From Mental Models to Machine Learning Models via Conceptual Models

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From Mental Models to Machine Learning Models via Conceptual Models

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Abstract. Although much research continues to be carried out on modeling of information systems, there has been a lack of work that relates the activities of modeling to human mental models. With the increased emphasis on machine learning systems, model development remains an important issue. In this research, we propose a framework for progressing from human mental models to machine learning models and implementation via the use of conceptual models. The framework is illustrated by an application to a citizen science project. Recommendations for the use of the framework are proposed.

Keywords: Machine learning · Mental models · Conceptual models · Data scientist · Citizen science

1 Introduction

Machine learning has continued to progress as a valued way to support decision making due to its ability to process large amounts of data, by extracting complex rules from those data. The models themselves are developed by data scientists who must possess both an understanding of the application domain and the mathematical models and algorithms needed to build the machine learning based systems. For data scientists, having a mental model of the application domains is crucial in order to avoid biases and mistakes in the results. This topic has emerged as the "black box" of artificial intelligence (AI) or explainable AI.

Conceptual models are used to capture and represent the parts of the real world that need to be included in an information system [1, 2]. Research on conceptual modeling has evolved over the past four decades from modeling database management systems to providing a mechanism for understanding the real world and abstracting concepts from the real world that are important for inclusion in an information system [3].

The objectives of research are to: recognize the important role that mental models play in the development of machine learning based information systems; analyze mental

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models as input to conceptual models; and propose how translating mental models into conceptual modeling can support machine learning. To carry out the research, we examine relevant literature in each of these areas and integrate them. The paper contributes a framework that captures end-to-end progression from the needed mental models of a data scientist to the creation of effective machine learning models. The framework is applied to an example to illustrate its effective use and recommendations made for its further application and development.

This paper proceeds as follows. Section 2 defines and reviews related concepts which are integrated into a framework in Sect. 3. Section 4 applies the framework and discusses its implications. Section 5 summarizes and concludes the paper.

2 Related Research

2.1 Mental Models

Mental models are mental representation of reality, the relationships between its various parts and a person's intuitive perception about his or her own acts in the world and their consequences [4–6]. Although they have been identified as useful for research in information systems, they remain an under-studied area. Instead, much work on systems analysis and design starts with the notion of extracting user requirements and then representing them in a conceptual model before they are translated into a form that is useful for implementation. In machine learning applications, this means transforming them into a format that can be used in machine learning algorithms and processes.

The theory on mental models is based on three assumptions [20]: (1) mental models represent what is *common* to a distinct set of possibilities; (2) mental models are *iconic,* that is, the structure of a model selectively conceives the structure of what it represents; and (3) mental models of descriptions represent what is *true* at the expense of what is *false*. Mental models are used for human reasoning based on deductive inference [23] and probabilistic inferences. Conception and use of mentals models suffer from biases, illusions, emotions and limitation of cognitive resources but help humans to draw conclusions by mixing deduction, induction and abduction [5].

Because of the complexity of mental models and human reasoning, conceptual modeling is a difficult process that tries to extract representations from individual mental models and negotiate a common understanding between members of a conceptual modeling team [22]. Thus, conceptual modeling is grounded in complex cognitive processes that start with the creation of individual mental models [27], which we can then translate into a conceptual model.

2.2 Conceptual Modeling

Conceptual modeling is often referred to as modeling: "some aspect of the physical and social world around us for the purposes of understanding and communication" (p. 289) [4]. Conceptual models attempt to represent user requirements of an application domain, with the purpose of creating a shared understanding among designers and users of an information system within given boundaries or application domains. Conceptual models help to structure reality by abstracting the relevant aspects of an application domain, while ignoring those that are not relevant. They can structure concepts into hierarchies, or simply identify and label associations among concepts in the real world.

A conceptual model formally represents requirements and goals. It is influenced by the perspective of the cognitive agents whose mental representations it captures and, in this sense, is a *social artifact* that is intended to capture the shared conceptualization of a group [7]. Conceptual modeling is well-recognized as being complex, but important.

Conceptual modeling has been influenced by various disciplines including software engineering, requirements engineering, psychology, and philosophy. Its modeling activities and methods have been applied to a wide range of domains and problems [10]. Jaakkola and Thalheim [25] highlight the importance of modeling on the development of artificial intelligence and machine learning tasks, with research emerging that identifies conceptual modeling as a way to support machine learning [8–11]. Conceptual models enable humans to gain an "intuitive, easy to understand, meaningful, direct and natural mental representation of a domain" [7]. In contrast, machine learning uses data as a way to identify regularities and patterns in data taken from a domain [14–16].

2.3 Machine Learning

Machine learning enables computers to learn from experience by applying statistical methods. While early machine learning systems used only low-level data, deep learning models attempt to learn concept hierarchies with concepts learned from simpler concepts, anchored in raw data [24]. Machine learning models are designed by four parameter sets: (1) data, (2) model architecture, (3) hyperparameters and (4) objective functions. Conceptual knowledge is only indirectly used for selecting and pre-processing data and selecting and designing model architectures. Therefore, embedding conceptual knowledge into machine learning is considered a "black art." It is further complicated by the general challenges associated with modeling a real-world application.

The development of any information system requires understanding and representing the real world, which is the role of conceptual modeling. Modeling is especially important for capturing and representing the complexity found in the development of artificial intelligence and machine learning tasks. Thus, incorporating conceptual modeling into machine learning activities should improve machine learning due to the emphasis of conceptual modeling on accurately modeling the real world. Even if data scientists who use the models, do not need to understand necessarily how to create conceptual models, they can use the conceptual models as a communication vehicle.

3 Framework for Mental Models to Machine Learning Models

The origin of data used in machine learning is often independent of the purpose of a machine learning task. For instance, sensor data in medicine or industry used as input data is framed by technical specifications and pictures on social media follow user motivations. Thus, the logic behind data is usually not transparent to data scientists leading to misunderstandings and biases. In essence, data scientists simply do not have the knowledge or time to deeply understand data and analytical tasks. Therefore, they take the data as-is and see "what the data is telling." Conceptual models are an important layer of shared human knowledge that qualifies data, provides logical structures used for interpretation of input and output data, and, thus, enables data scientists to deeply understand their tasks from a point of view that abstracts from data.

To assist in creating machine learning models that reflect the real world, as understood by a data scientist, Fig. 1 (adapted from [21]) provides a framework that captures the potential interactions among mental models, conceptual models, and machine learning (ML) models. Mental models are formed within a domain by a data scientist. Data scientists need to understand the problem being solved and the domain in which it occurs, as well as the potential machine learning models and methods that could be applied. Data scientists often acquire domain knowledge through interaction with domain experts, which they form into their own mental models. Conceptual models represent a shared conceptualization about an application using representation constructs, methods, and rules. Traditionally, conceptual models are transformed into logical models for implementation in a database. For machine learning-based systems, the relationships among the data, the conceptual models, and the machine learning models need to ensure that the machine learning models are appropriate for the application.

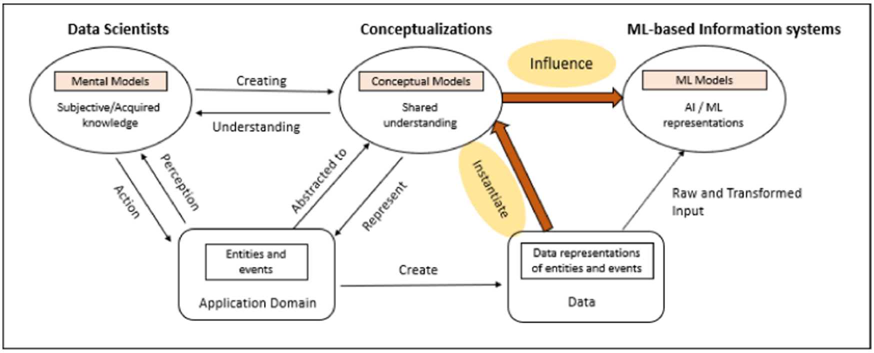

Fig. 1. Framework progressing mental models to machine learning models (adapted from [21])

The translation of conceptual models into database systems is based on models, such as the entity-relationship (ER) model. Current machine learning models cannot apply ER models, but use tabular data, 2D images or graphs as input [28]. The structure of the input data is often provided by a data scientist with only short textual descriptions of data features. For instance, the popular HR Analytics[1] dataset on Kaggle.com provides 13 input features including the following descriptions: "*enrolled_university: Type of University course enrolled if any*" and "*experience: Candidate total experience in years.*" It is unclear whether it considers only US universities or whether courses in mathematics at high school count as experience. Conceptual models should clarify.

For tabular data, the modeling decision involves the selection of data features. For instance, data features can represent facts, such as age, time series, categorical data or unstructured text. Two-D image data is structured as a matrix whose values are binary

[1] https://www.kaggle.com/arashnic/hr-analytics-job-change-of-data-scientists.

(black/white), grey or RGB. For graph data, data scientists make modeling decisions on which feature is represented as nodes and what is captured, by edges. In social network analysis, humans can be thought of as nodes and geographical proximity, the edges, for social network analysis. There are all decisions that must be made by data scientists based on their expertise. Although conceptual modeling abstracts from data and focusses on entities and relationships, machine learning emphasizes the importance of data for finding the most appropriate data features and data transformations.

4 Application of the Framework: Citizen Science Case

To illustrate the applicability and the value of our framework we present an application of machine learning in the context of citizen science. Citizen science refers to participation of the members of the general public (citizens) in scientific research [12–14].

Citizen science is emerging as a major societal movement and research approach, based on the support of regular citizens for data gathering and analysis. In biodiversity research, for example, it was estimated that, as of 2015, more than two million people were engaged in citizen science projects contributing up to $2.5 billion of in-kind value [15]. Citizen science has led to numerous discoveries, including of new exoplanets, biological species, novel celestial bodies, historical or geological phenomena [16].

As human society continues to face existential challenges, citizen science is increasingly viewed as an approach which can support addressing these challenges [17, 18]. This includes tackling humanity's "evil quintet" of climate change, overexploitation, invasive species, land use change, and pollution [15]. As Light and Miskelly [19] assert "[t]he urgency of environmental issues draws our attention to the management of finite resources, and the potential of digital tools to help us work with them effectively."

To demonstrate the application of our framework, we consider a case of citizen science, based on one of the author's own experience of developing a real citizen science project. The objective of this project is to map biodiversity of a region in North America with the sightings of wildlife by ordinary people; that is, citizens. The project has been online since 2010, and resulted in a large data set of observations, making it a prime target for the application of machine learning.

Machine learning can find additional patterns in the data provided by the citizens; for example, for effective environmental and conservation policies. One potential application of this data set is to predict the likelihood of animal encounters next to human infrastructure. For example, the likelihood of a particular kind of animal (e.g., a polar bear), appearing in the vicinity of a waste treatment facility. Such predictions can help to better plan infrastructure to reduce human encroachment into animal habitat and to minimize threats to animals due to dangerous infrastructure.

Mental Model. A data scientist must first form a mental model of the domain. Here, there are two focal domains: the domain of plants and animals; and the domain of human infrastructure. Each mental model is comprised of theories (e.g., of animal behavior and interaction with human artifacts), assumptions (e.g., some animals can learn with sufficient reinforcement), and conceptual structures (e.g., properties and kinds of infrastructure) held by the data scientists. These mental models are commonly incomplete or inaccurate. This is due to a natural lack of deep application domain knowledge by data scientists, who are trained in data management and machine learning techniques. If machine learning solutions are developed directly based on these "naive" mental models, the result could be biased or suboptimal.

Conceptual Models. As our Framework suggests, conceptual models can be used to remedy the lack of deep domain knowledge on the part of data scientists. Conceptual models make the mental models of data scientists explicit and hence verifiable and transparent. This allows both the data scientists and other stakeholders (e.g., domain experts such as biologists or infrastructure planners) to scrutinize the conceptual models (and hence, indirectly, the mental models of data scientists) and find gaps and biases.

In our citizen science application, assume that a data scientist uses own mental model to analyze the domain and determine whether a particular kind of infrastructure is dangerous or safe for different kinds of animals. Doing so, may result in the identification of common types of dangerous infrastructures for animals. For example, artificial dams may prevent fish from spawning, high velocity boats are known to damage whales and dolphins, and garbage treatment facilities may attract polar bears, which may stray then off their normal hunting grounds. Another common example is highways which are dangerous for most land mammals. Such mental models may help the data scientist obtain the requisite training data for the machine learning applications (by augmenting the sightings provided by the citizens with the information on the location of highways).

Creating a conceptual model would externalize the mental models by the data scientist, and subject them to external scrutiny. This might reveal important gaps in the domain knowledge of the data scientist. For example, contrary to a common misperception, birds are not safe from electricity and are commonly electrocuted on high power voltage lines. The absence of information on high-power voltage lines could easily be spotted by examining the entities in a conceptual model by the domain experts, who are, presumably, aware of this danger to birds. Upon making this observation known to data scientists, data scientists can update their mental model, and then, seek more representative and comprehensive training data to build the machine learning solutions.

Machine Learning Models. A data scientist can now train the machine learning algorithms using, for example, data that includes sightings of birds near high-voltage power lines. The result is a more accurate and unbiased machine learning solution, capable of better predicting the likelihood of encounters of animals with a dangerous human infrastructure.

5 Discussion

To develop machine learning solutions, data scientists must rely on their own mental models of the domains to identify relevant sources for the development (e.g., training, validation) of machine learning models, and to perform appropriate actions upon these data (e.g., data transformations). Generally, data scientists are non-domain experts, so their mental models of the requisite domains may not always be accurate, complete, or bias free. To rectify this problem, we proposed to use conceptual models – information technology artifacts especially tailored to representing mental models. Traditionally, conceptual models have been used to capture information systems requirements to guide database design and process engineering. However, the benefits from using conceptual modeling, although mainly applicable to selected contexts, are quite general.

By using conceptual models, data scientists can externalize their own mental models. Domain experts, and others, can examine the conceptual models, and indirectly, the mental models of data scientists. In the citizen science example, using conceptual models when forming solutions, enables experts to identify deficient mental models of data scientists, and build more representative and accurate machine learning models.

6 Conclusion

Machine learning applications continue to be widely developed and applied. One of the greatest challenges is modeling the application domain for which the machine learning applications will be used. This research proposes a framework for progressing from the mental models that data scientists create to representing them as conceptual models that supporting machine learning. The elements of the framework have been applied to a citizen science application to clarify the type of modeling applications for which the framework could be useful. Future research is needed to apply the framework to different applications and to assess each of the individual components.

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