QUALITY ASSESSMENT OF PROCESS MODELS IN PROCESS MINING: THE CASE OF PETRI NETS

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Abstract. *Nowadays, information systems produce and consume enormous quantities of data. The data produced by Process Aware Information Systems is stored as event logs and can be converted into visual representations by using Process Mining algorithms. This paper follows a case study design with in-depth analysis of discovered Petri Nets' quality. First, the theoretical dimensions of the research concerning the quality assessment of process models are presented, followed by a case study describing an electronic invoicing process. The process is analyzed using discovery Process Mining algorithms having as output Petri Nets. The results of four Process Mining algorithms are analyzed and qualitatively evaluated. Most process discovery algorithms consider only Fitness as qualitative criteria. Our study considers both Fitness and Precision metrics in the evaluation of discovered Petri Nets' quality. The overall metric is also discussed. The findings of this study show similar percentages of Fitness and Precision for 3 out of 4 analyzed models, the best overall percentage being 90%.*

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JEL classification: C55, M15, M21

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1. Introduction

In the context of Digital Era operational business processes are supported by information systems. Subsequently, a lot of data about user-computer interaction is generated. A Process-Aware Information System (PAIS) is defined as *a software system that manages and executes operational processes involving people, applications, and/or information sources on the basis of process models* [1]. Workflow Management Systems (WfMSs), Customer-Relationship Management Systems (CRMSs), Enterprise Resource Planning Systems (EPRs), and Business Process Management Systems (BPMSs) are only some examples of PAISs. There is a weighty difference between WfMSs and BPMSs as the last ones also support the diagnosis phase [2]. One of the most significant feature of PAISs is given by their capability to automatically generate event logs. However, there also are approaches that offer solutions for systems that are not automatically generating event logs [3],[4],[5]. Recently, an extension of PAISs was proposed, namely PAIS-DQ (Data Quality) [6]. Besides classical layers of a PAIS, as they were defined in [1]: Presentation, Process, Application and Persistence, a Data Quality layer was introduced in [6]. The last one applies only on the first three standard layers of a PAIS.

Event logs represent the starting of Process Mining [7]. The key aspects of Process Mining are based on Machine Learning methods combined with Business Process Management techniques. Most Process Mining approaches focus on the conversion of event logs into process models by using different algorithms. But discovery of diagrammatic models is not the only type supported by Process Mining, there also exist conformance checking algorithms designed to compare the event log to the discovered model, while the last type supported by Process Mining points out to enrich the semantics of discovered models.

One of the oldest modelling languages used in process modelling is represented by Petri Nets [8]. The semantics of Petri Nets is simple and the diagrammatic visualization consists of a bipartite graph comprising transitions and places. Afterwards, other modelling languages like Event-driven Process Chain (EPC), UML Activity Diagrams and BPMN diagrams emerged. A top-down quality framework that proposes process model quality features is SEQUAL [9]. The quality levels considered by SEQUAL Framework are based on Stamper's Semiotic Ladder [10]: physical, empirical, syntactic, semantic, pragmatic, and social. QoMo (Quality of Modelling) is another quality framework based on SEQUAL where several goals for modelling are defined (for instance product goals, usage goals, creation goals, validation goals and so on). In the same vein as PAISs have layers like *Data Quality*, process models' quality may be quantified by using the frameworks remained earlier, the quality of process models discovered from event logs is also evaluated using metrics like: *Fitness*, *Precision*, *Generalization* and *Simplicity* [12],[13].

Frequently, the quality of a discovered process model is measured only based on how the process model can reproduce the behavior seen in the event log. This metric is called *Fitness*. *Precision* measures the behavior seen in the process model, but it is not in the event log. The ability to replicate future behavior of the process model is called generalization, while simplicity refers to lasagna processes and how human readable they are [14].

This paper discusses a case study of Petri Nets evaluation. The event log used to compute the metrics describes an electronic invoicing process [15]. The quality of the discovered models is measured using conformance Process Mining algorithms.

The remaining part of the paper proceeds as follows. Section 2 presents the event log summary. This section explores basic information like the number of traces, resources or events. Moreover, a general process model extracted from the event log is also depicted. A Process Mining algorithm focused on frequent behavior is used. Section 3 introduces the discovery analysis approach as a comparison of the resulted process models together with the data from event log summary. Section 4 is concerned on the assessment of process models from *Fitness* and *Precision* perspectives. The overall metric is also evaluated. Finally, the conclusion section gives a brief summary and critique of the findings.

2. Event log summary

The event log used for the comparison of control-flow algorithms describes an electronic invoicing process and the tool used for the current study is ProM Framework [16]. In our analysis we considered only complete events. The event log consists of 20135 cases and 134383 events executed by 6 types of resources (from *group 1* to *group 6*). The process hidden behind the event log takes more than one month.

There are 7 activities mapped on the events: *Approve Invoice*, *Liquidation*, *Invoice Scanning*, *Scanning of Extra Documentation*, *Approve Liquidated Invoices*, *Marking Paid Invoices*, and *Payment Approval*. Each trace starts with *Invoice Scanning* activity and at the end of the process, the invoices are either marked as paid (*Marking Paid Invoices* activity), or approved (*Approve Invoice* activity). The minimum number of events from a case is 3, while the maximum number is 9. More than half of the cases (10726) follow the same pattern consisting of 7 activities: *Invoice Scanning*, *Scanning of Extra Documentation*, *Approve Invoice*, *Liquidation*, *Approve Liquidated Invoices*, *Payment Approval* and *Marking Paid Invoices*. The resources from *group 1* perform almost 30% of activities from the entire process.

The event log describes four types of possible variants. Each variant describes a simple process model: two of the variants generate sequential process models, while the other two provide sequential process models embedded with loops. The figure bellow depicts the behavior of each variant in terms of Heuristics Nets [17]. Although, the algorithm removes infrequent

behavior and is not able to relate routing sequences like decision or parallelism, loops are properly identified.

Figure 1. Heuristics Nets of event log

The *Dotted Chart* illustrates that resources work from Monday to Friday. Moreover, each type of resource executes specific activities, for example the resources belonging to *group 2* execute activity *Approve invoice*, while resources from *group 1* execute scanning activities like *Invoice Scanning* or *Scanning of Extra Documentation*.

Figure 2. Dotted Chart applied on the event log

Most control-flow algorithms (for instance Alpha Miner [18], Heuristics Miner [17], Evolutionary Tree Miner [12], [13]) use the *Causal Activity Matrix* in process models extraction.

From \ To	Approve Invoice+start	Approve Liquidated Invoices+start	Invoice Scanning+start	Liquidation+start	Marking Paid Invoices+start	Payment Approval+start	Scanning of Extra Documentation+start
Approve Invoice+start	0.0	0.0	0.0	0.7570204664445502	0.0	0.0	-0.9999503377036154
Approve Liquidated Invoices+start	0.0	0.0	0.0	-0.7516540642722117	0.0	0.9999371306425249	0.0
Invoice Scanning+start	0.0	0.0	0.0	0.0	0.0	0.0	0.9999503377036154
Liquidation+start	-0.7570204664445502	0.7516540642722117	0.0	0.0	0.0	0.0	0.0
Marking Paid Invoices+start	0.0	0.0	0.0	0.0	0.0	-0.9999371306425249	0.0
Payment Approval+start	0.0	-0.9999371306425249	0.0	0.0	0.9999371306425249	0.0	0.0
Scanning of Extra Documentation+start	0.9999503377036154	0.0	-0.9999503377036154	0.0	0.0	0.0	0.0

Figure 3. Causal Activity Matrix of event log based on Directly Follows miner

Figure 3 presents the corresponding *Causal Activity Matrix* of the event log. For instance, the matrix shows a *directly-follows* relation between *Approve Invoice* and *Liquidation* activities.

3. Discovery analysis

Discovery analysis represents the comparison of the resulted process models with the data from event log summary. We focus on the most frequent behavior. The Heuristics Net showing the most frequent paths was described in the previous section in order to offer an overview of the process. Next, we will describe the algorithms used in our analysis.

Alpha Miner [18] is the first Process Mining algorithm. The basic idea of Alpha Miner algorithm is to provide visual representations in terms of Petri Nets. Throughout time, several versions of this algorithm have been developed: Alpha+ [19], Alpha++ [20] and Alpha# [21]. Being the first Process Mining algorithm, it has a series of drawbacks as the incapacity of discover short loops, invisible tasks or duplicated tasks, but Alpha+ and Alpha++ solve these problems.

Figure 4. Petri Net discovery using different algorithms

Other Process Mining algorithms providing a Petri Net as result are Inductive [22] and ILP (Integer Liner Programming) Miner [23]. Hereinafter, a series of Petri Net models are

generated based on the event log. The employed algorithms are: Alpha Miner, Alpha# Miner, Inductive Miner, respectively ILP Miner. The resulted Petri Nets are depicted in Figure 4.

Alpha Miner discovers a Petri Net where transitions are displayed sequentially. Furthermore, *Liquidation* transition is not linked to any place. Alpha# Miner seems to provide a more reliable Petri Net. Both models provided by Alpha and Alpha# Miners are unsound. The Petri Net generated using ILP Miner is sound, but it has missing behavior (for example according to the resulted Petri Net, all traces end with *Marking Paid Invoices* transition).

Inductive Miner also proposes a sound Petri Net. Both, Inductive and Alpha# Miners use silent transitions in process discovery. However, Inductive Miner is able to discover two possible end transitions as the summary of event log indicated: *Marking Paid Invoices* or *Approve Invoice*. But it also includes one more end activity: *Approve Liquidated Invoices*. Consequently, the model is overfitting. At a first glance, Inductive Miner is the algorithm that provides the optimal Petri Net by comparing the data from event log summary to the resulted Petri Net. Next section presents the evaluation of algorithms from quality perspective of discovered process models.

4. Evaluation of algorithms

This section describes the approach used in the evaluation of Process Mining algorithms. The analysis is performed on algorithms whose output is a Petri Net. Although, Prom Framework supports a series of control-flow oriented algorithms, *Fitness* and *Precision* percentages are not computed for all of them. Consequently, the evaluated algorithms are: Alpha Miner, Alpha# Miner, Inductive Miner, respectively ILP Miner.

The quality of each discovered process model is summarized in Table 1. The Petri Net discovered using Inductive Miner guarantees a *Fitness* of 95%, *Fitness* being the metric which guarantees the mapping of every trace to the Petri Net. The lowest *Fitness* degree belongs to the Petri Net provided by Alpha# Miner (68%).

Table 1. Evaluation metrics for control-flow algorithms

Algorithm	Fitness	Precision	Overall
Alpha Miner	0.75	0.37	0.56
Alpha# Miner	0.68	0.56	0.62
ILP Miner	0.71	0.75	0.73
Inductive Miner	0.95	0.85	0.90

Nevertheless, the *Precision* computed for the Petri Net generated by Inductive Miner is lower than the *Fitness* metric because the Petri Net also allows the execution of traces that are not depicted by the event log (for example, according to the model, a trace may end with *Approve Liquidated Invoices* transition, but the event log describes only *Marking Paid Invoices* or *Approve Invoice* as ending transitions). The greatest *Precision* percentage belongs to ILP Miner, while the lowest *Precision* percentage is computed for Alpha Miner. The overall evaluation shows that Inductive Miner provides the best Petri Net with an overall metric of 90%.

5. Conclusions

This case study seeks to examine the quality of process discovery Process Mining algorithms having as output a Petri Net. *Fitness* and *Precision* are computed for the Petri Nets generated

by four Process Mining algorithms: Alpha Miner, Alpha# Miner, Inductive Miner, respectively ILP Miner. The overall metric is also computed.

Most process discovery algorithms consider only *Fitness* as qualitative criteria. Undeniably, the results of this study show that the model having the greatest *Fitness* (95%), also measures the greatest *Precision* (85%), specifically the Petri Net discovered by Inductive Miner. Nevertheless, there are Process Mining algorithms quantified with a considerable *Fitness* metric, but the *Precision* degree is not weighty (for instance Alpha Miner). On the other hand, Inductive Miner and ILP Miner provide similar values for both metrics (71% versus 75%, respectively 95% versus 85%).

This study may be extended by evaluating other types of models, for instance Process Trees, by including all four dimensions that evaluate the quality of discovered process models.

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