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DISCOVER MINER: A SIMPLE APPROACH TO OPTIMIZE PROCESS MINING MODELLING

DISCOVER MINER: UMA ABORDAGEM SIMPLES PARA OTIMIZAR A MODELAGEM DE MINERAÇÃO DE PROCESSOS

DISCOVER MINER: UN ENFOQUE SIMPLE PARA OPTIMIZAR EL MODELADO DE MINERÍA DE PROCESOS

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ABSTRACT
This article presents the Discover-Miner platform that apply four process mining models: Alpha Miner, Discover-Miner, Heuristic Miner, and X_Processes. The objective was to identify the best mining model, evaluating it based in one of three metrics: Fitness, Precision, and Generalization. The platform generates the metrics and Petri nets for each processed log. The methodology included the systematic application of the models to event logs, evaluating the results with the chosen metrics. It was concluded that the platform is useful in evaluating process mining models, helping managers choose the most suitable model. The study also provides guidelines for future research and practical applications, aiming to improve the efficiency and accuracy of business analyses.

Keywords: Process Mining Modelling. Model Discovery. Petri net. Optimization.

RESUMO
Este artigo apresenta a plataforma Discover-Miner, que aplica quatro modelos de mineração de processos: Alpha Miner, Discover-Miner, Heuristic Miner e X_Processes. O objetivo foi identificar o melhor modelo de mineração, avaliando-o com base em uma das três métricas: Aptidão, Precisão e Generalização. A plataforma gera as métricas e as redes de Petri para cada log processado. A metodologia incluiu a aplicação sistemática dos modelos aos logs de eventos, avaliando os resultados com as métricas escolhidas. Concluiu-se que a plataforma é útil na avaliação de modelos de mineração de processos,

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auxiliando os gestores na escolha do modelo mais adequado. O estudo também fornece diretrizes para futuras pesquisas e aplicações práticas, visando melhorar a eficiência e a precisão das análises de negócios.

Palavras-chave: Modelagem de Mineração de Processos. Descoberta de Modelos. Rede de Petri. Otimização.

RESUMEN
Este artículo presenta la plataforma Discover-Miner, que aplica cuatro modelos de minería de procesos: Alpha Miner, Discover-Miner, Heuristic Miner y X_Processes. El objetivo fue identificar el mejor modelo de minería, evaluándolo con base en una de tres métricas: Aptitud, Precisión y Generalización. La plataforma genera las métricas y redes de Petri para cada registro procesado. La metodología incluyó la aplicación sistemática de los modelos a registros de eventos, evaluando los resultados con las métricas seleccionadas. Se concluyó que la plataforma es útil para evaluar modelos de minería de procesos, ayudando a los gerentes a elegir el modelo más adecuado. El estudio también proporciona directrices para futuras investigaciones y aplicaciones prácticas, con el objetivo de mejorar la eficiencia y la precisión de los análisis de negocio.

Palabras clave: Modelado de Minería de Procesos. Descubrimiento de Modelos. Red de Petri. Optimización.

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INTRODUCTION

In recent years, the business landscape has undergone profound changes driven by rapid technological evolution and the relentless pursuit of operational efficiency. This dynamic context highlights the need to analyze and optimize business processes, essential for strengthening competitiveness and ensuring organizational sustainability (DAVENPORT e SPANYI, 2019). However, the complexity of these processes is often obscured by a lack of detailed understanding and the absence of precise models, limiting organizations' ability to identify strategic opportunities and implement significant changes.

According to Van Der Aalst et al. (2010), process mining emerges as an innovative approach resulting from the convergence of process science and data science. This approach offers a promising solution to the challenges faced by organizations, integrating established knowledge from disciplines such as management, statistics, and computing. Process mining provides a powerful set of techniques and tools to extract valuable insights from event logs generated by information systems, enabling a deep and automated understanding of organizational processes (VAN DER AALST, 2012).

In a landscape marked by transformations driven by rapid technological evolution and the constant pursuit of efficiency, a crucial challenge arises. The lack of detailed understanding of internal processes and the absence of precise models limits the ability of organizational leaders to identify improvement opportunities and implement significant changes.

Companies frequently face significant challenges when analyzing and optimizing their business processes efficiently. This research aims to overcome these challenges by simplifying the creation of more accurate and optimized business models through the analysis of extensive event logs and exploring the potential of process mining to provide practical insights for successful implementation in various organizational contexts.

Moreover, process mining models differ significantly in their construction and execution, resulting in distinct sets of outcomes. The task of defining an algorithm focused on specific metrics can be challenging. Therefore, the focus of this work is to assist in defining the best algorithm by comparing different models and determining the one that best meets the selected metrics.

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THEORETICAL FOUNDATION

The theoretical foundation is built upon three interconnected and interdisciplinary pillars: Process Science, Business Process, and Process Mining. Process Science is a comprehensive field that focuses on the detailed and systematic study of physical, chemical, and biological processes in natural and artificial systems. Its primary goal is the understanding of the fundamental principles governing

these processes, as well as the development of strategies and techniques to optimize and control their operations.

PROCESS SCIENCE

Process Science explores coherent sequences of changes across diverse domains, encompassing natural and artificial systems. Its interdisciplinary nature spans from physics to biology, aiming to comprehend fundamental mechanisms and devise strategies for optimization. Originating from early studies in chemistry, physics, and engineering, Process Science has evolved alongside technological advancements, integrating principles from various fields to understand and control processes at molecular and macroscopic levels.

As a pivotal research domain, Process Science addresses real-world challenges by fostering innovative solutions. Its relevance lies in providing deep insights into processes and offering methodologies to align interventions with specific objectives. Recognized for its instrumental role in problem-solving, Process Science continues to advance, contributing to the development of effective strategies in diverse fields, from industrial production to biological and medical applications.

Therefore, process science is recognized as a crucial field of research, providing a deep understanding of processes and offering approaches to design interventions aligned with our objectives and goals (VAN DER AALST, RUBIN, *et al.*, 2010).

BUSINESS PROCESS

According to Correia (2002), a business process is a sequence of activities that occur within an organization to add value to products and services, and meet customer needs. It emerged as an approach to improve organizational performance, beyond mere enhancement. Process mapping is a fundamental tool for analyzing and understanding the activities performed in a process, as well as the interrelationships between them and the process itself. This approach enables the identification of value-adding activities and non-

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value-adding activities, enabling continuous improvement and refinement of business processes.

Business process analysis is a fundamental technique for any organizational change approach, as it allows the identification of improvement opportunities in terms of quality, cost, and flexibility. Processes and activities are essential for adding value to products and services and meeting customer needs. As stated by (CORREIA, LEAL e ALMEIDA, 2002):

> "Process mapping is the tool for complete visualization and consequent understanding of the activities performed in a process, as well as the interrelation between them and the process, and it is the basic structure for Business Process Analysis."

Mapping provides a basic framework for business process analysis, allowing the identification of value-adding activities. Process mapping can be performed using techniques such as process flowcharts, swim lane diagrams, and value stream mapping.

PROCESS MANAGEMENT CYCLE

According to Dumas et al. (2018) the essential cycle of process management is a structured method for continuously improving an organization's operations. It starts with the identification and detailed mapping of existing processes, aiming to understand their activities and interactions. Next, a critical analysis is conducted to identify inefficiencies and evaluate performance in relation to organizational objectives.

The cycle is completed with regular collection of feedback, both from users and from the results achieved. This information fuels the process of continuous improvement, restarting the cycle. By following this method, organizations can adapt to changes, increase operational efficiency, and stay competitive. Process management thus becomes an iterative process that contributes to the long-term sustainability and success of the organization. As depicted by Hammer (2013) in the Figure 1.

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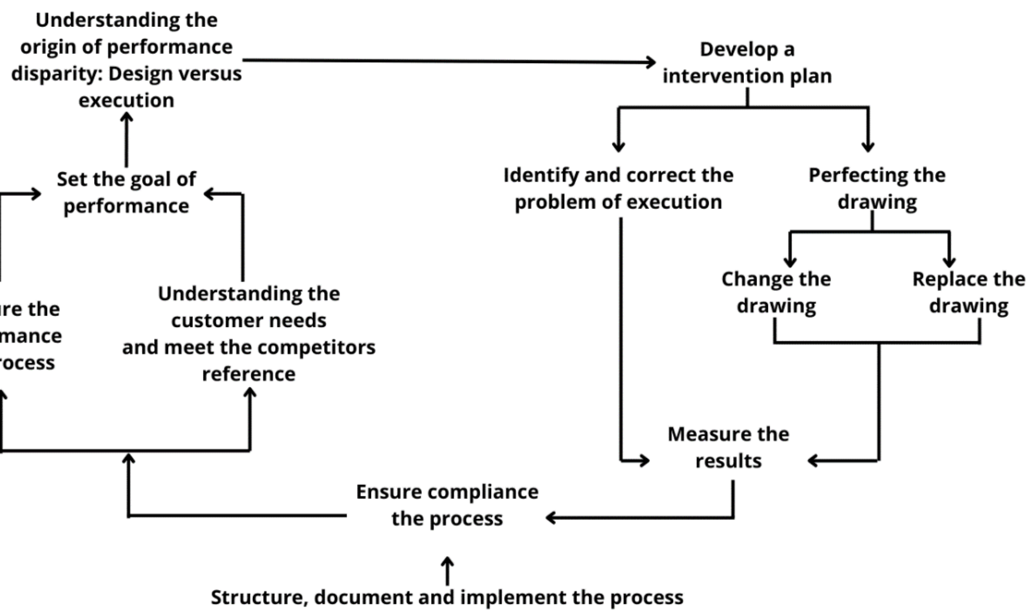
Figure 1:The essential cycle of process management.



Source: Hammer, (2013).

Following Hammer's (2013) train of thought, the process management cycle comprises several stages aimed at optimizing performance in business processes. The first phase involves the development of a formal process, which encompasses the detailed specification of activities to be carried out, by whom, where, under what conditions, with what level of precision, and other relevant considerations. Next, the process performance is continuously monitored, compared to goals set based on customer expectations, competition benchmarks, organizational needs, among other sources.

In this sense, the process management cycle involves the creation of a formal process, continuous performance monitoring, identification of sources of deficiencies, development of an intervention plan, establishment of performance goals, performance evaluation, implementation of improvements, and the cycle of continuous enhancement.

PROCESS MINING

According to Van Der Aalst, et al. (2012) "process mining, resulting from the combination of process science with data science, is an innovative approach aimed at analyzing and improving organizational processes through the exploration of event logs generated by information systems".

By combining the technical and analytical knowledge of process science with the skills to manipulate and interpret large datasets from data science, process mining offers valuable insights for understanding, optimizing, and automating business processes.

As Greyling & Hooste (2017) emphasizes, "process mining is an approach that focuses on the idea of first discovering meaningful patterns and structures in event log datasets, and then using these discoveries to build analytical and predictive models that can provide valuable insights into the underlying processes".

The analysis and improvement of business processes often rely on the existence of accurate process models that depict the operational characteristics of an organization. However, the lack of complete and accurate process models is a reality in many organizations. This is where process mining comes into play, using advanced techniques and algorithms to automatically discover and extract the underlying process models from event logs.

EVENT LOGS

Process mining techniques rely on event logs generated by information systems that support operations. In practice, these logs can vary considerably in their structure and content. However, they all share the fundamental characteristic of recording the occurrence of events at specific moments in time, where each event is associated with a specific instance of the process. More formally, an event log L is a set of traces such as: $L = \{\sigma \mid \sigma \in S, 1 \leq i \leq K\}$

Let S represent the set of all process records, and K is the total number of these records. A record is a non-empty sequence of events $\sigma = < e_1, e_2, ..., e_K >$. The set of all possible events is E, where each event has at least one identifier in uppercase and lowercase letters i, an activity label e, a resource assigned to perform the task e_i. The timestamp of the event can be associated with a transition in the activity lifecycle that generated the event e, typically the start or completion of the activity, although other transitions may be included. Additionally, the event may contain additional data attributes specific to each process (CAMARGO, 2021). Therefore, the event log is an exceptional part, and without it, process mining would not be possible.

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METODOLOGY

Process mining is a crucial discipline in data analysis and process optimization across a wide range of sectors, from industry to financial services. Recognizing the importance of this field, and based on a comprehensive review of existing mining algorithms and methodologies, we developed Discover-Miner. This software represents an approach to discovering the process model that presents

the best value according to the fitness, generalization, and precision metrics, integrating well-known algorithms such as X-Processes (FANTINATO, PERES e REIJERS, 2023), Inductive Miner (BOGARíN VEGA, CEREZO MENÉNDEZ, *et al.*, 2018), Alpha Mine (NAFASA, WASPADA, *et al.*, 2019), and Heuristic Miner (BURATTIN, SPERDUTI e VAN DER AALST, 2012), with the flexibility to choose metrics and visualize results in an intuitive interface. Discover-Miner was developed using the Python 3.11.0 programming language, leveraging a variety of powerful libraries and frameworks for data manipulation, log processing, and result visualization as PM4PY (BERTI, VAN ZELST e SCHUSTER, 2023).

ALGORITHMS USED IN DISCOVER-MINER

The choice of process mining models was based on functionality, robustness, and accessibility. The Alpha Miner (NAFASA, WASPADA, *et al.*, 2019) is ideal for discovering concurrent processes but is sensitive to noise. The Inductive Miner (BOGARíN VEGA, CEREZO MENÉNDEZ, *et al.*, 2018) generates more comprehensive models but can have inaccuracies with complex logs. The Heuristic Miner (BURATTIN, SPERDUTI e VAN DER AALST, 2012) is similar to the Alpha Miner, but with noise filtering, resulting in simpler and more robust models. The X_Processes (FANTINATO, PERES e REIJERS, 2021), a Brazilian algorithm, stands out for its easy accessibility on the platform and promising performance in tests. The combination of algorithms ensures the discovery of different perspectives of the process. The final choice was guided by the characteristics of the problem and the data, considering the limitations of each algorithm.

ALPHA MINER

According to Nafasa, Waspada, Bahtiar, & Wibowo (2019), the Alpha Miner is widely used in process mining to discover process models from event logs. It excels in handling concurrency in processes, making it suitable for analyzing online learning activities that occur simultaneously. The Alpha Miner automatically constructs Petri net models from event

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logs, eliminating the need for additional domain knowledge. However, it may struggle with short loops in log data, potentially leading to incomplete or inaccurate results. It’s not universally suitable for all process types, especially those with complex structures or non-linear control flow patterns.

INDUCTIVE MINER

As described by Bogarín Vega et al. (2018), the Inductive Miner is distinguished by its inductive approach to process model discovery, particularly effective in educational data. It excels in fitting models accurately to the patterns present in educational data, handling complexity and variability effectively. Its ability to infer patterns from data makes it adaptable and precise in discovering process models in educational contexts.

HEURISTIC MINER

According to Buratin et al. (2012), the Heuristics Miner is used for process mining to discover models from event logs by analyzing activity frequency and dependencies. It adapts well to continuous event flows and can build real-time process models. It employs various metrics and formulas to construct process models based on these dependencies, making it versatile for different types of processes.

X-PROCESSES

According to Fantinato et al. (2021), X-Processes is a configurable process discovery method highly dependent on quality metrics. It utilizes genetic algorithms to create and refine process models, ensuring efficiency through parallelism and island-based models. It excels in optimizing quality metrics such as recall, precision, generalization, and simplicity, making it suitable for producing high-quality process models that accurately reflect real-world business processes. Despite longer execution times, its flexibility and superior performance compared to other methods underscore its potential as a tool for systematic analysis and optimization of process model quality metrics.

These summaries provide concise insights into each algorithm’s capabilities and applications within process mining contexts. Adjustments may be necessary to fit specific citation styles or word count limits.

EVALUATION METRICS

Here we discuss the evaluation metrics considered to algorithms used in this work. A successful process mining study begins with a clear understanding of its objectives. Defining these needs upfront guides the choice of the appropriate algorithm and helps avoid underfitting the resulting model. Like any modeling endeavor, process mining requires balancing competing demands: precision, fitness, and generalizability. The following describes these three key modeling considerations (GREYLING e JOOSTE, 2017):

- Precision: The model accurately reflects reality, avoiding the inclusion of pathways that deviate from actual process executions.
- Fitness: The model's capacity to perfectly reproduce the observed behavior captured in the event log.
- Generalizability: The model's ability to extend beyond the specific event log used for its creation, allowing for broader inferences about similar processes.

Due to the practical limitations of simultaneously satisfying all these criteria, it is vital to determine the relative importance of each before conducting the process mining analysis.

DISCOVER-MINER INTERFACE

The Discover-Miner interface is designed to provide users with an intuitive and efficient experience, divided into two distinct phases: the data entry and configuration phase, and the results visualization phase. Let's explore each of these phases in detail.

Step 1 - Data Entry and Configuration: On the Discover-Miner's main screen as seen in Figure 2, users are presented with a user-friendly environment where it's possible to start the data mining process.

Step 2 - Results Visualization: After the analysis phase is completed, users are directed to the results tab, where they can explore and interpret the obtained insights. This phase of the interface is designed to provide a clear and comprehensive view of the discovered process models and their associated metrics as shown in Figure 3. The Discover-Miner interface was designed with a focus on usability and clear information presentation, providing users with the necessary tools to make informed decisions and optimize their business processes effectively. With its combination of advanced functionalities and accessibility, Discover-Miner represents a powerful tool for professionals and organizations seeking valuable insights from their process data.

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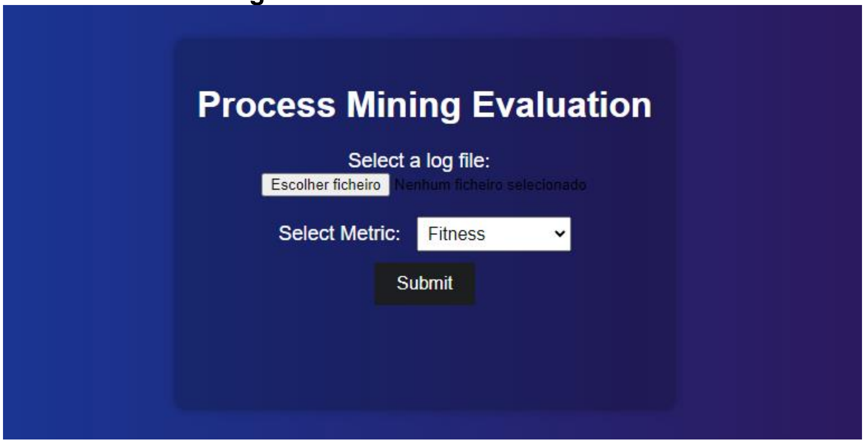
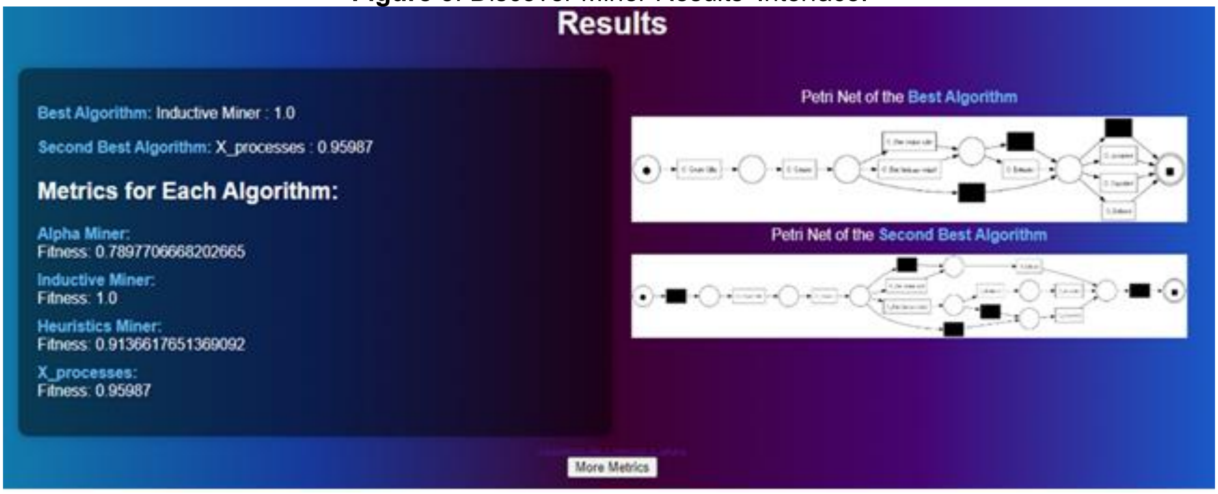
Figure 2: Discover-Miner Interface.



Source: Author, (2025).

Figure 3: Discover Miner Results' Interface.



Source: Authors, (2025).

KEY FEATURES

Discover-Miner represents a significant contribution to the field of process mining, facilitating the choice of the ideal model for specific data analysis. By offering a wide range of mining algorithms and metrics, the software assists users in selecting and defining models that best suit their research needs. An example is the X_Processes algorithm (FANTINATO, PERES e REIJERS, 2021), previously restricted in access, whose results are now available in an accessible and effective manner through the platform.

In developing Discover-Miner, we established the theoretical, conceptual, and practical foundations that guided the creation of this software. In the following sections, we explore in details the characteristics, functionalities, and results of Discover-Miner, highlighting its contributions to the field of process mining and its potential applications in various industrial and organizational contexts.

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EXPERIMENTAL RESULTS AND DISCUSSIONS

This session presents the results obtained from applying Discover-Miner to process logs. The fitness metric is the main focus of our analysis due to its crucial importance in the comprehensive assessment of the quality of the process model. This metric combines both the generalization and accuracy of the model into a single measure, allowing us to understand its ability to accurately represent real processes and to adapt to new scenarios. Furthermore, by calculating the fitness metric as a weighted average of the generalization and accuracy, we can adjust the weights according to the relative importance of each metric for the specific objectives of the analysis.

The analysis of results obtained from the process log provides valuable insights into the effectiveness of the employed mining algorithms, highlighting the importance of the fitness metric in evaluating model quality. Additionally, it enables a comparison among the identified process models, highlighting similarities and differences between the analyzed workflows based on their generalization and precision capabilities.

By understanding and interpreting the results highlighted in this session, readers will appreciate the application and diversity of the analyzed processes, as well as consider potential implications for optimizing and continuously improving organizational operations. Particularly notable is the platform's ability to perform these analyses across different algorithms, facilitating model selection and comparison.

Process log analysis is a fundamental practice in understanding and optimizing workflows in a variety of industrial and organizational contexts. This section presents the results obtained from the application of Discover-Miner in three distinct process logs, each representing a unique set of activities and events in different domains and sectors that will be presented below.

- **Log 1 - BPI Challenge 2020 Travel Permit Data**: This dataset, available in Van Dongen et al. (2020), contains events related to travel authorizations (including all events related to relevant prepaid travel cost claims and travel declarations). With 7,065 cases and 86,581 events, it is part of the BPI Challenge 2020, where the dataset contains events related to two years of travel expense claims (domestic or international). In 2018 events were collected for the entire university.
- **Log 2 - Log of Volvo IT Problem Management - BPI Challenge 2013**: This log comes from the BPI Challenge 2013, available in Van Dongen et al. (2013) and

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contains records of incidents and problem management from Volvo IT. With 7,554 traces and 65,533 events, this log provides insights into the incident and problem processes within the organization.

- **Log 3 - Dutch Financial Institution Loan Application Event Log Set**: This log consists of event logs related to the loan application process of a Dutch financial institution. Collected during 2016 and used in BPI Challenge 2017, available in Van Dongen et al. (2017), this data reflects changes in the application support system, now allowing for multiple offers per application, tracked by IDs. This dataset, created by Eindhoven University of Technology, provides a detailed view of real-world activity, with 31,509 traces and 1,202,267 events. With an average of 38,156 events per trace, this log provides a comprehensive understanding of the processes involved in the loan application, allowing for a detailed analysis of the patterns and efficiency of the process.

Following we have a meticulous analysis of the experimental results of the three logs stated above, considering the four algorithms presented in section Methodology and the metrics Fitness, Generalization and Precision.

Analyzing the data of Figure 4, we can draw the following comments. The Heuristics Miner exhibits good precision but inferior generalization compared to other algorithms, which may indicate that its model may not be as effective in capturing general patterns in the data. The Alpha Miner shows a lower fitness and a precision of 0.0, suggesting that it may not be suitable for capturing patterns in the complex travel authorization data. The X_processes demonstrate the best performance, with better results in all evaluated metrics, indicating good adaptation and generalization to the data and better precision capabilities.

Looking the Figure 5 at the fitness values, Inductive Miner performs best, achieving a maximum value of 1.0. This means that the model generated by this algorithm is highly adapted to the log data, suggesting an almost perfect match between the model and the actual incident and problem processes in the organization. Although the Heuristics Miner and X_Process algorithms achieved a high level of fitness, the fact that Inductive Miner achieved the maximum score suggests a better adaptation to Volvo IT's specific log data. These results have significant implications for operational efficiency and incident management at Volvo IT. A model that is highly adapted to the data can facilitate the identification of bottlenecks, the prediction of problems and the implementation of more effective solutions. Therefore, based on this analysis, Inductive Miner emerges as the most

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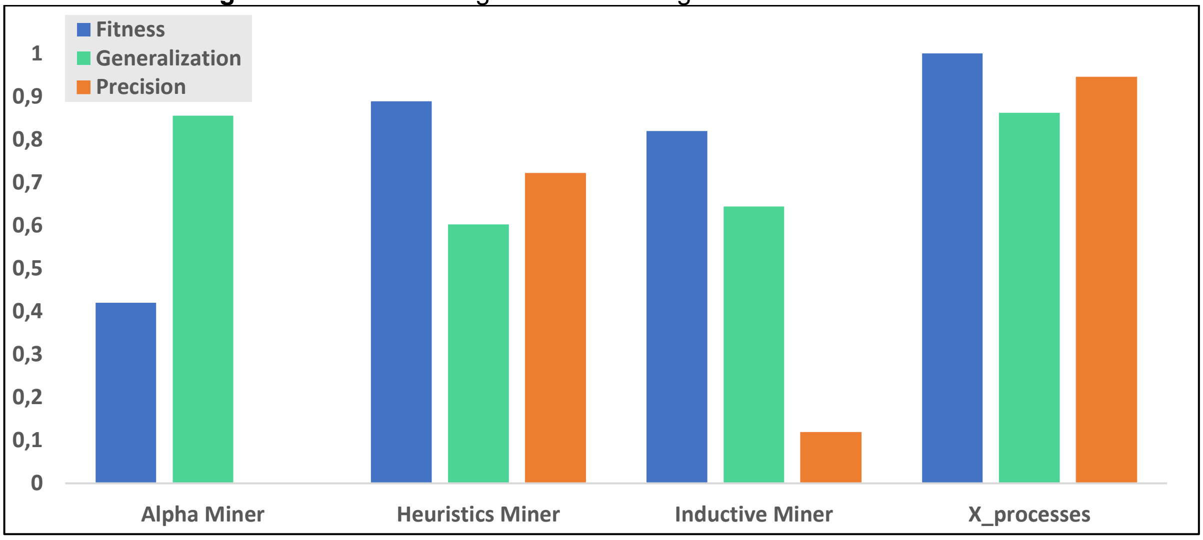
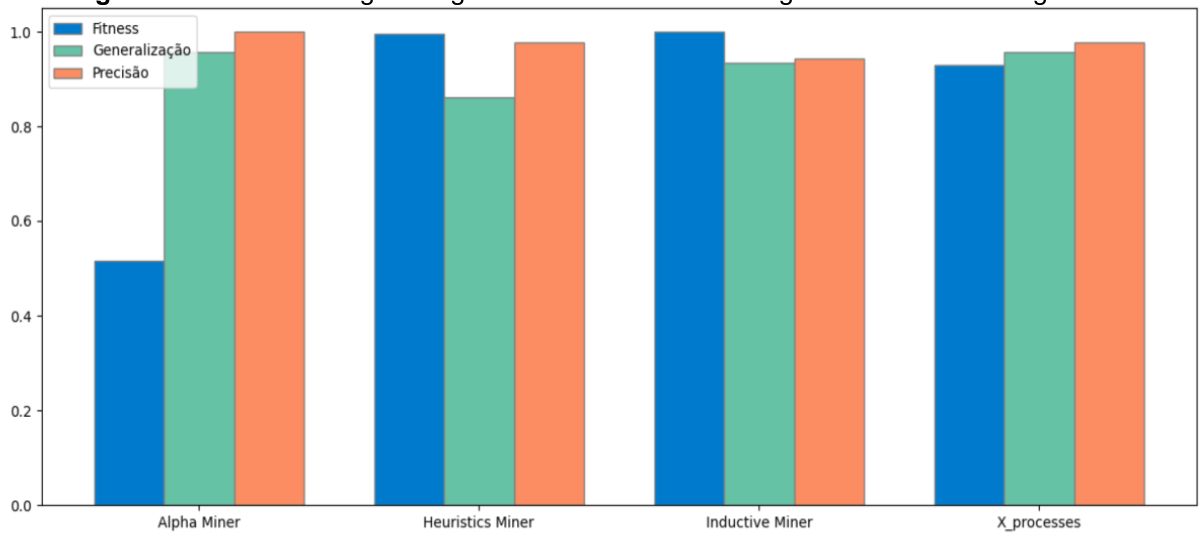
promising algorithm for modeling the incident and problem processes in this specific organization.

Figure 4: Metrics for Log 1 - BPI Challenge 2020 Travel Permit Data.



Source: Authors, (2025).

Figure 5: Metrics for Log 2 - Log of Volvo IT Problem Management - BPI Challenge 2013.



Source: Authors, (2025).

Analysing Figure 6, the X_processes stand out in this set of results as a well-balanced algorithm, exhibiting excellent results across all metrics evaluated. With a robust fitness value of 0.9521 and a high generalization of 0.9807, X_processes demonstrate an impressive ability to fit log data while also managing to generalize well to previously unseen cases. Inductive Miner stands out in this set of results, achieving maximum fitness, suggesting a perfect fit of the model to the log data. This indicates that the model generated by Inductive Miner accurately captures the underlying patterns of loan application

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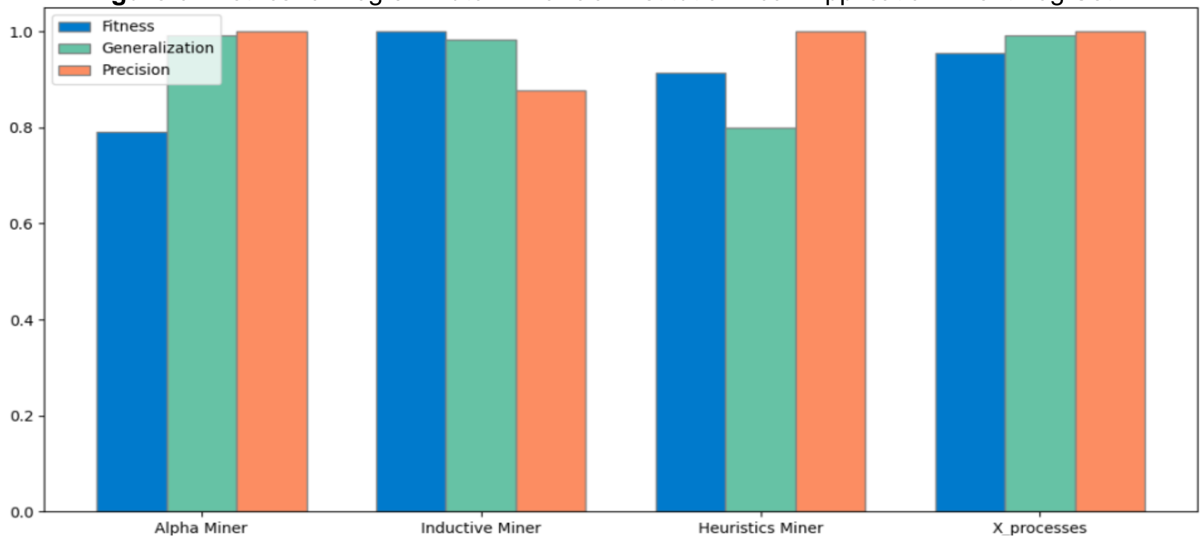
processes. Its accuracy is slightly lower, suggesting that while the model is good at predicting observed events, it may not be as effective at generalizing to unseen cases. On the other hand, Alpha Miner and X_processes also demonstrate solid results, with good fitness and generalization values. However, it is interesting to note that Alpha Miner has a lower fitness compared to Inductive Miner. This can be attributed to Alpha Miner's approach, which may be less robust in dealing with the complexity and variability of loan application processes. Heuristics Miner, although it has good accuracy, presents relatively lower generalization compared to the other algorithms, which may indicate that its model may not be as effective in capturing general patterns in the data.

Figure 6: Metrics for Log 3 - Dutch Financial Institution Loan Application Event Log Set.



Source: Authors, (2025).

These results, applying Discover Miner tool over a set of event logs, provide valuable insights for optimizing travel expense claim processes, enabling in depth analysis and identification of areas for improvement in this specific context.

CONTRIBUTIONS AND INNOVATIONS

Discover-Miner stands out for its ability to offer four process mining algorithms on a single platform, making it easy to compare and select the most appropriate model for each context. In addition, its intuitive interface allows users to visualize the metrics resulting from mining, but also the generated models in a graphical representation, such as Petri nets, offering a more complete and accessible understanding of the identified patterns. In developing Discover-Miner, we aimed to fill a gap in the process mining software market by offering a comprehensive and accessible solution that integrates the latest theoretical advances with a user-friendly interface and practical functionalities. We believe that this innovative approach can benefit a wide range of professionals and organizations, helping them to improve the efficiency, quality and transparency of their business processes. In developing Discover-Miner, we established the theoretical, conceptual and practical foundations that guided the creation of this software.

CONCLUSIONS

In conclusion, the Discover-Miner platform it stands out for its ability to offer a wide range of process mining algorithms on a single platform, facilitating comparison and selection of the most suitable model for each context. Additionally, its intuitive interface allows users to visualize the metrics resulting from mining, as well as the models generated in a graphical representation, such as Petri nets, providing a visualization of a process model from the entered data. Therefore, after analyzing and applying different logs, it becomes evident that the distinctions between the models pose a challenge when defining, based on the data and the metric for analysis, an algorithm that offers good results compared to other models available on the platform. As such, the conducted calculations enable the delivery of models comparing the four algorithms swiftly and with superior value for the defined metric, contributing to a fundamental step in process mining: the choice of a mining algorithm. The platform’s goal is to streamline this process, offering insights into both metric values and generated models, enabling ongoing research and analysis as needed.

Therefore, the selection of the process discovery algorithm must take into account not only the performance in specific metrics, but also the nature of the data and the analytical objectives, ensuring an accurate and meaningful analysis of the organizational processes.

As future works, we plan to do more experiments with more complex logs and new algorithms, as well as, try another metrics to evaluate these algorithms.

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