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A methodology for the semi-automatic generation of analytical models in manufacturing

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ABSTRACT

Advanced analytics can enable manufacturing engineers to improve product quality and achieve equipment and resource efficiency gains using large amounts of data collected during manufacturing. Manufacturing engineers, however, often lack the expertise to apply advanced analytics, relying instead on frequent consultations with data scientists. Furthermore, collaborations between manufacturing engineers and data scientists have resulted in highly specialized applications that are not relevant to broader use cases. The manufacturing industry can benefit from the techniques applied in these collaborations if they can be generalized for a wide range of manufacturing problems without requiring a strong knowledge about analytical models.

This paper first presents a model-based methodology to help manufacturing engineers who have little or no experience in advanced analytics apply machine learning techniques for manufacturing problems. This methodology includes a meta-model repository and model transformations. The meta-models define concepts and rules that are commonly known in the manufacturing industry in order to facilitate the creation of manufacturing models. The model transformations enable the semi-automatic generation of analytical models using a given manufacturing model. Second, a model-based Tool for ADvanced Analytics in Manufacturing (TADAM) is presented to allow manufacturing engineers to apply the methodology. TADAM offers capabilities to generate neural networks for manufacturing process problems. Using TADAM's graphical user interface, a manufacturing engineer can build a model for a given process to provide: 1) the key performance indicator (KPI) to be predicted, and 2) the variables contributing to this KPI. Once the manufacturing engineer has built the model and provided the associated data, the model transformations available in TADAM can be called to generate a trained neural network. Finally, the benefits of TADAM are demonstrated in a manufacturing use case in which a manufacturing engineer generates a neural network to predict the energy consumption of a milling process.

1. Introduction

Since its creation, the internet has facilitated the communication of information between humans around the world. Recently, the "Internet of Things" (IoT) has emerged to enhance information communication not only between humans but also between things and humans, and between things [1]. In IoT, a thing is an internet-connected object such as a car, a heart monitor, a sensor or a GPS chip. In the manufacturing industry, the connected objects provide capabilities to collect data at different stages of the product lifecycle. For example, data are collected by machine sensors at the design and production stages, and by the products (such as connected cars) at the service stage.

The IoT not only enables the collection of data, but also supports advanced analytics to extract useful insights with high returns on investments in the manufacturing industry. Manyika et al. [2] summarized the potential economic savings in factories that leverage IoT and advanced analytics (including facilities for discrete or process manufacturing as well as data centers, farms, and hospitals). The authors identified the top potential economic

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impacts anticipated by 2025 in factories using advanced analytics. The manufacturing industry could expect large gains by optimizing the operations ($633 to $1766 billion per year) or the inventory ($96 to $342 billion per year) as well as better anticipating the necessity of plant maintenance ($240 to $627 billion per year).

Applying advanced analytics with IoT requires a strong architecture for collecting and processing a high variety and volume of data in a timely manner. Fig. 1 presents a notional architecture to combine advanced analytics and IoT for providing insights extracted from the physical system data to the business level. This architecture is indicative of general operations in this domain and does not represent any particular implementation. It is shown here to provide a context in which the work in this paper takes place.

The manufacturing physical systems (1) compose the bottom layer of the architecture. The physical systems are machines, products and sensors that generate a large amount of data at a very high frequency. For example, a Boeing 737 generates 240 terabytes (10^{12}) of data during an average cross-country flight [3]. In 2010, the manufacturing industry stored more than 2 exabytes (10^{18}) of data according to the same report.

The data layer (2) stores the data or facilitates their streaming. It also cleans and pre-processes them. The quantity and the frequency of the data generation requires robust infrastructures frequently called “Data centers” to store all the data. It is also necessary to clean and structure raw data collected at the physical system level. Data may contain missing values or noise; instead of storing data that might be unusable, the data layer provides algorithms to fix the issues or eliminate corrupted data. Data are also structured at this layer for facilitating retrieval and analysis at higher levels. Executing the different tasks involved in the data layer in a timely manner is critical especially with streaming data. The data layer algorithms and infrastructure should enable timely execution of these different tasks.

Using advanced analytics, the application layer (3) processes stored or streaming data. The data processing enables the extraction of new knowledge from the data. There is a variety of possible advanced analytics tasks at the application layer from predictive analytics to simulation through UQ. Machine learning techniques are widely used at this level. Computational infrastructures are required to process large volumes of data in a timely manner. An example of a computational solution appropriate to process data is a Graphics Processing Unit (GPU). A GPU provides capabilities to perform parallel operations at a high frequency and could help process data efficiently at the application layer.

The insights extracted at the application layer are communicated to the business layer (4). Data volume and frequency is reduced compared to the other layers in order to provide information that manufacturing engineers can understand. Appropriate graphical user interfaces (GUIs) help engineers understand the information in order to make decisions that improve product quality and achieve equipment and resource efficiency. These decisions affect different stages of the product life cycle such as product design, product manufacturing, and product delivery and impact processes, shop floors, and supply chains.

Communication between these layers is critical and requires the development and integration of protocols and standards. Efforts have already started to facilitate communication in the manufacturing industry. MTConnect [4] is the result of an effort to structure machine monitoring data. It is an appropriate standard for communication between the physical systems layer and data layer. The Predictive Model Markup Language (PMML) [5] offers capabilities to standardize the communication of predictive models. A predictive model is developed using data and machine learning techniques to predict outcomes. PMML facilitates the communication between applications at the application layer and between the application layer and business layer.

The focus of this paper is the application layer. Different advanced analytics tasks are executed at this level. Predictive analytics and UQ are two tasks that have raised an important interest among the manufacturing community. As manufacturing engineers do not possess the required expertise to achieve these tasks, they usually collaborate with data scientists who provide the guidelines and knowledge for applying machine learning

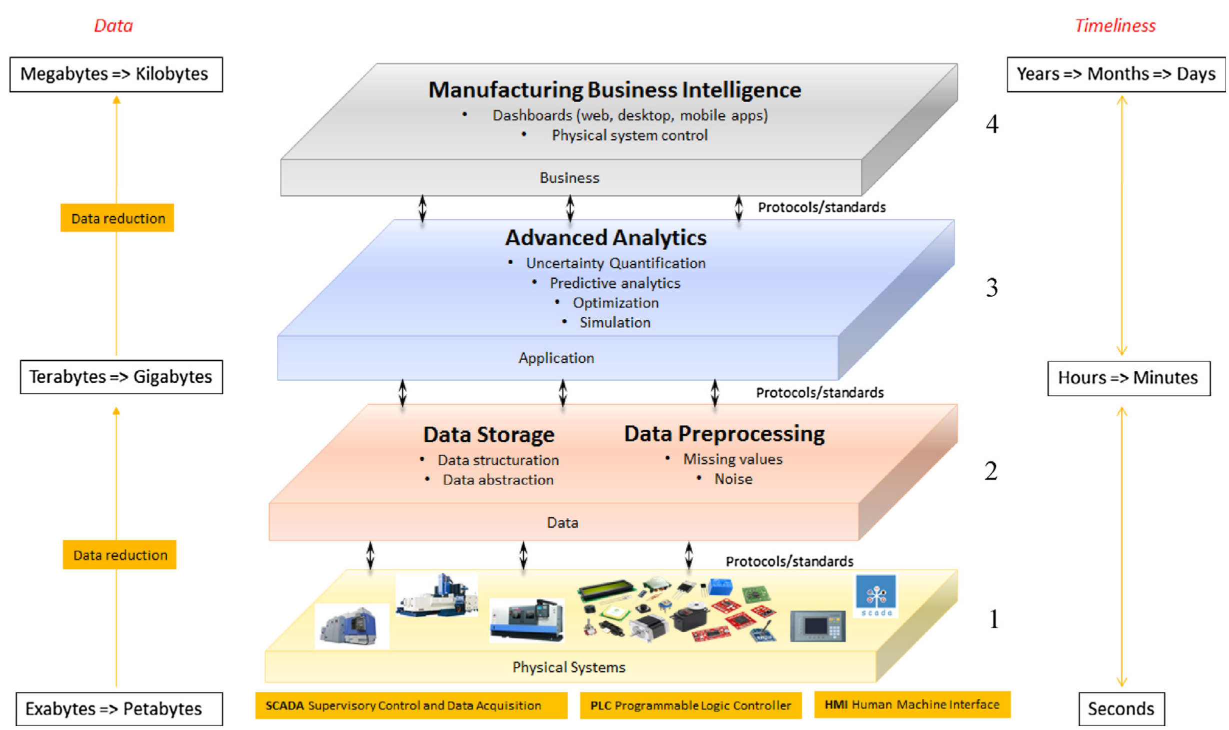

Fig. 1. Notional architecture for combining IoT and advanced analytics in manufacturing.