Machine Learning Solutions for Simulation and Reconstruction in Highly Granular Calorimeters

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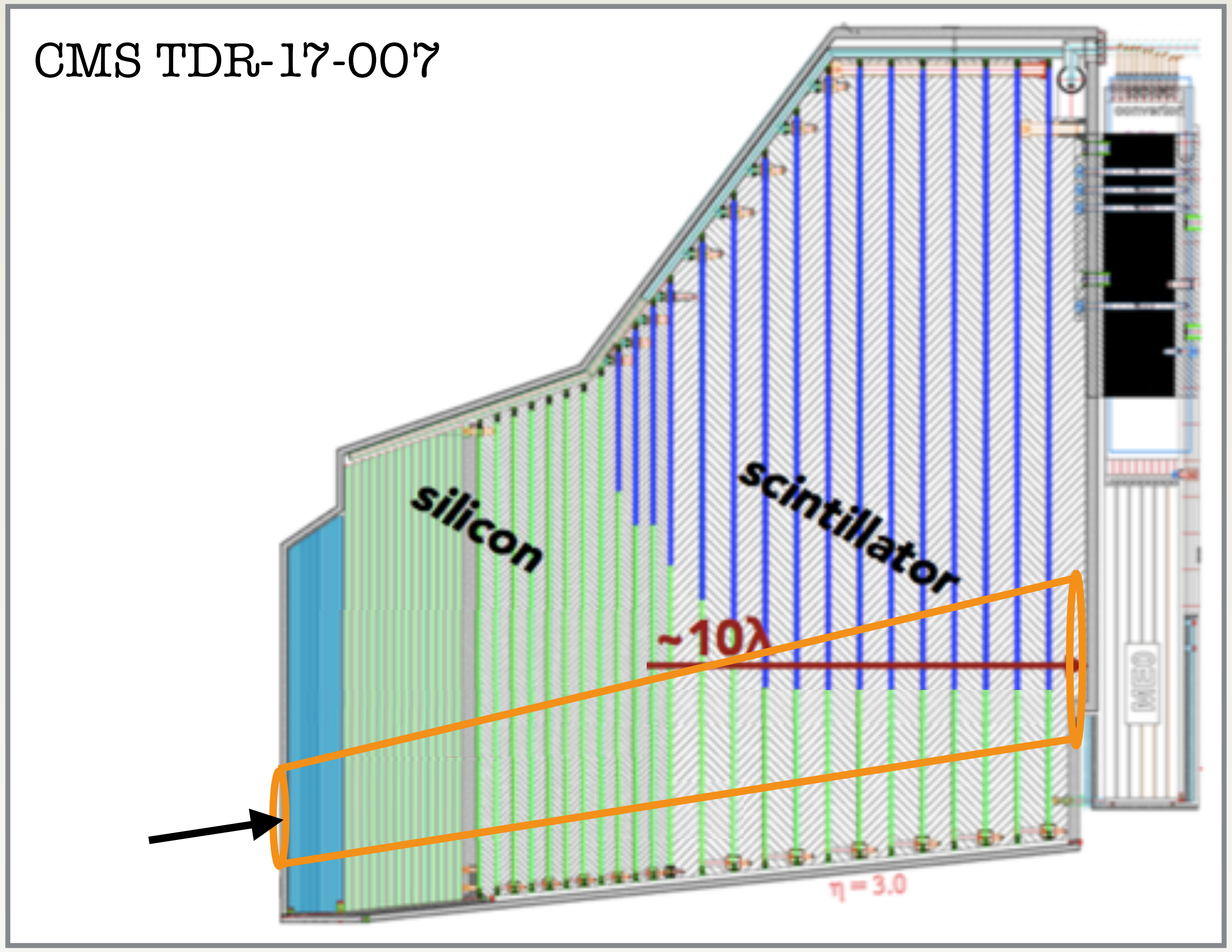
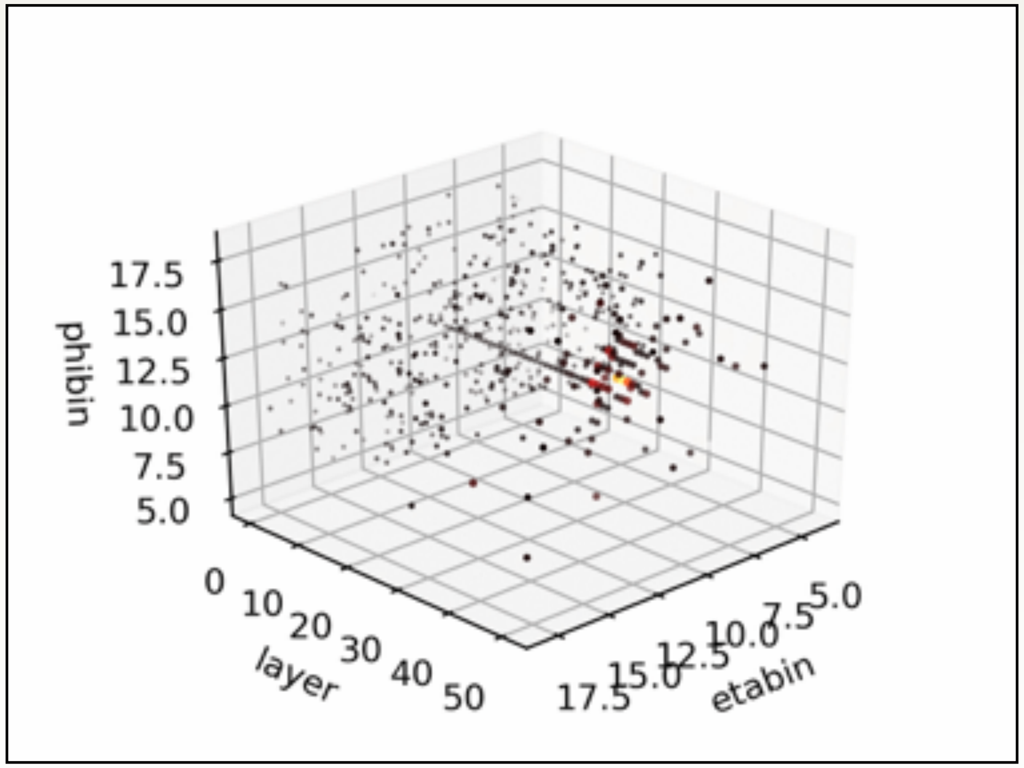
CMS HGCal as an Example

- HGCal produces 3D shower images
  - Space
  - Energy (+time) as colour
- Large amount of 'noise' from pile-up, close by particles
- Large number of inputs: 6M channels





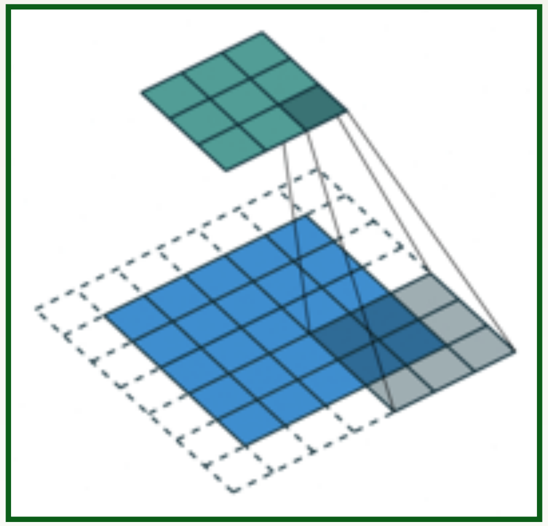
- Tasks:
  - Identify showers in noise
  - Identify particle type from shower shape
  } strong similarity to pattern recognition/ computer vision
  - Measure energy

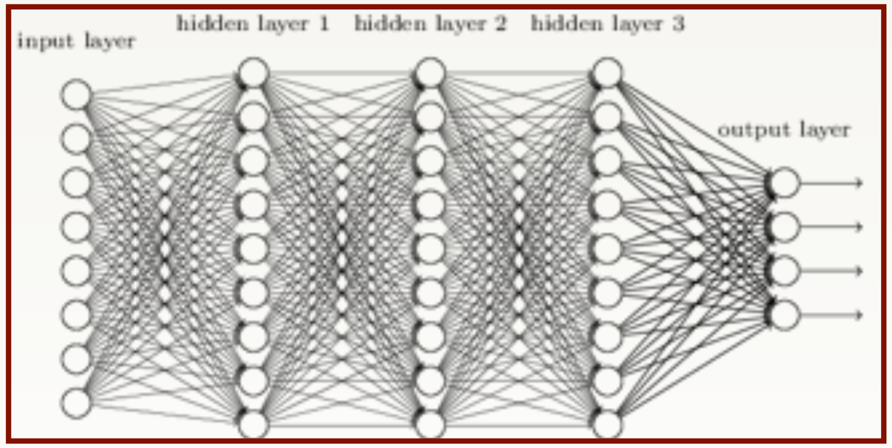
Deep Neural Networks (Computer Vision)

- Approach to handle large amount of raw inputs: DNN

- Three basic DNN types
  - Fully connected 'dense' (very powerful but many parameters)
  - Recurrent ('time' series, good for sparsity, slower*)
  - ✓ Convolutional (translation invariant structures)

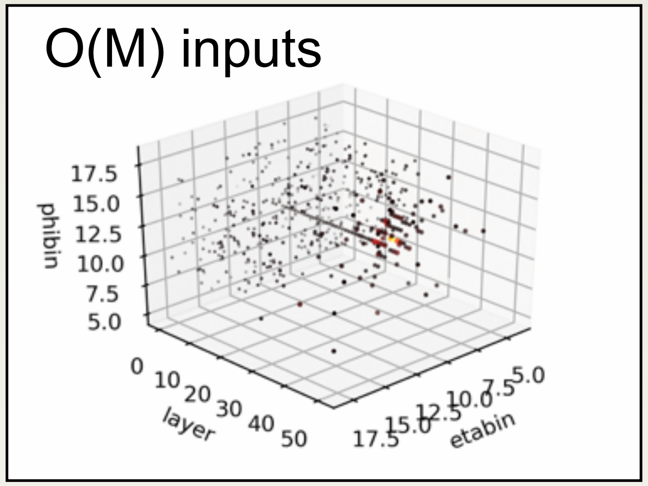
- For image processing: usually **convolutional** layers followed by a set of dense layers



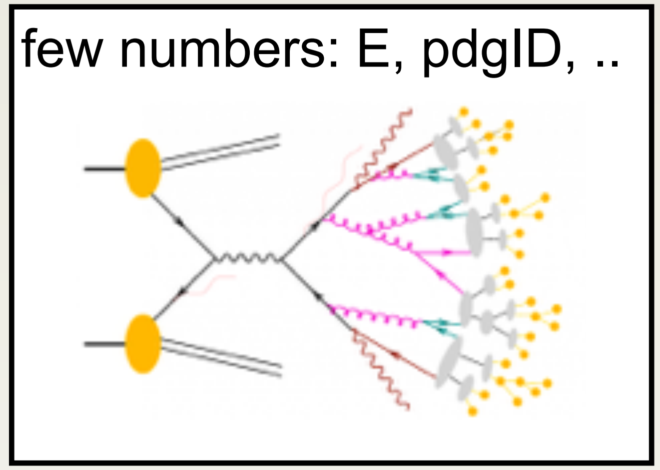


- DNNs are **fast** and **highly parallelizable**

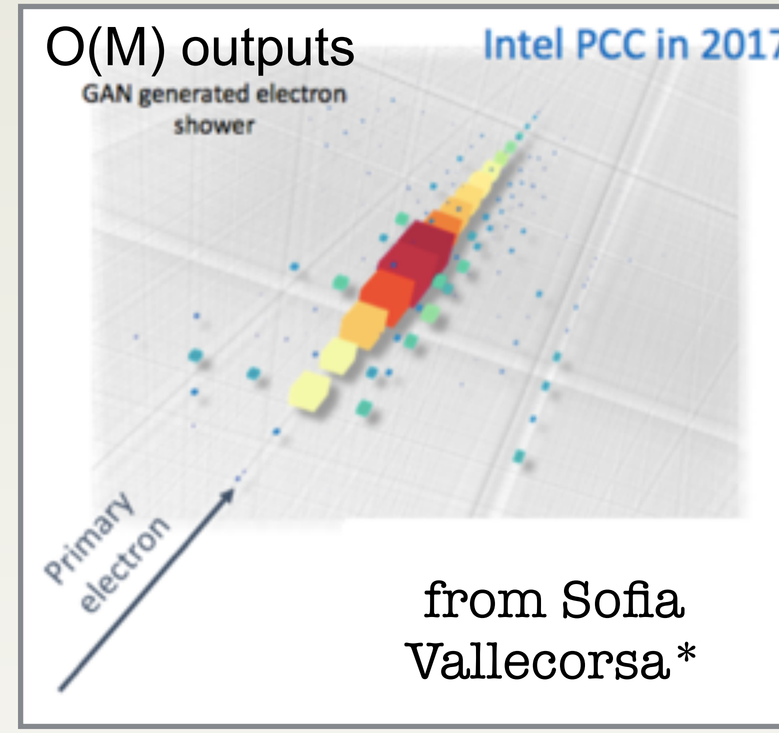
*in Tensorflow



recon-struc-tion



simu-lation (GAN)

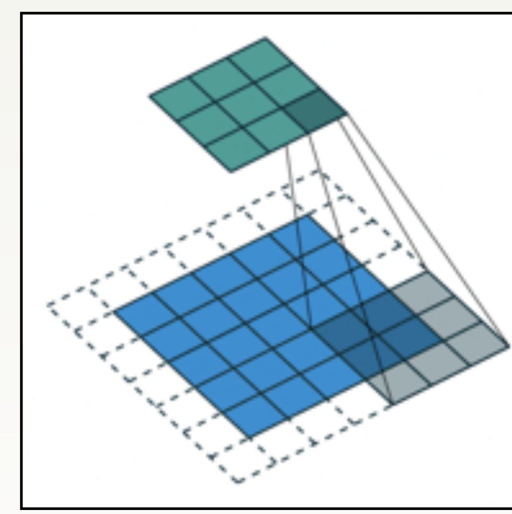


Reconstruction

- 3D Convolutional kernels scan 3D image and identify shower shapes / sum corresponding energies

Fast Simulation (GAN)

- 3D Convolutional kernels generate 3D image and assign energy



➡Both can be way faster than classical methods

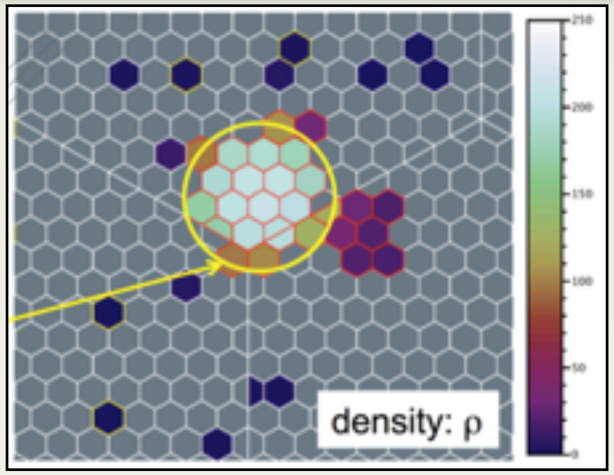
➡Possibility to implement directly in hardware (FPGAs)

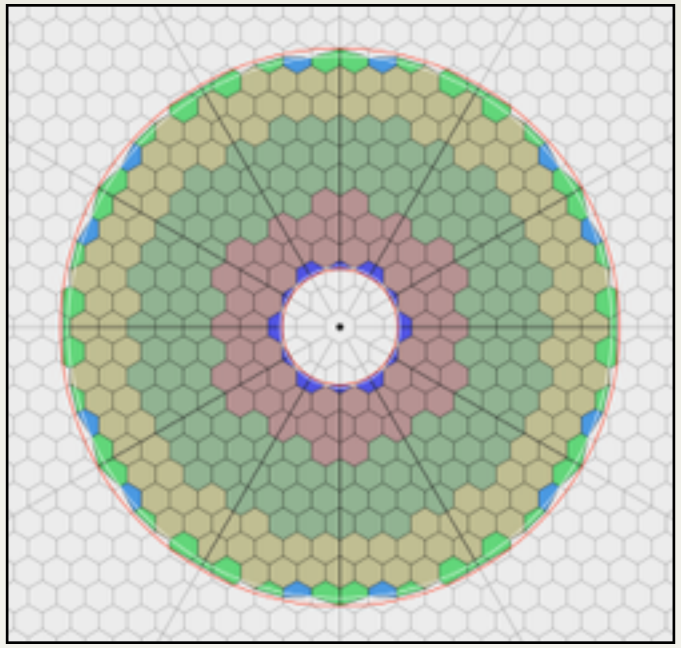
- Trigger applications

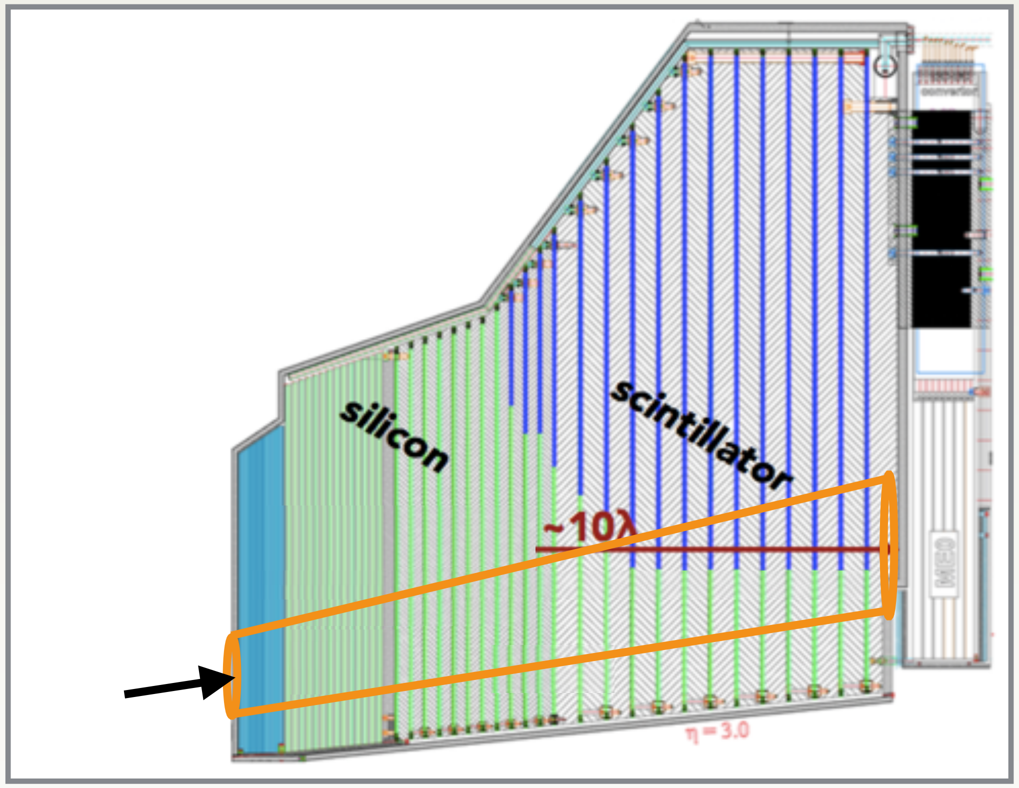
➡Studies have just begun (also other architectures will be investigated)

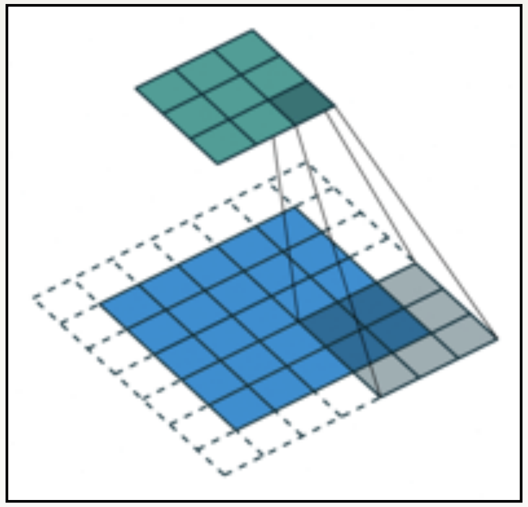
* and more details on simulation https://indico.cern.ch/event/699252/

Map Detector Structure to Neural Network







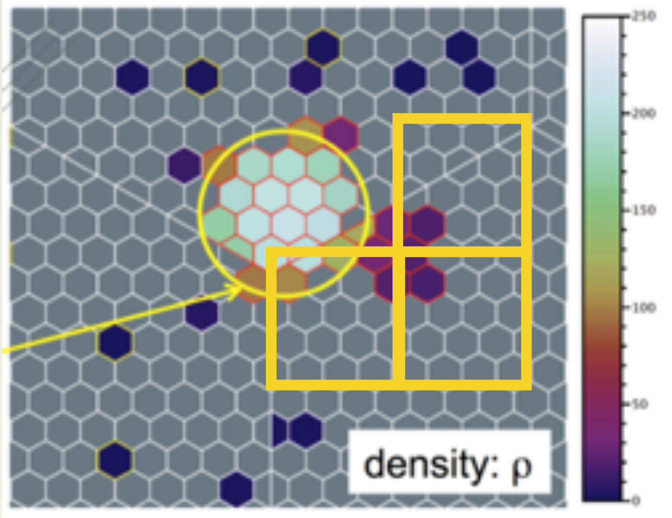


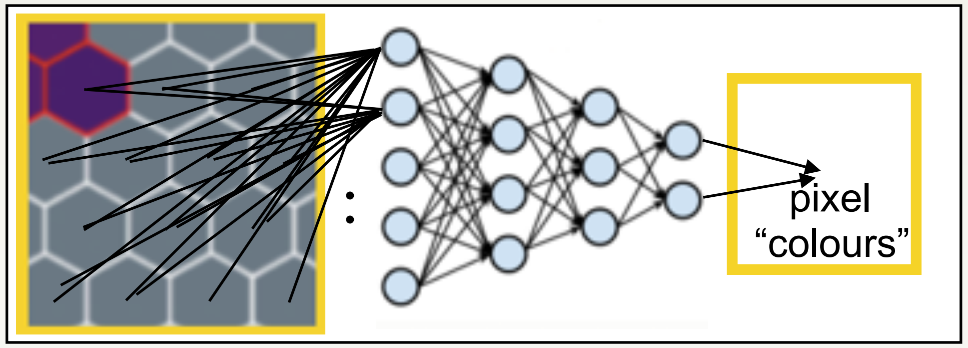
- Sensors hexagonal
- Sensor size/area changes with z,x,y
  - Physics based

- Uniform pixel size in all dimensions

➡Correct representation of the geometry is an issue for **any** non-uniform non-squared sensor design

Mapping of Sensors to Pixels: One Approach





- Chose rather coarse pixelisation

- Per sensor information
  - Position, area within the pixel
  - Energy, ...
- Add per-pixel position information

- Build pixel "colours" with a small dense, translation invariant network

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- Works fairly well (CMS TDR-17-007)
- Not optimal in terms of resources
  - adds huge amount of sparsity
  - increases training time (here about a week on 1080Ti)
- Even less optimal for simulation

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- Solving the mapping/geometry issue in a generic way will be important for future reconstruction techniques (or detector design choices)

Summary / Requirements

- DNNs will become very important for high granularity calorimeters
    - Fast, high performance
- Need input from / collaboration with DNN experts
- GPU resources are THE limiting factor for many studies
- For efficient studies, resources need to be available in a simple way and on-demand