

Software bottlenecks for 3D AI

X-IA #16 Santé : Molécules, Protéines et 3D

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Today's talk: a computer's perspective on 3D shapes

1. What is an **image**?
2. Software **bottlenecks** for AI research
3. What you can **expect** going forward

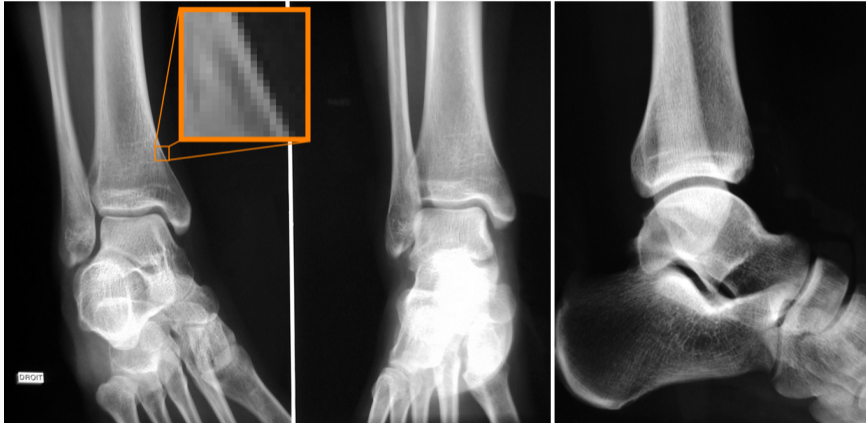
What is an image?

What do you see on a medical image? [Zyg]



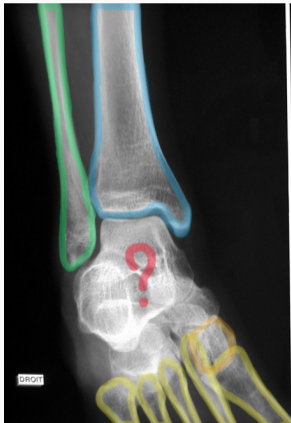
What do you see on a medical image? [Zyg]

1. Pixels

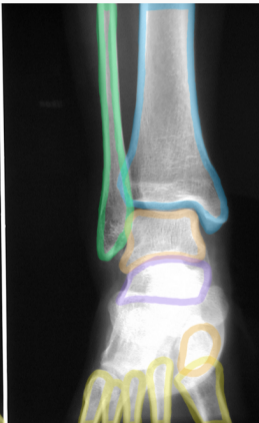


What do you see on a medical image? [Zyg]

1. Pixels



2. Anatomy

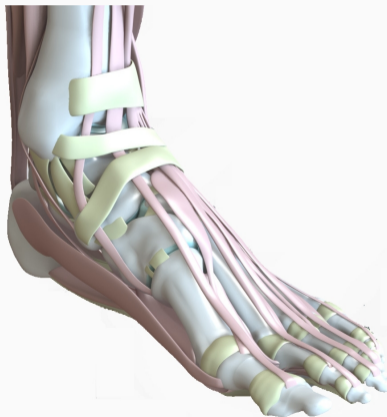


What do you see on a medical image? [Zyg]

1. Pixels

2. Anatomy

3. Function

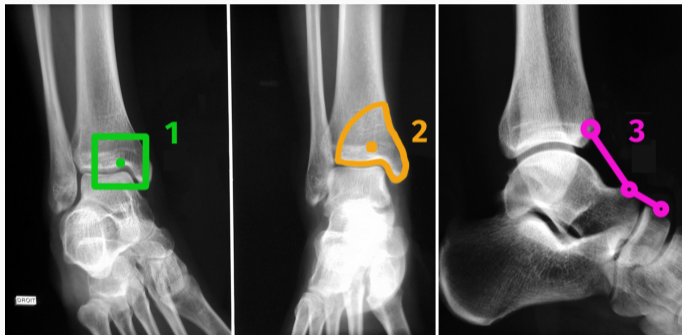


What do you see on a medical image? [Zyg]

1. Pixels

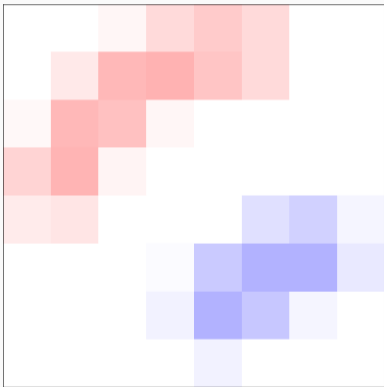
2. Anatomy

3. Function



Simplifying a bit, each level of analysis corresponds to a way of **grouping pixels** with their neighbors.

1st level: a pixel grid

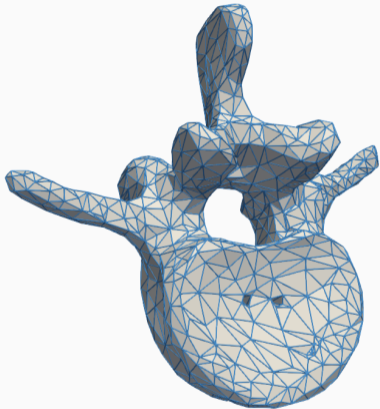


$N_x \times N_y \times N_z$ array of pixels.

Bitmap images and volumes:

- .bmp, .png, .jpg
 - Standard in **radiology**.
-
- + Ordered memory structure.
 - + Explicit neighborhoods.
 - + Fast **local** filters.
-
- **Texture** analysis.
 - Organ **segmentation**.
 - Pattern **detection**.

2nd level: point clouds and 3D surfaces



$N_{\text{points}} \times 3$ array of (x, y, z) coordinates.

Clouds of points (\pm triangles):

- .svg
 - Standard for **video games**.
- + Compact representation.
- + High precision geometry.
- + **Easy to deform**.
- **3D visualization**.
- Anatomical **atlas**.
- **Shape** analysis.

3rd level: biomechanical and/or physiological model [Zyg]



Volumetric mesh,
graph of interactions.

Mechanical/biological model:

- Finite elements, networks.
 - Standard for **CAD**.
-
- + Prior **knowledge**.
 - + **Robust** to noise.
 - + **Realistic** behaviour.
-
- **Physiological** interpretation.
 - **Infer** what cannot be seen (stress).
 - **Simulate** a surgery.

Strengths and weaknesses of these image formats

Looking for the **neighbors** of a point in 3D space?

- On a **grid** : **read** adjacent memory cells.
- With N **points** (x, y, z) : **computation** of N distances.

Want to **rotate** a bone by 10°?

- On a **grid** : **artifacts**, loss of details, transfers between memory cells.
- With N **points** (x, y, z) : **simple** arithmetics on the coordinates.

Computational **speed** \Leftrightarrow Training on **large datasets**.

To summarize

AI = **statistical regression** method + relevant **computational model**.

In biomedical imaging, we represent data as:

1. A 2D or 3D **pixel grid**.
2. An array of (x, y, z) **coordinates**.
3. A **web** of complex interactions.
4. All three at once!

In most cases, we define a large **structured formula**:

$$\text{image} \xrightarrow{F} F(\text{image}) \simeq \text{diagnostic}$$

F is a parametric computing **architecture**
 \simeq **model** to fit \simeq **network** to train.

Software bottlenecks for AI research

The AI revolution is driven by gaming computers

Digital images and machine **learning** have been studied for **decades**.

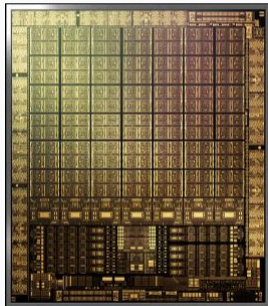
Breakthrough in 2010-15 : using **PlayStations** to do **science** became **easy**.

Research effort at all levels towards:

- Increasingly powerful **computers**.
- Increasingly convenient **software toolkits**.
- Increasingly relevant **models**.

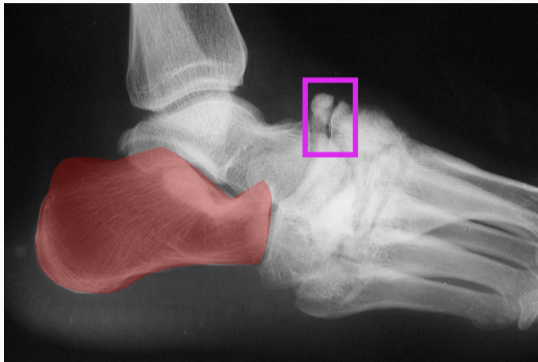
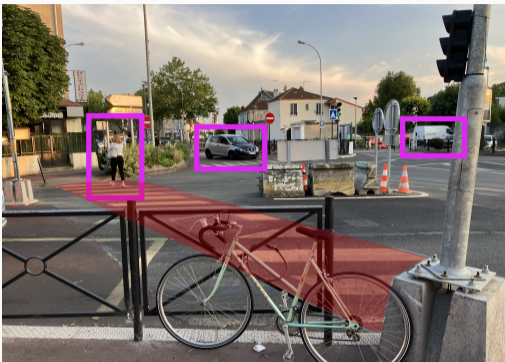
Spectacular results in a few applications

⇒ massive **investments**, industry + governments.



10,000 cores on a GPU.

For grid images: a mature ecosystem



Main motivation for AI in 2012-2022: **self-driving cars**.

Key challenges: **segment** the environment, **detect** other actors.

Two full software suites to manipulate **images as grids of pixels**:

TensorFlow (Google) and PyTorch (Facebook-Meta).

To go beyond prototypes, AI engineers need a full software suite

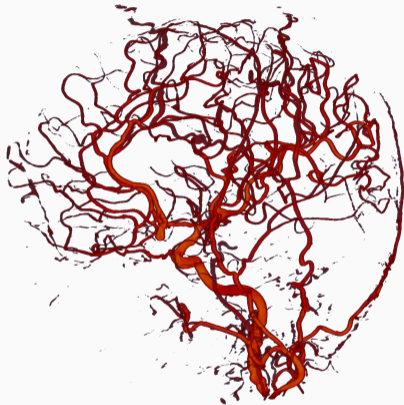
Graphics: Printer + Driver + **Photoshop** \Rightarrow Illustrations

Tabular data: GPU + **cuBLAS** + **PyTorch**
TensorFlow \Rightarrow “Classical”
neural networks

Pixel grids: GPU + **cuDNN** + **PyTorch**
TensorFlow \Rightarrow **Convolutional**
neural networks

**Point clouds
and graphs :** GPU + **CUDA** + **??** \Rightarrow **Geometric**
neural networks

For point clouds and graphs: work in progress

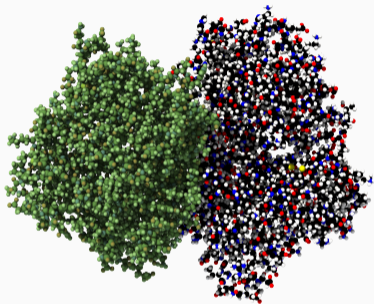


Brain arterial network.

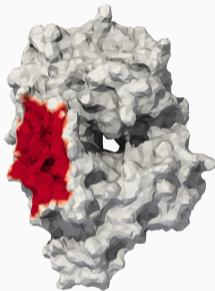
How do we **process this object**?

An ecosystem under construction:

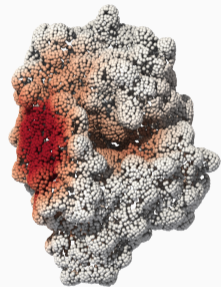
- **KeOps** : since 2017
 - Fast learning with **point clouds**.
- **PyG** : since 2018
 - Fast learning with **graphs**.
- **Warp**, **FEniCSx** and **PhiFlow** : since 2018
 - Fast learning with **physics**.
- **PyVista** and **Vedo** : since 2019
 - **3D visualisation**.
- **scikit-shapes**: released soon
 - Easy **morphometrics**.



(a) Raw protein data.

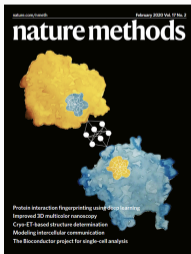
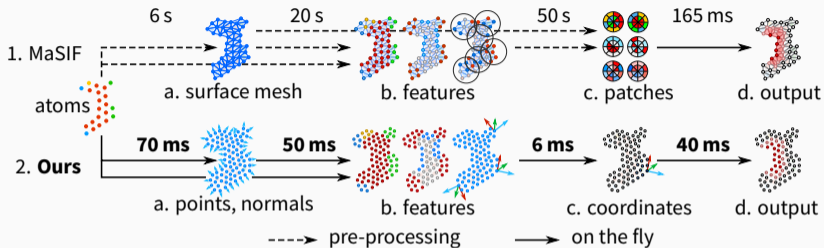


(b) Interface.



(c) Prediction.

Fast end-to-end learning on protein surfaces

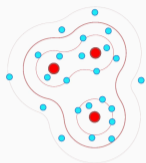


×100 - ×1,000 faster, lighter
and fully differentiable.

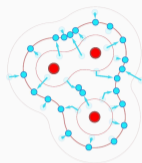
Idea 1: on-the-fly sampling of protein surfaces



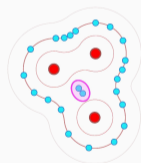
(a) Distance.



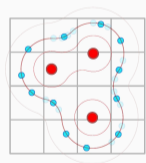
(b) Sampling.



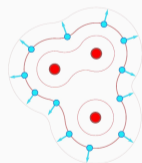
(c) Descent.



(d) Cleaning.



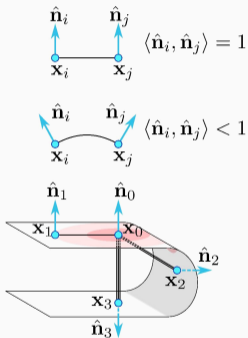
(e) Sub-sampling.



(f) Normals.

Fast, fully **differentiable**, heterogeneous batches (without padding).

Idea 2: quasi-geodesic convolutions

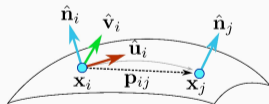


(a) Quasi-geodesic distance d_{ij} .

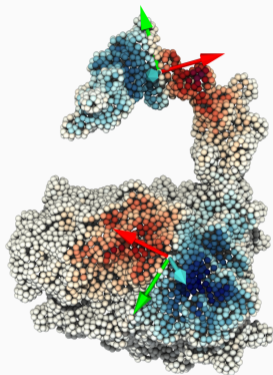
$$\mathbf{p}_{ij} = \underbrace{\left[(\mathbf{x}_j - \mathbf{x}_i)^\top \right]}_{\text{delta of positions}} \cdot \left[\hat{\mathbf{n}}_i \mid \hat{\mathbf{u}}_i \mid \hat{\mathbf{v}}_i \right]$$

$$\mathbf{q}_{ij} = \underbrace{\left[(\hat{\mathbf{n}}_j - \hat{\mathbf{n}}_i)^\top \right]}_{\text{delta of normals}} \cdot \underbrace{\left[\hat{\mathbf{n}}_i \mid \hat{\mathbf{u}}_i \mid \hat{\mathbf{v}}_i \right]}_{\text{local coordinate system}}$$

$$\text{Conv}(\mathbf{x}_i, \mathbf{x}_j, \mathbf{f}_j) = \underbrace{\text{Window}(d_{ij})}_{\text{quasi-geodesic patch}} \cdot \underbrace{\text{Filter}(\mathbf{p}_{ij}, \mathbf{q}_{ij})}_{\text{oriented filter}} \cdot \mathbf{f}_j$$



(b) Quasi-geodesic convolution.



Fast, fully differentiable, heterogeneous batches (without padding).

KeOps (www.kernel-operations.io) lets us implement:

- **Custom** operations that best reflect a biological prior.
- Zero need to talk about CUDA blocks, threads, etc.
- Great tool for **prototyping with geometric ideas**.

Main limitation: beyond 32 channels per convolution, register spilling.

This is just **one example** of architecture that is equivariant to isometries.

(Some?) general E3NN layers could also be accelerated.

Conclusion

- **Gaming computers** (GPUs) are the workhorses of AI.
A **full software suite** is required to rein in these machines.
- Since 2015, **biomedical imaging** rides a wave of investment from the **FAANG** for **natural** image processing.
- Breakthroughs: **segmentation**, **texture** analysis and lesion **detection**.
What about **surgical** planning, **morphometrics**, **vascular** analysis... ?
- An **investment in the numerical foundations** of the field is under way.
Tradeoffs between ease of use, versatility, speed, portability, etc.

References

 Freyr Sverrisson, Jean Feydy, Bruno E. Correia, and Michael M. Bronstein.

Fast end-to-end learning on protein surfaces.

bioRxiv, 2020.

 Zygote.

Solid 3d human foot and ankle model.

<https://www.zygote.com/cad-models/solid-3d-human-anatomy/cad-human-foot-ankle-model>.