PARSIMONIOUS NEURAL NETWORKS



Bypassing numerical simulations: deep learning perspectives in vertebrae modeling





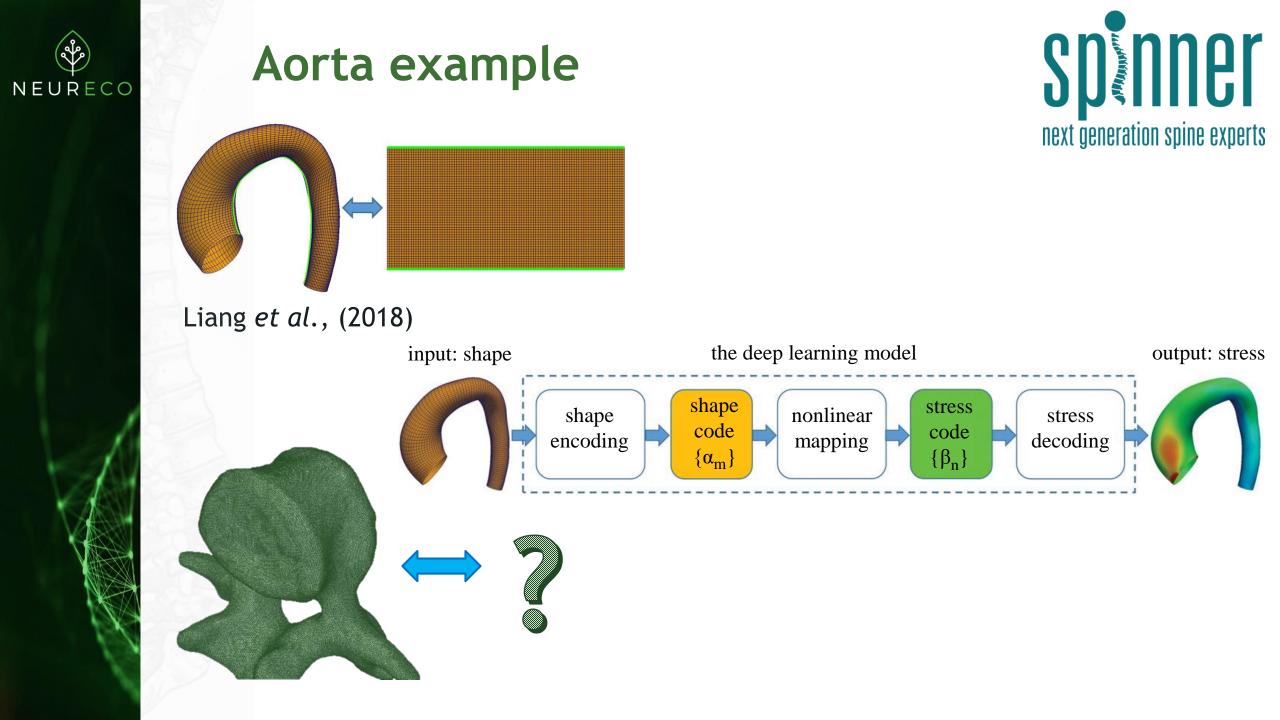
SPINNER



Deep Learning Methods and Reduced Order Modelling Techniques for Patient-Specific Spine Models

Project Aim

" To develop real-time biomechanical simulations of spinal surgical setups by integrating parsimonious deep learning approaches into the setup and execution of finite element simulations. "





Objective: Mesh Morphing for Anatomical Shape Parameterisation

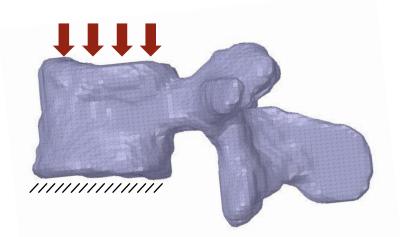


Objective : "By using a mesh morphing approach to parameterise the shape variations in a training set of lumbar vertebra, develop an artificial neural network to substitute the simulation of a lumbar vertebra under a compressive load."

Dataset (Yao et al., 2012):

- CT scans with manual segmentations
- 10 spines (50 lumbar vertebrae)
- Fully anonymised and publicly available at: SpineWeb.DigitalImagingGroup.ca

The Simulation:



Yao, J., Burns, J., Muñoz, H. and Summers, R., (2012). Detection of Vertebral Body Fractures Based on Cortical Shell Unwrapping. International Conference on Medical Image Computing and Computer Assisted Intervention, 7512, 509-516.

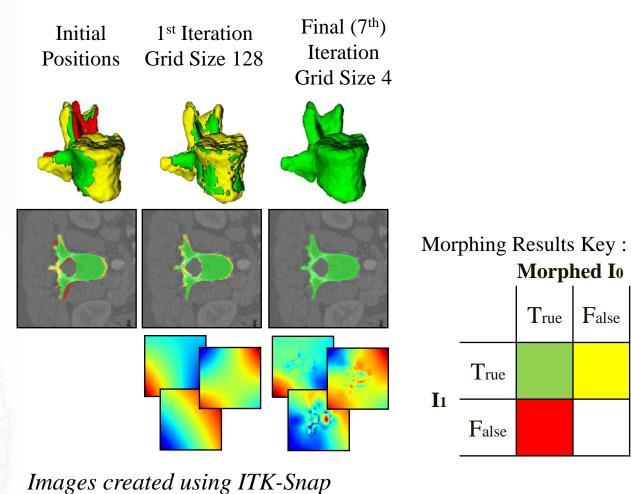


Mesh Morphing



Morphing Results

 $V_x, V_y \& V_z$

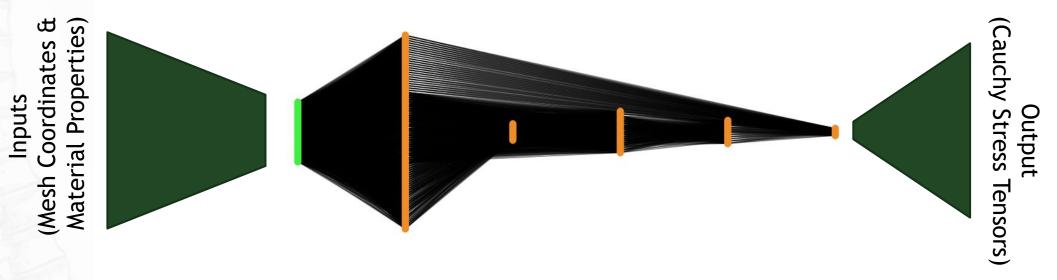


Fehrenbach, J. and Masmoudi, M., (2008). A fast algorithm for image registration. Comptes Rendus Mathématique, 346(9-10), 593-598.



Compressions & Neural Network





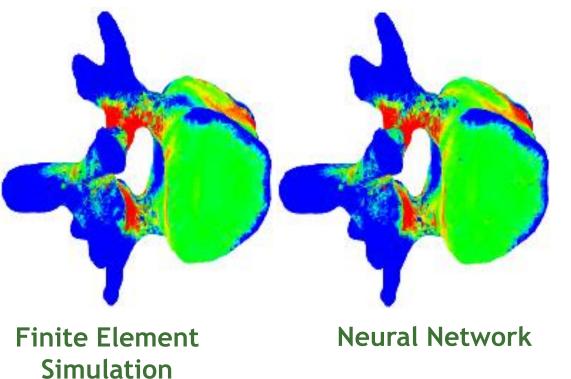
NeurEco Neural Network



Testing Set Results



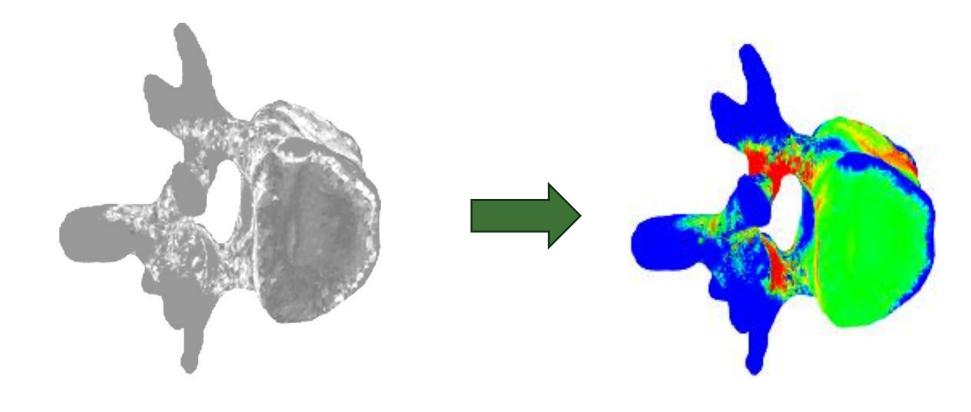
Testing Sample Results for $\sigma_{\scriptscriptstyle 11}$ of the Cauchy stress tensor



- Error 6.00% in the Euclidean norm of the output vector.
- Execution time of the ANN is around 1% of the execution time of the equivalent FEA simulation.



Perspective Skip everything and learn directly

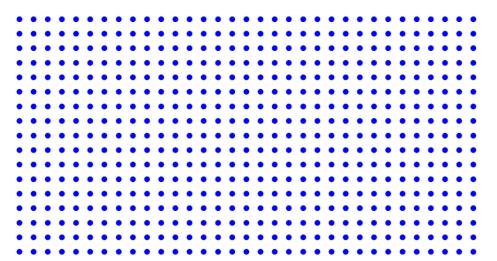




Convolutional approaches: Target applications

Work with structured data, for example

► The outputs of the solver



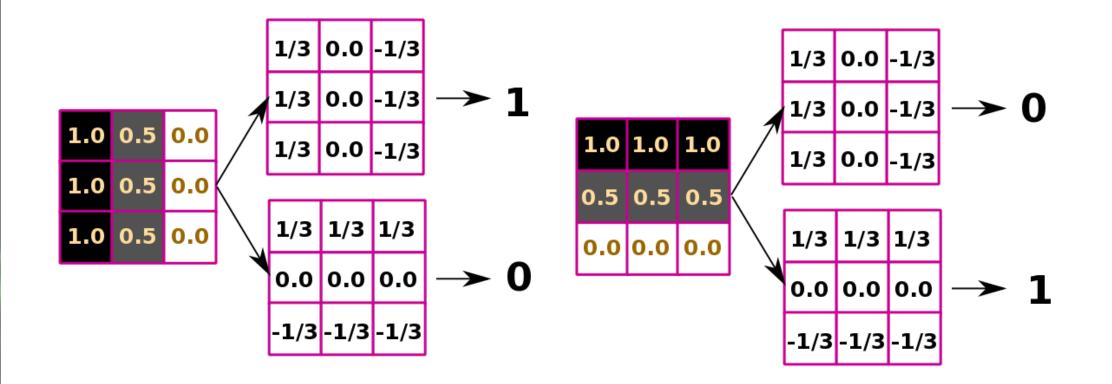






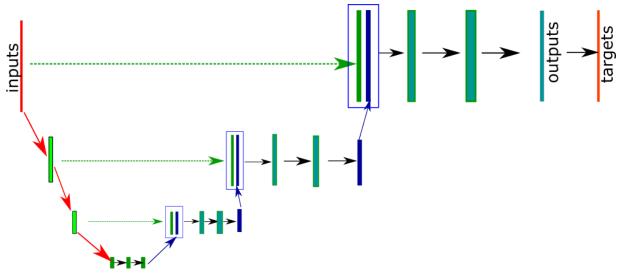


How convolution "sees" things?





Adagos version of U-Net for PDEs



- Convolutions with 3x3xd kernels, stride=1, preserves shape
- -----> Parallel propagation of information (no calculations)

Concatenation

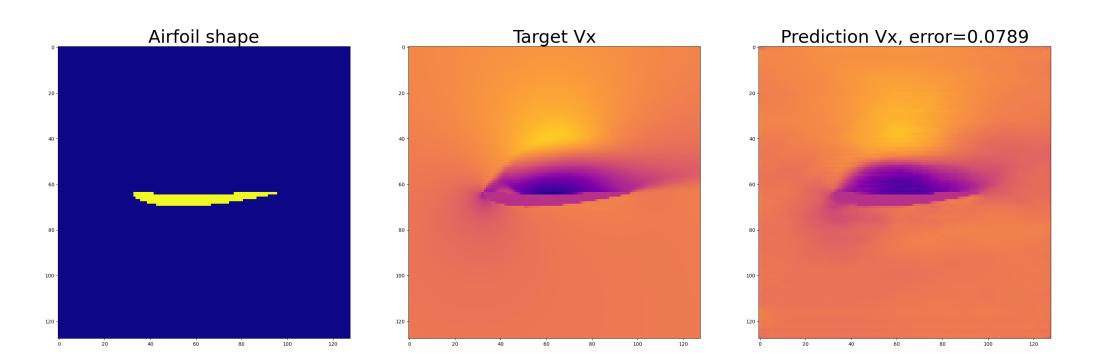
Compression. Wavelets constructions. For enrichment convolutions with 3x3xd kernels, stride=2, divides each spatial dimension size by two

Decompression, upconvolutions with 3x3xd kernels, stride=2, multiplies each spatial dimension size by two

- Inspired by PDE theory and wavelets theory
- Deterministic initialization
- Automatically deduced architecture
- Small size





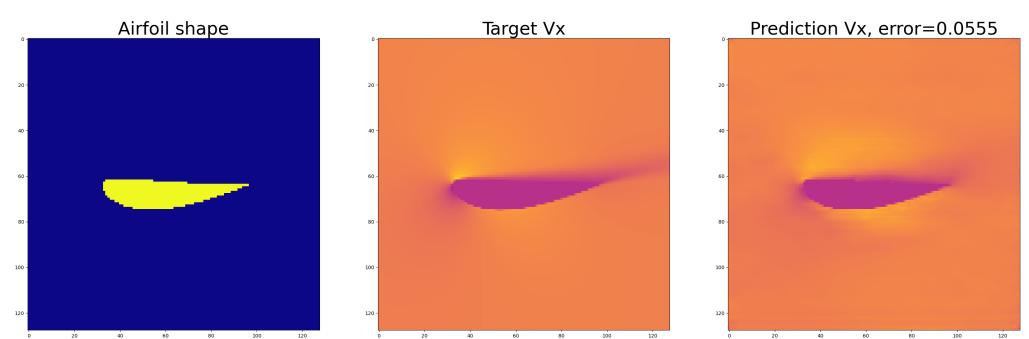




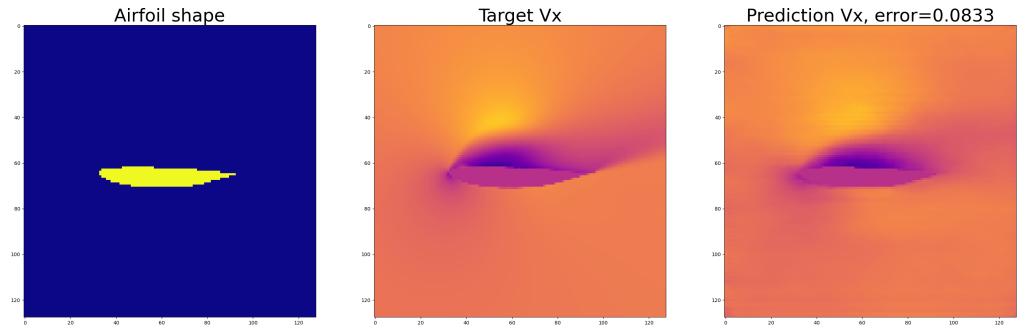




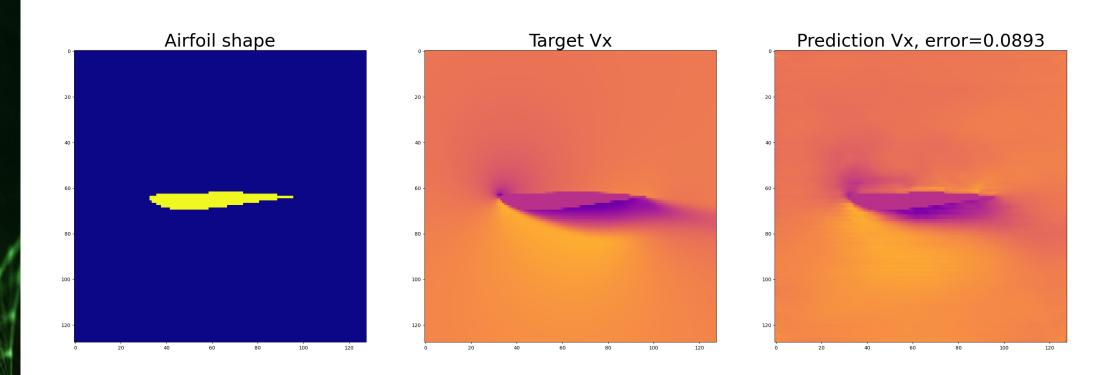




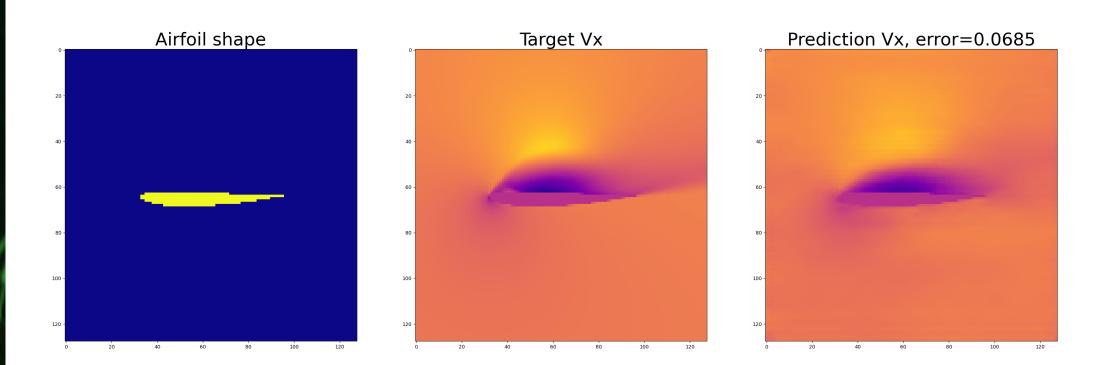














Thank You for your attention! Q&A