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# Computational linguistic and BIM for project management

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## *Abstract*

*The purpose of the paper is to investigate the state of the art of textual translation theories, methods and tools into numerical requirements to support information modelling and project management process. Traditionally, the requirements underlying the design and construction process are expressed through verbal qualitative evaluations and not numerically by the "Documento di Indirizzo alla Progettazione". The requirements expressed qualitatively lead to a difficulty in evaluating the project offer. The paper aims to draw up a state of the art on the possibility of using computational linguistics for the numerical translation of the basic documents of the construction process. The research aims to collect at national and international level theories, method, tools and application cases in the AEC sector and in other sectors, highlighting advantages, criticalities and possible implementations. Computational linguistics would allow to numerically translate the initial requirements. In this way the process is data driven and more manageable by the client. Requirements expressed in numerical terms are fundamental for the application and management of information modelling. Numerical requirements are machine readable and for this reason they could be managed by an artificial intelligence.*

***Keywords:*** *Project and Information management, Computational requirements, Computational linguistics, Machine Learning, Data driven process, Artificial Intelligence.*

## *Resumen*

*El objetivo de este trabajo es investigar el estado del arte de teorías y métodos de traducción textual en cuanto a los requisitos numéricos para apoyar el proceso de modelado de información y gestión de proyectos. Tradicionalmente, los requisitos subyacentes al proceso de diseño y construcción se expresan en evaluaciones cualitativas verbales y no numéricamente mediante el "Documento di Indirizzo alla Progettazione". Estos requisitos conducen a una dificultad en la evaluación de la oferta. El objetivo del trabajo es elaborar un estado del arte sobre la posibilidad de utilizar la lingüística computacional para la traducción numérica de los documentos básicos del proceso de construcción. El objetivo es recoger a nivel nacional e internacional teorías, métodos, herramientas y casos de aplicación en el sector AEC y en otros sectores, destacando las ventajas, las criticidades y las posibles implementaciones. La lingüística computacional permitiría traducir numéricamente los requisitos iniciales. De esta manera, el proceso se basa en los datos y es más manejable por el cliente. Los requisitos expresados en términos numéricos son fundamentales para la aplicación y gestión de la modelización de la información. Los requisitos numéricos son legibles por máquina y por esta razón pueden ser gestionados por una inteligencia artificial.*

***Palabras clave:*** *Gestión de proyectos e información, Requisitos computacionales, Lingüística computacional, Machine Learning, Data-based procesos, Inteligencia artificial.*

## Introduction

The purpose of the article is to investigate the State of the Art about theories, methods and tools for translating documents into numerical requirements and possible applications in the field of information modeling and project management. Computational linguistic well applies to BIM. Information modelling requires a precise and comprehensive definition of the initial requirements; the computational definition of the initial requirements is fundamental for the good application of information modelling and management. In order to understand the proposed methodology and its possible applications, it is necessary to explain the basic theories and the most recent developments and applications of computational linguistics. We present case studies of applications in various fields focusing on possible applications in the AEC sector, with a focus to possible data driven management of the construction process. The final chapter discusses possible applications and further developments.

## 1. NATURAL LANGUAGE PROCESSING (NLP): rule based, statistical and deep NLP

Computational Linguistics or Natural Language Processing (NLP) is a interdisciplinary field involving humanistic, statistical-mathematical and computer skills. The aim of NLP is to process languages using computers. The human language is defined as natural because it is ambiguous and changeable in time and space, interactive and relational. On the contrary, machine language is defined as formal because it is unambiguous and internationally recognized. The NLP must deal optimally with the ambiguity, imprecision and lack of data inherent in natural language. To manage the ambiguity of natural language, modern NLP relies on rule-based, statistical or machine learning approaches that allow automatic modeling through learning processes. (Callison-Bourne and Osborne 2003). NLP is a subfield of artificial intelligence (AI) that aims at making natural language machine understandable so that the text or human speech could be processed by computers (Cherpas 1992; Zhang and El-Gohary 2015).

NLP tasks may take two main approaches: a machine learning (ML) - based approach (i) or a rule-based/statistical approach (ii). A ML-based approach uses ML algorithms for text processing (Pradhan 2004), whereas a rule-based approach uses manually coded rules (Soysal 2010). Rule-based methods require more human effort for rule development, but have better text processing performance (Crowston 2010). From another point of view, NLP approaches could be either shallow or deep. Shallow NLP conducts partial analysis of a sentence or extracts partial, specific information from a sentence. Deep NLP aims at full-sentence analysis towards capturing the entire meaning of a sentence (Zouaq 2011). Deep NLP requires elaborate knowledge representation and reasoning, which are currently a challenge for AI (Tierney 2012; Zhang and El-Gohary 2015).

### 1.1. Rule based and statistical NLP

The statistical approach to the NLP is generally better than the traditional/manual rule-based approach because:

- Statistical NLP affords rapid prototyping. Rule based systems take a long time to implement.
- Statistical systems are robust (Junqua 2001). Statistical system will always produce outputs, regardless of the inputs entered.
- Statistical systems are cheaper than rule-based systems. Process of creating a statistical system is automated, the process of creating a rule-based system is manual. (Callison-Bourne and Osborne 2003)

### 1.2. Deep NLP: Artificial Neural Network for NLP

Among the various NLP techniques based on ML, those based on ANNs seem to have more chance of success because:

- ANNs are similar of the structure of the human brain and they are very effective for solving complex problems where data is noisy, prone to error or incomplete (Rumelhart 1986; Sivanandam 2006; Bala 2014).
- ANNs can manage noisy and ambiguous data from the human natural language and they are very similar to the human method of learning.
- ANNs are very powerful pattern recognizers and classifiers, but ANNs operate as a black box (Jain 2014).
- ANNs are composed of a large number of interconnected processing elements called neurons. ANNS are characterised by their structure, the connection between the processing elements, the data for training or learning wich determinate the weights on the connections and the activation function. (Waziri et al. 2017)
- ANNs have the ability to overcome the lack of data, which can be summarized in the phrase "Fill in the blank". This makes it particularly suitable for use in the NLP. (Waziri et al. 2017)

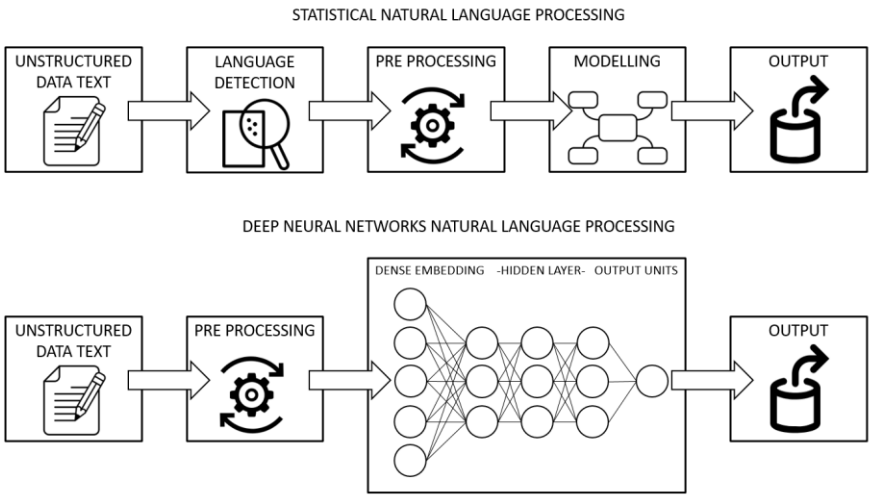


*Fig. 1 Differences between the structure of statistical and deep NLP*

ML-based methods efficiently manage the sparsity and non-structuring of learning data. Among the techniques of ML for NLP based on ANN ensure computational processing of text documents better, because they can respect the complexity, articulation and multidimensionality of human natural language. By translating text into machine language, text information can be managed and used with methods, techniques and tools typical of project and information management. In summary, the NLP, based on ANN, transforms text documents into structured information resources (Callison-Bourne and Osborne 2003).

Despite the numerous advantages of the ANN (like the self-organization and the capacity to fill the void of data) compared to the rule based and statistics NLP, it offers few explanations on the relations found between the data and the connection among neurons with the ouput data. The phenomenon is called black box effect which makes difficult to explain what is learned from the net (Paliwal 2011; Waziri et. al 2017).

The latest efforts in the field of AI are aimed at overcoming the black box effect and the production of explainable AI model, called XAI model (Gunning 2017).

## 2. NLP Application

### 2.1. NLP for Project Management

Project Management Institute's Pulse of the Profession points out that: "When projects do not meet their original goals and project objectives, inaccurate business analysis/requirements management is cited as the primary cause 47% of the time." (Frenette and Kyriakidis 2016)

The increasing complexity and size of projects in the AEC sector makes it difficult to identify and verify initial requirements expressed in natural language. As a result, there are numerous errors and shortcomings in the definition of requirements at the early stages of concept and design, with inefficiencies in terms of time, cost and quality. The use of NLP can help the project manager and the client to express project requirements in an alpha-numerical and quantifiable terms without possibility of misunderstanding, increasing the project's chances of success. The use of NLP in the early stages of defining project requirements can be considered a risk mitigation technique. The use of the NLP for the definition of requirements and predictions with a view to monitoring the progress of the project through ANN, leads to an optimization of requirements definition and the process of assessing the progress of the project.

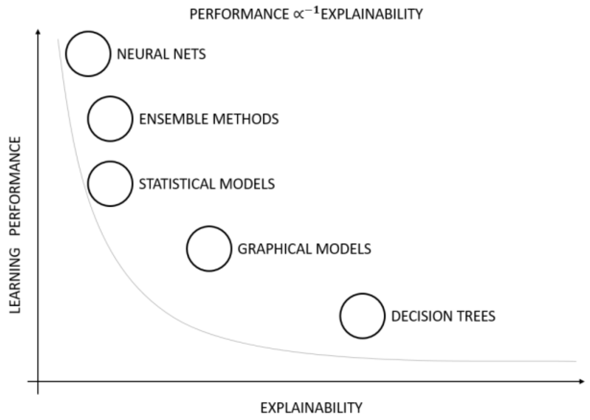


*Fig. 2 Explainability and performance graph of AI learning method. Source: Gunning, D. (2017)*

### 2.2. NLP for Requirements Engineering: automotive software and AEC project

The process of creating an automotive software has strong similarities with the process of designing a building, characterized by poor coordination and sharing of initial requirements and knowledge of a complete picture of the project. Complex systems such as automotive software and buildings are usually divided into subsystems that are specified and developed in isolation and then integrated. In the automotive sector, as in the AEC sector, the different subsystems are developed by separate teams using their own design processes and requirements documentation, with limited knowledge of the relationships with other subsystems (Vogelsang 2013). Fragmentation of knowledge affects the quality of the final design product. Knowledge fragmentation affects a large number of requirements documents for each subsystem, written by different people, with different structure (Schlutter and Vogelsang 2018). In the paper, the authors describe a natural language processing approach to transform a set of heterogeneous natural language requirements into a knowledge representation graph (Schlutter and Vogelsang 2018). The graph provides a comprehensive and relational view of concepts and requirements.

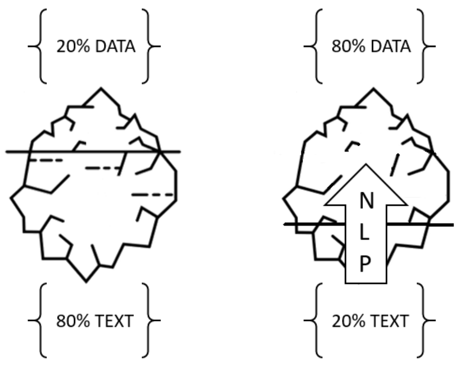


*Fig. 3 NLP for project management: translating text into structured data*

Given the similarities between the two sectors, the NLP approach described could be used in the AEC sector to reduce the fragmentation and ambiguity of the requirements set out in the heterogeneous text documents. The homogeneity of the requirements would allow a complete view of the process, limiting the inefficiency and the gap between expected and actual quality in the final product.

### 2.3. NLP and Information Modelling and Management

Alphanumeric translation of text documents into formal and structured data is a prerequisite for information modelling. As is well known from the MacLeamy Curve, the initial phase of defining requirements is fundamental for the good application and effectiveness of the information modeling method. The NLP for requirements definition can be integrated with the information modelling and management of the preliminary phase of design and construction process.

Jordan Kyriakidis CEO of QRACorp in a recent webinair about NLP in project management, said: " Imagine a world where a computer application reads a document instead of you and points out all the places where the requirements writer has been too vague, imprecise, or has not provided enough detail? How about one that compares all the requirements documents in the organization and lets you know when it detects inconsistencies between your work and others? Or maybe one that knows the jargon of the profession in which you work, and can point out misuse of terms? Or one that is able to look through your requirements and tell you what is missing?" (Frenette 2016)

During the Webinair Jordan Kyriakidis argues that NLP approach can reduce time and cost in defining requirements by avoiding errors, loss of information and ambiguities in defining project objectives.

## 3. NLP and BIM for AEC sector: application

### 3.1. BIM and NLP for a construction management information system

Growing complexity of construction projects have increased the number of companies from different locations to project groups. This has led to an increase in the amount of data and information exchanged (Anumba and Evbuomwan 2003). In this environment, information management systems are necessary.

In addition, the possible costs of recovering lost information are very high, as this has an impact not only on the progress of the individual project, but also on the customer's ability to manage similar future projects. As pointed out by Teicholz project information should be integrated in three dimensions:

- horizontal integration of several disciplines participating in a construction project;
- vertical integration of several phases in the life cycle of a facility;
- longitudinal integration over time, which is also linked to the acquisition of knowledge that will improve performance or make better decisions in the future. (Teicholz 1999)

As described above, possible information loss or misreporting has an impact on the entire project lifecycle and the client's decision making on future projects. A large percentage of the information exchanged among construction companies is stored in text data files, the management of the information contained in these documents are essential.

In their paper Caldas and Soibelman propose an automatic hierarchical classification to improve the organization and access to unstructured text documents in construction management information systems and to facilitate the integration of these documents into BIM based system models (Caldas and Soibelman 2003). Text information management in the AEC sector is crucial because a large percentage of project information is stored in text documents and these documents contain valuable information for decision making, data analysis and knowledge management (Zhang and El-Gohary 2015).

## 3.2. NLP and BIM for automated compliance checking

The NLP approach can support Automated compliance checking in a BIM based process (Zhang and El-Gohary 2015). Construction projects must comply with a variety of standards code. The manual conformity control process is time-consuming, costly and error-prone (Han 1998; Nguyen 2005). Automated compliance checking (ACC) should reduce Code Checking time, costs and errors (Tan 2010; Salama 2013).

The authors of ther paper (Zhang and El-Gohary 2015) point out that in addition, the proposed method has many other potential benefits:

- allowing potential non-compliance cases to be identified in advance, which could save significant time and cost due to changes and/or rework (Ding 2006),
- promoting the adoption of Building Information Modelling (BIM) and increase the cumulative benefits of adopting BIM as BIM would allow ACC (Pocas Martins 2010),
- enabling more efficient integration of stakeholder inputs into design and exploration of what-if design scenarios because a designer would be better able to experiment with different design options and verify compliance more efficiently in terms of time (Niemeijer 2009),
- reducing violations of regulations due to easier and more frequent CC (Zhong 2012).

The survey carried out by shows how the automatic identification of the limits set by the regulations through NLP in support of automated code checking (ACC) through the BIM model can lead to a substantial reduction in time and errors.(Zhang and El-Gohary 2015)

## 3.3. NLP and CBR for risk management

### *3.3.1. Safety risk management*

Case Based Reasoning (CBR) is an important approach in the risk management of construction projects. It emphasises that previous knowledge and experience of accidents and risks are extremely valuable and could help to avoid similar risks in new situations. Databases on construction accidents have been created and are growing in size. However, these documents are written in natural language retrieving information quickly and accurately from the database is still the major challenge. In order to improve the efficiency and performance of data recovery, the paper proposes a Natural Language Processing (NLP) approach (Zou et al. 2017). The paper goes on to describe how in recent years, with the development and increasing use of NLP, researchers have introduced NLP to the construction industry to address problems of analysis and management of textual documents, such as:

- retrieval of CAD drawings (Hsu 2013),
- automatic analysis of injury reports (Tixier 2016),
- automatic grouping of construction project documents based on textual similarity.

The authors underline how NLP is a promising technique to assist the recovery of CBR knowledge and cases. However, very few studies have been found in this field. (Zou et al. 2017)

### *3.3.2. Construction risk management*

The paper analyses the bidding process for construction and a possible application of NLP in this phase. Bidding process takes place in the early stages of a construction project. Bidders must fully understand the uncertainties of the project before making decisions. The risk of uncertainty of construction projects is determined by the content of the bid document. If the information provided in the bid notice is not accurate and unclear, the uncertainty of the projects increases. The study applied four representative classification algorithms. The authors used the 80% of the total data for training and 20% as test data (Lee and Yi 2017).

The authors in their research propose a NLP approach to predict risks in the bidding process of construction projects, by analysing the uncertainty of the bidding document and using it as a factor to predict the bidding risk of a project. The model for forecasting tender risk was conducted using the pre-bid clarification information. Text mining was carried out on pre-bid RFI documents, which are in an unstructured text data format, and the results of text mining were used as the main influencing factors for the risk forecasting models. The authors conclude by arguing that the results of this study should reinforce the possibility of further similar studies in the future, since it increases predictive accuracy by incorporating the uncertainty of the bidding document, which is rarely taken into account in previous studies (Lee and Yi 2017).

In summary, the papers reported highlight the use of the NLP as a methodology and tool for risk mitigation applicable in the field of safety and in the pre-bid phase. The NLP is useful for supporting the project manager in project risk mitigation.

### 3.4. Rule based NLP for risk mitigation in procurement management

As the size and complexity of construction projects have increased significantly, the number of disputes between the parties involved during construction work is constantly increasing. To avoid such disputes, participants need to be sure of their contractual positions and rights. The process of drafting and reviewing construction contracts is crucial. Most international construction projects require contract management teams to examine all possible contract risks during tendering periods. However, it is very difficult to review a large number of contracts in a short period of time. The authors of the paper propose a model of automatic extraction of poisonous clauses (Lee et al. 2019).

Therefore, in their paper the authors proposed an automatic model for extracting contractual risks based on the NLP that would automatically detect poisonous clauses in construction contracts. In validating the performance of the automatic model developed in their study, the authors found that the accuracy and recall were both 81.8% compared to manual revision. This study is significant as a model has been developed that can carry out a prior review of contractual risks (Lee et al. 2019).

The NLP approach proposed is therefore effective in automatically reading and extracting poisonous clauses from construction contracts. The algorithm, suitably modified, can be used to read and extract data from documents other than construction contracts.

## 4. Conclusion: NLP for requirements engineering

Given the importance of the correct and complete definition of the initial project requirements for the successful application of project and information management, the NLP approach to support the translation of the requirements into numerical and alpha-numerical terms could help reduce the gap between expected and actual quality. Methods, techniques and application cases of NLP have already been tested with good results. However, no case of systemic application to construction project has been found since the early stages of planning. The cases of NLP use in the AEC sector reported are limited to phases subsequent to the pre-design and planning phases. The use of NLP for the definition of initial requirements would have a greater impact if applied at an early stage. The NLP approach could be used for the definition of the initial requirements of a public client helping the public actor to define, in the Italian case, a Documento di Indirizzo Progettuale (DIP) on a numerical and alpha-numerical basis and not on a simple text basis. Through the alphanumeric translation of the DIP, the public client would be the main actor in a Data-driven construction process, increasing its ability to understand, manage and direct the outcome of the design. The numerical translation of the requirements would like to make the entire process computable first, and then digitally manageable, which would see the client as the actor able to contribute directly to the design (Ciribini 2016). NLP supports requirements engineering by transforming the classic qualitative demand based on text data into a computational demand based on formal and structured data.The requirements thus defined would be the basis of the information management process in a data driven process. During a data driven process, the monitoring of the objectives to be achieved can be more effective and immediate, reducing the risk of overcoming time and costs and not reaching the expected quality level.

## 5. Further developments

The main further development of requirements translated into a computational form, through NLP, is the possibility of being readable and digitally managed by an artificial intelligence set up for the purpose. The AI, if properly instructed, could support the evaluation phase of the project to verify the degree of compliance of the project with the requests coming from the translation of the DIP. The system structured in this way would be configured as a decision support system for assessing the progress of the project. The monitoring of the project progress would be automatically managed by the AI to avoid errors and costs in economic and temporal terms.

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