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Semantic segmentation through Artificial Intelligence from raw point clouds to H-BIM representation

This work describes a semi automatic workflow for the 3D reconstruction of Heritage Building Information Models from raw point clouds, based on Artificial Intelligence techniques. The BIM technology applied to historical architecture has made it possible to create a virtual repository of many heterogeneous pieces of information in order to make the process of storing and collecting data on the built heritage more effective. The modelling phase of an artefact is the most complex and problematic in terms of time, as the large architectural heritage of historical buildings does not allow the use of parametric models, so that manual modelling of components is required. Current scientific research focuses on automating this phase by means of segmentation and classification methods: these are based on associating different semantic information to the products of the three dimensional surveying as point clouds or polygonal meshes. To address these problems, the proposed approach relies on: (i) the application of machine learning algorithms with a multi level and multi resolution (MLMR) method to semantically classify 3D heritage data; (ii) the use of annotated data identified by relevant features to boost the scan to BIM process for 3D digital reconstruction. The procedure is tested and evaluated on the complex case of the Church of Santa Caterina d'Alessandria in Pisa, Italy. The classification results show the reliability and reproducibility of the developed method.

Keywords:
Artificial intelligence; Semantic Segmentation; H-BIM; Scan to BIM; Machine learning

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BACKGROUND

The current state of the Scan-to-BIM process highlights the lack of a structured path that transforms raw point clouds into structured parametric models, typical of an H-BIM environment, for the purpose of adequate restoration and conservation interventions. In this field, semantic segmentation techniques are emerging as privileged tools to adequately organize and classify the complex system of analytical and surveying data relating to an object or architectural site (Grilli, et al., 2017).
Manual classification of 3D data, as part of Scan-to-BIM workflows, is not only labour-intensive and expensive, but also involves a high degree of subjectivity, non-repeatability and non-reproducibility of the process. In recent years, significant progress has been made in automatic classification processes relying on Artificial Intelligence (AI) methods, as Machine Learning (ML) and its subset Deep Learning (DL), which, on the contrary, are objective, replicable and repeatable. The standard supervised ML techniques require the algorithms to take as input some manually annotated parts of the point cloud, together with the socalled features, i.e., geometric and/or radiometric attributes selected by the operator that facilitate learning and the distinction of the required classes. On the other hand, DL strategies provide for the automatic generation of features, which learn thanks to the use of large quantities of annotated input data (Teruggi, et al., 2020).
Since the advent of Building Information Modelling (BIM) techniques, modelling of existing sites and buildings, starting from surveying, has constituted a challenging issue. Although BIM techniques are to date consolidated for new construction, their application to existing buildings is still limited; this causes the majority of built heritage not being maintained, refurbished or deconstructed yet (Macher et al., 2017; Volk et al., 2013).
Reverse engineering techniques, aiming at recovering conceptual architectural shapes based on existing structures, have been applied in order to retrieve lost information, detect side effects and synthesize higher abstractions, based on real-ideal shape comparison (Canfora, et al., 2007; Koschke, 2000).

METHODOLOGY

In this contribution, semi-automatic classification methods are used to associate the different semantic and descriptive information to the raw results of the three-dimensional survey and, finally, representations based on H-BIM are created to visualise the results according to the ML strategies described by (Croce, et al., 2023; 2021). The case study on which the methodological approach is tested is the Church of Santa Caterina d'Alessandria in Pisa, where the classification is based on the analysis of the geometric properties of the three-dimensional data, the latter acquired by laser scanning. Taking as input the raw 3D models derived from laser scanning or photogrammetry, a supervised ML algorithm is applied to read, classify and render the different architectural classes that make up the church according to a Multi-Level and Multi-Resolution (ML-MR) approach; in order to reconstruct the three-dimensional model, as we can see in Figure 1.
Specifically, a raw point cloud obtained from the 3D survey is iteratively sub-sampled to make the computational process less demanding. On a small part of it, called training set, the classes of the architectural elements are identified and annotated, forming a set of classes on which the ML model is trained. The training data is also supported by so-called covariance features (Weinmann et al., 2015; Blomey et al., 2014), as shown in Table 1, which make it possible to distinguish one class from another, highlighting the geometric classes of the 3D data. In this way, the local behaviour of the cloud is highlighted, by means of features as "Verticality", "Planarity" and "Omnivariance" or "Surface variation". The choice of the appropriate geometric features and local neighbourhood radius of each 3D point where they

Fig. 1 - The three main phases of the proposed methodology

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Table 1: Covariance features

Feature Name	Expression
Linearity	$L_\lambda(\varrho) = \frac{\lambda_1 - \lambda_2}{\lambda_1}$
Planarity	$P_\lambda(\varrho) = \frac{\lambda_2 - \lambda_3}{\lambda_1}$
Sphericity	$S_\lambda(\varrho) = \frac{\lambda_3}{\lambda_1}$
Omnivariance	$O_\lambda(\varrho) = \sqrt[3]{\lambda_1 \lambda_2 \lambda_3}$
Eigenentropy	$E_\lambda(\varrho) = -\sum_{i=1}^{3} \lambda_i \ln(\lambda_i)$
Surface variation	$SV_\lambda(\varrho) = \frac{\lambda_3}{\sum_{i=1}^{3} \lambda_i}$
Sum of eigenvalues	$\Sigma_\lambda(\varrho) = \sum_{i=1}^{3} \lambda_i$
Anisotropy	$A_\lambda(\varrho) = \frac{\lambda_1 - \lambda_3}{\lambda_1}$
Verticality	$V_\lambda(\varrho) = 1 - \lvert\langle[001], e_3\rangle\rvert$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

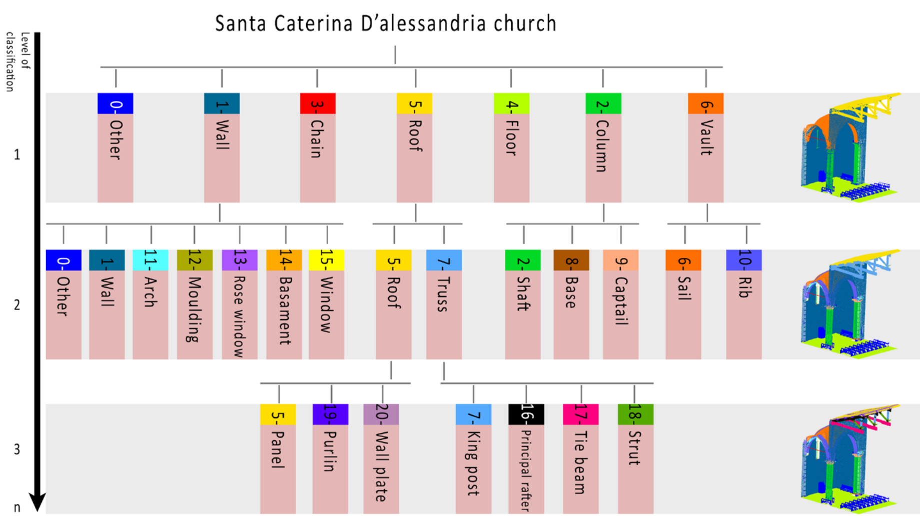
$$Recall = \frac{TP}{TP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$F - measure = 2 \cdot \frac{Recall \cdot Precision}{Recall + Precision}$$

Table 2: accuracy metrics

Fig. 2: Hierarchical methodology approach



are calculated is fundamental for the identification of architectural elements (Grilli et al., 2019).
A predictive model is trained on this data to automatically classify the entire data set obtained from the survey. A Random Forest model (Breiman, 2001) is chosen as classifier: Random forests are a combination of tree predictors (Ntree) such that each tree depends on the values of an independently chosen random vector, having the same distribution, for all trees in the forest. The generalization error of a forest of tree classifiers: (i) converges to a limit as the number of trees in the forest increases; (ii) depends on the strength of individual trees in the forest and the correlation between them.
At the end of the process, an annotated point cloud is obtained in which the different classes of typological elements are labelled. To quantitatively evaluate the performance of the classification, the accuracy metrics commonly used in machine learning are considered: "Accuracy", "Recall", "Precision" and "F-measure" (Goutte and Gaussier, 2005) showed in Table 2. These metrics are obtained from the direct comparison between automatic prediction and manual annotation on a validation set, considering both correctly predicted and mis-classified values.
The on-diagonal elements stand for the True Positive (TP) values (correctly classified instances of the dataset), while the off-diagonal elements provide a measure of misclassifications: True Negatives (TN), False Positives (FP) and False Negatives (FN) values.
At the end of the process a completely semantically annotated point cloud is obtained, where the different architectural components are distinguished according to the classes identified, as shown in Figure 3, with respect to the components of the covering structure.
The result of each class is processed and treated independently, reconstructing parametric geometries that can be imported into H-BIM platforms thanks to visual programming algorithms implemented in Rhino's Grasshopper. This step ensures the autonomous management and computerisation of each class derived from

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the segmentation, and the semantic data can be more easily shared, retrieved, visualised, and archived (Ceccarelli, 2021).
For the H-BIM reconstruction, a reverse engineering software (Geomagic Design X) is considered, as its key aspect is the automatic

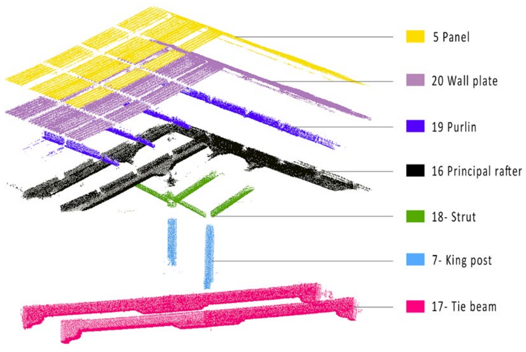

Fig. 3: roof cloud comparison and BIM reconstruction

generation of meshes, necessary for the three-dimensional reconstruction of the model as close as possible to the actual state. Defined by (Chikofsky, E. and Cross, J. I., 1990) as the process of analysis for (i) identifying system components and their interrelationships and (ii) creating representations of the system in another form or level of superior abstraction.
The proposed workflow is illustrated in Figure 4. Following the acquisition of surveying data, it is structured in the following points:
- Selection of a set of features;
- Manual annotation on a small portion of the dataset (training set), to identify element classes;
- Automatic propagation of class labels to the entire dataset via a RF classifier and accuracy evaluation;
- Generation of the annotated 3D point cloud.
- Model reconstruction in H-BIM environment
The application of supervised ML allows, at the end of this process, to obtain the semantically annotated point cloud. Subsequently, through visual programming algorithms, the labelled elements are imported and modelled in a BIM environment.

RESULTS

The choice of the local neighbourhood radius is performed based on considerations made on the recurring dimensions of the elements present in the dataset, relating, for example, to the thickness of some architectural mouldings and the radii and diameters of the columns (Croce et al., 2023). In any case, values lower than the radius of the neighbourhood provide better performance in describing finer details, while higher values apply a kind of attenuation filter (Kaiser, et al., 2019).
The feature selection process allowed to iteratively remove less relevant features; many selected features that resulted significant for the classification task are provided in Figure 5.
For the manual annotation of the training set, a small part of the point cloud is taken into account (Figure 6), which exhaustively described all architectural forms present – hence considered representative of all 20 classes.
After the manual annotation of the training set, a Random Forest model (with Ntree=100, the choice of this value is based on the results of the tests carried out by (Breiman, 2001)) was developed considering as features:
- Selected geometric features derived by combination of the eigenvalues of the covariance matrix;
- Z coordinates;
- RGB values;
- Laser scanner intensity.
The predictive model so elaborated is applied to the remaining part of the dataset, not previously annotated, in order to obtain the results of the manual classification for the entire point cloud (Figure 7).
The model was validated according to the metrics described in the previous paragraph and the results for the elements of the coverage at the third classification level are shown below (Figure 8).
In a latter phase, the different classes of the point cloud are imported in BIM environment, to provide

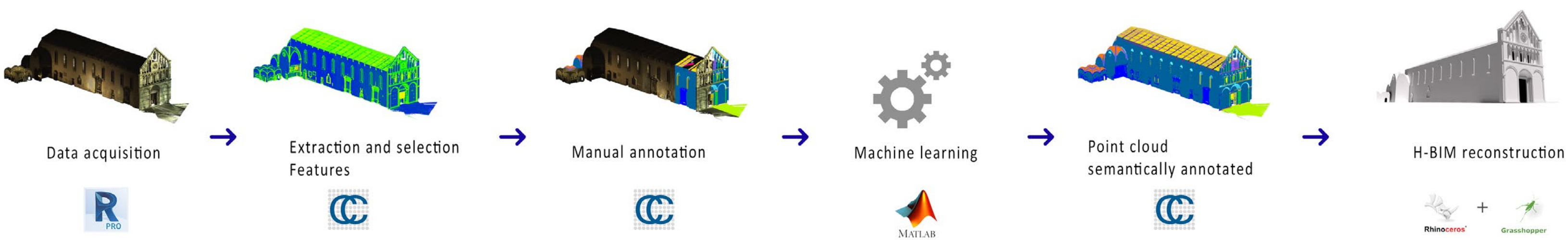

Fig. 4: Proposed workflow scheme

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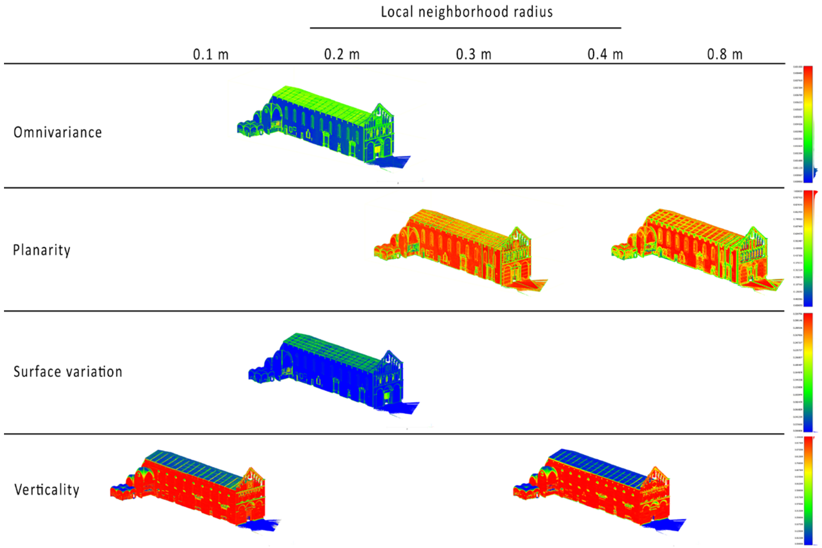


Fig. 5: Selection of relevant features

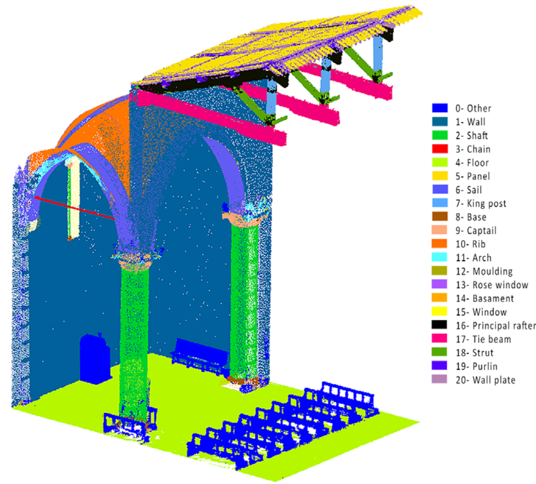


Fig. 6: Training set

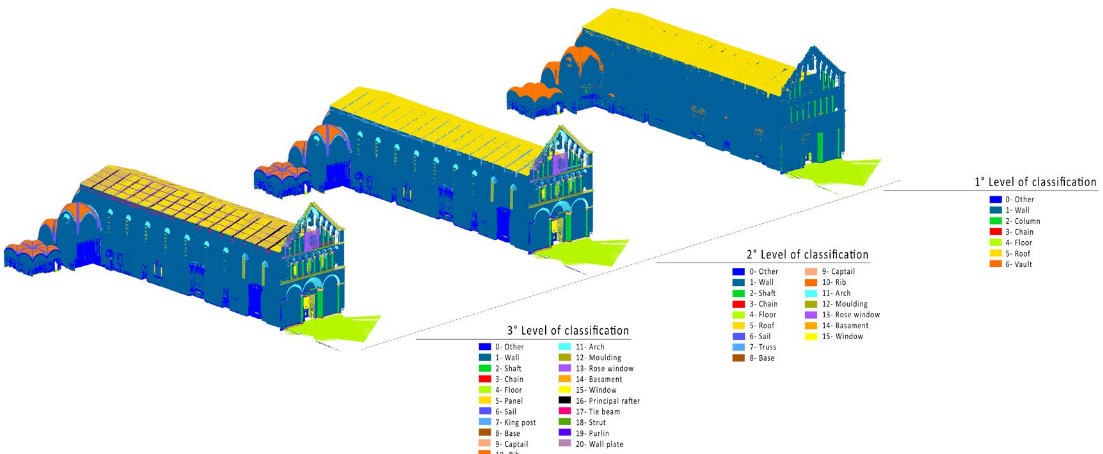
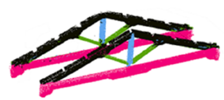


Fig. 7: Semantically annotated points clouds



	Accuracy	Precision	Recall	F-measure
7- Truss	99.88	98.13	97.27	97.70
16- Principal rafter	99.78	99.60	99.66	99.63
17- Tie beam	99.97	99.98	99.97	99.98
18- Strut	99.87	99.33	99.43	99.38

Fig. 8: Classifier performance at the third classification level

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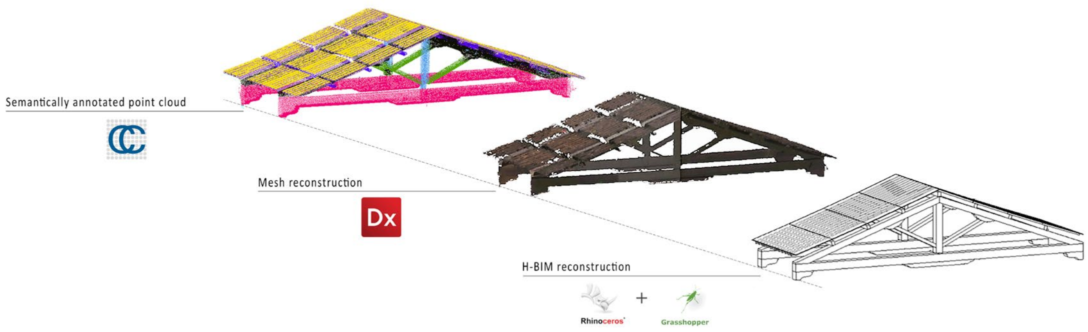

Fig. 9: H-BIM reconstruction workflow

the H-BIM reconstruction of the fully segmented point cloud.
To ease the 3D modelling process, the reverse engineering software Geomagic Design X is considered; specifically, the previously classified classes are exported in .e57 format (file not directly openable in Autodesk Revit) and individually imported within the software. Meshes are generated for each imported class, and subsequently merged to generate a unique mesh that can be imported as a.dxf file within the Rhinoceros three-dimensional modelling environment. In this phase, the expertise of an experienced operator is crucial, particularly for the manual modelling of solid geometries based on initial point cloud data. The workflow for this process is illustrated in Figure 9 for the third classification level.
The methodology presented follows an iterative approach and can be applied to each identified class.
Finally, the "deviation for mesh" tool in Geomagic Design X is leveraged to compare the automatically generated mesh with the initial point cloud; a maximum deviation of 10 mm is observed in the part highlighted in green on the scale bar, as shown in Figure 10.
This deviation of the points is due to the fact that the extrados of the elements reconstructed by mesh was not visible in the TLS relief, as the instrument was placed at different points on the ground.
The extension of the procedure to all data classes allows the reconstruction of a conceptual model, as shown in Figure 11, which could be subsequently imported into Autodesk Revit, for future implementations in terms of addition of documentary resources, conservation status information and so forth.

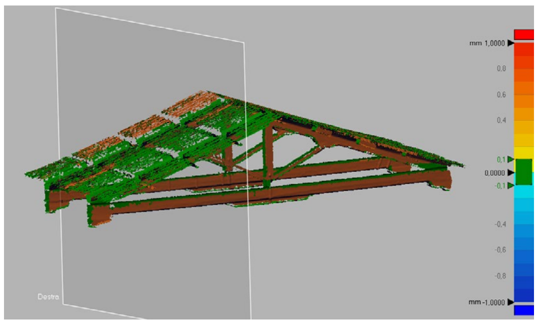

Fig. 10: Deviation analysis

CONCLUSIONS

The study of the Church of Santa Caterina d'Alessandria in Pisa, object of the present work, has allowed to apply an integrated methodology for the semi-automatic transition from the raw 3D survey data to semantically rich H-BIM representations. Relying on a semantic segmentation process (MLMR), the methodology is applied to historic buildings and assets, where the classes of recurring typological elements can be recognized based on construction rules. Semantic information is transferred and propagated to heritage elements, assets that have similar characteristics and that can be classified within the same typological classes. The results obtained on

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this dataset are promising and suggest a possible applicability of the proposed workflow to further and even more complex datasets characterized by the repetition of archetypes of recurring shapes.
The use of Geomagic Design X software allowed the automatic creation of the mesh from the semantically annotated point cloud which can be imported into the BIM environment, but the manual intervention of an expert operator was required for the solid reconstruction and correspondence of the model to the actual state.

INNOVATIVE AND ORIGINAL ASPECTS

Application of Machine Learning algorithms for the automatic recognition of architectural elements.
Acceleration of the semantic segmentation process by validating the test on a reduced set of features.
Time reduction in the Scan to BIM process.
Validation of multi-level multi-resolution semantic segmentation procedure.

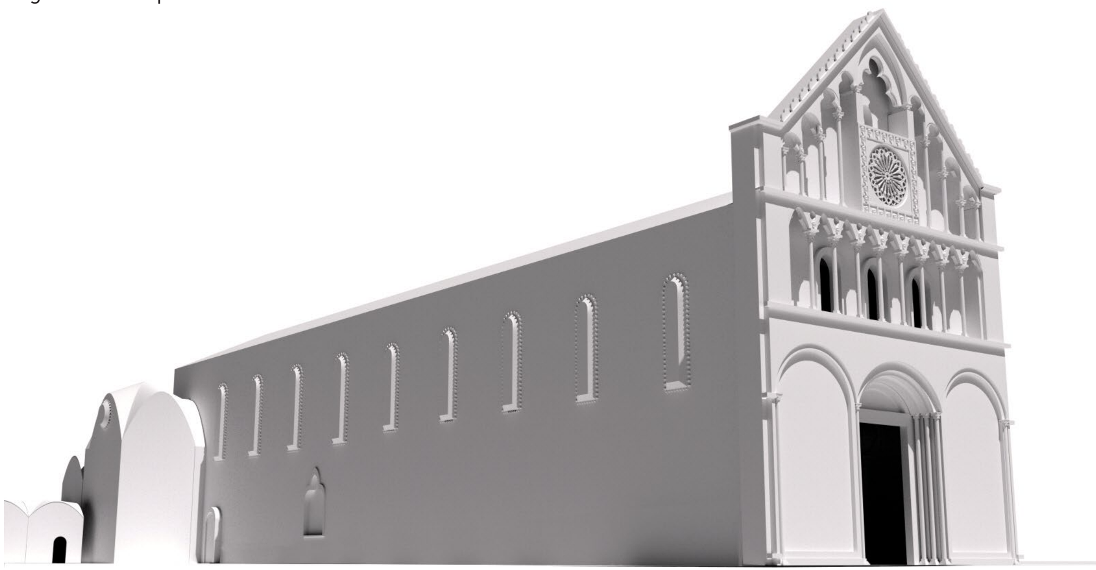

Fig. 11: Resulting conceptual model for Santa Caterina d'Alessandria Church

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