phule Pune University, Maharashtra, India

BE Student, Dept. of I.T., G.H.R.I.E.T, Savitribai Phule Pune University, Maharashtra, India

ABSTRACT: Process mining includes conformance checking as one of its methods .Conformance analysis focus on finding the inconsistencies of system between a process model and corresponding execution log and their quantification by the formation of metrics, in terms of precision and generalization .To check the conformance of event log and process model ,incremental approach is proposed which differs from related work due to the concept of weighted artificial negative events ,leading to unrefined result. Fitness between log and the model is measured along with appropriateness, whereas generalization is difficult to calculate.

KEYWORDS: Conformance Checking, Process Mining, Artificial Negative Events, Precision , Generalization.

I. INTRODUCTION

Results of activities like process development, design and maintenance of software process is collection ser of process model activities which are applied to artifacts. Conformance checking technique examines the similarities and differences of the observed behavior of event log with model behavior for variety of reasons. Conformance checking can also be led to an approximate calculation of a process model thus discovered from event log. Process model discovered from different process discovery technique need to be compared objectively. It focuses on replay fitness that is the ability to make the copy of the event log. As it is simple to construct models that allows lots of behavior without being accurate, secondly precision i.e.to avoid overfitting and against the unwanted behavior of the model using generalization, lastly simplicity to make the process model easy to implement.

In this paper we proposed several variants of the technique

Conformance,i.e. “Is there a good match between the comparison estimated events and the model?”.A process model can be prescriptive or descriptive in nature.

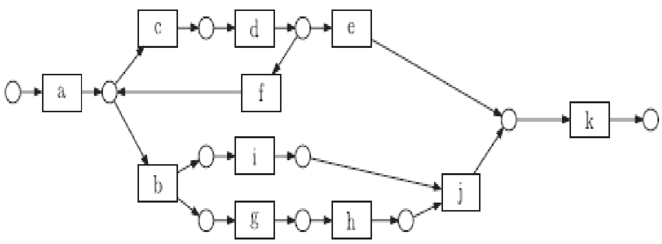

Fig: perfect model
Fitness+, Precision +, Generalization+, Simplicity+

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II. Related work

Many software process methods and tools presuppose the existence of a formal model of a process In this article we describe a Markov method that we developed specifically for process discovery, as well as describe two additional methods that we adopted from other domains and augmented for our purposes.

Process Mining: Discovery, Conformance and Enhancement of Business Processes. In this paper we studied that one common process mining task pertains to process conformance checking, where existing process models are compared with real-life behavior as captured in event logs so as to measure how well a process model performs with respect to the actual executions of the process at hand.

Improved artificial negative event generation to enhance process event logs. In this paper we studied that the use of negative events for conformance checking itself was first proposed in, an improved strategy for artificial negative event induction is applied , extending it with a novel weighting method in order to tackle the problem of event log completeness, so that obtained conformance assessments are more robust when dealing with less complete event logs (i.e. logs containing only a subset of all possible process execution behaviour.

III. Proposed SYSTEM

To calculate the performance of process model we propose a novel conformance checking method which performs with respect to actual execution of a process which is recorded in an event log.
An assessment of the scalability of the proposed metrics is provided in this section as well. a generation algorithm is proposed to induce negative events in an artificial manner in an event log, which can be summarized as follows. We propose a scoring method which can be used to weight negative events in terms of their confidence .The validity of the approach was illustrated by evaluating the proposed artificial negative event weighting method and by performing an experimental setup to benchmark our metrics in comparison with related techniques.

IV. Pseudo code

Algorithm1 : Weighted artificial negative event generation algorithm

1. Given an activity σ_i in trace σ Ɛ L, event log L with activities $A_{L.}$
2. Function NE (σ_i)
3. Let N:= Φ
4. For each a Ɛ $A_L \setminus \sigma_i$
5. Let s:=1
6. For each υ Ɛ L do
7. For each υ_i Ɛ υ : υ_j = a do
8. Let ws := i-1
9. Let mw := 0
10. Let l:=1
11. While l< Min(i,j) – 1 ^σ_i-1 = υ_j-1 do
12. Let mw := mw+1
13. Let l := l+1
14. Let uwr :=ws-mw/ws
15. Let N= N+(a_s^-)
16. Return N

The calculation of this weight is done as follows:
we calculate the score for a negative event with activity $a \in AL\backslash\{\sigma i\}$ (lines 3–4). For each trace υ containing activity a at υj (lines 5–7), the event window before υj is compared with the event window before σi in the original trace σ in order to obtain the "unmatching window ratio", i.e. the length of the unmatching window divided by the total window length in σ, working backwards from σi and υj:

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$\frac{|window| - |matching\ window|}{|window|}$ (lines 8–15).

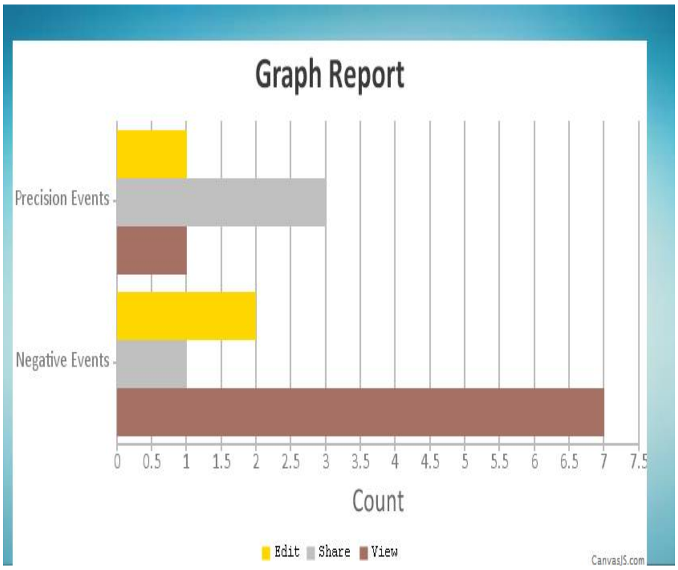
The weighting for each negative event can be summarized As follows: A weighting of 0 (minimum) indicates that a trace was found containing the same full prefix as seen before the negative event under consideration, indicating that this behaviour in fact did occur and as such cannot be supported at all as being disallowed (i.e. negative) behaviour. A weighting of 1 (maximum) indicates that there did not exist any trace where the candidate negative event's activity occurred and was preceded by a matching prefix (even of length1).The scalability of the weighted negative artificial event induction procedure as described above is weak. The complexity of inducing all weighted artificial negative events in an event log L with Algorithm 1 can be expressed as follows: O_$(|L| \times |\mu|) \times (|AL|) \times (|L| \times |\mu| \times |\mu|)$_.To overcome the problem of scalability Ukkonen's algorithm used in order to construct a suffix tree over the event log in order to quickly perform window lookups. This improves negative event induction.

V. RESULTS

There are two main objective of generating robust set of negative event i.e. correctness and completeness. Where correctness prevents generation of incorrect negative events and completeness induce "non-trivial" negative events. Negative event induction algorithm configures the completeness assumption made on an event log by considering window size parameter. This algorithm has two drawbacks as follows:

1. It lags in detecting occurrences of negative events.
2. Inducing set of negative events it is time consuming step.

So, scoring method is used in this proposed architecture to overcome the drawbacks to weight negative event according to their confidence. The first validation task investigates whether the weight given to generated artificial negative events is able to correctly differentiate between correct and incorrect negative events.



VI. CONCLUSION AND FUTURE WORK

A technique for checking the ability of process model is working well in terms of precision and generalization. We proposed an approach by evaluating Artificial negative events and comparison with related techniques . The system introduces an important metrics that does not rely on probabilistic estimator by using new generalization technique . method to determine precision and generalization. Firstly introduces a improved artificial negative event strategy by using weighing method which deals with incomplete log which helps to improve scalability. The proposed artificial

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negative event strategy forms two metrics named as generalization and precision. It illustrates that how metrics work with Petri nets, and it perform trace replay by using heuristic and log model alignment approaches .prom plug-in has all used methods and techniques .

The Weighted Behavioral Generalization (gwB) metric determines a process model's .Thus, while assessing both precision and generalization the same weighted negative event can be used .

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