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Building Information Models' data for machine learning systems in construction management

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Abstract

Qualitative and quantitative data are important in construction management. However, despite the capabilities of construction informatics, such data and its sources have scarcely been fully and systematically utilized for predictive purposes. Building Information Models (BIM) are such a data source. Within BIM, information structures enabling interoperability and providing utilizable data throughout the various Levels of Development (LODs) of a building – for example, Industry Foundation Classes (IFCs) – can be fully and meaningfully exploited through data mining, and more particularly, via machine learning. In this paper, the capabilities of the information structures found in IFCs to be used as data sources for developing machine learning predictive models, will be examined. In addition, and by conceptually tying such data with constructability, their suitability for predicting – through such machine learning models – the delivery cost and time overheads of a construction project, will be considered.

Keywords: Building Information Models; construction informatics; data mining; Industry Foundation Classes; machine learning

1. Introduction

Construction management (CM) strives to optimize a project's performance (namely, its delivery time, cost and quality) [1]. A key factor to successful CM is the collection, understanding, and processing of relevant data [2,3]. Within construction informatics (CI) – namely, the interdisciplinary applied field combining construction, information systems and computer science and studying issues related to design, processing, representation, communication and use of construction-specific information in humans and software [4] – methodologies are explored for such meaningful data utilization [5], including data mining, machine learning (ML), and Building Information Models (BIM) – with the latter also serving as data sources [2,3,5]. Data mining is the set of processes that computationally discover and comprehend patterns in datasets, with a combined human-machine effort [2,6]. ML, used in state-of-the-art data mining [2,7], is the exploration of algorithms that enable computing systems to "learn" and make data-driven predictions by building a model from a sample dataset [7]. While the discretization of ML varies in the relevant literature, it is largely categorized into supervised (SML), unsupervised (UML), and hybrid (HML). SML utilizes datasets featuring a known structure and labelled instances to train and validate suitable algorithms, assuming that the reasoning of the application domain is known [8,9]. UML deals with datasets having unlabelled instances and hidden patterns [7]; after presented with some data, the UML system has to develop relational models from that data "on its own" [9]. HML mixes two or more approaches and can include semi-supervised and reinforced learning [9]. Finally, BIM are sets of interacting policies, processes and technologies for digital building design and lifecycle project data management [2,3]. BIM can,

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in principle, contain numerous interoperable information structures with ordered utilizable data, applicable throughout the lifecycle and the various Levels of Development (LODs) of a building project – for example, Industry Foundation Classes (IFCs), aecXML, and change logs [10].

Qualitative (e.g. lessons-learned databases) and quantitative (e.g. cost and time overheads) data, found either in BIM or elsewhere, can be utilized within CM [2,3,4,11]. However, despite the capabilities of CI, this has scarcely been done systematically [2], but rather in a fragmented informatory manner [2], or for more narrow applications [2,12]. Empirical knowledge is still the main driving force of construction management, even when aided by construction informatics tools like BIM [2,13] and ML [3,14]. But while experience is essential, a more holistic CI-aided utilization of existing data could enhance construction managers' decision-making and action-taking regarding project performance [14]. Data found within BIM, and especially in IFCs, can aid in such an effort [10], and ML can help in exploiting such data [2,13].

In this paper, the capabilities of BIM as data sources for ML models within CM, and their suitability for predicting the delivery cost and time overheads of a building, will be examined. In the second section, a literature review on notable construction-related ML uses, and the absence of BIM data utilization for project performance prediction, will be showcased. In the third section, data structures within IFCs will be highlighted and tied with constructability in a conceptual framework for ML modelling. In the fourth section, conclusions regarding the current effort are drawn.

2. Machine learning modelling within the construction sector

ML is central within the digital transformation of research and the industry [15], and indeed within construction [16]. In the latter, the earliest attempts on ML implementation generally refer to the computer-aided acquisition and processing of design- and construction-related expert knowledge [17,18]. Since then, SML systems have been developed to support bidding processes, such as in the analysis of contractual texts for relevant requirements [19], and building code compliance checking [20,21]. SML inference models have been used to estimate the completion time of whole projects or individual components [22,23]. In [24], SML algorithms were tested for developing a building energy consumption predicting system, whereas in [25] the energy consumption of office buildings was investigated via a hybrid approach. SML for image recognition has been proposed and tested for construction surveillance issues (such as concrete quality, on-site worker movement, and construction injury prediction) [12], analysis of pictures of roofs to prevent occupational accidents [26], web image processing to detect road surface cracks [27], and automated on-site detection of workers and heavy equipment [28]. Apart from the system in [12], SML has also been deployed to identify root causes of occupational accidents [29], and has been coupled with the cross-industry standard process for data mining (CRISP-DM) framework to develop on-site safety leading indicators [30]. Moreover, SML has been intertwined with plot analysis to assess key project performance indicators [31], and with deep learning (namely, gradient-based optimization to adjust parameters throughout a multilayered network, based on errors at its output [32]) for the electroencephalography-based recognition of construction workers' stress while performing on-site tasks [33] and the detection of non-certified work on-site [34]. In a SML deployment touching on the Internet of Things (IoT), data was collected from sensors in an operating building, and then used to reduce the occurrence of design errors [35]. Construction productivity has also been assessed with SML [36], as well as buildability during the project design phase [37]. SML has even been tested to predict construction costs [38] and the attributes of structural materials [39]. There are far fewer notable examples of UML deployment, such as in aiding design integration by implementing construction knowledge and experience [40], and deriving construction project risk sources [41]. Moreover, HML implementation has been relatively scarce (e.g. [25]). There have been mixed systems, utilizing SML and UML either complementarily or interchangeably, such as cooling control systems in office buildings [42], and the use of the results of [41] in a SML system appraising the constructability of technical projects [43,44].

The study and ML-induced utilization of BIM data has been given smaller attention, even less so for predicting project performance (e.g. in terms of time and cost) [45]. Among the few related efforts, the following are the most notable:

- Data pre-processing in: (a) the development of as-built BIM models (e.g. through the classification of apartment rooms [46], heritage buildings [47], sensor-independent point cloud data as part of the scan-to-BIM process [48],

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and through masonry wall defect surveying [49]), and (b) the textual classification of maintenance work orders for the integration of BIM with facilities management [50].

- Leveraging the capabilities of BIM for quality control and code compliance [51,52].
- Knowledge discovery within BIM, as part of cognitive assistance frameworks [53,54,55,56,57,58].

The efforts especially mentioned in the last bullet present the most advanced cases of processing and exploiting BIM data; however, they mainly focus on the improvement and back-propagation of BIM models themselves. In [53,57,58] this approach is indeed coupled with the development of predictive systems, but in distinct contexts (e.g. energy performance prediction [55]), and not for assessing major indicators of project performance (time, cost and quality).

3. Data in IFCs and constructability for machine learning predicting indicators of project performance

The Industry Foundation Classes (IFCs), were designed to provide a universal basis for information sharing over the whole building lifecycle [10,47], as de facto standards for representing BIM. IFCs define entity-relationship data models, encompassing entities organized into object-based inheritance hierarchies [10,47]. IFCs are considered comprehensive and support a wide variety of buildings objects, such as IfcWall, IfcBeam, IfcWindow and IfcRoof, together with the option of interconnecting an unlimited set of properties and quantities to each object. All base objects have globally unique identifiers (GUID) that can be made persistent for the project – thus allowing multiple IFCs to merge deterministically, while keeping their data integrity without human intervention. Using the IfcRelation feature, any object can also relate to other objects, making it possible to form constraints and relations between building parts. A major difference between IFC and general 3D-file formats is the representation of space – every instance of an IFC-object must belong to a spatial context. Special space-enclosing structures are the sites (IfcSite), buildings (IfcBuilding), storeys (IfcBuildingStorey), and rooms (IfcSpace). In addition, IFCs have a, less used, support for processes and resources. IfcProcess is the base class for processes (e.g. tasks and events) and may be assigned to products to indicate the output of performed work. IfcResource is the base class for resources (e.g. materials, labor, equipment) and their associated cost- and time-related constraints, and may be assigned to processes to indicate tasks performed on behalf of a resource.

Data ordered with IFC can be reviewed and studied with BIM model checking software tools, such as Solibri. Then, it can be suitably mined manually, with semantic and/or latent techniques ([53,54,55,56,57,58]), or with dedicated data parsers [59], and exported into file formats as input for ML suites; examples of such formats are .arff files for the Waikato Environment for Knowledge Analysis (WEKA), or structured .csv files to be incorporated in ML libraries of the Surprise Scikit, a Python-powered scientific toolkit for recommender systems. But for this data to be translated into meaningful independent input variables, and then connected with meaningful dependent output variables as part of a ML modelling (and especially SML) addressing the research gap mentioned in the previous section (namely, the absence of BIM data utilization for the prediction of a building project's performance, and especially its delivery cost and time overheads), it needs to be incorporated in a suitable theoretical and conceptual framework. One such framework is constructability, namely the optimal use of construction knowledge and experience in planning, design, procurement, and field operations to achieve the project objectives of time, cost and quality [43]. Situations where construction knowledge and experience are not implemented properly, resulting in the widening of the gap between the "as-designed" and "as-built" project states and ultimately in sub-optimal project objectives, are defined as constructability problems [43]. In the data mined from IFC-ordered BIM (e.g. components types and system types, manufactured products), the elements mainly translated into constructability problems are geometric and dimensional discrepancies, detected design clashes, construction site spatial and schedule clashes, timeframe conflicts, logistics and material quantity problems, and the number of reworks. By exploiting (a) the direct connection of constructability to the overall project objectives rather than narrow applications, (b) its affiliation with construction knowledge and experience implementation, and (c) the capabilities of CI technologies to extract and process data that can be interpreted as constructability problems, a novel predicting system that will holistically extend the perception and enhance the decision-making and action-taking of construction managers, can be formulated. Derived from the aforementioned insights, an early conceptual framework of such a formulation can be delineated in the following steps:

Step 1. Data collection. For a large number of building projects, BIM data displaying the as-designed and (whenever applicable) the as-built states will be sought; this data may be (a) quantitative, including components and system types, manufactured products, geometric and dimensional discrepancies, and design clashes; and (b) qualitative, such as descriptions of spatial and schedule clashes, timeframe conflicts, logistics and material quantity problems, and the number of reworks. This data will reveal constructability problems (i.e. the input variables of the ML system), and will be extracted and exported into suitable file formats. Then, for the same projects, documented data on the corresponding delivery cost and time overheads (i.e. the output variables) will be sought via expert input.

Step 2. Variable formulation. Independent variables: Depending on the form of the constructability problems-related data, meaningful independent variables (e.g. "Number of reworks") measured through the values of the collected data will be produced through UML techniques such as vector quantization and linguistic clustering [43,44], or qualitative techniques relying on expert input (e.g. brainstorming sessions). Dependent variables: Depending on whether the building delivery time and cost data is discrete or continuous (e.g. whether a building's completion delay is expressed in months or with yes/no statements), the dependent variables (namely, "Overheads on the intended cost" and "Delay in the time of completion"), will be formulated to be used for classification or regression, respectively. This will also lead to the choice of the relative SML scheme in Step 3.

Step 3. System formulation. The choice of the SML scheme to be trained and validated depends on the data form and amount, and the variables' type and number. Multiple experiments will be conducted within a suitable ML platform, with numerous SML schemes. In the current research and practice, support vector machines (SVM) and support vector regression (SVR) are, respectively, the most widely used schemes for binomial classification or regression, and variations of the random forest scheme are the most widely used for the multinomial cases [9,43].

Auxiliary mathematical, methodological and software tools may be utilized within Steps 1-3, e.g.: (a) non-negative matrix factorization for data normalization and pre-processing (Steps 1-2), (b) multi-input Analytical Hierarchy Process (AHP), for variable labelling (Step 2), (b) the "kernel trick", to aid in the non-linear function SVM or SVR (Step 3), (d) n-fold cross-validation, for the simultaneous SML training and validation (Step 3), (e) the WEKA platform (Step 3), (f) Surprise Scikit (Steps 2-3), and (g) the programming language Python (Steps 2-3).

Step 4. Integration of results. The ML system can be integrated as a working prototype within BIMs of new buildings, for the verification of its predicting results – namely, whether a new building will display delivery cost and time overheads, in relation to the detected constructability problems affecting it. This will take place through suitable programming routines and/or graphical user interfaces (such as PyQt, featured in the Anaconda platform).

Such a novel methodological framework and subsequent modelling can furtherly strengthen the placement of ML within CI (and particularly, BIM), for the benefit of construction managers and related disciplines.

4. Conclusions

IFC-ordered data contained in BIMs, are a rich and utilizable source for optimizing construction management. They can be understood and processed through the lens of constructability, extracted via the relative tools and methodologies, coupled with expert input, and used for training and validating machine learning systems predicting the delivery cost and time overheads of a building. This paper offers the first theoretical and conceptual insights of such a process. Future work will hopefully encompass the actual realization of the conceptual framework through data mining and expert processes, as well as the related ML algorithm deployment and experimentation for the derivation of the final results.

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