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PM4Py: A process mining library for Python

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ABSTRACT

PM4Py is a Python library providing a comprehensive array of tools for process mining. This paper presents an in-depth overview of the PM4Py library, including its integration with other Python libraries and its latest features, such as object-centric process mining. Furthermore, we discuss the significant impact of PM4Py within academia, industry, and the open-source community, evidenced by its wide adoption and substantial evolution. In short, the PM4Py library is an essential tool for researchers and practitioners, paving the way for advancements in process mining.

Code metadata

Current code version	**2.7.4**
Permanent link to code/repository used for this code version	https://github.com/SoftwareImpacts/SIMPAC-2023-301
Permanent link to Reproducible Capsule	https://codeocean.com/capsule/6602453/tree/v1
Legal Code License	GPL-3.0 license
Code versioning system used	GIT
Software code languages, tools, and services used	Python 3.10
Compilation requirements, operating environments & dependencies	https://github.com/pm4py/pm4py-core/blob/2.7.4/requirements.txt
If available Link to developer documentation/manual	https://pm4py.fit.fraunhofer.de/
Support email for questions	pm4py@fit.fraunhofer.de

1. Introduction

Process mining [1], a link between data science and process science, enables organizations to gain insights from event data generated during the execution of operational processes to understand and improve their processes. Three central disciplines can be distinguished in process mining: process discovery [2,3], conformance checking [4,5], and process enhancement [6]. PM4Py is a Python library that contains many algorithms from these disciplines, enabling data-driven decision-making and helping organizations uncover optimization potential in their processes.

In response to the growing need for advanced process mining tools, PM4Py was developed to address the diverse challenges in this area. This library fills a noticeable gap in the market and provides a comprehensive and flexible solution for managing complex process mining scenarios. PM4Py addresses the diversity of real-world processes and covers a wide range of techniques. As an open-source project, PM4Py encourages community participation and broad adoption. Thus, it facilitates the application of process mining and fosters an evolving, interactive community in the field.

PM4Py had its start with the publication of the initial paper [7], and since then, it has grown substantially, gaining a larger user community with over 1,086,889 downloads as of July 31, 2023.[1] This growth is a testament to the library's effectiveness and has encouraged ongoing improvements. This paper will explore the latest features of PM4Py and its potential applications in the rapidly expanding field of process mining.

The remainder of this paper is organized as follows. Section 2 offers a comprehensive overview of PM4Py, detailing its essential features and illustrating its integrations. Section 3 delves into the impact of PM4Py. Finally, Section 4 concludes the paper, providing a concise summary and emphasizing the ongoing potential and future directions of PM4Py in the ever-evolving landscape of process mining.

The code (and data) in this article has been certified as Reproducible by Code Ocean: (https://codeocean.com/). More information on the Reproducibility Badge Initiative is available at https://www.elsevier.com/physical-sciences-and-engineering/computer-science/journals.

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[1] According to https://pepy.tech/project/pm4py

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Code Listing 1: An example process mining analysis conducted using PM4Py

```
import pm4py

# a log in the XES format is imported
log = pm4py.read_xes('tests/input_data/receipt.xes')

# the log is filtered on the top 5 variants
filtered_log = pm4py.filter_variants_top_k(log, 5)

# a directly-follows graph (DFG) is discovered from the log
dfg, start_activities, end_activities = pm4py.discover_dfg(filtered_log)

# a process tree is discovered using the inductive miner
process_tree = pm4py.discover_process_tree_inductive(filtered_log)
# the process tree is converted to an accepting Petri net
petri_net, initial_marking, final_marking = pm4py.convert_to_petri_net(process_tree)
    process_tree = pm4py.discover_process_tree_inductive(filtered_log)
# the accepting Petri net is converted to a BPMN diagram
bpmn_diagram = pm4py.convert_to_bpmn(petri_net, initial_marking, final_marking)

# the discovered process models are shown on the screen as .svg images
pm4py.view_dfg(dfg, start_activities, end_activities, format='svg')
pm4py.view_process_tree(process_tree, format='svg')
pm4py.view_petri_net(petri_net, initial_marking, final_marking, format='svg')
pm4py.view_bpmn(bpmn_diagram, format='svg')

# we compare the original log versus the discovered model
fitness = pm4py.fitness_token_based_replay(log, petri_net, initial_marking, final_marking)
precision = pm4py.precision_token_based_replay(log, petri_net, initial_marking, final_marking)

print(fitness) # 0.984
print(precision) # 0.758

# we check if the discovered model is a sound workflow net
is_sound_wfnet = pm4py.check_soundness(petri_net, initial_marking, final_marking)[0]
print(is_sound_wfnet) # True
```

2. Software overview

This section provides a comprehensive overview of the PM4Py library, detailing its main features, support for various standard event log and process model formats, visualization capabilities, and an illustrative example of using the library for process mining analysis.

2.1. Main features

This section briefly reviews PM4Py's central features. Section 2.1.1 overviews algorithms implemented in PM4Py. Section 2.1.2 presents the process-mining-specific data formats that are supported by PM4Py. Finally, Section 2.1.3 briefly presents built-in visualizations offered by PM4Py. The provided code in Code Listing 1llustrates a complete process mining workflow using PM4Py.

2.1.1. Implemented approaches

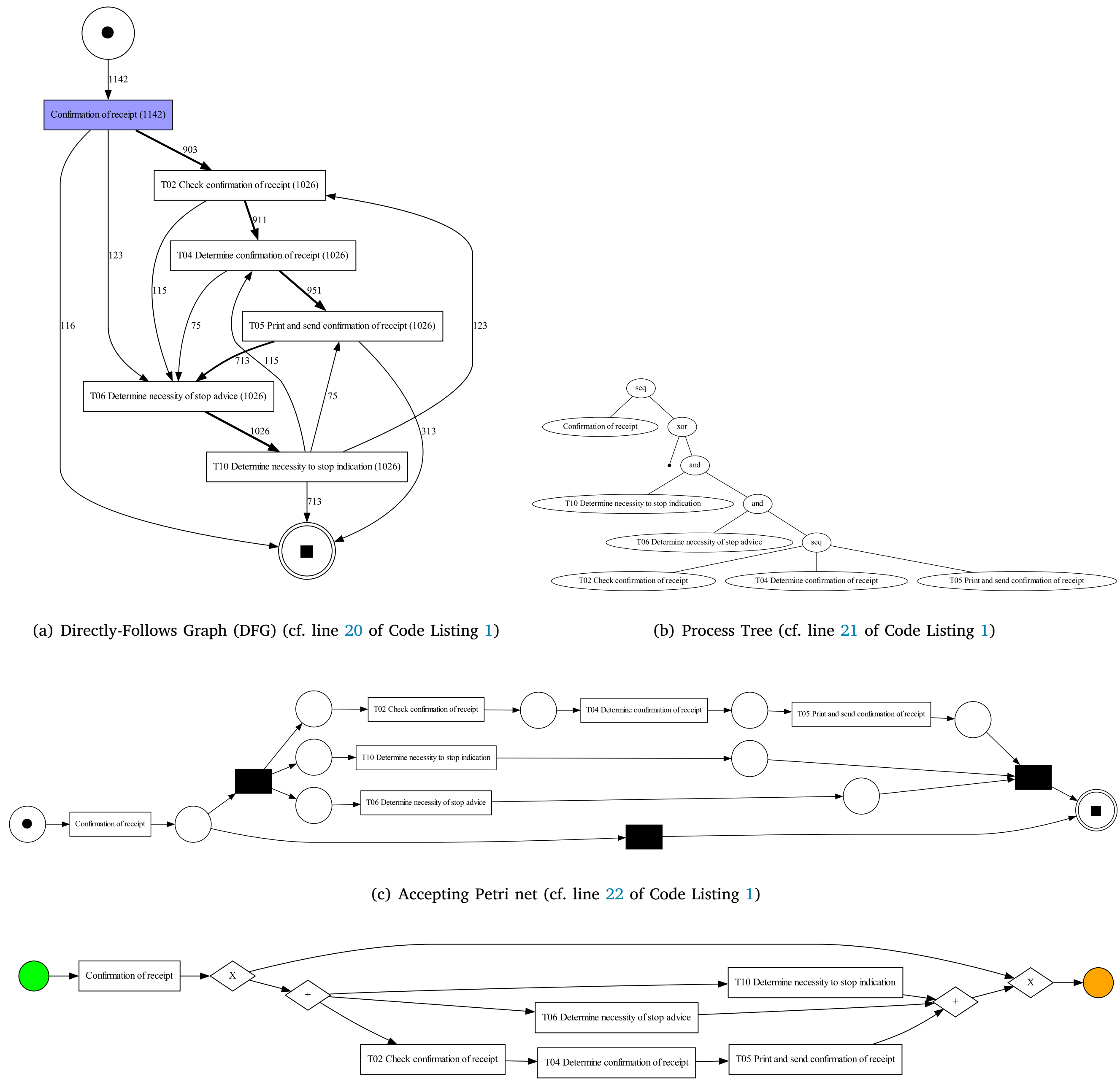
PM4Py provides an array of implemented approaches; consider Fig. 2 for a comprehensive overview. For *process discovery*, it includes the alpha miner [8], inductive mining algorithms [9–11], the heuristics miner [12], the ILP miner [13], the correlation miner [14], the prefix tree approach [15], and causal nets [1]. Moreover, it supports fundamental abstractions such as directly-follows graphs (DFGs) [1] and transition systems [1]. In the specialized area of *object-centric process mining (OCPM)* [16], PM4Py is equipped with methods like OC-DFG discovery [17], OC-Petri nets discovery [18], and feature extraction [19].

Regarding *conformance checking*, PM4Py leverages footprints [1], the token-based replay technique [20], and alignments [21] to compare observed with modeled process behavior systematically. PM4Py further refines this verification using decomposed/recomposed alignments [22] and log skeleton [23] methods. Also, conformance checking using Earth Mover Distance (EMD) [24], and LTL Checking [25] are supported by PM4Py.

PM4Py allows evaluating the *log-model quality* through multiple metrics such as *fitness*, for instance, using token-based replay [20] or alignments [26], ETConformance *precision* [27,28], *generalization* [26], *simplicity* [29], anti-alignments [30], and multi-alignments [31]. Other process mining fields covered by PM4Py include process tree generation [32], decision mining [33], soundness checking with WOFLAN [34]), and trace clustering [35]. Beyond the process-focused perspective, PM4Py offers insights into *social and organizational aspects* of processes through social network analysis [36], role discovery [37], and resource profiling [38]. Moreover, it allows to analyze batch processing scenarios [39], in which a resource executes an activity for different cases in a short amount of time. Also, differential privacy [40] is implemented to protect sensitive information.

2.1.2. Supported data formats

PM4Py has been designed to work seamlessly with a variety of standard event log and process model formats, making it highly adaptable to different systems. It supports the traditional event log format XES [41], and for object-centric event logs, the OCEL [42] format is utilized. Regarding process models, PM4Py supports the Petri nets format PNML [43] as well as the process trees format PTML [44]. Furthermore, the popular BPMN 2.0 [45] format is also supported. By supporting such a wide range of formats, PM4Py is capable of increasing interoperability and facilitating extensive usage.



(a) Directly-Follows Graph (DFG) (cf. line 20 of Code Listing 1)

(b) Process Tree (cf. line 21 of Code Listing 1)

(c) Accepting Petri net (cf. line 22 of Code Listing 1)

(d) BPMN Diagram (cf. line 23 of Code Listing 1)

Fig. 1. Visualizations of the process models discovered in Code Listing 1.

2.1.3. *Visualizations*

PM4Py offers diverse visualizations for process mining artifacts, for instance, cf. Fig. 3. Consider Fig. 1 showing various different process model formalism visualized using PM4Py: directly-follows graphs (cf. Fig. 1(a)), process trees (cf. Fig. 1(b)), accepting Petri nets (cf. Fig. 1(c)), and BPMN models (cf. Fig. 1(d)). Besides process model visualizations, various other visualizations are implemented in PM4Py. For instance, the dotted chart visualization (cf. Fig. 3(a)) and the performance spectrum (cf. Fig. 3(b)) [46] allow to visually detect temporal performance patterns in event data. Moreover, decision trees (cf. Fig. 3(c)) elucidates decision factors. Such visualizations are important for process comprehension and optimization.

3. Impact overview

This section explores the impact of PM4Py, its role in academic innovations, and derived tools that build upon PM4Py. In terms of applications, PM4Py's potential is vast and diverse. Organizations across various sectors have used it, including healthcare for optimizing patient

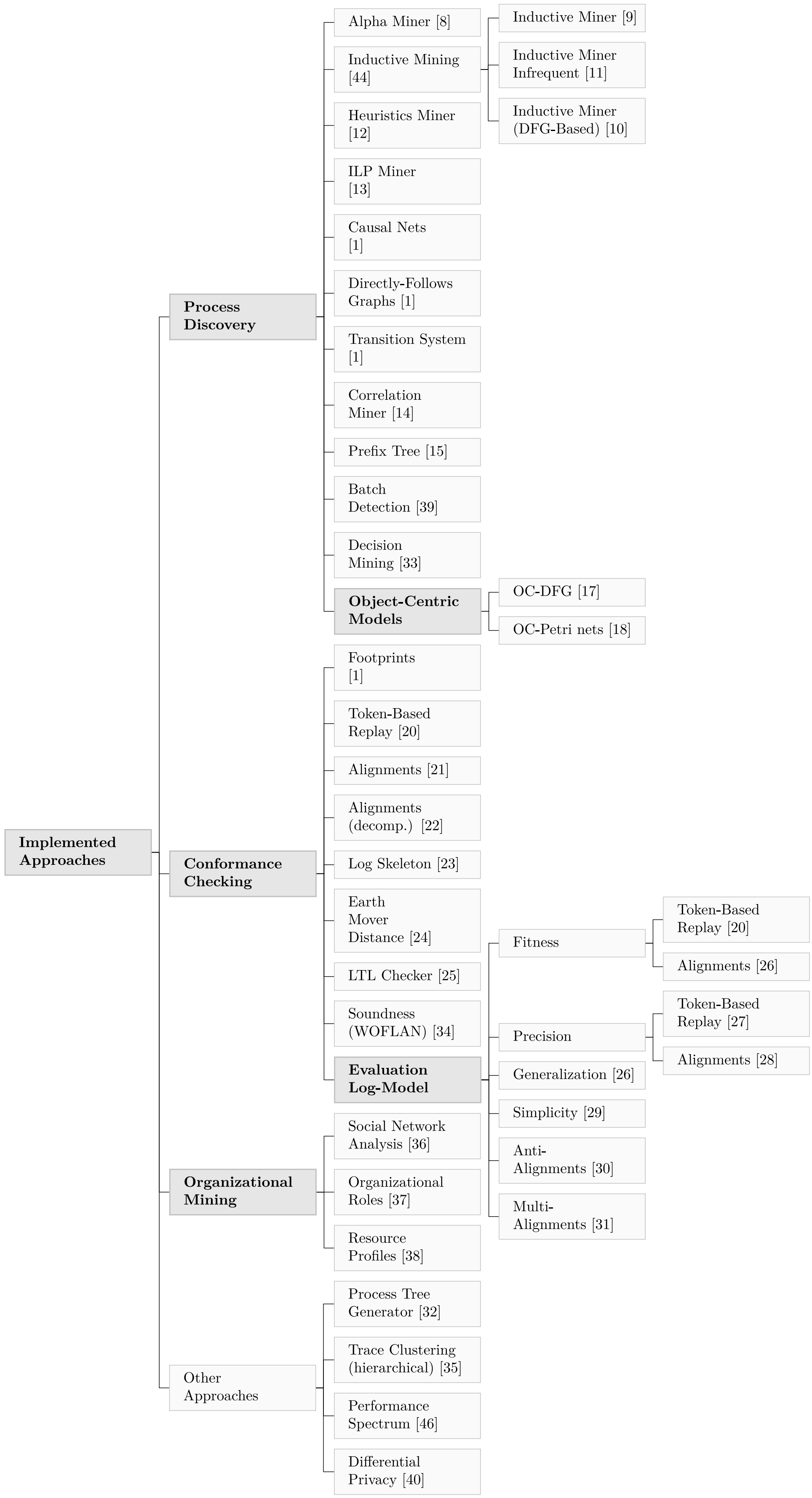
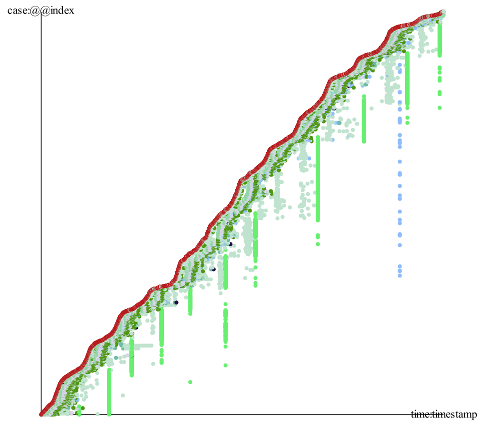
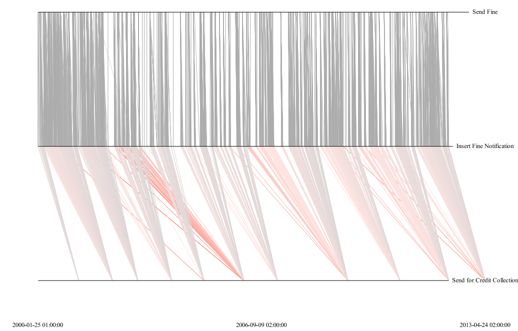


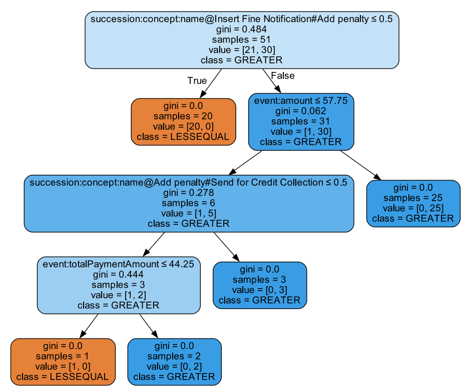
Fig. 2. Overview of various approaches and algorithms implemented in PM4Py.



(a) Dotted Chart visualizing the events from a publicly available event log [47]



(b) Performance spectrum showing temporal patterns from a publicly available event log [47] between the activities 'Send Fine', 'Insert Fine Notification', and 'Send for Credit Collection'



(c) Decision Tree (for the duration of a case) for a publicly available event log [47], correlating the features to the duration of a case (two classes, greater or smaller than the median throughput time, are identified).

Fig. 3. Example visualizations offered by PM4Py using the open-access event log [47].

pathways[2] [48], finance to improve transaction processes[3] [49], and IT for threat detection[4] [50].

3.1. Research advances

PM4Py's contribution to the academic sector is significant as an indispensable tool in process mining research and education. It encourages breakthroughs and advancements in this expanding field and serves as a foundation for prototyping and developing new algorithms in process mining. Furthermore, the library embraces recent research developments like object-centric process mining, shifting from a traditional case-centric view to capturing complex inter-object relationships. PM4Py also utilizes machine learning for predictive process mining [51], enhancing anomaly detection [52], process conformance checking [53], and forward-looking capabilities. Moreover, PM4Py has been instrumental in realizing several high-impact research studies, as demonstrated by its utilization of well-cited publications. The study [54], which outlines a data-driven approach for creating digital twins in smart factories using machine learning and process mining techniques, has been cited 55 times. Moreover, in [55], a novel solution for detecting changes in process behavior over time has been proposed, building upon PM4Py functionalities, and has garnered 32 citations.

3.2. Tools

The PM4Py library serves as the foundation for numerous process mining software tools; below, we briefly present some selected tools. The Process Mining Toolkit (PMTk) [56] includes several process mining capabilities in one end-user-oriented tool, including process discovery, visual analysis of processes, and conformance checking. OPerA [57] focuses on object-centric performance metrics, providing insight into object lifecycles. Cortado [58] innovates process discovery by utilizing domain knowledge and enabling incremental process model discovery. DTween [59] and Impacta [60] enable the creation of a digital twin of an organization. In summary, these tools, built on the

[2] PM4Py has been used for data preprocessing and process discovery purposes. In particular, the discovered models were DFGs and Petri nets discovered using the inductive miner.

[3] The discovery of directly-follows graphs helped in the audits; the discovery of social networks was used to assess the degree of automation in the financial process.

[4] Several process discovery techniques implemented in PM4Py have been used (alpha miner, heuristics miner, inductive miner) to represent the underlying process. Moreover, alignment-based conformance checking has been used to check the conformance.

PM4Py library, demonstrate the versatility of process mining while confirming the usefulness of PM4Py.

3.3. Statistics

PM4Py's growth and popularity are evidenced by its significant GitHub and PyPI metrics. On GitHub,[5] PM4Py has received over 554 stars and has been forked over 235 times, reflecting its wide distribution. With 43 contributors, 106 pull requests, and 310 closed issues, it is a testament to a vibrant community using and contributing to PM4Py. Finally, PM4Py's distribution is substantial, with over 1,086,889 downloads.[6] PM4Py has a considerable academic influence beyond software metrics, with the first paper [7] being cited in 231 scholarly articles, affirming its standing in the process mining field.

4. Conclusion

PM4Py is a Python library implementing various process mining approaches and supporting widespread data formats. The library has demonstrated its effectiveness as a versatile open-source toolkit for process mining. Its rich feature set and extensive integration with other Python libraries provide a powerful toolbox for academic researchers and industry practitioners. The significant growth in its user community, complemented by substantial user contributions, is a testament to the tool's utility and adaptability—various software tools and implementations of novel process mining approaches built upon PM4Py. PM4Py is committed to continued innovation and community engagement to consolidate further its role as a leading platform for process mining. Through this continual evolution, PM4Py aims to keep empowering its users to harness the potential of process mining.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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