Interactive Business Process Comparison Using Conformance and Performance Insights - A Tool*

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Abstract. Process mining techniques make the underlying processes in organizations transparent. Historical event data are used to perform conformance checking and performance analyses. Analyzing a single process and providing visual insights has been the focus of most process mining techniques. However, comparing two processes or a single process in different situations is essential for process improvement. Different approaches have been proposed for process comparison. However, most of the techniques are either relying on the aggregated KPIs or their comparisons are based on process models, i.e., the flow of activities. Existing techniques are not able to provide understandable and insightful results for process owners. The current paper describes a tool that provides aggregated and detailed comparisons of two processes starting from their event logs using innovative visualizations. The visualizations provided by the tool are interactive. We exploit some techniques recently proposed in the literature, e.g., *stochastic conformance checking* and the *performance spectrum*, for conformance and performance comparison.

Keywords: Process mining, Event logs, Comparison visualization, Performance spectrum, Earth mover's distance

1 Introduction

Process mining [1] is a branch of data science that analyzes business processes starting from the information contained in *event logs*. Event logs store the events executed inside processes w.r.t. time, process instances, activities, and the corresponding resources. For instance, in a bank, the act of opening an account (*Activity*), for the customer number *123* (*Process Instance, or Case ID*) by John (*Resource*), at *01/10/2021 14:00:10* (*Timestamp*) is considered as an event. The sequence of events for one process instance (*Case ID*) w.r.t. their timestamps

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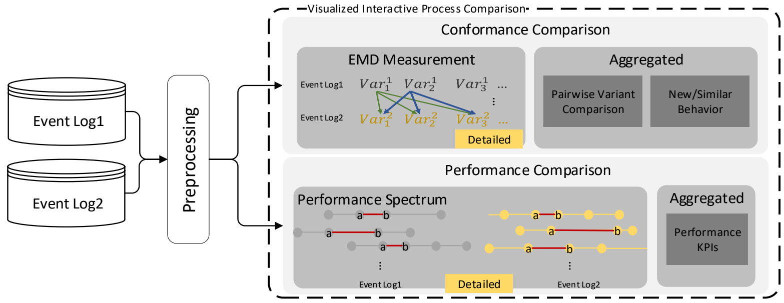

Fig. 1: The overview of the proposed tool for comparing two processes using their event logs. After preprocessing the event logs, two main modules are designed and implemented for detailed and aggregated comparisons of two processes, w.r.t. behavior and performance similarity. For instance, using *EMD* (*Earth Mover's Distance*), the cost of mapping one behavior from the first log to the second one is calculated. Using the *Performance Spectrum*, the execution times between activities a and b are compared in two event logs.

is called a *case*. A *trace* is the sequence of activities of a case. For instance, for customer*123* (a case), $\langle$*open account*, *deposit money*, *withdraw money*, ...$\rangle$ is the corresponding trace.

Several techniques, such as process discovery (the automatic discovery of a business process model using the event log), conformance checking (the comparison between the behavior of an event log and the corresponding process model), model enhancement (the annotation of the process model with frequency and performance information) have been provided in the process mining context. Visualizations often accompany these techniques. For instance, one of the techniques which provides an insightful visualization of event logs is the *dotted chart* visualization [17]. Such visualizations are the main resources to compare the behavior of different processes (*process comparison*) since the analyst can visually spot the differences. Process comparison is also essential to create valid simulation models, and what-if analyses [13]. To compare two processes w.r.t. their event logs, two significant aspects of the processes can be considered, the control flow (sequence of activities) and the performance patterns. In this paper, we focus on these aspects and demonstrate the features and functionalities of our proposed tool.

We elaborate on the motivation of designing and developing the proposed tool in Section 2. The scientific novelty and features provided by the tool are introduced in Section 3. In Section 4, we explain the tool in practice along with the technical aspects, and Section 5 concludes this paper by discussing the future work and limitations.

2 Motivation

In this section, the open issues are highlighted by exploring the related work. Then, the techniques that are used by the proposed tool to address these requirements are briefly explained.

Several approaches have been proposed for the comparison of processes using their event logs, e.g., in [18], a case study involves resources and activities comparisons. In [11], the authors propose a case study for process comparison among different hospitals with the focus of activity flows. In [2], the idea of process cubes is presented and applied to compare the processes in the context of education. Then, the results of queries are visualized using standard techniques such as dotted charts. In [4], the authors use process cubes to analyze and compare different aspects of business processes where they generate multidimensional processes. However, as discussed in [19], the complexity of considering all the dimensions and the effort to generate a multidimensional process is high, and it is not easy to provide an understandable visualization for the user.

Most of the current approaches for process comparison are not advanced enough in both aspects, i.e., conformance checking and performance analysis. For instance, standard comparison techniques exploit conformance checking between the event logs and the corresponding process models [5]. In addition, for performance comparison, general metrics [8] are mainly considered for the comparison. Although detailed comparison techniques such as using *Earth Mover's Distance* address this issue, e.g., in [10] and [15], there still exists a gap in transforming insights into comprehensive visualizations.

This paper proposes a tool for systematically comparing two processes or the outcomes of changed processes in different contexts. This tool supports and complements the existing comparative process mining techniques. We use a comparison technique for processes that graphically depicts the differences. Two main comparison areas are based on the distance between conformance and performance of two processes. The proposed tool visualizes the performance and compliance findings interactively. Figure 1 represents an overview of the proposed tool's architecture and modules. It includes three main modules, (A) preprocessing, (B) conformance comparison, and (C) performance comparison. The conformance comparison is inspired by the distance metrics proposed in [10] and [15]. For performance analysis, we exploit the idea of performance spectrum described in [7].

3 Approach

The comparison modules provided by our tool use different conformance and performance analyses initially proposed to analyze a single process. We adapt them for comparative purposes and create interactive visualizations for such comparisons. The modules are explained in Subsection 3.1 and Subsection 3.2.

3.1 Conformance Comparison

This section explains the provided method for the comparison of the control flow based on the activities and the paths recorded in the event log. We use a stochastic conformance checking technique to identify differences. A process consists of different process instances showing the possible paths that can be

Table 1: An example of EMD measurement for two event logs [15]. The reallocation function allocates 1 out of 50 traces $\langle a, b, c, d\rangle$ in L_1 to the same trace in L_2 and 49 traces to the trace $\langle a, e, c, d\rangle$ which is the most similar one in L_2. The sum of the table's values indicates the general EMD value, i.e., the difference between the two event logs.

A_{L_1} \ A_{L_2}	$\langle a, b, c, d\rangle$	$\langle a, c, b, d\rangle$	$\langle a, e, c, d\rangle^{49}$	$\langle a, e, b, d\rangle^{49}$
$\langle a, b, c, d\rangle^{50}$	$\frac{1}{100} \times 0$	0×0.5	$\frac{49}{100} \times 0.25$	0×0.5
$\langle a, c, b, d\rangle^{50}$	0×0.5	$\frac{1}{100} \times 0$	0×0.5	$\frac{49}{100} \times 0.25$

taken using the process model. All the possible paths that are unique traces, i.e., sequences of activities, are considered the process behaviors. Given two event logs L_1 and L_2, we denote A_{L_1} and A_{L_2} as their sets of sequences of activities. Given this information, we look for the matches and mismatches from two viewpoints; *aggregated* and *detailed*:

- *Aggregated Metrics*: we consider one of the event logs as a base and identify the non-existing behavior in another event log. For instance, if $A_{L_1}=\{\langle a, b, c\rangle, \langle a, b, e, d\rangle\}$ and $A_{L_2}=\{\langle a, b, c\rangle, \langle a, b, e, f\rangle\}$:
  - *Removed behavior* from L_1 in comparison with L_2: $A_{L_1} \setminus A_{L_2}=\{\langle a, b, e, d\rangle\}$
  - *New behavior* from L_2 in comparison with L_1: $A_{L_2} \setminus A_{L_1}=\{\langle a, b, e, f\rangle\}$

  And the measures $\frac{|A_{L_2} \setminus A_{L_1}|}{|A_{L_1} \cup A_{L_2}|}$ and $\frac{|A_{L_1} \setminus A_{L_2}|}{|A_{L_1} \cup A_{L_2}|}$ are the fraction of the new and removed behaviors, respectively. The pairwise comparison of the behaviors of processes and their frequencies, which indicate their importance in each event log, is also considered. One of the results of these metrics using an example is shown in Figure 2.
- *Detailed Comparison*: we use the idea of Earth Mover's Distance (EMD) for the detailed comparison between traces of two event logs. EMD indicates the amount of effort required to change one pile of earth into the other. We use the conformance techniques provided in [10] to compute the EMD measurement between two event logs. The frequency of each trace is considered as the pile that needs to be moved, and the normalized edit distance (Levenshtein) is used to calculate the distance between every two traces. EMD solves an optimization problem that minimizes the cost of converting one event log to another one, i.e., it finds the best reallocation function. The outcome of applying the proposed EMD measurement to two sample event logs is shown in Figure 3. The x-axis and y-axis represent the unique traces in the first event log (L_2) and the unique traces in the second event log (L_1), respectively. Thus, each row is the relative effort that the first unique trace in L_1 needs to be transformed into one or more unique traces in L_2. The details of functions and formal definitions are discussed in [13].

3.2 Performance Comparison

General performance KPIs at a high level of aggregation, e.g., the average waiting time of traces, or the average service time are too abstract to be used as

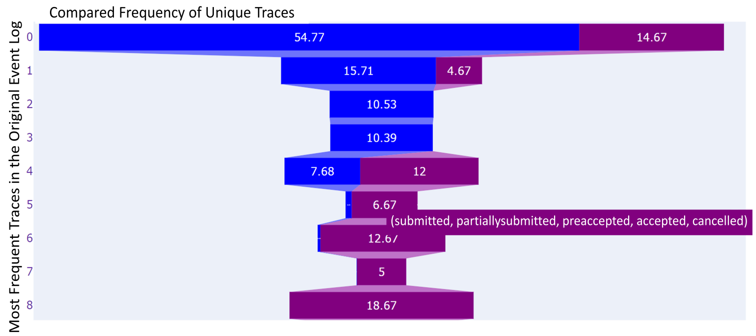

Fig. 2: The comparative frequency chart represents the similar behaviors, removed behaviors, and the new behaviors w.r.t. the second event log.

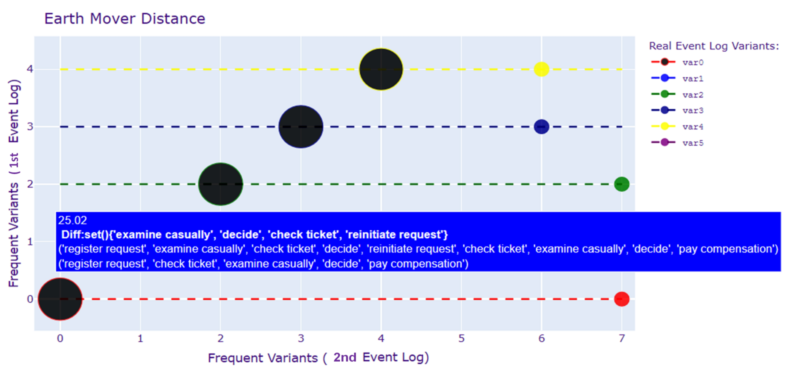

Fig. 3: Two example event logs are compared in detail. The EMD diagram depicts the differences between the two event logs in terms of the activity flow. For example, the cost of mapping each trace to the second event log is based on the activities, the order of activities, and the frequency of traces, i.e., the distance between two logs.

comparison metrics. Therefore, besides the usual metrics, we propose the usage of the performance spectrum [7]. The performance spectrum is a concept introduced to visualize the performance of a process at a detailed level. If we consider a single path between two activities a and b, the performance spectrum shows all the temporal segments going from an event having activity a to an event having activity b in the cases of the event log. This permits to identify the time intervals with higher/lower performance, the queuing pattern (FIFO/LIFO), and other performance patterns that are useful for predictive purposes [6,9].

We use the information of the performance spectrum to calculate statistics for each segment (namely, the *average time* and the *frequency*) that are compared between two event logs. Figure 4 shows the result of the introduced performance measurement for two example processes. It represents different aspects of the results: (1) new/eliminated segments, (2) frequency of each segment, and (3) duration of each segment. For instance, given L_1 and L_2, each segment's colors refer to an event log, the size refers to the average time difference between the segments, and the transparency indicates the frequency (darker, more frequent).

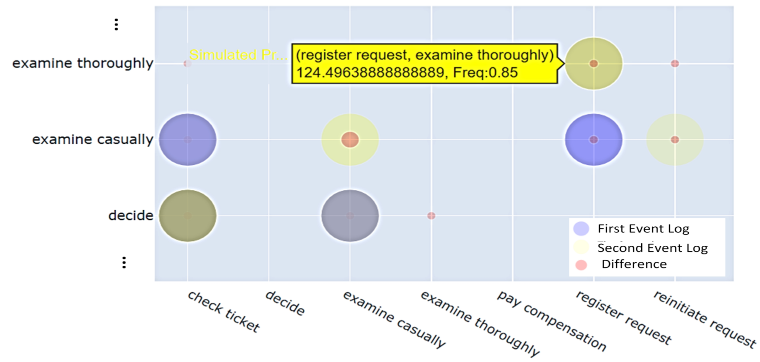

Fig. 4: Part of the performance measurement for the example process is based on the aggregated performance spectrum. Each event log is represented by a different color, i.e., blue for the original and yellow for the simulated one. Overlapping segments are represented by the gray color (same duration between segments). Each point's transparency and size indicate the frequency and duration of the segment in the event logs.

The gray color represents the overlapped segment in two event logs with similar performance metrics, the blue color shows the segments in the original log L_1, and the yellow points represent the new segment existing in L_2. The implementation also includes the option to display only the differences (red points).

4 Tool

In this section, we describe the availability, components, and maturity of the tool.

4.1 Availability

The tool is implemented as a web application. The code is publicly available.[3] The tool is implemented in Python, and the web-based interface has been implemented using Flask. By uploading two event logs, the comparison results w.r.t. different aspects are presented interactively. The process mining insights are on the basis of [3], [15], and [16]. The tool is also available as a Python library, which makes further extension and integration for different purposes possible.

4.2 Components

The tool offers four different components. For the conformance comparison, the *EMD Comparison* tab provides the Earth Mover's distance between the traces of the first event log against the traces of the second event log. With the selection of the variants, it is possible to focus the visualization on a given set of variants. The *Variants Frequency Comparison* tab compares the relative frequencies of the variants recorded in the first and second log. The *Overlap Between Logs* tab

[3] https://github.com/mbafrani/VisualComparison2EventLogs

shows how much the behavior between the two logs overlap. Finally, the *Aggregated Performance Spectrum* tab compares the performance of the segments in the first and the second event logs. In the component, it is possible to visualize the comparison between the performance, the aggregation of the performance in the first event log, or the aggregation of the performance in the second one.

4.3 Maturity

The authors have used the tool in multiple projects.[4] For instance, it has been used for assessing the quality of the simulation results in [14,12]. Moreover, a comparison of production lines with different settings, e.g., removing one of the stations and introducing concurrency in the process, has been done w.r.t. the process behaviors as well as performance aspect in the *Internet of Production* project of the RWTH Aachen University.[5]

5 Conclusion

The goal of process mining techniques is to provide insight into the processes of organizations. Several techniques such as process model discovery, conformance checking, and social network analysis are proposed to analyze an event log, while some limitations exist in the comparison between two processes. Given the complexity of the comparison task, such techniques are valuable when the result is able to be presented comprehensively. This paper proposed innovative and interactive visualizations to understand the differences between two processes using their event logs. Our approach is implemented as a tool that can be used with other process mining and comparison techniques to capture the difference. In the current version, the tool supports comparing the traces of the two event logs and the performance comparison. As future work, we aim to support process comparison w.r.t. resources, i.e., social network analysis and roles, and embed expert knowledge.

References

1. van der Aalst, W.M.P.: "Process mining - Data Science in Action", second edition. Springer (2016). https://doi.org/10.1007/978-3-662-49851-4
2. van der Aalst, W.M.P., Guo, S., Gorissen, P.: Comparative process mining in education: An approach based on process cubes. In: Data-Driven Process Discovery and Analysis. pp. 110–134. Springer Berlin Heidelberg, Berlin, Heidelberg (2015)
3. Berti, A., van Zelst, S.J., van der Aalst, W.M.P.: Process mining for python (PM4Py): Bridging the gap between process-and data science. In: Proceedings of the ICPM Demo Track 2019, co-located with 1st International Conference on Process Mining (ICPM 2019), Aachen, Germany, June 24-26, 2019. p. 13–16 (2019), http://ceur-ws.org/Vol-2374/

[4] https://www.researchgate.net/project/Forward-looking-in-Process-Mining
[5] https://www.iop.rwth-aachen.de

4. Bolt, A., van der Aalst, W.M.P.: Multidimensional process mining using process cubes. In: Enterprise, business-process and information systems modeling. pp. 102–116. Springer (2015)
5. Carmona, J., van Dongen, B.F., Solti, A., Weidlich, M.: Conformance Checking - Relating Processes and Models. Springer (2018). https://doi.org/10.1007/978-3-319-99414-7
6. Denisov, V., Fahland, D., van der Aalst, W.M.P.: Predictive performance monitoring of material handling systems using the performance spectrum. In: International Conference on Process Mining, ICPM 2019, Aachen, Germany, June 24-26, 2019. pp. 137–144. IEEE (2019)
7. Denisov, V., Fahland, D., van der Aalst, W.M.P.: Unbiased, fine-grained description of processes performance from event data. In: Business Process Management. pp. 139–157. Springer International Publishing (2018)
8. Hornix, P.T.: Performance analysis of business processes through process mining. Master's Thesis, Eindhoven University of Technology (2007)
9. Klijn, E.L., Fahland, D.: Performance mining for batch processing using the performance spectrum. In: Francescomarino, C.D., Dijkman, R.M., Zdun, U. (eds.) Business Process Management Workshops - BPM 2019 International Workshops, Vienna, Austria, September 1-6, 2019, Revised Selected Papers. Lecture Notes in Business Information Processing, vol. 362, pp. 172–185. Springer (2019). https://doi.org/10.1007/978-3-030-37453-2_15
10. Leemans, S.J.J., Syring, A.F., van der Aalst, W.M.P.: Earth movers' stochastic conformance checking. In: BPM Forum 2019. pp. 127–143 (2019)
11. Partington, A., Wynn, M., Suriadi, S., Ouyang, C., Karnon, J.: Process mining for clinical processes: A comparative analysis of four australian hospitals. ACM Trans. Manage. Inf. Syst. **5**(4) (Jan 2015). https://doi.org/10.1145/2629446
12. Pourbafrani, M., van der Aalst, W.M.P.: Gencpn:automatic cpn model generation of processes. In: 3rd International Conference ICPM 2021, Demo Track
13. Pourbafrani, M., van der Aalst, W.M.P.: Interactive process improvement using simulation of enriched process trees. In: 2nd International Workshop on AI-enabled Process Automation (2021)
14. Pourbafrani, M., Jiao, S., van der Aalst, W.M.P.: SIMPT: process improvement using interactive simulation of time-aware process trees. In: , RCIS 2021, Proceedings. Lecture Notes in Business Information Processing, vol. 415, pp. 588–594. Springer (2021). https://doi.org/10.1007/978-3-030-75018-3_40
15. Rafiei, M., van der Aalst, W.M.P.: Towards quantifying privacy in process mining. In: International Conference on Process Mining - ICPM (2020), International Workshops. pp. 1–13 (2020)
16. Rafiei, M., van der Aalst, W.M.P.: Group-based privacy preservation techniques for process mining. Data Knowl. Eng. **134**, 101908 (2021). https://doi.org/10.1016/j.datak.2021.101908
17. Song, M., van der Aalst, W.M.P.: Supporting process mining by showing events at a glance. In: Proceedings of the 17th Annual Workshop on Information Technologies and Systems (WITS). pp. 139–145 (2007)
18. Syamsiyah, A., Bolt, A., Cheng, L., Hompes, B., R.P., J.C.B., Dongen, B., Aalst, W.: Business process comparison: A methodology and case study. pp. 253–267 (05 2017)
19. Vogelgesang, T., Kaes, G., Rinderle-Ma, S., Appelrath, H.J.: Multidimensional process mining: Questions, requirements, and limitations. In: CAISE 2016 Forum. pp. 169–176. CAISE 2016 Forum (June 2016), `http://eprints.cs.univie.ac.at/4689/`