Leveraging Artificial Intelligence for Business Process Management (Extended Abstract)

A Contribution to Reference Model Mining, Predictive Process Monitoring, and Process Discovery

Jana-Rebecca Rehse

University of Mannheim, Germany
rehse@uni-mannheim.de

1 Introduction

Digitization as the megatrend of the 21st century has the potential to influence many aspects of human life [2]. Based on recent technological advances and the ensuing growth in maturity, Artificial Intelligence (AI) can be seen as the main driving factor behind this development. It is expected to revolutionize the ways in which humans work, learn, communicate, consume, and live. From a business point of view, digitization and AI offer great potential, while simultaneously posing a significant risk [4]. In the last decade, many companies were outperformed by their more digitized competitors, causing severe losses or even bankruptcy. With its potential for automation and innovation, AI is expected to continue or intensify this development. On the other hand, the market for AI software applications is expected to grow tremendously in the coming years [1]. Business leaders are often aware of these developments, but unsure how to leverage the potential of AI for their own business processes. There is, hence, an ongoing need for AI research, both to develop new methods and technologies and to transfer them into entrepreneurial practice.

Modern and digitized business processes are centered around data, which not only triggers its execution, but also influences the decisions that lead towards the overall process goal [13, 4]. Given the advanced digitization of business processes and the widespread availability of data, business process management (BPM) is a well-suited field for AI application. Most current research focuses on AI for process execution. However, BPM contains other tasks, which could also benefit from AI either automating laborious tasks and freeing more human capacity or allowing new and previously impossible insights into the process. The available process data is a good starting point for BPM researchers to develop new AI methods that also support process development, modeling, implementation, monitoring, and optimization. This is the vision of this thesis, as formulated in the guiding question: How can AI technologies be applied for BPM?

Concretely, the thesis investigates the application of AI technologies in three exemplary BPM subtopics at different maturity stages regarding both research and practical adoption: Reference Model Mining (RMM), Predictive Process Monitoring (PPM), and Process Discovery (PD). The different starting points, in addition to the different goals and data availability, provide researchers with different challenges that require different solutions and the use of different technologies. This shows both the variety and the spectrum of opportunities of applying AI in BPM.

2 Contributions to Reference Model Mining (RMM)

For the topic of RMM, the main research question focuses on the lack of maturity and practical adoption of currently existing techniques, calling for the development of new methods to overcome this obstacle (RQ 1: How can current RMM methods be enhanced to foster their practical adoption?). The question is divided into three different subquestions, regarding the state-of-the art in RMM and its advancement by means of AI. For the first subquestion (RQ 1.a: What are current challenges in inductive reference model development?), we analyzed the current state-of-the-art in inductive reference modeling and reference model mining in order to identify critical challenges and apparent research gaps [11]. Inductive methods for reference modeling, which construct new reference models by generalizing and subsuming a set of individual models, are easier to automate than deductive ones, which derive reference models from accepted theories and principles. We performed a thorough literature review and found 18 relevant papers, which listed 20 apparent challenges. The five most frequent ones included the choice of modeling language, the enforcement of modeling conventions, establishing correspondences between nodes from different individual models, differing degrees of abstraction between the individual models and the algorithmic complexity of existing approaches.

Some challenges can be overcome by widening the scope of RMM techniques to derive reference models not only from other individual process models, but also from instance-level data that record the behavior of information systems. Compared to type-level data, instance-level data is larger and more widely available, which are important requisites for applying AI methods. Therefore, for the second subquestion (RQ 1.b: How can a reference model be mined from event log data?), we developed two new approaches for mining reference models from event logs [6, 8]. Both are based on instance-level process log data and provide stakeholders with an appropriate basis for their decision-making process in reference model development, as their requirements regarding model size and scope may differ depending on their intended use. The first approach describes a technique that uses trace clustering to derive a hierarchy of reference models with differing specificity and generality from a large process log. The second approach uses a similar technique, but instead of traces, activities are clustered to mine a hierarchy of reference model components, whose size and generality and, therefore, reuse potential determine its position in the hierarchy.

Another emerging shortcoming is the lack of methodical support for finding the right RMM approach (RQ 1.c: How can a suitable RMM method be selected for a given application case?). Different approaches will produce different reference models for the same input data, without providing any guidance on where and how this reference model should be used. To overcome this challenge in the practical adoption of RMM, we developed the concept of "Situational Reference Model Mining", i.e., the idea that the intended reference model purpose determines the requirements to a reference model and, therefore, the approach that is best suited for mining it [9]. This approach combines automated mining techniques with manual effort, in order to combine their advantages.

To address the application of AI in BPM for RMM, we focused on methods that combine automated approaches with human intelligence to achieve better results with fewer resources. The tools analyze and structure the available input data according to rational criteria. Their data-centric view assists the human reference model developer, who is able to also take soft factors into account. In this regard, our contributions do not directly target AI in a narrow sense. Instead, they foster the collaboration of humans and systems, where each party brings its individual assets towards the solution of the problem.

3 Contributions to Predictive Process Monitoring (PPM)

The guiding research question for PPM is centered around the application of state-of-the-art deep learning technology for predicting the next events in a process sequence (RQ 2: How can deep learning techniques be used to develop new methods for PPM?). It is separated into two subquestions, regarding the development of a new method for next-event prediction and its practical application and enhancement. In order to address the first subquestion (RQ 2.a: How can deep learning be used to predict the next events in a process sequence?), we presented a novel approach to predicting the next process event using deep learning [3]. Compared to the state-of-the-art in next event prediction, we achieved higher precision values and demonstrated that process prediction is possible using an implicit process representation in a neural network. Given an incomplete process instance, our network is able to predict next events, associated resources, and the time required to complete both the current step and the whole instance. After demonstrating its feasibility and evaluating its accuracy with respect to comparable approaches, we applied it in a realistic environment (RQ 2.b: How can such a prediction be prototypically applied and further enhanced?). Therefore, we adapted the method to be used in the DFKI-Smart-Lego-Factory demonstrator [5]. During its realization and demonstration, we witnessed that both users and visitors could benefit from further explanations of the network's results. This led to a first concept for including Explainable Artificial Intelligence techniques in the Smart-Lego-Factory [12].

Our contribution to PPM is the design of a new AI system in form of a trained neural network. It is novel in the sense that it does not receive any information about explicit process structure. Instead, it independently develops an implicit understanding of the structure and is able to reason about future process behavior. Users do not have to provide any information beyond a process log, but they also cannot access the implicit representation of the process behavior except when making predictions.

4 Contributions to Process Discovery (PD)

The main research question for PD addresses the validity of process discovery evaluations, separated into two subquestions (RQ 3: Which influences may threaten the validity of process discovery evaluations?). This question differs from the other two, because it is a knowledge question instead of a design question. It is motivated by existing artifacts (process discovery methods and quality metrics) and contributes to the investigation of a problem context, such that eventually, new design questions can be asked, and new artifacts can be created.

The first subquestion (RQ 3.a: How is the quality of process discovery evaluations influenced by unobserved process behavior?) is concerned with the influence potential unobserved behavior in an event log might have on the quality assessment of the discovered model. We conducted an empirical study, which examines how the epistemological problem of induction (generalizing singular observations) influences established notions of measuring the quality of the discovered models [10]. The results supported our original hypothesis, that the more unobserved behavior there is, the less reliable the quality measurement becomes.

The second subquestion (RQ 3.b: Which mistakes can be made during a process discovery evaluation that will compromise its validity?) is motivated by the results of the first one. If established measures for process discovery quality do not factor in the influence of unobserved behavior, then there might also be other threats to their validity. After identifying a list of 20 potential threats (hyperbolically named "process mining crimes"), we perform a literature review to determine their prevalence [7]. Based on the observation that none of the inspected papers is crime-free, we suggest a catalog of process discovery guidelines, which may contribute to avoiding process mining crimes in the future.

Our research on PD did not focus on the development of new AI systems, but pursued the notion of rationality in process mining. What constitutes a "good" process discovery result and how can we measure it? Our goal was to establish a common notion of process discovery quality, which can be used by humans and AI systems alike. When comparing process discovery approaches with potentially differing rationality functions, this quality notion can be used as a measure for meta-rationality, allowing researchers to develop new approaches and evaluate the existing ones. Hence, our contributions to PD facilitate the development of new AI-based methods for process discovery, while simultaneously enabling human process miners to compare and improve the quality of their own approaches.

5 Conclusion

As there are infinite possibilities to use AI in BPM, this summarized thesis can only provide some suggestions. Illustrating the demonstrative nature of our results, we exemplarily examined three BPM subtopics and how they could benefit from AI technology. They provide readers with a first idea of how diverse AI research might be even in a comparably narrow field like BPM. For each subtopic, we either introduce new methods that advance its state-of-the-art or gain new knowledge, which may enable the development of such methods in the future.

AI in general and machine learning in particular have multiple limitations and their application to BPM is no exception. Machine learning approaches, particularly deep learning, need large amounts of training data to produce viable results. This data has to be collected, recorded, stored, and checked, which can become a practical challenge when working with real-life process systems. In addition, AI systems are unable to handle unknown situations or take “soft factors” into account. In general, AI is well suited for solving a particular class of problems. Whether or not a particular problem in BPM falls into this class, remains to be decided on a case by case basis. Research on AI for BPM can take many different forms and purposes, all of which intend to contribute to the advancements of business processes and the companies that run them.

References

1. https://www.statista.com/statistics/607960/worldwide-artificial-intelligence-market-growth/
2. Brynjolfsson, E., McAfee, A.: The second machine age: Work, progress, and prosperity in a time of brilliant technologies. WW Norton & Company (2014)
3. Evermann, J., Rehse, J.R., Fettke, P.: Predicting process behaviour using deep learning. Decision Support Systems **100**, 129–140 (2017)
4. Koehler, J.: Business process innovation with artificial intelligence: Levering benefits and controlling operational risks. European Business & Management **4**(2), 55–66 (2018)
5. Rehse, J.R., Dadashnia, S., Fettke, P.: Business process management for industry 4.0 – three application cases in the dfki-smart-lego-factory. it–Information Technology **60**(3), 133–141 (2018)
6. Rehse, J.R., Fettke, P.: Mining reference process models from large instance data. In: Dumas, M., Fantinato, M. (eds.) Business Process Management Workshops. pp. 11–22. Springer (2017)
7. Rehse, J.R., Fettke, P.: Process mining crimes – a threat to the validity of process discovery evaluations. In: Weske, M., Montali, M., Weber, I., vom Brocke, J. (eds.) Business Process Management Forum. pp. 3–19. Springer (2018)
8. Rehse, J.R., Fettke, P.: Clustering business process activities for identifying reference model components. In: Daniel, F., Motahari, H., Sheng, M. (eds.) Business Process Management Workshops. pp. 5–17. Springer (2019)
9. Rehse, J.R., Fettke, P.: A procedure model for situational reference model mining. EMISA Journal **14**(3), 3:1–3:42 (2019)
10. Rehse, J.R., Fettke, P., Loos, P.: Process mining and the black swan: An empirical analysis of the influence of unobserved behavior on the quality of mined process models. In: Teniente, E., Weidlich, M. (eds.) Business Process Management Workshops. pp. 256–268. Springer (2018)
11. Rehse, J.R., Hake, P., Fettke, P., Loos, P.: Inductive reference model development: Recent results and current challenges. In: Mayr, H., Pinzger, M. (eds.) INFORMATIK. pp. 739–752. GI (2016)
12. Rehse, J.R., Mehdiyev, N., Fettke, P.: Towards explainable process predictions for industry 4.0 in the dfki-smart-lego-factory. KI - Künstliche Intelligenz **33**(2), 181–187 (2019)
13. van der Aalst, W.: Process Mining: Data Science in Action. Springer, 2 edn. (2016)