Point Cloud Segmentation for Scan to BIM: Review of Related Tecniques

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Abstract

The creation of as-built BIM models sees in the scan to BIM modeling one of the most time-consuming activities. Scan to BIM modeling refers to the creation of BIM objects from information derived from point clouds acquired through laser scans or photogrammetric techniques.
Numerous studies have been conducted in recent years to identify automation or semi-automation procedures for the scan to BIM modeling process, which consists of different aspects: the recognition of objects within the scene, the modeling of their geometry and the recognition of the relationships between them.
The present work aims to analyze actual trends in the automation of scan to BIM activities, highlighting the most used approaches and methodologies currently presented in order to provide a key to understanding the development of a theme still at the dawn of its expression.

Keywords
BIM, point cloud, scan to BIM, machine learning, review.

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Introduction

The development of as-built BIM models from point clouds, acquired through laser scans or photogrammetric techniques, is a process that consists mainly of three activities [Tang et al. 2010]:

1. The recognition of the objects present in the scene
2. Modeling the geometry of recognized elements
3. The recognition and definition of the existing relationships between the elements

The automation of this process consists of the automation of the above-mentioned activities, which can be translated into point cloud segmentation activities (1) and activities of geometry extraction from point clouds (2 and 3). The complexity of the task consists in translating the result of these activities into the logical structure of the BIM methodology.
The study focused on the analysis of the studies carried out on the extraction of information from point clouds for the purpose of creating three-dimensional digital models, with particular attention to BIM models.

Methodology

An analysis was carried out, using Scopus database, on the articles published from 2010 to 2022 which presented as search keys the words: “Segmentation”, “Point Cloud”, “BIM”, “Scan” (Fig. 1).
Of the documents thus obtained, the information concerning: Author, Title of the document, Year of publication, Citation count, DOI, Publisher, Abstract, Autor keywords were extracted from the database.
The OSViewer software was used for a preliminary analysis of the information obtained, then Python code was used to analyze the presence of specific keywords chosen by the author.
The analysis technique used involves searching specific keywords through the keywords and the abstract of each article. The algorithm, written in Python, pre-processes the string representing the abstract and the string representing the keywords by reporting all the characters in capital letters and eliminating the characters “.” , “-” and “ “(space). The analysis on the presence of the keywords is then performed on the strings thus transformed. This presence is counted only once for each record in order to not suffer distortions in the results due to the possible presence on several occasions of the same keyword on the same article.

Results

The analysis conducted on the Scopus database produced 518 results of articles related to the above filters. The same search was carried out selectively on different keywords:

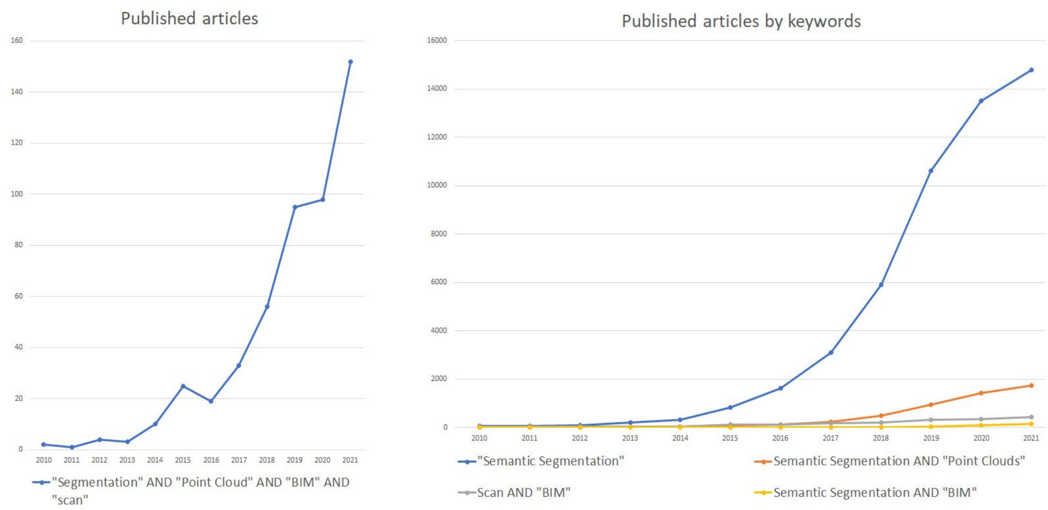

Fig. 1. Published articles referenced to key words.

“Semantic Segmentation”, “Semantic Segmentation” & “Point Clouds”, “Scan” & “BIM”, “Semantic Segmentation” & “BIM”. The analysis shows how the segmentation of point clouds for activities related to BIM modeling, despite appearing to be a field in strong growth in recent years, is still at an embryonic stage compared to the research carried out on semantic segmentation of point clouds and this fact appears even more markedly in reference to research on semantic segmentation in general.

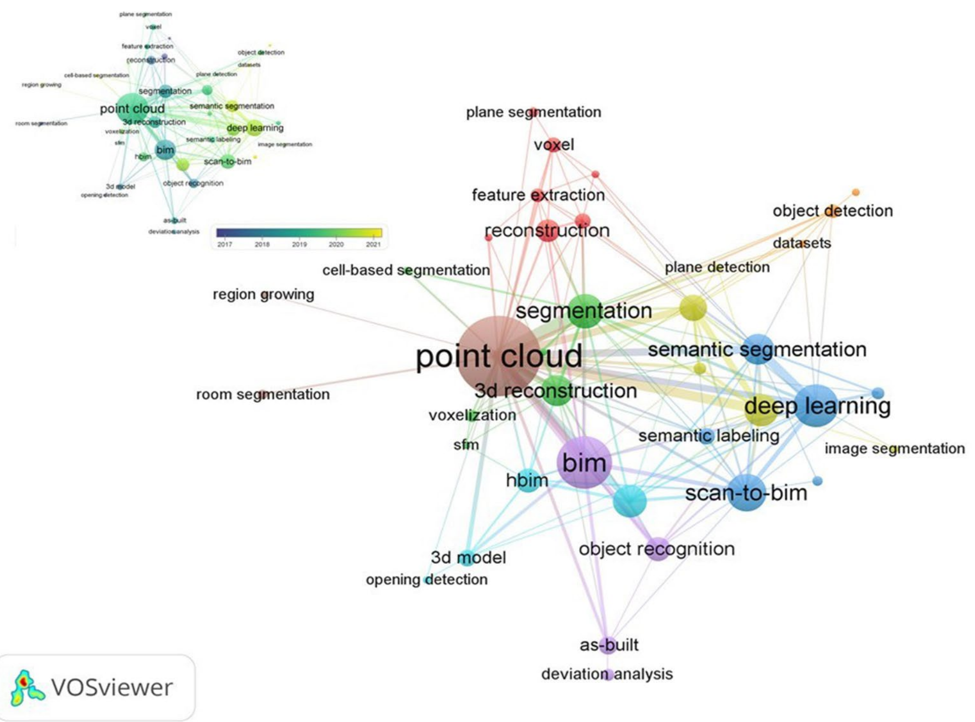

Fig. 2. Graph of recurrent themes produced whit VOSviewer software.

The processing of data through the OSViewer software produced the maps represented in figure 2 which allowed a first evaluation on the techniques and themes most used and addressed in relation to the search keys (Fig. 2).
Of the 518 items considered, 226 articles are related to the keywords “BIM” or “Scan to/vs BIM”. An analysis of these articles was carried out in order to further aggregate the dataset according to specific themes. The first topic addressed concerns the decomposition of the dataset between the articles dealing with the segmentation of point clouds for activities related to the BIM methodology and the articles dealing with the semantic segmentation of point clouds in relation to the BIM methodology.

Segmentation Techniques

The segmentation of a point cloud leads to the subdivision of the cloud into non-overlapping regions, which represent specific structures or objects united by similar geometric characteristics. Point cloud segmentation can be done through the following approaches [Xie et al. 2020]:
- Edge-based
- Region growing
- Model fitting
- Clustering

The presence of such approaches in the database was analyzed using as search keys:
- EDGE BASED: EDGEDETECT, EDGEBASED, DETECTEDGE
- REGION GROWING: REGIONGROWING, SEEDPOINT

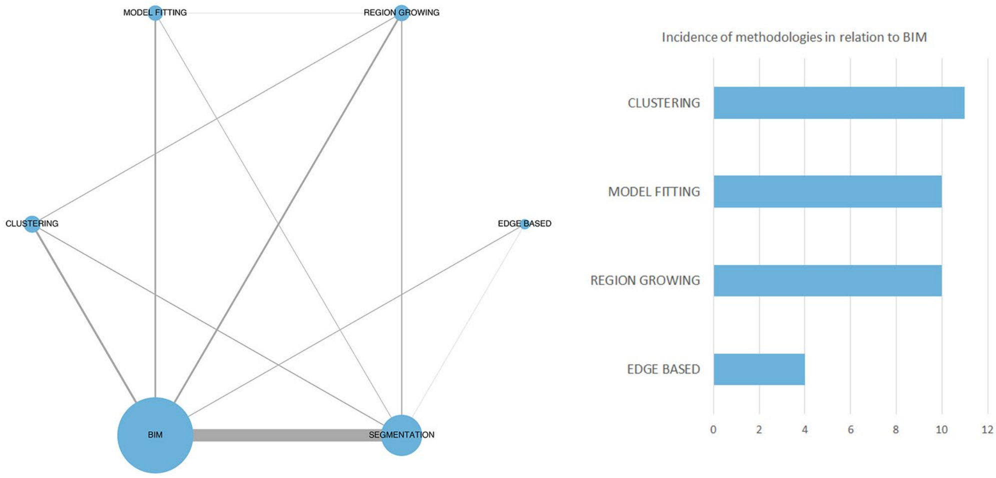

Fig. 3. Incidence of segmentation techniques.

- MODEL FITTING: HOUGHTRANSFORM, RANSAC, RANDOMSAMPLECONSENSUS, MLESAC, MSAC, PROSAC, HOUGHBASED, MODELFITTING
- CLUSTERING: KMEANS, MEANSHIFT, GRAPHBASED, FUZZY, CMEANS, KNN, KNEARESTNEIGHBORS, MARKOVRANDOMFIELD, CONDITIONALRANDOMFIELD, VCCS, BESS.

The size of the nodes represents the incidence of the key in the dataset, the size of the arcs is proportional to the number of times that two keys are detected together in the same record (Fig. 3).

Semantic Segmentation via Machine Learning Approaches

The semantic segmentation procedure generates, unlike the segmentation procedure, information about belonging to a certain class for each point, and is usually carried out through supervised machine learning models and deep neural networks (Fig. 4).
The approaches analyzed for the semantic segmentation of point clouds were first of all those concerning supervised machine learning models (excluding deep neural networks), which include [Xie et al. 2020]:

- Support vector machine (SVM)
- AdaBoost
- Cascade of binary classifiers (BC)
- Decision tree / Random Forests (RF)
- Bayesian discriminant classifiers (BDC)
- Markov networks (MN)

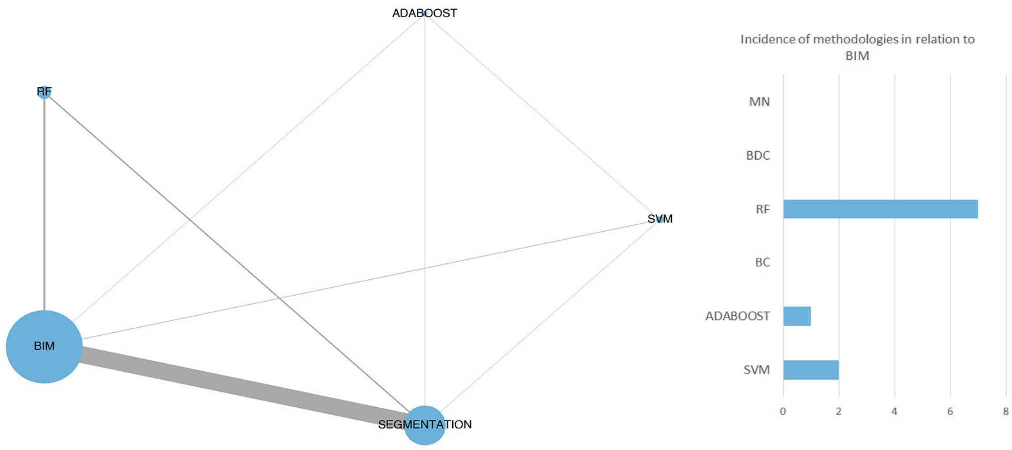

Fig. 4. Incidence of Machine Learning techniques.

The search keys used are:
- SVM: SVM, SUPPORTVECTORMACHINE
- ADABOOST: ADABOOST
- BC: BINARYCLASSIFIER
- RF: RANDOMFOREST, DECISIONTREE
- BDC: BAYESIANDISCRIMINANT, NAIVEBAYES
- MN: MARKOVNETWORK

Semantic Segmentation via Deep Learning Approaches

The approaches concerning the use of deep neural networks for semantic segmentation of point clouds are divided into three macro-areas [Xie et al. 2020]:
- Multiview based (MB)
- Voxel based (VB)
- Directly point processing (PB)

The Multiview based approach involves extracting a series of 2D views from the point cloud (Fig. 5). These views are then processed through convolutional neural networks. The main problems in the use of this approach lie first of all in the loss of spatial information that the transformation of a point cloud into a series of 2D views entails, secondly in the impossibility of realizing a satisfactory number of 2D views that can represent complex scenes.
The Voxel based approach involves the transformation of the point cloud into a three-dimensional matrix consisting of voxels, which is subsequently processed through 3D convolutional neural networks. The main problem inherent in the use of this approach lies in the loss of data that the transformation into voxel of a point cloud entails.
The most relatively recent approach involves the use of deep neural networks without pre-processing the 3D data, thus overcoming the main problem associated with the two previous methods, namely the loss of information that both types of pre-processing entail.
The reference of these methodologies in the database was searched using among the keys the names of the main network architectures developed in recent years (Fig. 6). The keys used are:
- MB: MVCNN, MULTIVIEW, VIEWBASED, 2DCNN, SNAPNET
- VB: 3DCNN, SEGCLOUD, VOXNET, FCNN, CRF, VOXEL
- PB: POINTNET, DGCNN, 3PRNN, POINTWEB, POINTSIFT, SPLATNET, RGCNN, POINTCOV, RANDLANET, RANGENET, CANUPO

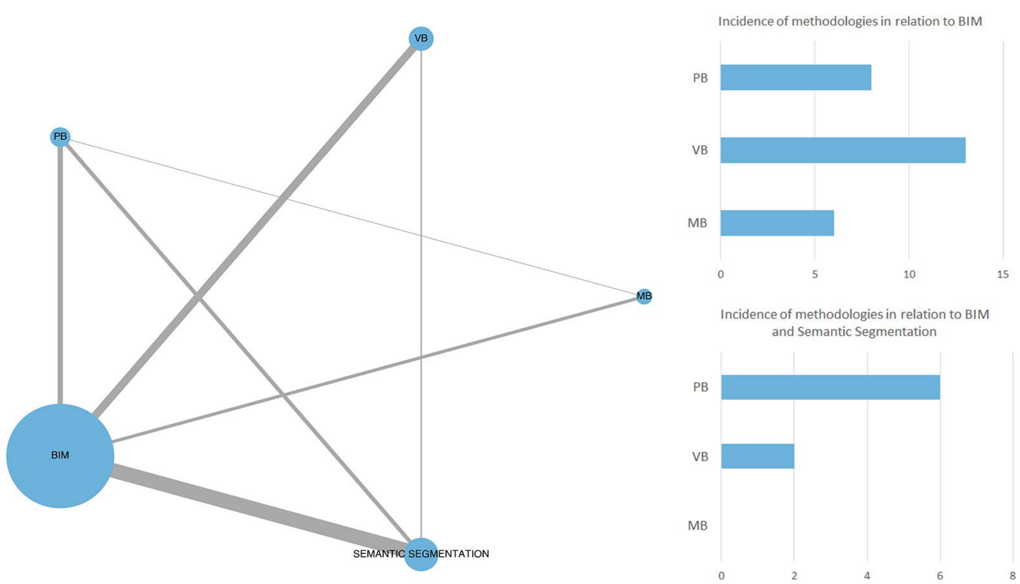

Fig. 5. Incidence of Deep Learning techniques.

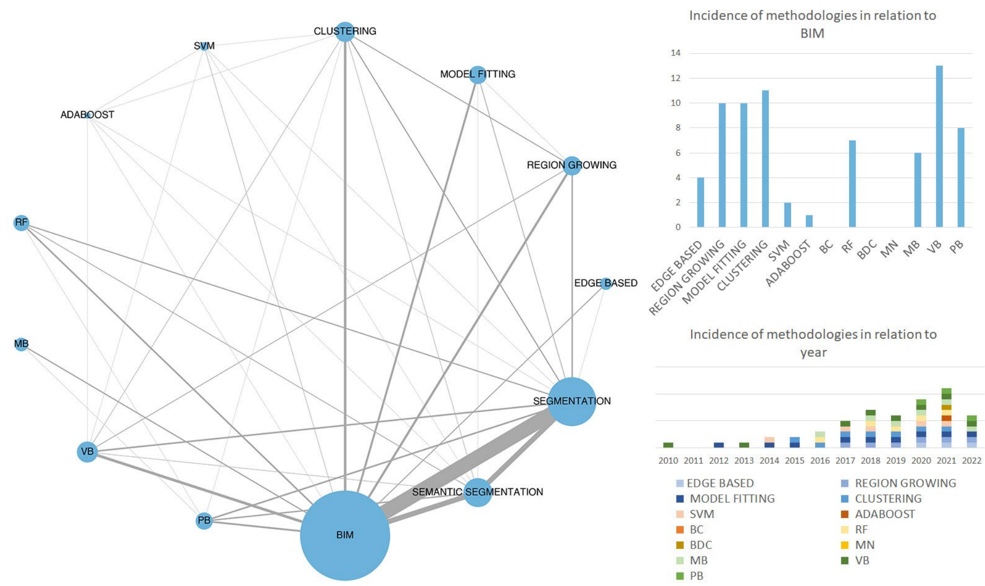

Fig. 6. Incidence of all analyzed techniques.

The use of voxels is not limited to semantic segmentation activities of point clouds through deep neural networks, so to avoid including articles using voxels in the search, but not for the purpose of semantic segmentation through deep neural networks, only articles with explicit reference to semantic segmentation are included.

Cited Studies

Referencing to EDGE BASED techniques, Chen, Kira, and Cho propose an approach for the classification of points belonging to point cloud based on the conversion of the cloud into its graph representation [Chen et al. 2019]. The classified points are then associated with an existing BIM model for deviance analysis between bim and built model.

In relation to REGION GROWING approach, Xiong presents a method for the automatic conversion of point clouds into digital information models, which involves the creation of planar surfaces from a voxelized version of the input cloud [Xiong et al. 2013]. The extraction of the surfaces takes place using region growing algorithms. The algorithm learns the features that distinguish the different types of surface and the relationships between them in order to classify the surfaces as belonging to walls, ceilings, floors. The recognized surfaces are further analyzed in order to recognize the openings present. The output of the algorithm is a model based on semantically classified surfaces, which is considered to be the basis for a subsequent work of generating a volumetric model to be exported in IFC format.

Regarding MODEL FITTING methodologies, Jung proposes a semi-automated methodology for the creation of BIM models, which provides for the automatic generation of CAD drawings starting from point clouds through the extraction of main planes representing walls, floors, ceilings, openings through RANSAC algorithm [Jung et al. 2014]. The CAD drawings thus obtained are imported into the BIM environment for manual modeling. Zhang proposes a method for the extraction of planar patches from point cloud using sparsity-inducing optimization based algorithm for the recognition of dependence between cloud points and through spectral clustering procedures for the recognition of linear dependence between the previously extracted segments [Zhang et al. 2015]. Model parameters of the extracted planes are derived using MLESAC and SVD while α-shape algorithm traces the contours of planar structures. Yang, Cheng and Wang propose a semi-automatic approach for modeling metal structures from point clouds [Yang et al. 2020]. The approach is based on the use of an algorithm that combines on PCA and cross-section fitting techniques to derive the position and direction of each circular metal structure present. Normal-based region growing algorithm and RANSAC algorithm are later used for modeling the connections between structural components.

Referencing to the approaches based on CLUSTERING techniques, Bassier and Vergauwen propose an approach to automatically group wall segments starting from point clouds using Conditional Random Field [Bassier, Vergauwen 2019]. Zeng, Chen and Cho propose a semi-automated method of detecting objects in point clouds that involves processing the cloud with pre-trained deep feature extractor in order to generate a 50-dimensional feature vector for each point [Zeng et al. 2020]. The resulting feature space is clustered using k-means clustering, while at the geometric level the space is clustered using region growing algorithms.
Regarding the SVM and ADABOOST techniques, Perez-Perez, Golparvar-Fard and El-Rayes propose a segmentation methodology of point clouds for generating BIM models [Perez-Perez et al. 2021]. Segmentation takes place using region growing algorithms while semantic and geometric label assignment takes place using SVM and ADABOOST classifiers respectively. The Conditional Random Field (CRF) method leverages the neighborhood context to increase accuracy in label assignment. The coherence between semantic and geometric labels is strengthened by Markov Random Field (MRF) in order to assign the final semantic label to each point.
In relation to RF techniques, Bassier, Van Genechten and Vergauwen propose a method for identifying elements present in point clouds for scan-to-BIM purposes [Bassier et al. 2019]. The methodology involves the use of a Random Forest classifier for the classification of floors, walls, beams, roofs and ceilings starting from a series of planar primitives obtained from the pre-segmentation of a point cloud. Classification is seen as preparatory to a subsequent development of class-specific reconstruction algorithms in order to create BIM objects. Croce proposes a semi-automatic approach for the reconstruction of BIM models starting from point clouds [Croce et al. 2021, pp. 145-152]. The approach consists of two main phases: the first phase consists of the semantic segmentation of the raw point cloud using Random Forest classifier. The segmented point cloud represents the input for the second phase, in which each class extracted via semantic segmentation is imported into BIM authoring software Autodesk Revit as a single point cloud. In the BIM environment, the RANSAC algorithm is used to deconstruct the cloud into a series of geometric primitives. If an object cannot be described using geometric primitives, a Revit family will be created. Croce proposes a similar method for the generation of 3D geometry to be integrated into BIM models starting from point clouds [Croce et al. 2021, p. 461]. The approach involves the semantic segmentation of the point cloud using Random Forest classifier and the generation of geometry through visual programming, through the use of the Rhinoceros Grasshopper plug-in.
Regarding the VB approaches, Babacan, Chen and Sohn 2017 propose an approach based on the voxelization of a point cloud in order to use convolutional neural networks for semantic segmentation [Babacan et al. 2017]. Deidda, Pala and Sanna 2020 develop a methodology based on the voxelization of a point cloud and the use of skeleton extraction algorithms for deriving a 3D graph of the structure [Deidda et al. 2020].
Referencing to the PB approaches, Pierdicca proposes a framework for the semantic segmentation of point clouds through Dynamic Graph Convolutional Neural Network (DGCNN), tested on the ArCH dataset [Pierdicca et al. 2020]. Matrone and Martini analyze the impact of fine-tuning and data augmentation techniques in increasing the performance of the modified DGCNN neural network, called DGCNN-Mod+3Dfeat [Matrone, Martini 2021]. In Lee, Park and Ryu's essay a graph-based hierarchical DGCNN (HGCNN) model is proposed for the semantic segmentation of railway bridges having electric poles [Lee et al. 2021]. In Yin's proposal a neural network model, ResPointNet++, is proposed for the semantic segmentation of point clouds for scan to BIM activities [Yin et al. 2021]. The proposed model is tested on a dataset of 4 industrial scenes labeled according to 5 semantic categories typical of structural and plumbing components.

Conclusions

Deep neural networks for scan to BIM activities are currently linked to the semantic segmentation of clouds. These methodologies, increasingly analyzed in recent years in reference to the BIM methodology, suffer from scarcity in the presence of data that a deep neural network needs for training. ArCH represents an example of a Dataset built for semantic segmentation activities related to Cultural Heritage. In order to make the use of deep neural networks more effective in this area, it is necessary to develop new public datasets related to construction activity. In the field of semantic segmentation, approaches based on Random Forest classifiers have obtained excellent results and are currently widely analyzed and used. Point cloud segmentation must be accompanied by geometry extraction processes for the translation of cloud segments into the corresponding BIM objects. In this perspective, techniques based on region growing and model fitting algorithms are particularly effective in the extraction of geometric primitives representing semantically segmented points. The approach consisting in the development of geometry reconstruction algorithms specific to each class of objects is also considered particularly effective. Referencing to BIM modeling, the reconstruction of geometry involves the extraction of the parameters necessary for the creation of a specific BIM object, as well as the relationships between these elements, and clustering of elements belonging to the same class according to common characteristics that allows to type these elements within the model.

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