

# Neural Network for Classification and Assembly of Nuragic Amphorae

*M. Magalini<sup>(1)</sup>, S. Barone<sup>(2,3)</sup>, A. Bombini<sup>(2)</sup>*

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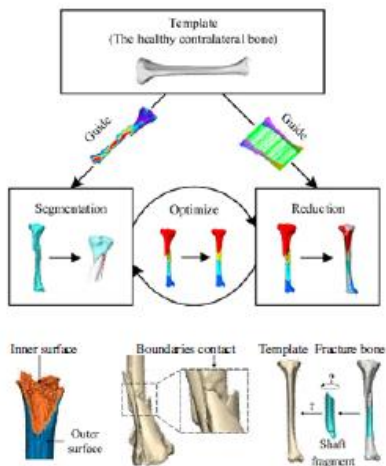
*2 -INFN- Firenze*

*3- Università degli studi di Firenze*

# Why?

The problem of **3D fragment reassembly** - i.e., reconstructing a complete object from its pieces - has important applications in many fields, including cultural **heritage conservation**, **palaeontology**, **biology**, **medicine**, **industry**.

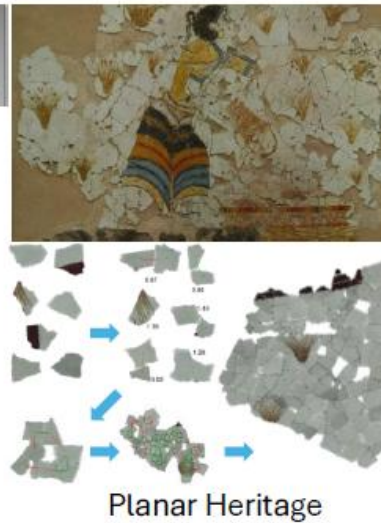
DOI: 10.1111/cgf.70081



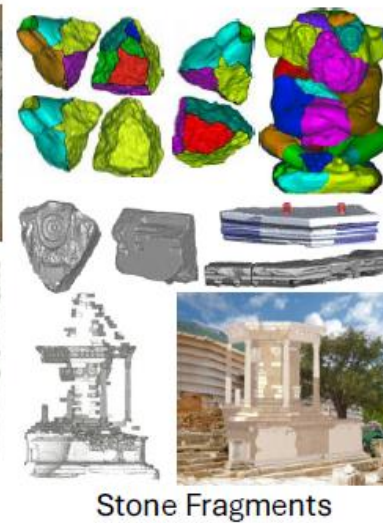
Bone reduction



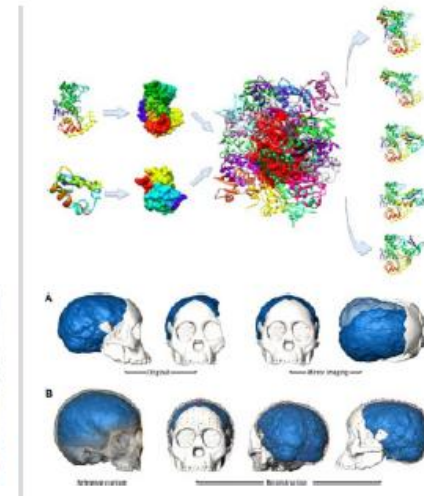
Thin-shell Objects



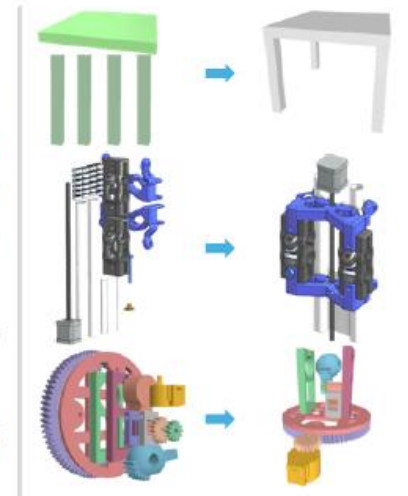
Cultural Heritage



Stone Fragments



Reassembly in science



Part assembly

# Why?

In **archaeology**, pottery reassembly is crucial to the study of ancient sites, as the analysis of vessel types provides key insights into:

- ❑ site chronology
- ❑ production technologies
- ❑ cultural traditions
- ❑ economic networks

Usually, reconstruction is performed **manually**, involving very **large numbers of fragments**, making the process **time-consuming**, inaccurate, and subjective to individual expertise of archaeologists and conservators.

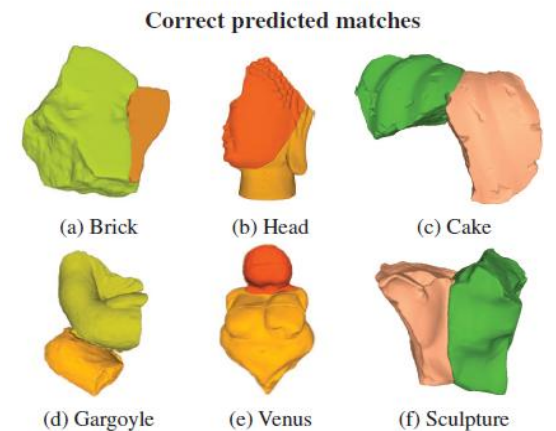
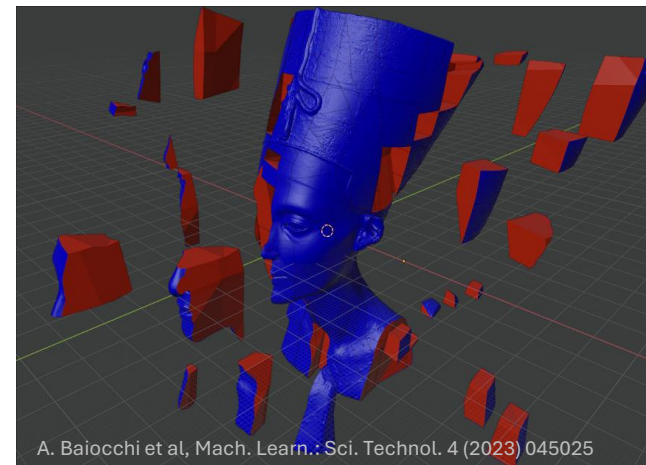
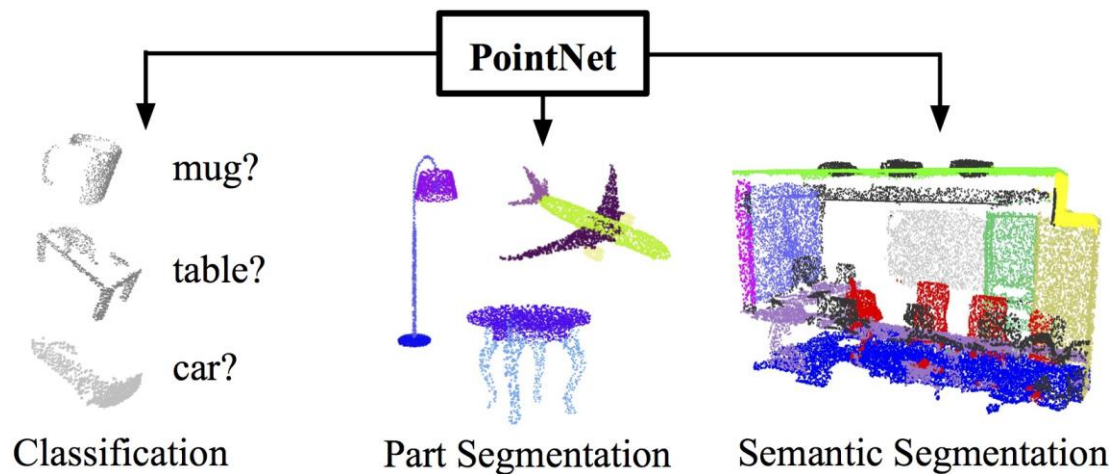
**Computer science and AI can help!**



# An help from artificial neural network

Advances in **digitisation devices** and **computational methods** have gradually shifted the problem from 2D ‘texture-based’ approaches to more complex **3D ‘geometry-based’ solutions**.

With the recent success of **artificial neural networks**, learning-based techniques for **surface segmentation, shape classification and matching** have emerged as a promising research direction → automatically discover patterns and features from data, **without relying on hand-crafted geometric rules**, and can therefore generalise more robustly across different systems



<https://arxiv.org/pdf/1612.00593>

2023 IEEE/CVF International Conference on Computer Vision Workshops (ICCVW) | 979-8-3503-0744-3/23/\$31.00

# An help from artificial neural network

A key breakthrough was the introduction of architectures such as **PointNet** (Qi et al., 2017) and **PointNet++** (Qi et al., 2017) and dynamic graph convolutional neural network (**DGCNN**) (Wang et al., 2019), which for the first time enabled **direct processing of 3D point clouds**, an unstructured representation of 3D points in space sampled from an object.

→ Digital archaeology: object classification, fragment matching , fragment positioning relative to the original models

■ **Existing studies** using real digitised pottery typically involve **very few samples** (fewer than ten objects), highlighting the gap between proof-of-concept and scalable application

■ **Scarcity of large open-access datasets**, both synthetic and real, specifically tailored to archaeological object reassembly tasks



S. Sellan “**Breaking Bad**: A Dataset for Geometric Fracture and Reassembly”



Tsesmelis et al., Re-assembling the past: The **RePAIR** dataset and benchmark for real world 2D and 3D puzzle solving

**Table 3:** Comparison of publicly available datasets for fractured object reassembly. Datasets are listed chronologically.

Datasets	Objects/Groups	Pieces per Object	Total Pieces	Breakdown Type	Data Type	Data Origin	Ground Truth
TU Wein [HFG*06]	7	6-30	101	Real	3D	Artifacts	Roughly
Presious [TP13]	7	3-30	69	Real	3D	Cathedrals	Partial
BreakingBad [SCW*22]	10474	2-100	8442044	Synthetic	3D	-	✓
FantasticBreaks [LPM*23]	150	2	300	Real	3D	Household	✓
FIRES [WZW*23]	15	7-18	123	Real	3D	Pottery	✓
RePAIR [TPK*24]	18	2-44	1070	Real	2D/3D	Frescoes	Partial

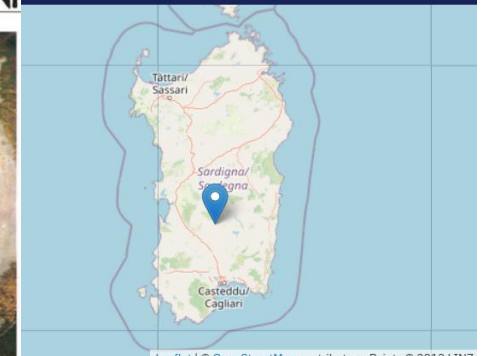
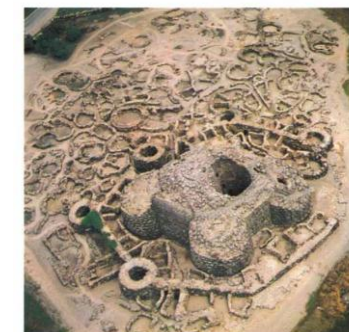
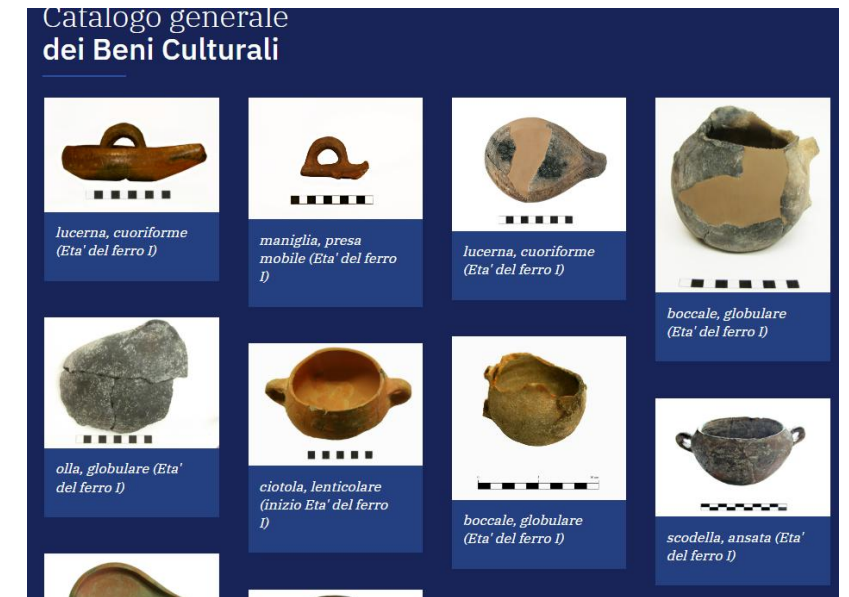
DOI: 10.1111/cgf.70081

# A collaboration with the Barumini fundation

People involved: INFN-To, INFN-Fi, INFN-Roma1, Soprintendenza Archeologia, di Cagliari, Barumini Sistema Cultura Foundation

1. To create and publish a large open-access **dataset of 3D models of virtually broken** amphorae (including digitized amphorae from Barumini) → specifically designed for object reconstruction tasks via AI-assisted restoration methods;
2. To design, test and validate a **neural network** capable of:
  - a) processing 3D point cloud data of pottery shards, **identifying their typology (classification)**
  - b) evaluating **adjacency matches probability** between fragment pairs

→ to support archaeologists in their daily work





Front view:

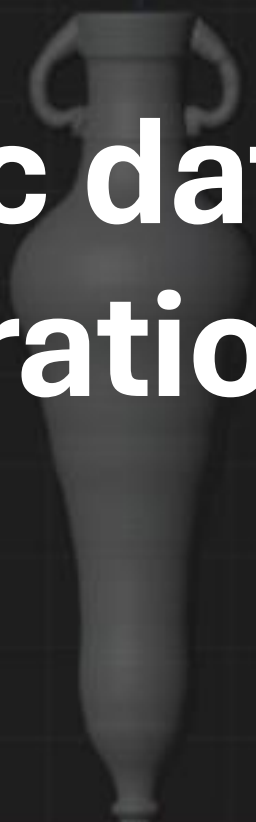
# Synthetic dataset generation



Aegyptienne\_1\_  
DR443  
Class\_1



Aegyptienne\_2\_  
DR444  
Class\_2



Aegyptienne\_Bitronc  
onique\_3\_DR164  
Class\_3



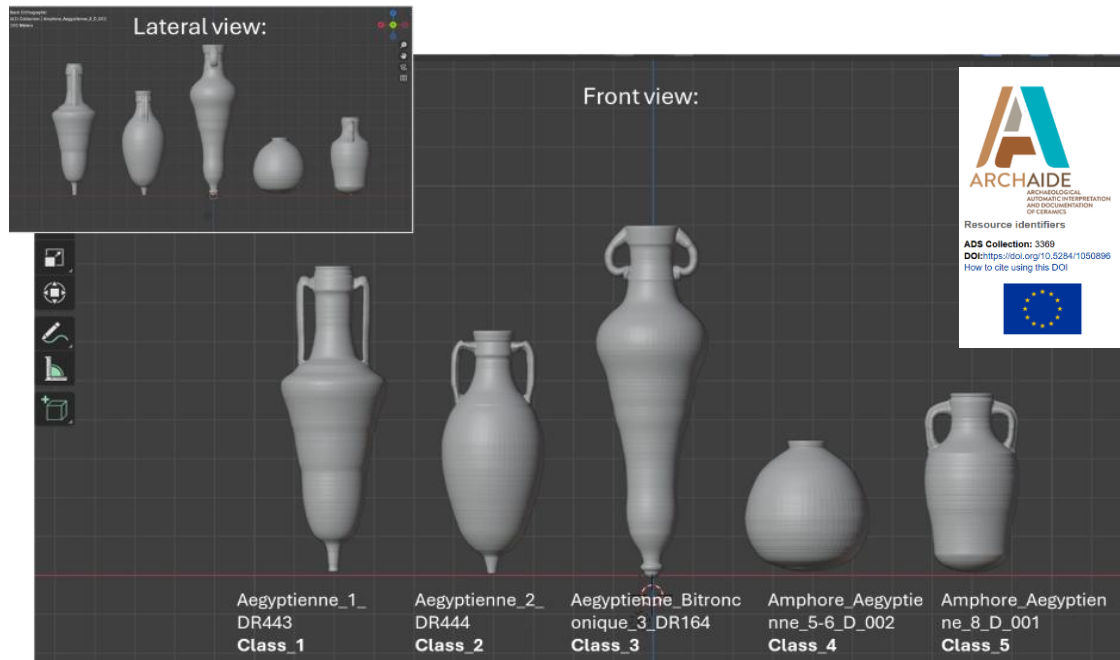
Amphore\_Aegyptie  
nne\_5-6\_D\_002  
Class\_4



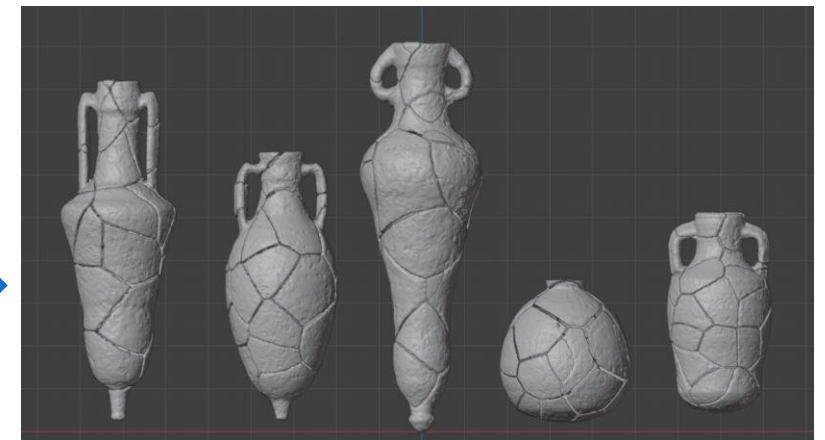
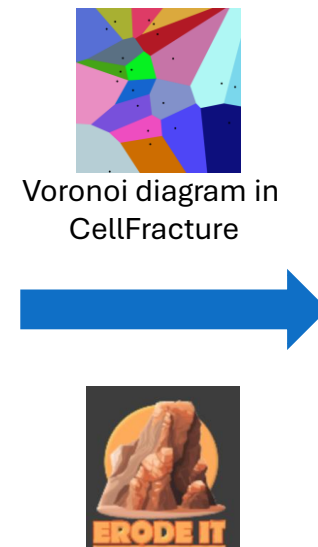
Amphore\_Aegyptien  
ne\_8\_D\_001  
Class\_5

# A pipeline in the Blender Python API

Creation of a **synthetic dataset** starting from an **open access database of .stl volumes of amphorae** (CC0); we selected 5 models of Egyptian origin:



Using the python API of Blender we wrote a custom code that **artificially break** them in multiple different pieces and apply an **erosion effect**



Save data in **point clouds format + json dictionary as Adjacency matrix** for the fragments

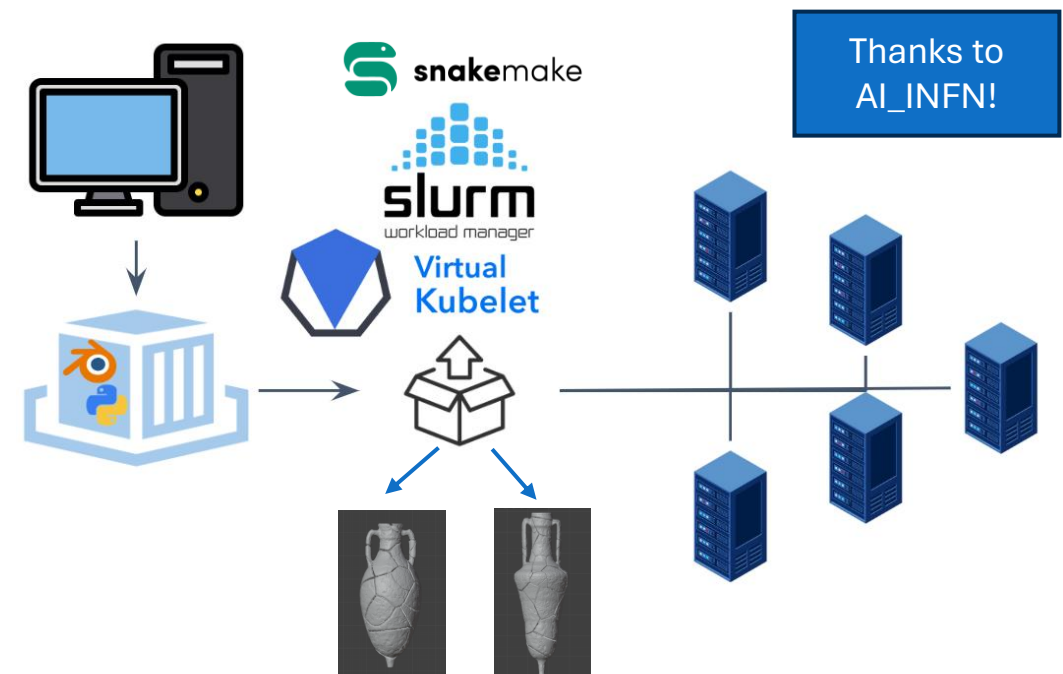
# Scaling computationally

To *simulate* hundreds of break patterns *per class*, we need a **parallelisable, distributed approach**. We did it using *containerisation* of the blender script, using **Apptainer** containers.

Apptainer creates single, isolated .sif files containing all the needed libraries and kernels to run the entire code (comprising the OS kernels!)

This allows for an easy distributed approach, perfect to scale on **HPC resources** (when available!)

We can thus **dispatch** (using slurm, or VKD, or snakemake) **the single generation to an independent node**, and store on a NFS or WebDAV FS (manage storage and access to data on the network)



Starting dataset for classification task: 10 independent breaks for each of the 5 classes (approximately 30 fragments per break).

**Next step: increase the dataset including other amphorae models**

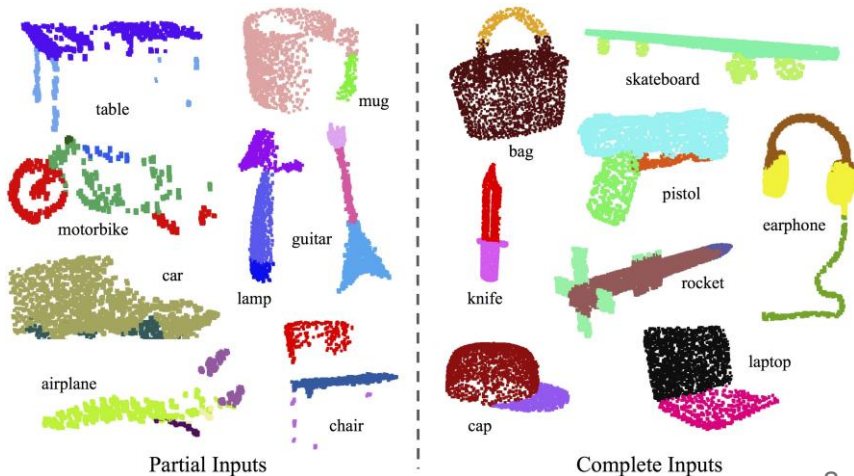


# Point clouds processing using GNN

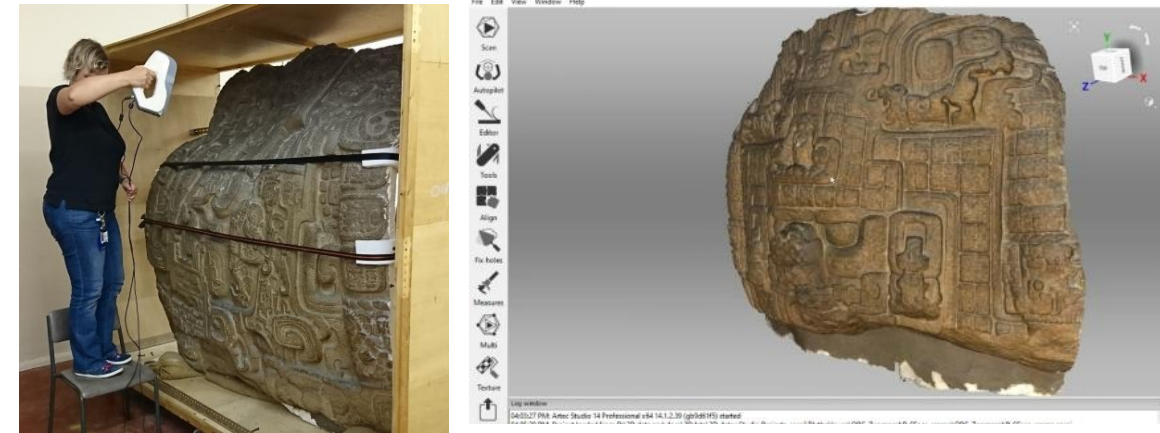
# Data: point clouds

A point cloud is a **discrete set of points in d- dimensional space** (typically  $PE \mathbb{R}^3$ ) that represents the geometric shape of an object.

- ❑ Light (vs voxels, meshes) → widely used format for 3D model representation
- ❑ **Unordered structure** → permutation-invariance property
- ❑ invariant to rigid motions



<https://doi.org/10.48550/arXiv.1612.00593>



<https://www.artec3d.com/it/cases/british-museum-google-maya-project>

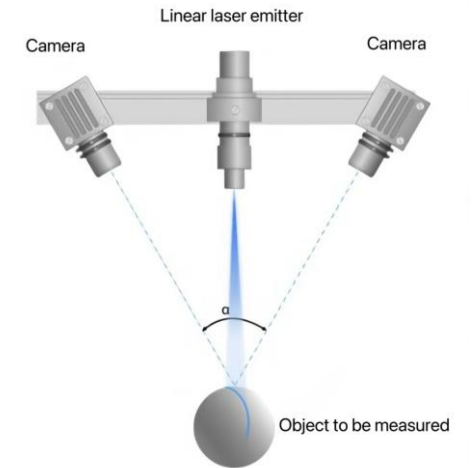


Figure: Principle of laser 3D scanning technology

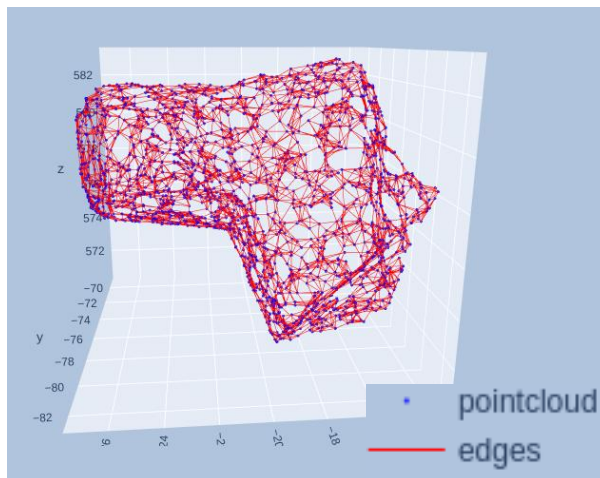
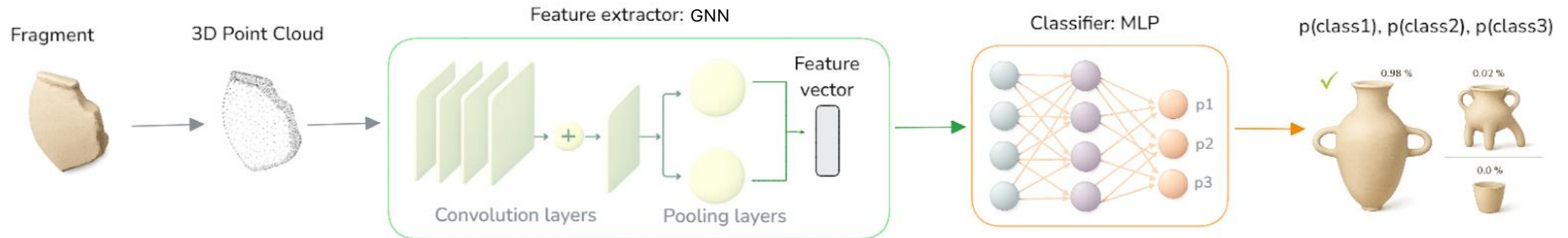
<https://www.3devok.com/news/comparative-study-fringe-laser-and-speckle-scanning-techniques/>

Accessible, cheaper, high performance devices → huge amount of 3D data

3D digitisation techniques:  
**photogrammetry, laser scanner**

# Nuragic Amphorae fragment classification using GNNs

After having created the dataset, we can interpret the generated fragments as **3D point clouds with connecting edges** → *graphs*.



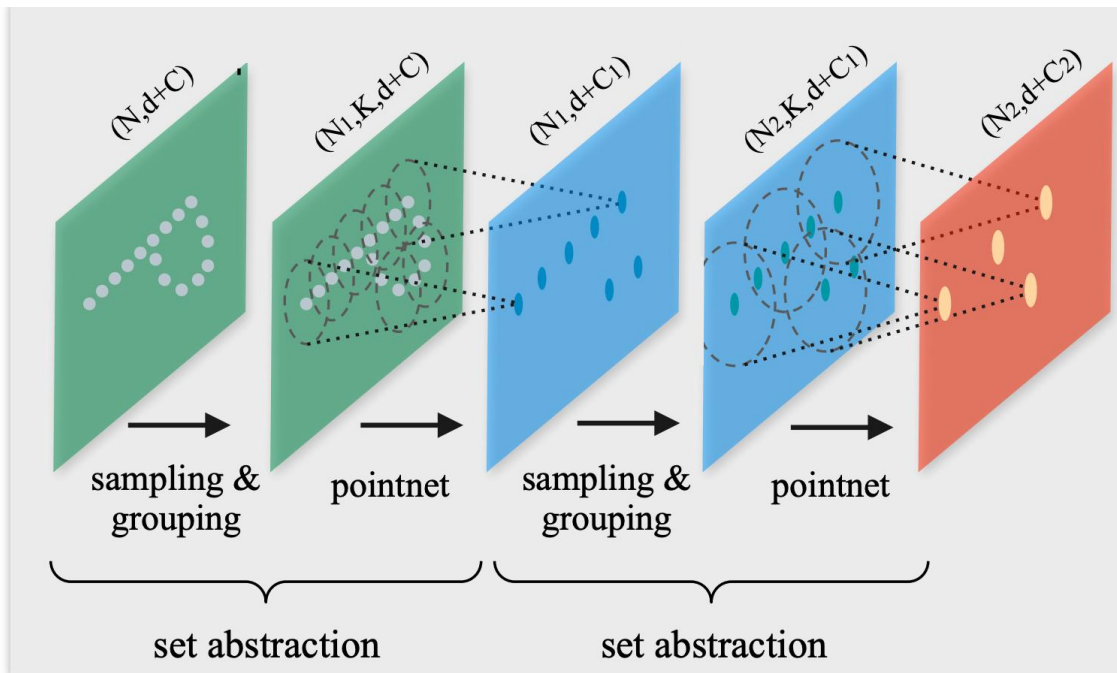
**Fragment classification:** estimate the probability that a given fragment belongs to a specific Nuragic pottery class (e.g., Tripode, Anfora, Calice).

- Feature extractor:** Graph Neural Network (PointNet, PointNet++)
- Classification head:** MLP

# PointNet++

Point Net family of models is a novel type of NN that directly **consumes point clouds respecting the permutation-invariance property**.

**PointNet++** processes point clouds **iteratively** by following a simple scheme: grouping, neighbourhood aggregation, and down sampling



- ❑ The **grouping phase** constructs a graph in which nearby points are connected (e.g., kNN, radius)
- ❑ The **neighbourhood aggregation phase** executes a **GNN** layer that, for each point, aggregates information from its direct neighbours
- ❑ The **downsampling phase** implements a **pooling** scheme suitable for point clouds

# The PointNet layer

PointNet layer: input N local regions of points obtained from previous aggregation (e.g. via kNN):

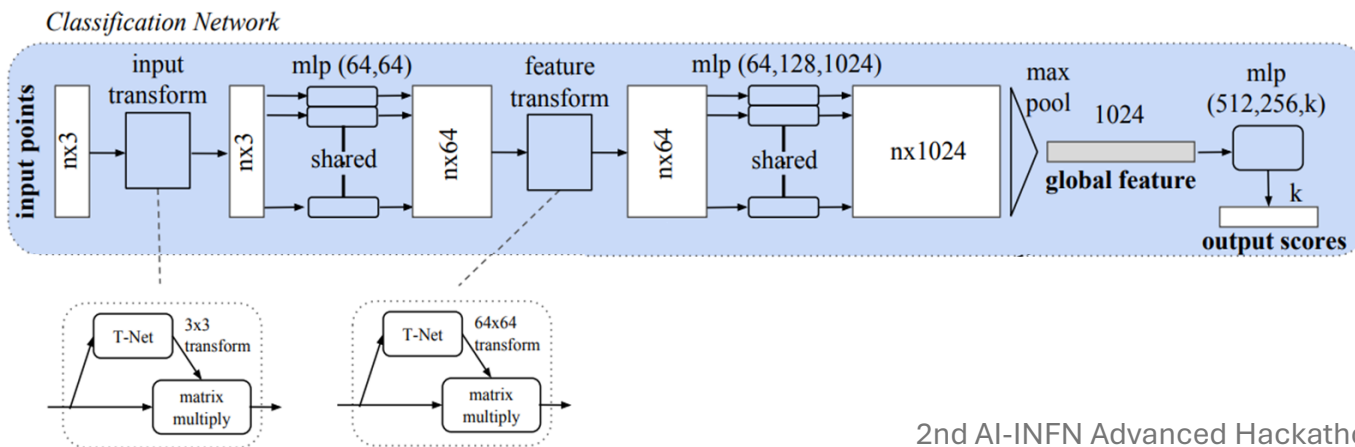
**Max pool** (permutation invariant!) aggregate information on **neighbouring points** of the centroid-i

Centroid-i features

$$x'_i = \max_{j \in N_i} f_{\theta}(x_j, p_j - p_i)$$

The coord of points in a local region are firstly translated into a local frame relative to the centroid point

MLPs parameterized by  $\Theta$



Qi, Charles R., et al. "Pointnet: Deep learning on point sets for 3d classification and segmentation." Proceedings of the IEEE conference on computer vision and pattern recognition. 2017.  
arXiv:1612.00593v2

# The PointNet layer

PointNet layer as a **Message Passing layer**:

1. Compute 'message' on each node
2. Aggregate messages over edges

$$f(\text{graph}) = \phi(\psi(\cdot), \gamma(\text{graph})) = \text{graph}' \rightarrow$$

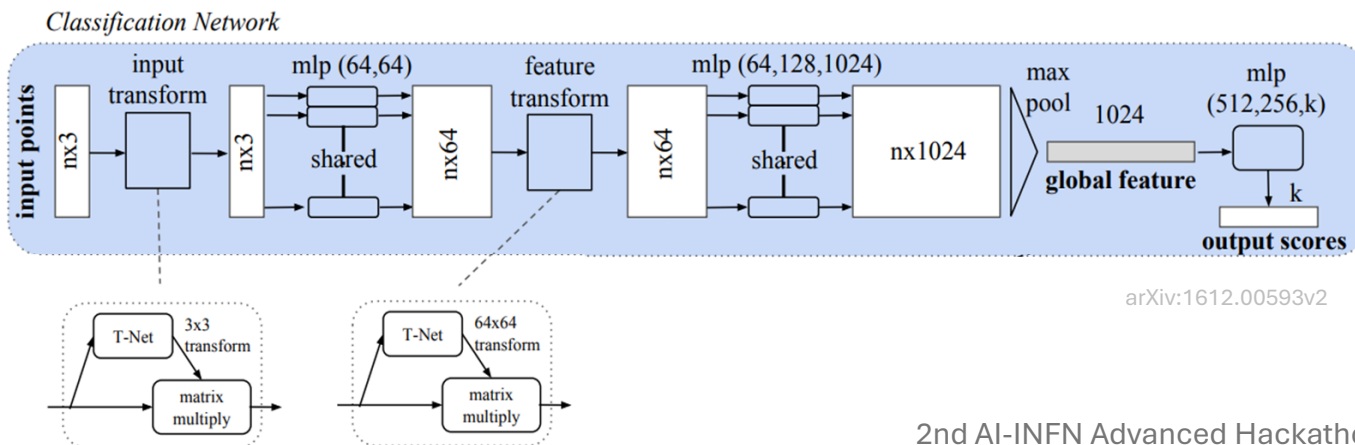
Template formula for a generic MP layer.

$$x'_i = \max_{j \in N_i} f_{\theta}(x_j, p_j - p_i)$$

**Message:** MLP on features + relative location

**Passing:** maximum pooling over neighbours

The PointNet layer is the basic building block for **local pattern learning**: by using **relative coordinates** together with **point features** it can **capture point-to-point relations in the local region**.

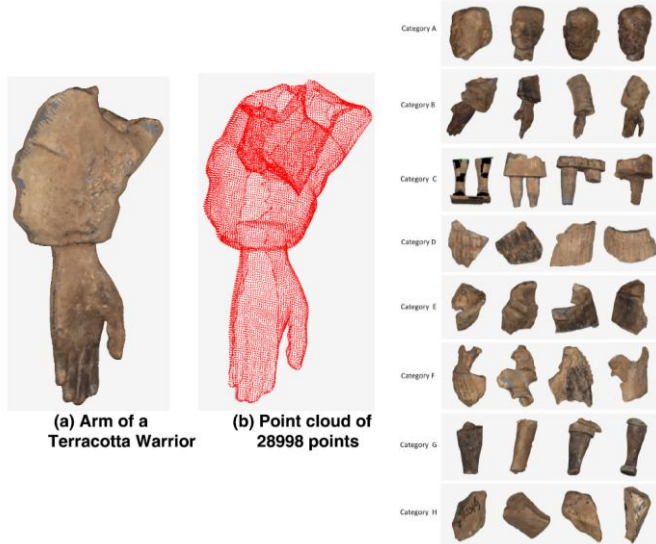


# An example from literature: Chinese terracotta warriors

IEEE Access  
 Received November 25, 2019, accepted December 23, 2019, date of publication December 30, 2019,  
 date of current version January 8, 2020.  
 Digital Object Identifier 10.1109/ACCESS.2019.2962708

**Classification of 3D Terracotta Warrior Fragments  
 Based on Deep Learning and Template Guidance**

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<sup>1</sup>School of Information Science and Technology, Northwest University, Xi'an 710127, China  
<sup>2</sup>Xinshu College, Ningxia University, Yinchuan 750021, China  
 Corresponding author: Guohua Geng (ghgeng@nwnu.edu.cn)



- ❑ First work to apply PointNet to classify 3D fragments in the field of CH
- ❑ Terracotta sculptures created for China's first emperor more than 2,000 years ago.
- ❑ Goal: fragments **classification** into different groups according to their **body part**
- ❑ 878 fragments from 50 Terracotta Warriors + Monte Carlo sampling to **augment the training data** → 4390 fragments from 10 categories
- ❑ Training (3510 fragments): 4-5 hours to converge with TensorFlow and 2 GeForce RTX 2070 GPU. Adam optimizer. Cross Entropy Loss.

Reference	Input	Sample size	Method	Accuracy (%)
[12]	image	527	SIFT+SVM	71.27
[14]	image	6000	CNN-based	89.54
[15]	volume	2096	Residual Network	83.59
This work	point cloud	4390	PointNet+ Template-guide	90.94

**TABLE 5.** Time consuming for proposed method and manual approach.

Method	The number of fragments	Time
Manual approach[36]	3-5	About 8 hours
This work	5	About one minute

From Italy (and INFN):

**CrossMark**

**PAPER**

**OPEN ACCESS**

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 PUBLISHED 6 November 2023

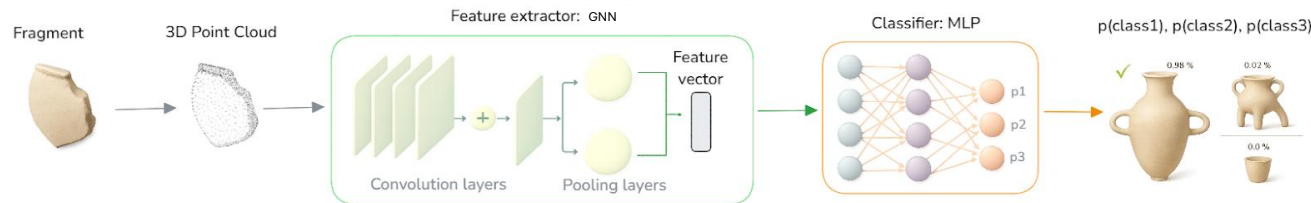
Artificial neural networks exploiting point cloud data for fragmented solid objects classification

A Baiocchi<sup>1</sup>, S Giagu<sup>2</sup>, C Napoli<sup>1</sup>, M Serra<sup>1</sup>, P Nardelli<sup>2</sup> and M Valleriani<sup>2</sup>

<sup>1</sup> Department of Physics, 'Sapienza' University, Rome, Italy  
<sup>2</sup> Department of Computer, Control and Management Engineering, 'La Sapienza' University, Rome, Italy  
<sup>\*</sup> Author to whom any correspondence should be addressed.  
 E-mail: [alessandra.baiocchi@uniroma1.it](mailto:alessandra.baiocchi@uniroma1.it)

# Some ideas for the fragment matching

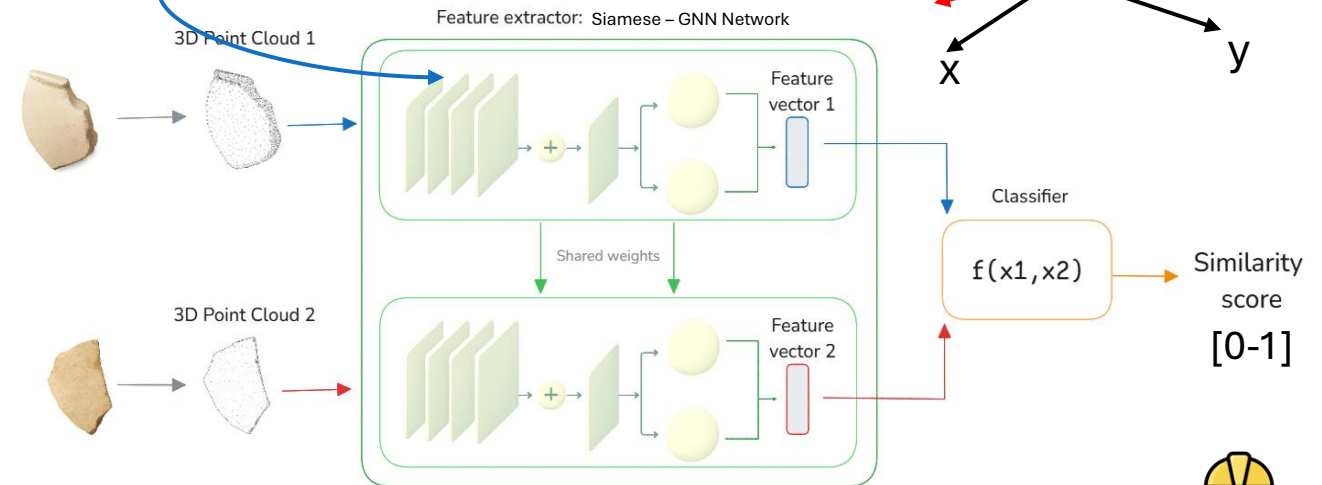
## Branch 1



**Branch 2 - Pairwise matching:** computing the probability that two fragments share a common border.

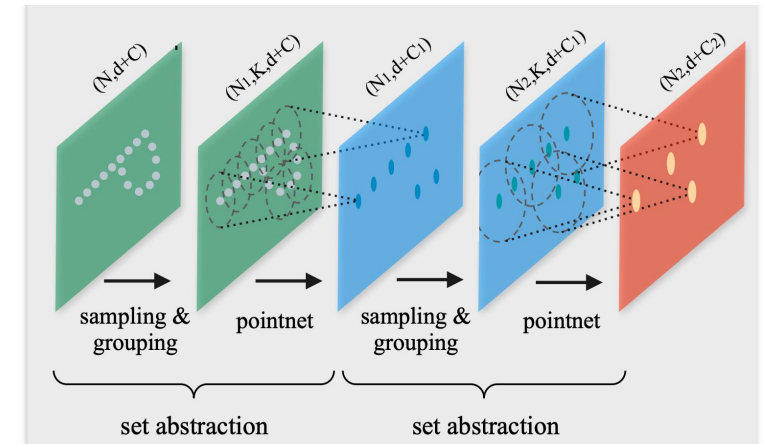
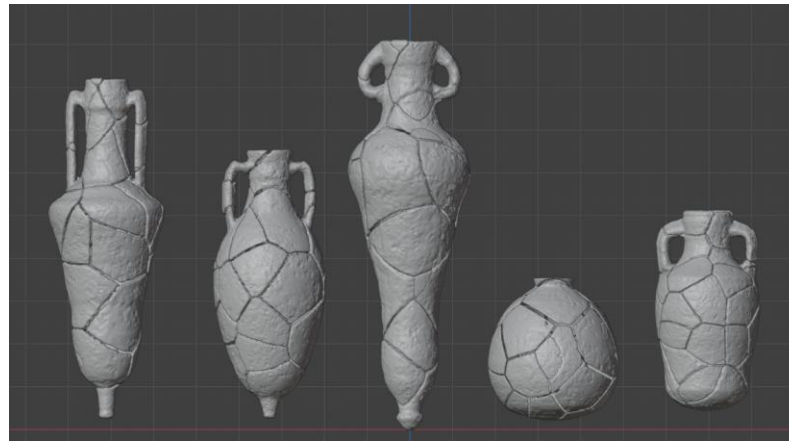
**Siamese learning approach:** fragments with matching fracture surfaces will be mapped to corresponding similar feature vectors, leading to high similarity scores

This procedure will be iterated on all possible fragment pairs belonging to a single object.



# Summary and conclusions

- ❑ The **reassembly problem is crucial in archaeology** and can deeply benefit from application of deep learning
- ❑ Main challenge: create suitable dataset for training and **learn to manipulate unstructured data such as point clouds** → proper deep learning architectures (e.g., PointNet++)
- ❑ **Generation of a synthetic dataset** for amphora reassembly problem using a combination of Python and Blender and implementation of a **distributed approach** using Apptainer
- ❑ PointNet family architectures: how to use them for classification tasks / fragment matching of Nuragic amphorae



# Thank you!

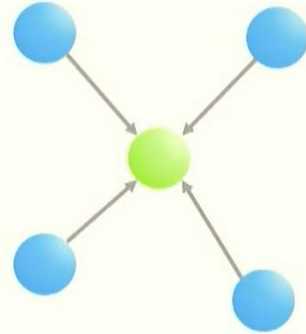
*Team: M. Magalini, S. Barone, A. Bombini, F. Taccetti, M. Serra, M. Ginolfi, A. Re, A. Lo Giudice, L. Castelli, L. Giuntini, G. Salis*



## PointNet++ as Message Passing

1. **Message:** MLP on features + relative location
2. **Passing:** Maximum over neighbors

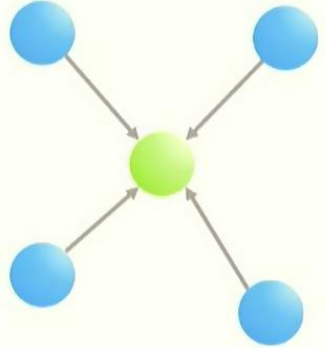
$$x'_i = \max_{j \in N_i} f_{\theta}(x_j, p_j - p_i)$$



## EdgeConv as Message Passing

1. **Message:** MLP on 'relative features' (edges)
2. **Passing:** Maximum over neighbors

$$x'_i = \max_{j \in N_i} f_{\theta}(x_i, x_j - x_i)$$



## GCN as Message Passing

1. **Message:** Linear transformation of features
2. **Passing:** Weight by degree, average

$$x'_i = \sigma(W_0 x_i + \sum_{j \in N_i} \frac{1}{c_{ij}} W_1 x_j)$$

