Metodi e Modelli 3D per l’analisi, la classificazione e l’interpretazione di reperti archeologici

Silvia Biasotti

Bianca Falcidieno

CNR - IMATI

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Pavia

Milano

- ✓ afferisce al DIITET
- ✓ 3 sedi
  - Pavia, presso Polo Universitario
  - Milano, presso Area della Ricerca (Area 1)
  - Genova, presso Area della Ricerca

Genova

- ✓ personale
  - 57 strutturati, 20 in formazione
- ✓ missione
  - fornire competenze e infrastrutture per lo sviluppo della matematica applicata e dell’informatica matematica come strumenti per affrontare le sfide dell’ingegneria e della società

www.imati.cnr.it

CNR-IMATI

PAVIA	GENOVA	MILANO
Modellistica Matematica	Modellazione, analisi e confronto di forme geometriche	Modellizzazione di sistemi stocastici
Analisi Numerica e Calcolo Scientifico	Elaborazione parallela e distribuita	Sviluppo ed applicazioni di modelli statistici
	Rappresentazione della conoscenza	
Studio teorico di PDE	**Geometria e topologia computazionale**	**Modelli statistici per studi sperimentali e osservazionali**
Metodi numerici per la soluzione di PDE	**Modelli e Strumenti per HPC e sistemi distribuiti**	**Statistica bayesiana**
	Formalizzazione della conoscenza, semantic web	**Modelli stocastici**
meccanica di contatto, elasticità lineare e deformazioni, plasticità, elettromagnetismo,..	*design, confronto, riconoscimento, similarità e motori di ricerca 3D, big data 3D*	*processi ambientali, industriali, ingegneria, finanza, biologia medicina,..*

competenze

IMATI - *prospettiva scientifica*

geometria

analisi numerica

statistica e stocastica

HPC e architetture di calcolo

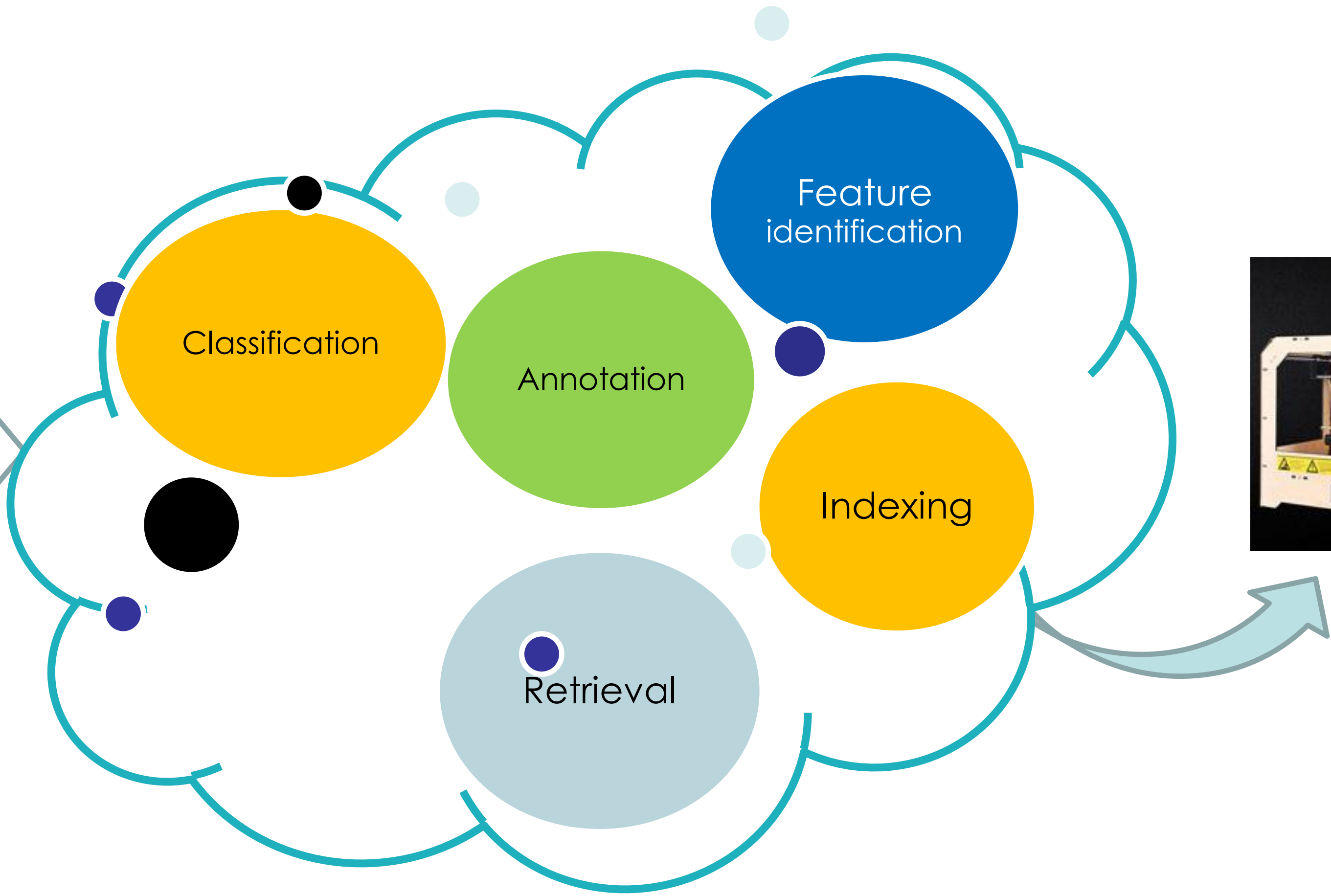
Metodi e modelli per la simulazione di processi in ambiti scientifici caratterizzati da dati geometrici complessi

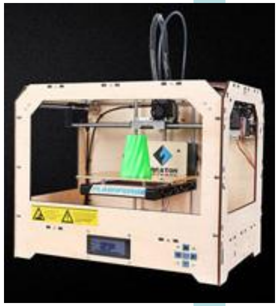
formalizzazione della conoscenza

Beni Culturali – Medicina - Progettazione Industriale – Ambiente

ruolo distintivo di IMATI nel DIITET

Shape and Semantics Group research





Results in the last 3 years

- **13 EU Projects** (3 H2020, 1 ERC)
- **20 National/Regional projects**
- **≈ 130 International Publications** (60 ISI journal papers)
- **≈ 20 Research Fellows and Students** per year
- **≈ 900 K Euro average external revenues** per year
- **9 International Conferences and Workshops** organized & chaired (Graphics & Cultural Heritage October 2016)

<u>Eurographics Genova 6-10 maggio 2019</u>

more than 100 presentations, new think tank sessions, electronic theater, industrial program, 3 co-located workshops

Learning at EG2019

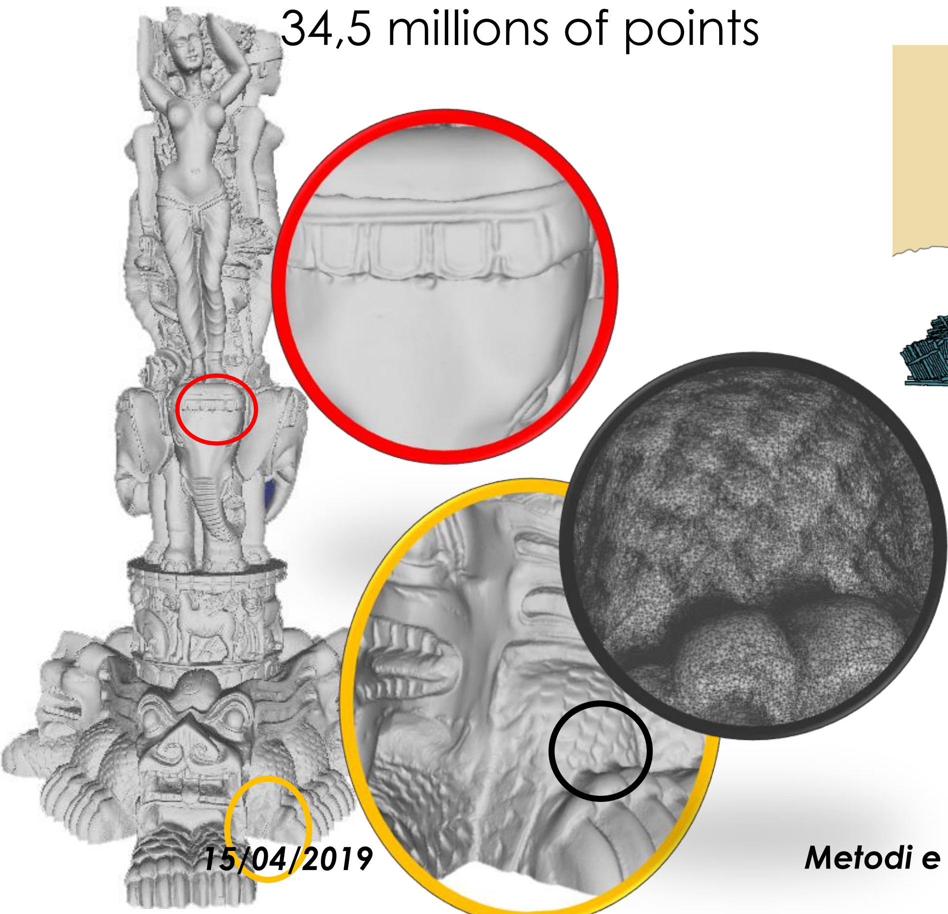
- 2 Tutorials
  - T1: Deep Learning for Computer Graphics and Geometry Processing
  - T4: Learning Generative Models of 3D Structures
- 4 Paper sessions
  - FP10: Learning to render
  - FP12: Learning to animate
  - FP15: Learning images
  - SP5: Learning and Networks
- 2 Think tanks
  - TT1: CreativeAI - AI meets Graphics – Challenges and Opportunities Ahead
  - TT2: The future of avatar-human interaction in VR, AR and mixed reality applications

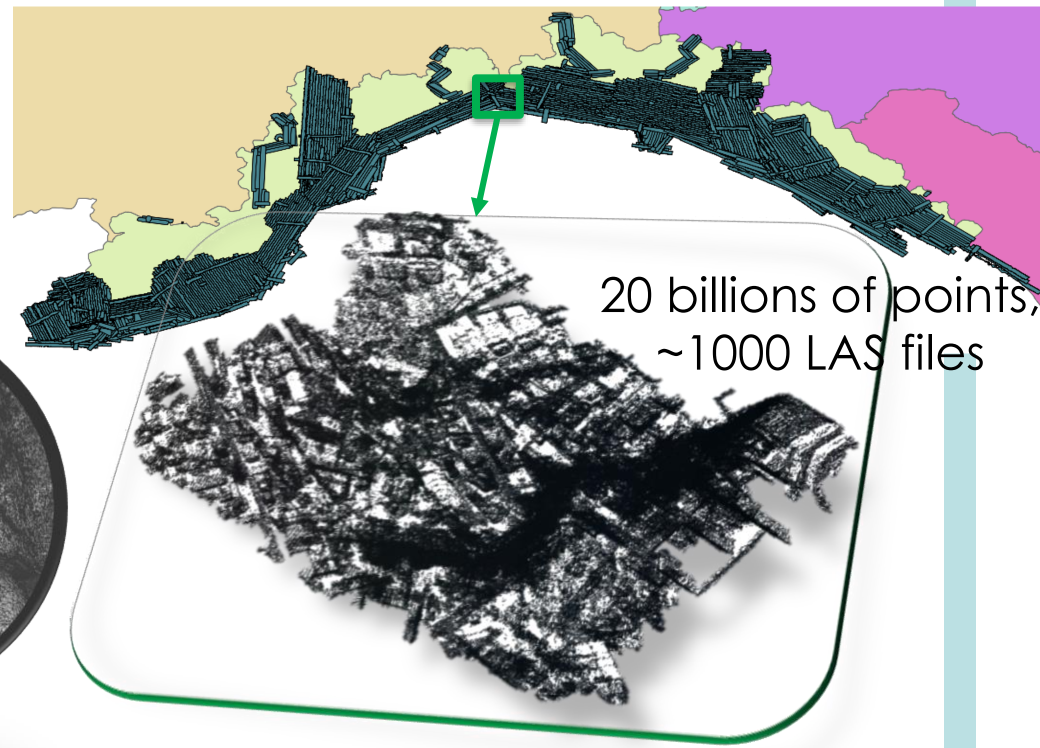
how to classify and explore collections of 3D data?

with a special eye to archaelogical 3D data

3D models & big data

- ✓ 3D models are intrinsically complex
  - high resolution scans are now available and contains millions or billions of points (and faces)





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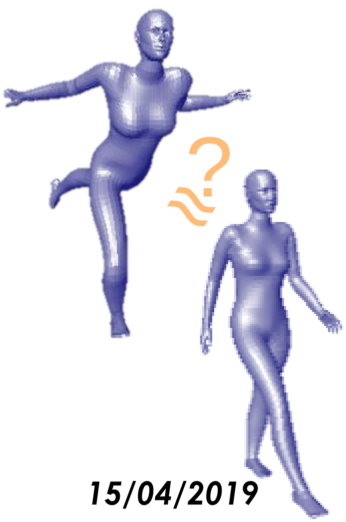
  - high quality scans are now available and contains millions or billions of vertices (and faces)
- ✓ 3D models cannot be handled as images
  - illumination, views, occlusions are not an issue...
  - but issues are: pose invariance, incompleteness, noisy data, …



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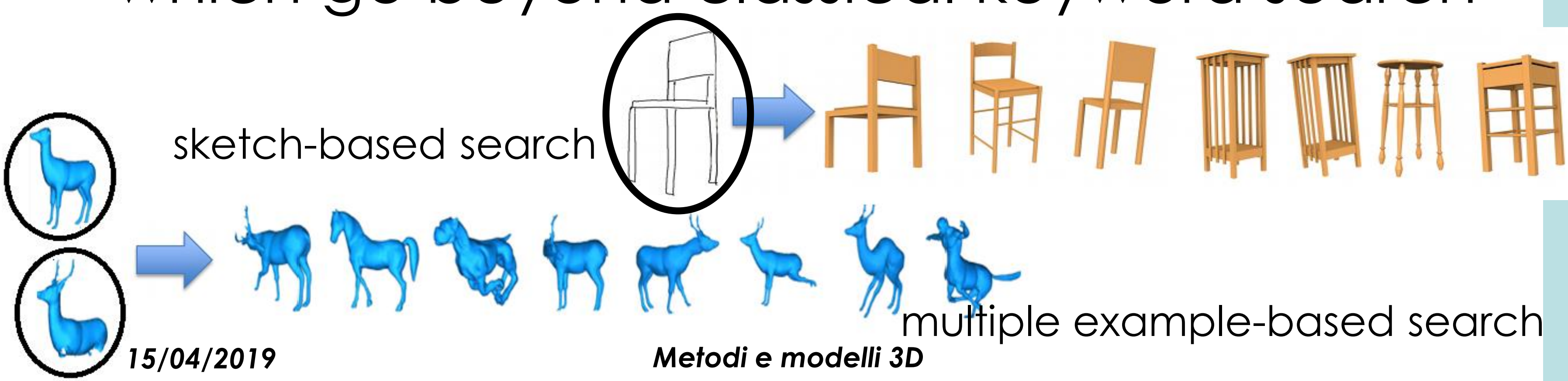

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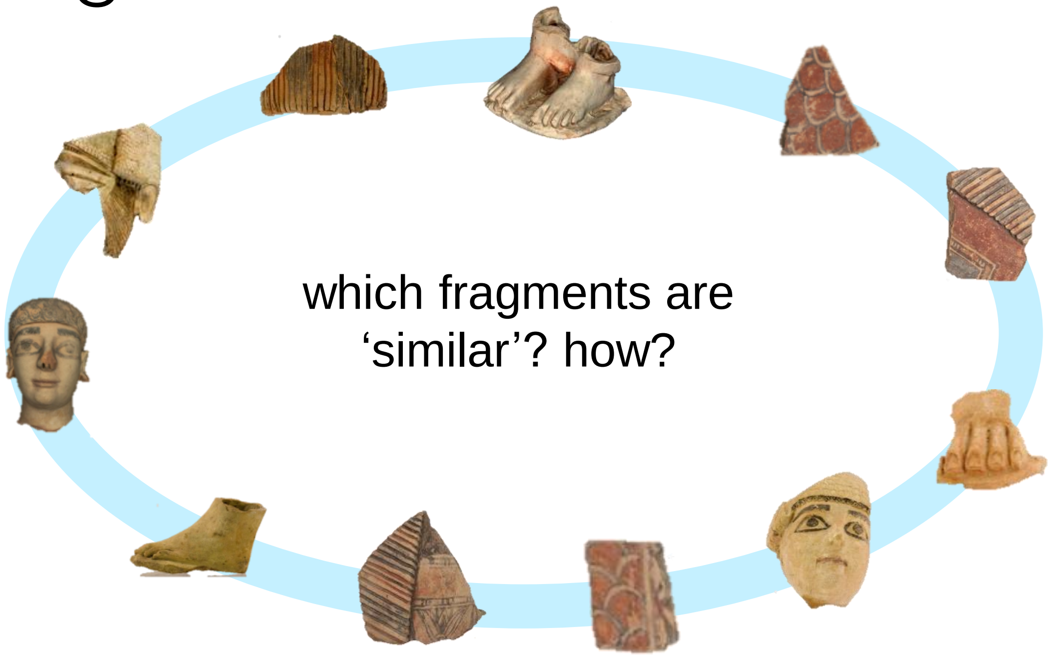
- 3D content needs modalities for searching which go beyond classical keyword search
- we are addressing similarity reasoning in collections of 3D models with heterogeneous properties and shape
  - geometric shape…
  - … but also material, color, decorations, common parts

search by geometric similarity: what do we mean?

- ✓ to what extent are similarity techniques able to support archaeologists in the their cataloguing and classification work?



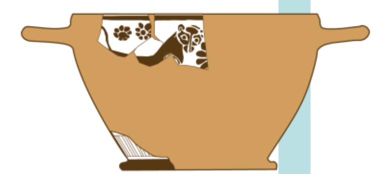
- ✓ the concept of similarity must be flexible to adapt to the different user requests

challenges

- to create software tools to allow archaeologists & curators to reconstruct **shattered** or **broken** CH objects
- to **recognise associations** between artefacts to allow new knowledge and understanding of past societies
- to **identify** and **re-unify** parts of a cultural object that has been **separated across collections**

Re-Unification

Re-Association



Re-Assembly

we need to tune similarity the specific use case

what kind of similarity ⟷ **what properties are relevant**

- if two fragments belong to the same statue, then probably they have the same thickness
- if two fragments belong to the same statue and are contiguous to each other, then probably
  - they have the same curvature
  - the decorations are compatible

distinction among fragments that are sherd-like and fragments with an almost *volumetric* shape

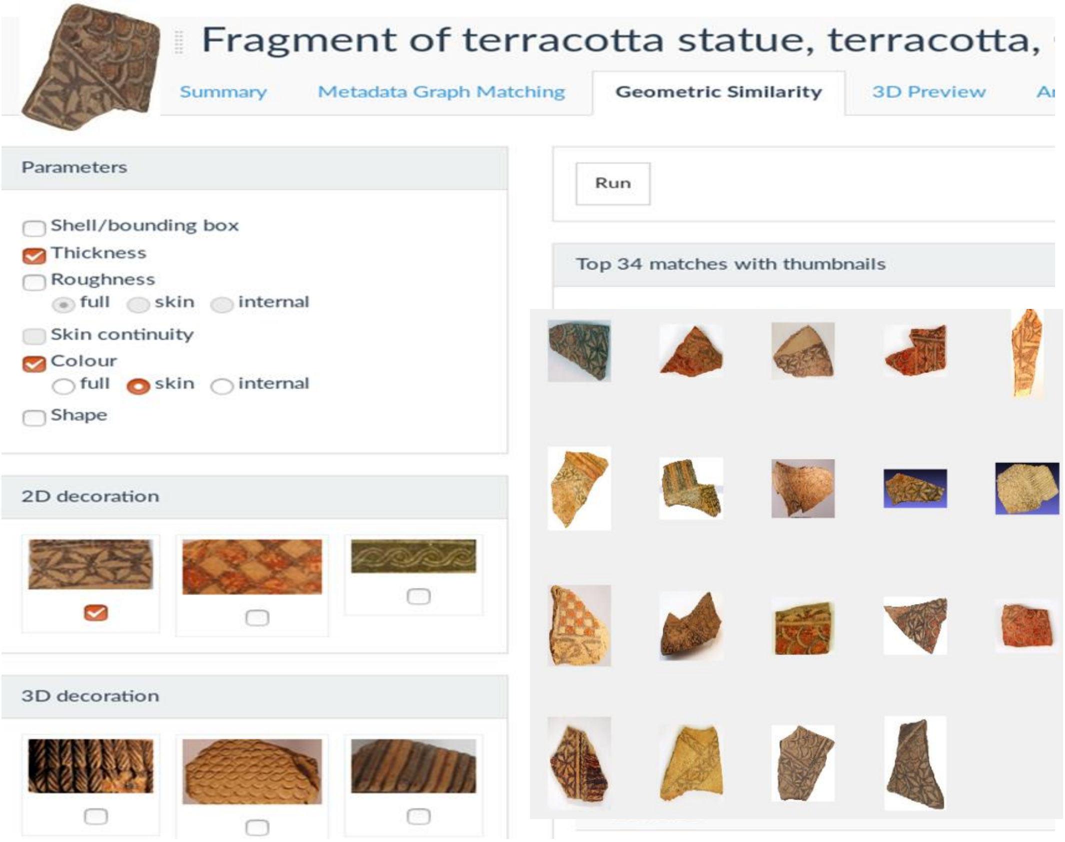
similarity assessment: information about..

- ✓ geometry/morphology
  - shape of sherds / fragments – 3D scanning
  - shape of features
    - patterns, decorations, features,..
- ✓ color
  - scanning process
  - chemical analysis, pigment composition
- ✓ x-ray fluorescence, …
- ✓ museum catalogues
- ✓ archeological descriptions
- ✓ curated data

results

✓ thickness, curvature, shape & decorations drive the GRAVITATE "similarity engine"

http://gravitate-project.eu/?q=content/dashboard



Biasotti et al., (2019), Context-adaptive navigation of 3D model collections, **Computers&Graphics**

an example on man-made objects

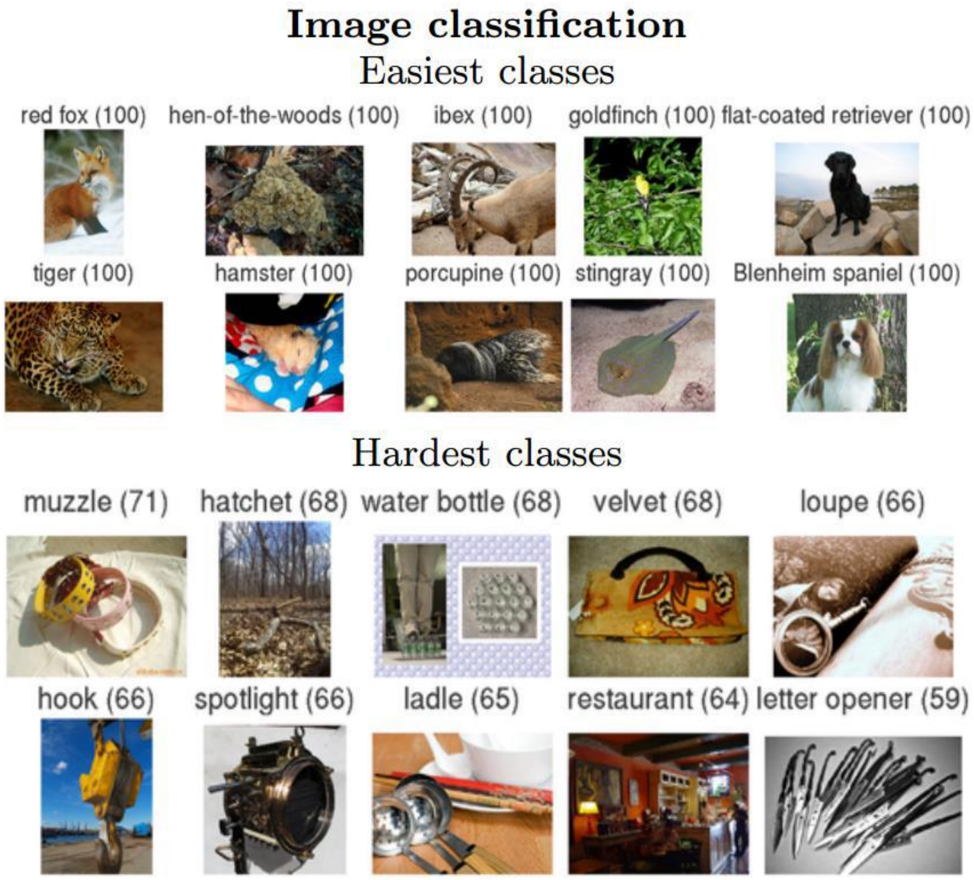
- ✓ multi-criteria search, extension to generic repositories

color
shape
shape + thickness

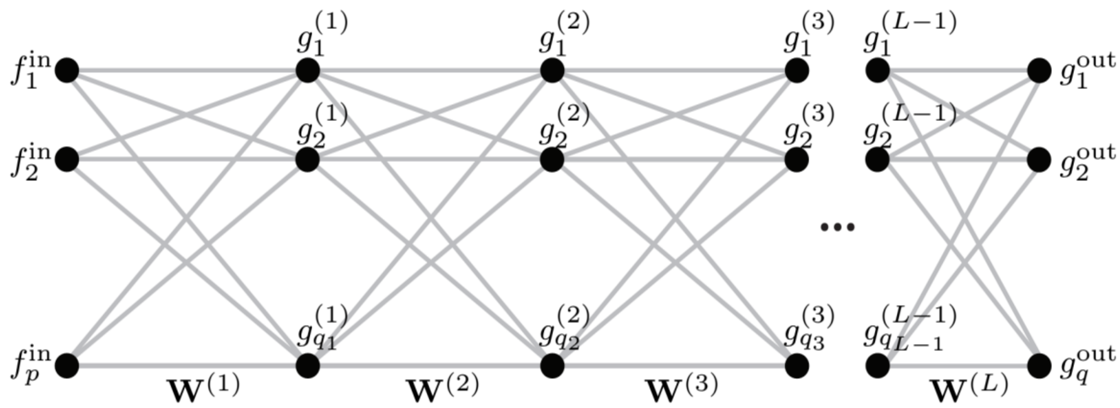
- ✓ management of cross- and multi- modality searches and datasets (sketches, images, 3D models, time-varying objects, object sub-parts, features, etc..)

deep learning: the technique that quietly changed Computer Vision

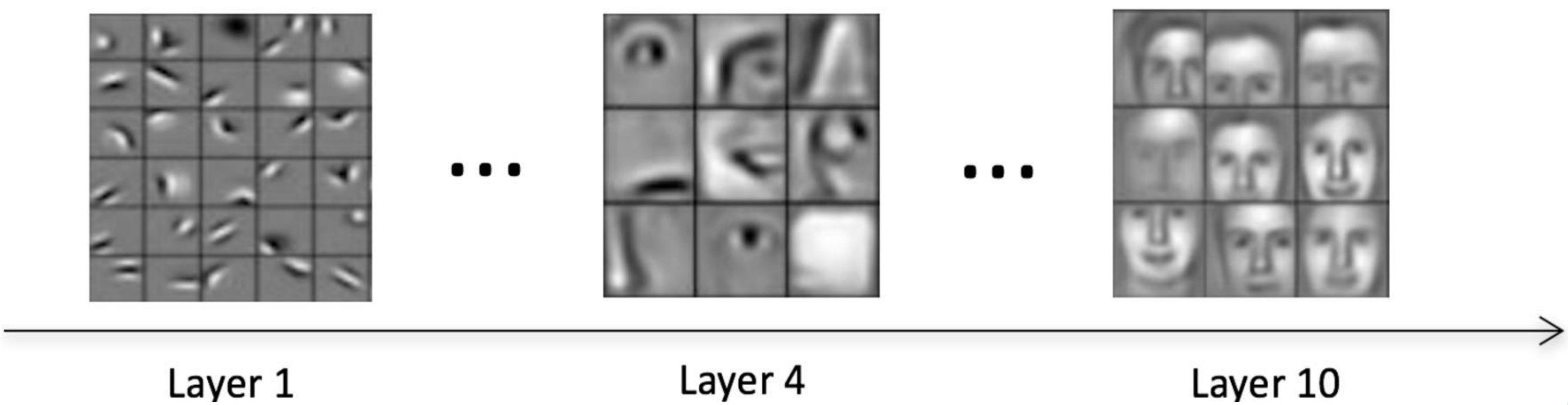
- ✓ **2012**: A deep convolutional neural network wins the ImageNet Large Scale Visual Recognition Challenge



deep neural networks on images



Deep neural network consisting of L layers

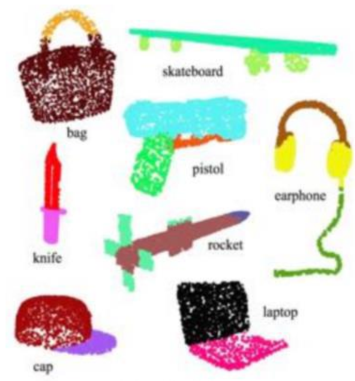


from simple to abstract structure

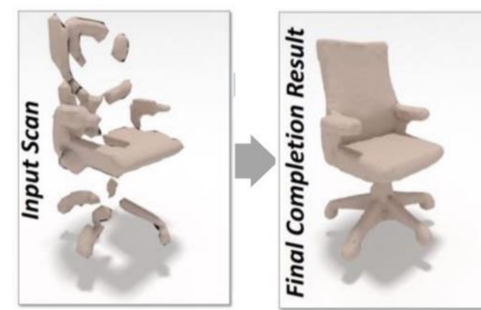
...and 3D data?

a tutorial on 3D DeepLearning, CVPR 2017, http://3ddl.stanford.edu/

- ✓ content analysis
  - object classification
  - scene parsing
  - correspondence



- ✓ 3D synthesis
  - reconstruction from images
  - shape completion and modeling

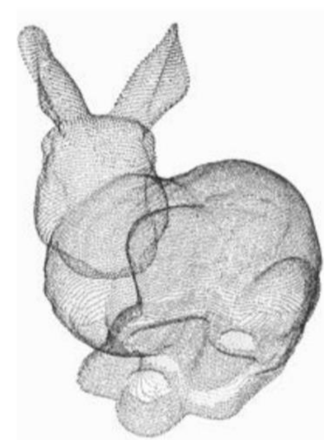


- ✓ 3D assisted image analysis
  - cross-view image retrieval

- ✓ images have a unique representation with a regular data structure, where as **3D objects do not**

1	44	33	12	20	23	35	14
51	16	40	32	46	48	28	17
29	60	3	63	49	55	36	7
52	22	26	41	38	10	61	53
2	24	19	11	34	43	5	8
57	9	37	42	25	21	27	18
30	56	50	64	4	59	6	13
58	47	45	31	39	15	62	54

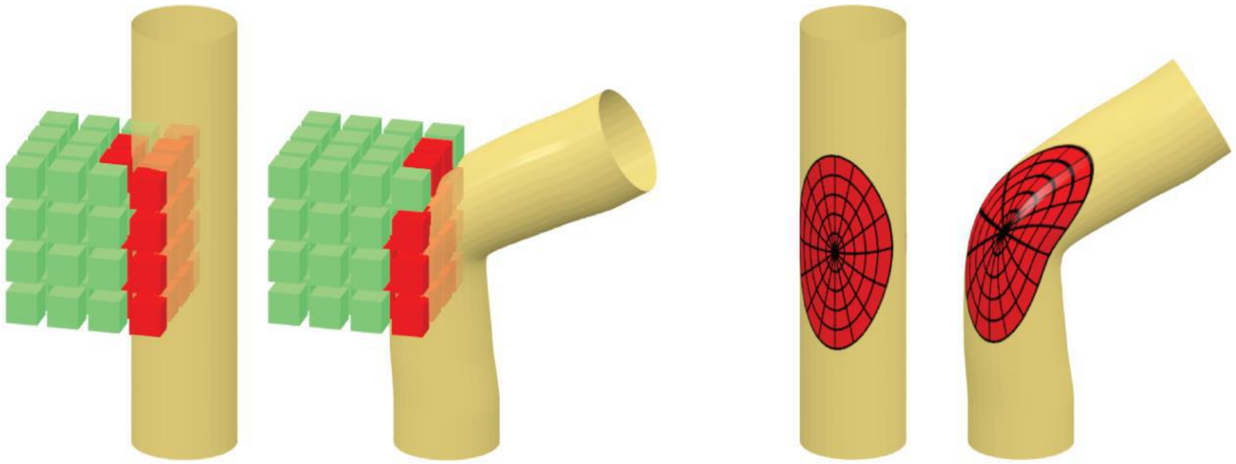
meshes



point cloud

two possible approaches

- ✓ converting to regular grids and use traditional architectures for Euclidean data
- ✓ defining non-Euclidean CNNs

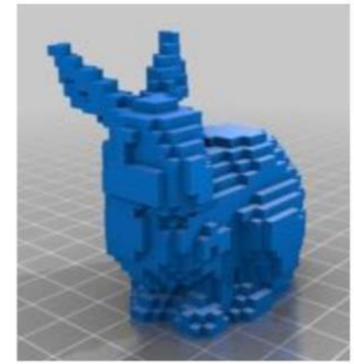


Extrinsic

Intrinsic

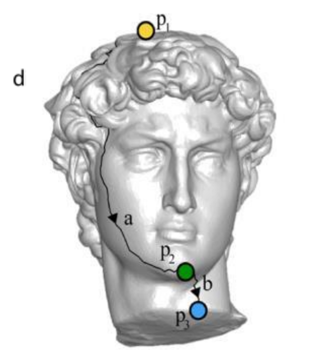
converting to regular grids

- voxel-based representations

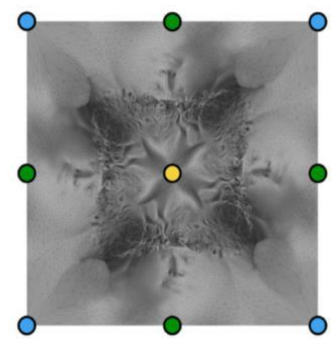


- multiple 2D views

- embedding domains



Surface $\mathcal{S}$ with sphere topology



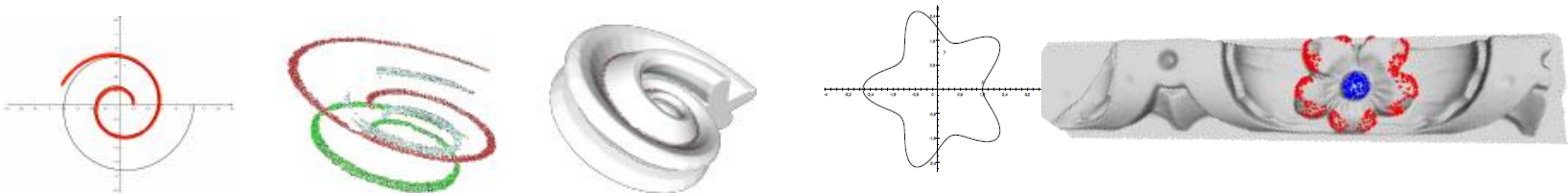
Flat-torus $\mathcal{T}$ with 4 replicas of $\mathcal{S}$

the impact of deep learning on data analysis and math

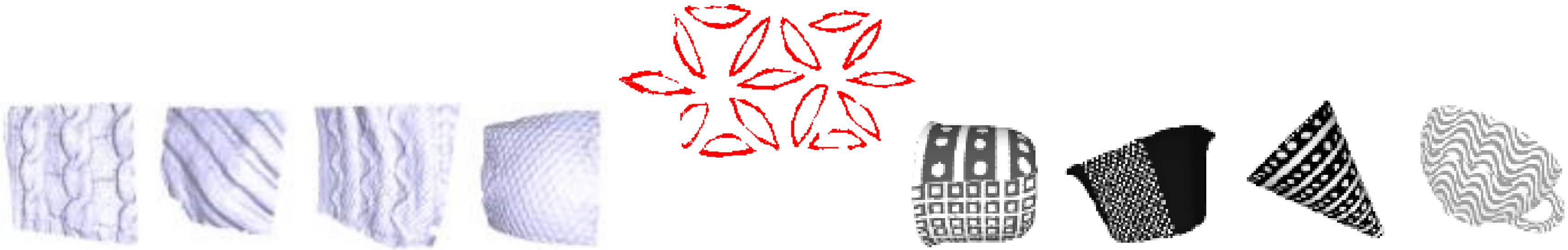
- should we *"fight back and seek ways to fuse ideas from deep learning into our more solid foundations"*?
  [Michael Elad: *Deep, Deep Trouble*, https://sinews.siam.org/Details-Page/deep-deep-trouble]

- the **challenge** for **geometry** and **topology** could be **to model what cannot be**, or **requires too much effort to be**, learned automatically *(e.g., built-in invariance or **lack of large training sets**, e.g., CH)*

- pattern recognition for surfaces
  - recognition of complex features: semantic elements, decorations, patterns, style,...



Torrente, Biasotti & Falcidieno (2018) *Recognition of feature curves on 3D shapes using an algebraic approach to Hough transforms*. **Pattern recognition**



Moscoso Thompson & Biasotti (2018) *Description and Retrieval of Geometric Patterns on Surface Meshes using an edge-based LBP approach*. **Pattern recognition**

Moscoso Thompson & Biasotti, (2019), Color patterns retrieval on surface meshes using the edgeLBP description, **Computers&Graphics**

some thoughts

- computational methods have the potential to support archeological studies with *quantitative evaluations* of their findings

towards 3D annotations

- we humans *think fast (*intuition or heuristic process*) and slow* (conscious, rule-based reasoning).
  - typical machine learning algorithms like deep neural networks usually just think fast

- we humans are able to model information.
  - with deep learning based solutions, the interpretability of the solution is an issue