Topic 1: Exploratory Process Mining

Exploration is a fundamental phase in many data science disciplines, including process mining. In process mining, exploration typically occurs during the initial analysis of event logs, process discovery, or when unexpected questions arise. Despite its importance, most research has focused on technical aspects, with limited attention to the exploratory phase itself.

The goal of this seminar thesis is to provide a comprehensive understanding of exploratory process mining. The participant should analyze its activities, challenges, and insights based on existing literature. Additionally, the thesis should summarize the current research focus in this area and identify any gaps. If applicable, similarities and differences to exploratory practices in other data science domains can also be discussed.

Literature:

- [1] Zerbato, F., Soffer, P., & Weber, B. (2021). <u>Initial insights into exploratory process mining practices</u>. In Business Process Management Forum, 145–161.
- [2] Sorokina, E., Soffer, P., Hadar, I., et al. (2023). <u>PEM4PPM: A cognitive perspective on the process of process mining.</u> In International Conference on Business Process Management, 465-481.
- [3] Zerbato, F., Soffer, P., & Weber, B. (2022). <u>Process mining practices: Evidence from interviews.</u> In International Conference on Business Process Management, 268-285.

Topic 2: Natural Language Semantics in Process Mining

Process mining involves analyzing event logs to gain insights into underlying business processes. These logs typically contain traces representing sequences of events performed for specific cases. Traditional techniques treat traces as sequences of abstract symbols, focusing solely on control-flow aspects of processes. More advanced, semantics-aware methods incorporate the meaning of events or their associated data attributes, enabling deeper insights. For instance, semantic analysis can uncover behavioral similarities between activities or reveal underlying business objects. Recent advances in Natural Language Processing (NLP), particularly in Large Language Models (LLMs), have significantly enhanced the potential for semantics-aware process mining, for instance in tasks like anomaly detection, prediction, and process discovery.

The goal of this seminar thesis is to identify and categorize techniques that utilize natural language semantics in process mining. The participant should examine (1) the types of semantics-aware tasks tackled in research, (2) the NLP concepts employed, and (3) the applications of these tasks in process mining. Finally, the thesis should propose a categorization framework for semantics-aware tasks and suggest future research directions.

- [1] Rebmann, A., & van der Aa, H. (2022). <u>Enabling semantics-aware process mining through the automatic annotation of event logs.</u> Information Systems 110, 102111.
- [2] Busch, K., Kampik, T., & Leopold, H. (2024). <u>XSEMAD</u>: Explainable semantic anomaly detection in event logs using sequence-to-sequence models. Business Process Management, 309-327.
- [3] Rebmann, A., et al. (2024). <u>Evaluating the ability of LLMs to solve semantics-aware process</u> <u>mining tasks.</u> International Conference on Process Mining, 9-16.

Topic 3: Business processes and their context

Business processes do not operate in isolation; they are embedded within a broader organizational, operational, and technical context. Understanding this context is essential for accurately modeling, analyzing, and improving processes. The context can include factors such as business goals, organizational roles, external regulations, system architectures, and even dynamic conditions like market trends or customer behavior.

This seminar project explores the relationship between business processes and their surrounding context. It aims to investigate how context is defined, captured, and used in process modeling and analysis. The project includes reviewing different types of context (e.g. organizational, temporal, environmental), how they influence process behavior, and how context-aware approaches are applied in fields such as process mining, workflow management, and decision support. A key objective is to summarize existing approaches that integrate context into process analysis and to identify challenges and opportunities for future research. This includes looking at how context can be used to improve process predictions, adapt workflows, or detect deviations.

Literature:

- [1] Grisold, T., et al. (2024). A context framework for sense-making of process mining results. International Conference on Process Mining, 57-64.
- [2] Franzoi, S., Hartl, S., Grisold, T., van der Aa, H., Mendling, J., & vom Brocke, J. (2025). Explaining process dynamics: a Process Mining Context Taxonomy for sense-making. Process Science, 2(1), 2. [3] van der Aalst, W. M. P., & Dustdar, S. (2012). Process mining put into context. IEEE Internet Computing, 16(1), 82-86.

Topic 4: Agentic Artificial Intelligence

Agentic AI refers to systems that can autonomously pursue goals, make decisions, and take actions based on their environment, often over extended periods and with minimal human intervention. Unlike systems that perform single, well-defined tasks, agentic AI exhibits initiative and adaptability, often coordinating multiple tasks to achieve broader objectives. This topic is relevant for business process management (BPM) because such systems could autonomously manage or improve processes, interact with other systems and users, or respond to dynamic business environments.

The goal of this seminar thesis is to provide an overview of Agentic AI and its (potential) applications in BPM. The participant should (a) explain the idea and technical realizations of an agent and (b) analyze existing and envisioned BPM applications. A special focus should be placed on the relation to existing technologies, like Robotic Process Automation.

- [1] Vu, H., Klievtsova, N., Leopold, H., Rinderle-Ma, S., & Kampik, T. (2025). <u>Agentic Business Process Management: The Past 30 Years and Practitioners' Future Perspectives</u>. arXiv preprint arXiv:2504.03693.
- [2] Dumas, M., et al. (2023). <u>Al-augmented business process management systems: a research manifesto</u>. ACM Transactions on Management Information Systems, 14(1), 1-19.
- [3] Kirchdorfer, L., Blümel, R., Kampik, T., van der Aa, H., & Stuckenschmidt, H. (2025). <u>Discovering multi-agent systems for resource-centric business process simulation</u>. *Process Science*, 2(1), 4.

Topic 5: Process Model Understandability

Business processes are typically documented in the form of (graphical) business process models, using modeling languages such as BPMN. One important purpose of those models is that they serve as a foundation for analyzing, communicating, and improving processes, making their clarity a key determinant of their utility. When models are difficult to understand, misunderstandings can arise, leading to poor decision-making, misaligned implementations, and reduced collaboration among stakeholders. Hence, the understandability of process models is essential for ensuring their value in business process management.

The goal of this seminar thesis is to provide an overview of the current research on process model understandability. Specifically, the participant should identify factors that influence the understandability of process models and the ways in which they are measured. Since the body of literature in this field is large, the participant should focus on the understandability of process models from a process mining point of view.

Literature:

- [1] Figl, K. (2017). <u>Comprehension of procedural visual business process models: a literature review</u>. Business & Information Systems Engineering, 59, 41-67.
- [2] Dikici, A., Turetken, O., & Demirors, O. (2018). <u>Factors influencing the understandability of process models: A systematic literature review</u>. Information and Software Technology, 93, 112-129. [3] Reijers, H. A., & Mendling, J. (2010). <u>A study into the factors that influence the understandability of business process models</u>. IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans, 41(3), 449-462.

Topic 6: Windowing Strategies in Process Mining

Process mining is an emerging discipline within process science that focuses on analyzing and improving business processes by systematically using event data recorded by information systems. In many process mining tasks, event data must be analyzed in parts. For example, in the context of event streaming, it is not feasible to store and process an entire infinite stream. Instead, techniques are needed to divide the stream into smaller, manageable segments. Similarly, when working with event logs that record events over a fixed period in the past, it is often necessary to select specific parts of the data depending on the analysis objective. This helps uncover changes or patterns in the process over time. In both cases, the use of windowing techniques becomes essential.

The goal of this seminar project is to investigate and summarize existing windowing strategies used in process mining for both event streams and event logs. A key challenge is that these strategies are often not explicitly mentioned in paper titles or abstracts. Instead, they are commonly embedded within preprocessing steps or specific components of proposed methods, making their identification require a careful and detailed review of the literature.

- [1] Imenkamp, C., et al. (2025). <u>Determining window sizes using species estimation for accurate process mining over streams</u>. CAiSE, 109-124.
- [2] Bauer, M., Senderovich, A., Gal, A., Grunske, L., & Weidlich, M. (2018). <u>How much event data is enough? A statistical framework for process discovery</u>. CAISE, 239-256.
- [3] Burattin, A. (2022). Streaming process mining. Process Mining Handbook, 349-372.

[4] Kabierski, M., Richter, M., & Weidlich, M. (2023). <u>Addressing the log representativeness problem using species discovery</u>. International Conference on Process Mining, 65-72.

Topic 7: Multi-perspective conformance checking

Conformance checking in process mining aims to compare real-life event logs with predefined process models to detect deviations. Traditional approaches often focus on the control-flow perspective—i.e., whether the sequence of activities in the log aligns with the allowed behavior in the model. However, real-world processes are inherently multi-perspective, involving not just control flow but also data, time, and resources. Multi-perspective conformance checking aims to assess alignment between models and logs across these different dimensions simultaneously.

The goal of this seminar thesis is to explore the techniques and frameworks developed for multiperspective conformance checking. The participant should investigate (1) Which additional perspectives are typically considered (e.g., data, time, resource), (2) How these perspectives are modeled and aligned with event data (e.g., through data-aware Petri nets, Declare constraints), and (3) What types of deviations can be detected (e.g., data inconsistencies, time violations, unauthorized resource usage) and how they are evaluated. The thesis should also discuss trade-offs between completeness, precision, and scalability in multi-perspective checking, and analyze how these methods compare to control-flow-only techniques.

Literature:

- [1] Mannhardt, F., et al. (2016). <u>Balanced multi-perspective checking of process conformance</u>. Computing 98, 407-437.
- [2] Burattin, A., Maggi, F.M. and Sperduti, A. (2016). <u>Conformance checking based on multiperspective declarative process models</u>. Expert systems with applications 65, 194-211.
- [3] Felli, P., et al. (2021). <u>CoCoMoT</u>: <u>conformance checking of multi-perspective processes via SMT</u>. Business Process Management, 217-234.

Topic 8: Guidance in Visual Analytics and its applicability to Process Mining

Visual Analytics (VA) combines automated data analysis techniques with interactive visual interfaces to support human reasoning and decision-making. Within this domain, *guidance* is defined as the process of progressively narrowing the gap that hinders effective data analysis. It plays a key role in directing user attention, suggesting relevant views, highlighting patterns, and filtering data. Unlike fully automated systems, guidance in VA supports a *human-in-the-loop* approach, where users remain in charge of the analysis while receiving suggestions, prompts, or visual cues. These mechanisms help manage complexity, reduce cognitive overload, and enable more efficient and focused exploration, especially when analyzing large and intricate datasets, such as those found in process mining.

In the context of process mining guidance has the potential to significantly improve usability and analytical accuracy. It could help users navigate through complex process variants and interpret discovered models more effectively. However, despite its promise, the concept of guidance has not yet been systematically explored within the process mining field. Therefore, this seminar thesis

should investigate the types of guidance used in VA, examine how they are implemented, and evaluate how they could be adapted to support specific tasks in process mining. If relevant, a distinction between the different sub-disciplines of process mining (e.g., discovery, conformance, enhancement) should be made. Overall, the goal is to provide a clear and structured overview of guidance in VA and its applicability to process mining.

- [1] Ceneda, D., Gschwandtner, T., May, T., Miksch, S., Schulz, H. J., Streit, M., & Tominski, C. (2016). Characterizing guidance in visual analytics. IEEE transactions on visualization and computer graphics, 23(1), 111-120.
- [2] Pérez-Messina, I., Ceneda, D., El-Assady, M., Miksch, S., & Sperrle, F. (2022, June). <u>A typology of guidance tasks in mixed-initiative visual analytics environments</u>. In Computer Graphics Forum, 41(3), 465-476.
- [3] Pérez-Messina, I., Ceneda, D., & Miksch, S. (2024). <u>Enhancing Visual Analytics systems with guidance: A task-driven methodology</u>. Computers & Graphics, 125, 104121.