Conceptual Modelling and Artificial Intelligence

Overview and research challenges from the perspective of predictive business process management

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Abstract. Currently, the visibility of Artificial Intelligence (AI) and society's expectations of AI are very high, particularly compared to other research topics, namely Modelling. However, between Conceptual Modelling (short: Modelling) and AI exist many interesting and important interrelationships. This position paper overviews possible applications of AI for Modelling and Modelling for AI. After this general discussion, the field of predictive business process management is focused as a particular application case of AI and Modelling. Predictive process management uses machine learning for predicting the future state of a running process instance. The paper closes with some general remarks and research challenges.

Keywords: Artificial Intelligence, Modelling, Business Process Modelling, Deep Learning, Explainability

1 Motivation

The field of Artificial Intelligence (AI) receives tremendous public visibility and expectations of the society regarding the transformational potential of AI are extremely high. Although it is not the first time that AI receives so much attention in society, it is safe to say that the field has made some important and remarkable progress, e.g. machine translation, speech recognition, image classification, or playing board games archives results and quality levels which were not foreseen a decade before.

On the other hand, the field of Conceptual Modelling (short: Modelling) does not receive similarly high attention from the general audience. Moreover, from the tremendous success of using data for machine learning often the conclusion is drawn that the explicitly, hand-crafted making of a model which represents a domain is not necessary or useful during system development anymore. Such a negative conclusion about the importance of Modelling is false and dangerous because it is well-known that AI in general and machine learning in particular has important application prerequisites and severe limitations under particular application characteristics [1, 2].

Hence, it is much more fruitful to explore and to elaborate the various and rich intellectual interrelationships between AI and Modelling. At the moment, no clear understanding exists in how Modelling and AI fit together. Against this background, the main objective of this position paper is to elaborate on interrelationships between AI

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and Modelling. As such, this short position paper does not aim to make a final statement on this topic, but it stimulates further discourse.

The paper unfolds as follows: After this introduction, Section 2 frames and position the fields of AI and Modelling. General application potentials of AI and Modelling are overviewed by Section 3. Section 4 focusses on the case of predictive process management. The paper closes with some remarks and research challenges.

2 Background

2.1 Artificial Intelligence

The field of AI has a long history and its original foundation is typically dated back to the 1950s [3]. Since then, numerous research projects were undertaken and several well-established subfields of AI emerged, e.g. knowledge representation, natural language processing, automated planning, data mining, pattern recognition, machine learning, robotics, or computer vision. Note, that for each subfield mentioned, well-established textbooks are available. Furthermore, the progress of these subfields is documented by well-established conference tracks, e.g. the renowned International Conference on Artificial Intelligence (IJCAI). Several of these subfields are not well integrated [4].

Typically, three different approaches to AI can be distinguished:

- Narrow AI: Just a precisely defined task should be automated, e.g. playing chess, finding the shortest path between two cities, or steering a car. The accomplishment of the task typically involves some level of natural intelligence.
- General AI: The objective of general AI is to build a machine that has all the physical and intellectual capabilities of a human person.
- Super AI: The objective of super AI is to build a machine that is much more intelligent than a human.

Note, the level of super AI is not yet reached when a machine is superior concerning one particularly defined task. Such superiority of a machine is already achieved in numerous tasks, e.g. machines are now better than humans in many board games. Instead, super AI implies that the machine is in *principle* more intelligent than a human being. How super AI can exactly be defined and whether or when super AI can be realized is not clear, but under discussion [5].

One further important distinction between different approaches to AI is the distinction between symbolic and sub-symbolic techniques. Symbolic AI uses explicit symbols to capture the domain knowledge; sub-symbolic AI applies ideas from interacting components of large systems; knowledge is typically represented by artificial networks. Symbolic AI is often referenced as “Good Old-Fashioned Artificial Intelligence”, short: GOFAI.

2.2 Conceptual Modelling

Modelling is typically understood as an interdisciplinary field that is used in many different disciplines as a method or instrument to capture knowledge or to assist other (research) actions [6]. One possible distinction of this heterogeneous research field is the kind of understanding of what a model is and what approach is used to represent a model. In the following just explicitly stated models are understood as models. From that perspective a continuum of different modelling approaches can be distinguished, ranging from completely informal to strict, formal modelling understanding:

- Informal modelling: Just natural text or graphical symbols are used to represent a model.
- Formal modelling: A formal modelling language has a precise syntax, clear semantics, and well-understood pragmatics. These aspects include notation, semantic domain, modelling procedure and others [7]. Typical examples are Petri Nets or State Charts.

Between the mentioned continuum many more approaches exist, e.g. Business Process Modelling Notation, entity-relationship modelling, Unified Modeling Language, and others. From the perspective of informatics, modelling is used in different subdomains, e.g. model-driven software development, theoretical analysis of organizations or hardware systems, specifying database systems, workflow specification, and many other application domains.

3 Applications of Artificial Intelligence and Modelling

Models and modelling are used in several fields of AI (*Modelling4AI*, not exhaustive):

- Natural Language Processing: Models of language are used for natural language processing, e.g. syntax, semantics, and pragmatics of natural languages are represented by models, e.g. [8].
- Automated Planning: In the domain of automated planning, a planning domain is represented by a model. In such a model relevant planning states and possible actions for manipulating the planning states are specified, e.g. [9].
- Machine Learning: In machine learning, models are used to describe the experiences which are made by solving the learning tasks. For instance, a classifier automatically learned is typically understood as a model which represents the characteristics of the learned classes, e.g. [10].
- Computer Vision: In computer vision models are used to describe graphical sceneries, e.g. which graphical objects exist [11].
- Robotics: The possible behavior of a robot is specified by a model, e.g. [12].

AI can be used to solve different modelling problems (*AI4Modelling*, not exhaustive):

- Pattern mining in models: Mining typical modelling patterns can be done to identify similar modelling components that can be reused, e.g. [13].

- Finding matches between modelling constructs: Similar modelling constructs in different models can be automatically identified, e.g. [14].
- Modelling assistance: During the modelling process, the modeler can by assisted by syntactic, semantic, or pragmatic guidance, e.g. [15].
- Model-to-Text, Text-to-Model or Picture-to-Model: Natural texts / pictures can be transformed into models and vice versa, e.g. [16, 17].
- Automatic modelling and model correction: The construction of a model is automated by automated planning, or models can be automatically corrected [18].

4 The case of predictive business process management

To elaborate more deeply on particular challenges, the case of predictive business process management is presented. Business process monitoring is a phase of the business process management life cycle [19]. Typical examples of business processes are order-to-cash, purchase-to-pay, and complaint-to-resolution. Running process instances, also known as cases, are monitored and managed during the process execution, also known as process run-time. Typically monitored parameters and process characteristics are its current status, the executed process steps, the time taken to execute particular steps, or the throughput time (see Fig. 1). The objective of predictive process management is to gain insights about the future of a case. Based on the current case status, the future of the case is predicted. Typical questions are: What will be the next action to be taken for this case? When will the next event occur? When will this case terminate? Will the case be completed on time?

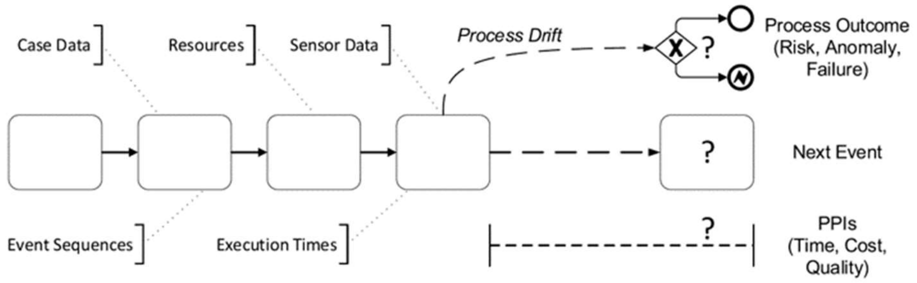

Fig. 1. Input data and predictands of process prediction (source: [20])

The conventional approach for this scenario is to develop a theoretical model of the process reality, comprised of the identified process steps and the possible state transitions with their transition probabilities. For model building, the system's boundaries must be defined and the causal structure between possible process events and state transitions must be identified from the given process reality and transformed into an adequate model. However, building these models of organizations and their processes is challenging, as the context and rules for process execution cannot be easily identified, or are too complex to be easily comprehensible.

A different approach in this example is the use of deep learning, which is based on data that represent prior observed process instances. These process instances are used to train a deep artificial neural network (ANN). In an example application, historical process traces generated by a workflow management system are used as the basis for deep learning [21]. These process traces consist of process steps, process execution times, organizational units responsible for the execution of different tasks, and other information. The approach described by Evermann et al. [21] is but one example of using AI in process modelling, other examples of deep learning in the business process management domain are discussed by Di Francescomarino et al [22].

Using deep learning has not only advantages but one important drawback, too. In classical model building, the model can be intuitively and immediately grasped and understood by humans as it is represented explicitly. In contrast, lacking an explicit representation of theory, an ANN cannot be easily understood in terms of traditional theory elements, such as constructs, causes, etc. This is unsatisfying from both a pragmatic as well as a scientific perspective.

Although the overall problem of interpreting an ANN remains unsolved, several approaches have made significant progress in overcoming this drawback. Because humans think in terms of features, we want to be able to reason back from the network architecture description to a feature description and demonstrate that various network components "encode" or recognize different features. For example, image recognition research shows features that are encoded in convolutional filters. In the context of predictive process management, we have identified hidden-state activations for each process activity, process hallucinations (how an ANN represents a domain without seeing real data), and other explanation techniques for explaining the prediction results [21, 23].

5 Research challenges and outlook

The particular case of integrating AI and Modelling, namely, using deep learning for predictive process management, exemplifies several challenges:

- Understanding of the term modelling and model: The idea of modelling is intensively used in the field of AI. However, the precise understanding of a model and usage of modelling is different. Hence, a comprehensive conceptual discussion of important characteristics and application possibilities of Modelling in AI would be necessary.
- Network architecture: Although the general idea of ANNs is quite simple, there exists a wide variety of different network architectures, e.g. recurrent neural network (RNN) and convolutional neural network (CNN). The network architecture determines the capabilities of integration of deep learning into process modelling.
- Data: The presented case for predictive business process management relies on data being available. Data is used for training the ANN, for testing, and for the validation of its performance.
- Representation of data: Data is not just "given" to the ANN in any form, it must be represented appropriately. Different theoretical approaches for such a representation are known. Past research has shown that problem representation has a major influence on problem performance. In particular, the word2vec approach has led to

significant progress in the area of text processing. Similarly, different theoretical approaches for representing process instances are available, e.g. “process2vec”.

- Changing process behavior: Predictive business process management currently relies on historic process behavior. As such, the data does not reflect future process changes. The detection and prediction of such process drifts would be useful.
- Hybrid Modelling: In AI it is common to combine symbolic and sub-symbolic approaches. Such idea of hybrid modelling is more or less unknown in the domain of predictive business process management. However, it would be very useful, if a priori knowledge of process behaviour can be encoded in an ANN before training.
- Training algorithm: While the backpropagation training algorithm has been used since the 1970s, important theoretical advances and pragmatic improvements have been made in the last two decades, leading to novel variants of backpropagation.
- Trained ANN: The ANN is trained using training data. Training adjusts the connections between the thousands or millions of artificial neurons. This demonstrates that the trained ANN is an important theoretical building block. After testing and validating the network, it can be used for transfer learning and feedback-learning. A trained ANN is not specific to its training data: It is able to answer questions or make predictions about cases not contained in its training data set.
- Transfer learning: Known approaches to predictive business process management start learning from scratch. It would increase the productivity if it would be possible to use pretrained ANN for different process types.
- Explainability: Although some first approaches to explain process predictions are known, more research on this topic is needed.
- Particular machine learning challenges: The evaluation shows promising results. Nevertheless, particular machine learning challenges occur, e.g. overfitting, robustness against new training data, the influence of data manipulation, insufficient distinction learning, or the integration of predefined process models with machine learning approaches.

To sum up: The particular case of predictive business process management demonstrates interesting interrelationships between traditional business process modelling and machine learning. Although promising results are achieved, challenging further integration possibilities are open. This particular case demonstrates just one particular example, how Modelling and AI can be used together. As sketched in this paper, many more interesting challenges for the integration of AI and Modelling exists which have to be explored more deeply in the future.

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